ARTIFICIAL INTELLIGENCE IN RETAIL: THE AI-ENABLED VALUE CHAIN

by

Kim Oosthuizen

Dissertation presented for the degree of Doctor of Business Management

in the Faculty of Economic and Management Sciences

at

Stellenbosch University

Supervisor: Dr Elsamari Botha

Co-supervisor: Prof Martin Butler

April 2021

DECLARATION: PLAGIARISM

By submitting this dissertation electronically, I, **Kim Oosthuizen**, declare that the entirety of the work contained therein is my own, original work, that I am the sole author thereof (save to the extent explicitly otherwise stated), that reproduction and publication thereof by Stellenbosch University will not infringe any third-party rights and that I have not previously in its entirety or in part submitted it for obtaining any qualification. This dissertation includes one original article published in peer-reviewed journals or books and three unpublished publications. The development and writing of the articles (published and unpublished) were the principal responsibility of myself and, for each of the cases where this is not the case, a declaration is included in the dissertation indicating the nature and extent of the contributions of co-authors.

Date: April 2022

ABSTRACT

The competitive landscape is shifting for retailers, and many are scrambling to stay ahead of the competition by investing in new technologies like Artificial Intelligence (AI), automation, robotics and blockchain. Traditional retailers face disruption from competitors that can deliver value to their customers faster through these new technologies. AI, in particular, is earmarked to transform retailing, and its influence on retail is projected to be substantial. However, empirical research on AI in retail remains limited. This study investigates how AI is transforming the retail value chain through a qualitative two-stage research design, using four articles to answer the research question: *How is AI transforming the retail value chain?*

The Leavitt Diamond model and the jobs-to-be-done theory are used to answer the research question. First, this study used all the Leavitt Diamond Model variables (i.e. structure, technology, tasks and people) to examine how AI transforms the retail value chain. The process offered a more comprehensive view of the organisational factors that need to be considered when adopting AI in the retail value chain. Previous research typically focuses on only one of these components.

Articles one and three broadens our understanding of applying jobs theory and outcomes-based innovation in the context of AI in the retail value chain. In article one, the jobs-to-be-done approach was used as a lens to conceptually cluster the jobs AI technologies can perform in the retail value chain. The article conceptually proposed four AI technology dimensions that can fulfil most of the roles in the “traditional” retail value chain. Article one introduced a conceptual framework to understand AI's role in the retail value chain proposing an alternative AI-enabled value chain.

Article two conducted a detailed review of AI's different tasks across the retail value chain. In article three, an outcomes-based approach was used to present a framework of four outcomes for applying AI in the retail value chain and tested the association between the AI outcome and the value chain stage. Therefore, this study proposes the appropriate theoretical lens to understand better the use of AI in the retail value chain. However, it also improves this framework in the final chapter, presenting an adapted conceptual lens. Finally, article four aimed to understand retailers' challenges better when implementing AI, using Leavitt’s Diamond Model.

The overall findings suggest that AI transforms the retail value chain in three ways. First, the iterative nature of AI requires the shape of the retail value chain to change from linear to circular, with data and insight at the core of the successful value chain. Second, AI changes how retailers attain goals in the retail value chain through achieving specific outcomes. The outcomes are dependent on where AI is applied in the retail value chain. Third, there is a complex interplay between structure, technology, people and tasks when implementing AI into the retail value chain, transforming how retailers operate.

This study broadens the understanding of how new technologies impact value chains in general and retail value chains in particular. For retailers to successfully implement AI into their business, they need a clear understanding of how it impacts people, organisational structure, other technology, and organisational tasks. This study created a framework of eight imperatives retailers need to consider when implementing AI, offering a holistic view of the consideration needed across people, structure, tasks and technology to ensure successful integration of AI into the business.

Keywords

AI, Artificial Intelligence, Retail, Value Chain, Digital transformation, Leavitt Diamond Model

ACKNOWLEDGEMENTS

I dedicate this dissertation to my husband, Shaun. Without your support, I would not be here right now. Thank you for constantly pushing me to become a better version of myself and supporting me to pursue my PhD. Your endless support and motivation during late nights, weekends and early mornings helped me get through times when I needed it most. Thank you for listening to all my arguments about AI in retail. I am sure you are over it by now. Thank you for being my biggest supporter.

To my friend Suzanne, thank you for being my cheerleader from afar and continuously checking in on how I am doing and if I need a quick chat. Thank you for also listening to all my rants about AI in retail; being a fellow retailer, you know where I am coming from.

To Elsamari, I am not sure if a simple Thank you is enough; you are my mentor, my friend and inspired me to be a better academic. Thank you for all your insights, recommendations, chats, direction and support through this journey. This dissertation would not be what it is today without your guidance. I learned so much from you, and I am incredibly grateful that you were my supervisor. I hope our relationship continues to grow in the future. As I always tell you, we are going to take over the world.

To Martin, thank you for your assistance during the past year and all the work you have done in the background.

Finally, to the University of Stellenbosch Business School, thank you for supporting me throughout my journey and giving me the opportunity to pursue my PhD.

DECLARATION: LANGUAGE EDITING

9 Arum Close

Durbanville

7550

6 September 2021

Stellenbosch Business School

PO Box 610

Bellville, CAPE TOWN

7530

Dear Sir/Madam,

Declaration of language and technical editing

I, Christelle Woudberg, hereby declare that I have personally read through the research assignment of Kim Oosthuizen and have highlighted language errors. I have also made technical editing changes where applicable.

Yours sincerely

Christelle Woudberg

6 September 2021

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

List of Appendices

ACRONYMS AND ABBREVIATIONS

AI	Artificial intelligence
B2B	Business to business
CAQDAS	Computer-aided qualitative data analysis software
CEO	Chief executive officer
DL	Deep learning
DNN	Deep neural networks
ERP	Enterprise resource planning
IT	Information technology
IoT	Internet of things
ML	Machine learning
PRISMA	Preferred Reporting Items for Systematic Review and Meta-Analysis
QUAN	Quantitative
QUAL	Qualitative
RL	Reinforcement learning
RFID	Radio frequency

LIST OF DEFINITIONS

Artificial intelligence

This study uses Poole and Mackworth (2010: 3) definition of AI as "computational agents that act intelligently". In the simplest sense, AI uses big data, algorithms, and programs to provide a particular goal or output (Paschen et al., 2019, p. 149; Shankar, 2018, p. 6) (see Chapter 2, in particular, Section 2.2.1 for detailed discussion).

AI systems

AI systems refer to computer systems with human-like intelligence (Wierenga, 2010, p. 2), which encompasses these systems' abilities "to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Kaplan & Haenlein, 2019, p. 17).

AI technologies

AI is an umbrella term, and it encompasses various intelligent technologies in different stages of value creation (Sicular et al., 2019, p. 3). Moreover, the term AI encompasses different intelligent technologies under the AI banner (Kaplan & Haenlein, 2019). For example, AI encompasses computer vision, chatbots, machine learning, deep learning, intelligent applications and virtual assistance, to name a few (see Chapter 2, in particular, Section 2.2.3 for detailed discussion).

AI Methods

AI methods refer to AI's various logics to determine the output or its intended goal. The AI methods are classified into three types, namely, "analytical, human-inspired AI and humanized AI"; the method depends on the intelligence the AI exhibits (Kaplan and Haenlein, 2019, pp. 18–20). The role of the various AI methods are to perform specific tasks to solve business problems (see Chapter 2, in particular, Section 2.2.4 for detailed discussion).

Leavitt Diamond Model

In 1965, Harold J Leavitt designed a model to manage change in an organisation. In the model, he indicates that organisations are complex structures of interrelated systems designed for a particular purpose (Boella & van der Torre, 2006; Leavitt, 1965) and subsequently developed the Leavitt Diamond Model. He argues that to compete in an ever-growing volatile environment, organisations can manipulate one of four interrelated sets of variables, task, structural, technological or human variable, to improve performance (see Chapter 2, in particular, Section 2.4 for detailed discussion).

Retail value chain

The term value chain describes a set of activities performed to design, produce, market, deliver and support products within businesses (Porter, 1985). In retailing, the value chain encompasses all the stakeholders and processes needed for retailers to deliver an end product or service to a customer (Hagel et al., 2016, p. 4) (see Chapter 2, in particular, Section 2.3 for a detailed discussion).

Chapter 1: INTRODUCTION

1.1 INTRODUCTION

Digital disruption is a term used when new digital technologies impact the structure and operations of businesses, transforming organisations internal business processes, changing customer interactions to drive experiences, and changing how value is created throughout business models. New technologies disrupt traditional business models by changing marketplaces, bringing new competition and changing the customer purchase journey (Bolton et al., 2019, p. 15; Carlsson, 2018, p. 424; Kietzmann et al., 2018, p. 265). The driving force behind this growth in the digital era is increased computing processing power (Burström et al., 2021, p. 90), mobile connectedness, the vast availability of data (Campbell et al., 2020, p. 2) and cost more effective technology driving the digital era forward at a pace (Lee & Shin, 2020, p. 158). Computing power has increased exponentially in recent years, and the cost of storage continues to decrease, fuelling the digital disruption of various industries (Campbell et al., 2020, p. 2). Examples of industries transformation are the music industry transforming from vinyl to digital, retailers transitioning from brick-and-mortar stores to online platforms, the medical industry using robots for surgery and news agencies moving from article to digital channels. In addition, the rate and pace with which new technologies enter and alter the market have exponentially increased (Brynjolfsson et al., 2013, p. 23; Gupta, 2018, p. 1), and the combinations of these technologies have unpredictable consequences where market boundaries are blurred (Day & Schoemaker, 2019, p. 4). Therefore, the digital era is one of the most significant transformations of society, and it encompasses many elements of business and everyday life (Hagberg et al., 2016, p. 694).

The technologies driving the digital disruption are artificial intelligence (AI), blockchain, big data, augmented reality, the internet of things (IoT), 3D printing and cloud computing (Xu et al., 2018, p. 2944). At the forefront of disrupting technologies is artificial intelligence (AI) (Dwivedi et al., 2021, p. 2). AI can be defined as "computational agents that act intelligently" (Poole & Mackworth, 2017, p. 3). Today, AI plays a significant role in our day-to-day activities, such as unlocking a phone through facial recognition, personalising content on social media and finding the best route to work. In addition, AI systems are changing the business landscape and how businesses operate by (i) approving home loans in banks, (ii) flagging inappropriate comments on news platforms, (iii) predicting how patients will respond to clinical trials in hospitals, (iv) enabling robot and human interaction in factories, (v) helping track items in warehouses, and (vi) managing customer relationships for wholesalers (Daugherty & Wilson, 2018, location. 344; Fountaine et al., 2019, p. 4) to name but a few.

To remain competitive and survive in an ever-changing and diversified customer market, retailers have started adopting new technologies, including various AI-powered solutions. Juniper Research (2019) suggests that retailers spending on AI technologies could reach $12 billion by 2023. Furthermore, major retailers that have invested in the technology are generating economic wins with AI (Guha et al., 2021, p. 28; Weber & Schütte, 2019, p. 272).

AI's influence on retail is projected to be substantial (Guha et al., 2021, p. 28; Kietzmann et al., 2018, p. 265; Shankar, 2018, p. 6) for various reasons. First, there are multiple touch points across the customer shopping journey in retail. This not only diversifies data sources but rapidly generates an enormous amount of data (Lee, 2017, p. 593). AI can provide retailers with insights to reduce shortcomings in data analysis by recognising patterns and providing insights into customer and sales data (Acharya et al., 2018, p. 92; Ameen et al., 2021, p. 1; Gupta, 2018, p. 170). Second, managing customer interaction across retail channels can be complex, and AI can improve customer service by answering customer queries 24 hours a day (Roy et al., 2017, p. 150; Y. Xu et al., 2020, p. 190). Third, overly complex retail value chains generate inefficiencies in operations, and AI can streamline operations through automating manual tasks and reducing costs (Gupta, 2018, p. 21; Manyika & Bughin, 2018; Verhoef et al., 2021, p. 891). Nevertheless, while there is great excitement about AI, it has yet to fully deliver on its promise (Ransbotham et al., 2017, p. 1). Capgemini (2018, p. 16) calculated a $300 billion opportunity for retailers investing in AI. However, only 30% of retailers use AI for some business processes.

Increasingly, academic research has focused on how retailers can benefit from implementing AI, especially for customer usage and experience. Authors Grewal et al. (2017), Hagberg et al. (2016), Jain & Gandhi (2021), and Shankar (2018) broadly discussed the opportunities retailers could experience with artificial intelligence technologies. However, these studies are predominately conceptual. While a few focused on specific applications or use cases of specific AI technologies in retail (Ameen et al., 2021; Esch et al., 2021; Pillai et al., 2020; Pizzi et al., 2021). Although the literature covers a wide variety of research subjects, most of the literature focuses on customer-facing applications of AI and not on the entire retail value chain.

Despite AI being earmarked to transform retail, there is limited empirical research to address the relationship between AI and the retail value chain. Therefore, this study investigates how AI is transforming the retail value chain. The following section discusses the study's background, summarises the literature gap, and articulates the research questions. This is followed by discussing the articles used to investigate the research questions. After that, the research methodology for this study is discussed.

1.2 BACKGROUND OF THE STUDY

This section discussed the disruption in the traditional value chain, AI, and the relationship between AI and the retail value chain.

1.2.1 Disruption in the traditional value chain

In his seminal work, Michael Porter (1998) used the term value chain to describe a set of activities performed to design, produce, market, deliver and support products within businesses (Hagel et al., 2016, p. 4). The value chain is a set of processes that provide value across primary activities (for example, inbound logistics, operations, outbound logistics, marketing and sales, and service) and secondary activities (including firm infrastructure, human resource management, technology development and procurement) (Porter, 1998, Location. 1045). The activities in the traditional value chain move in a sequence of linear steps, which facilitates the process from product design to the point of consumption (Reinartz et al., 2019, p. 352). For example, in retailing, the value chain (see Figure 1.1) encompasses all the stakeholders and processes needed for retailers to deliver an end product or service to a customer (Hagel et al., 2016, p. 4). From supplier to manufacturer to retailer, each stakeholder in the value chain adds value to the customer.

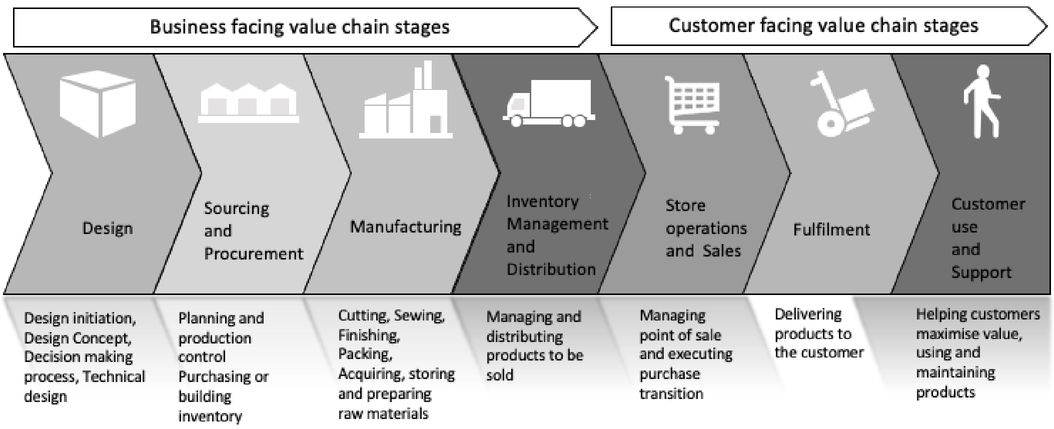


Figure 1.1: The traditional retail value chain

Adapted from (Hagel et al., 2016; Reinartz et al., 2019; Rieple & Singh, 2010)

New technologies are challenging the traditional value chain. For example, there has been a shift away from purely operating in traditional store formats to integrated omni channel environments (Lee, 2017, p. 593). Today, most customer shopping journeys involve a digital channel, making the delineation between physical and digital channels even more blurry and hard to predict. The omnichannel evolution has changed the retail landscape and brought on new competition for traditional retailers who did not need to compete before (Oh & Polidan, 2018, p. 31). The distance between manufacturers and the end customer is decreasing, and new competitors that were once suppliers only are now fighting for the same market share. For instance, Nike now sells directly to customers and connects with them through their digital apps, getting closer to understanding their needs and wants (Barseghian, 2019). Consumers are more connected than ever (Kietzmann et al., 2011, p. 241), and many traditional firms were surpassed by innovative, fast-growing digital entrants (Jin & Shin, 2020, p. 309). New digital technologies have disrupted the traditional retail business model by changing marketplaces from brick and mortar only to omnichannel and significantly altering the customer purchase journey (Bolton et al., 2019, p. 15; Carlsson, 2018, p. 424). Like Alibaba and Amazon, online retailers have adversely affected traditional retailers like Toys R Us and RadioShack. They have used their digital resources to disrupt the retail industry and seemingly unrelated industries, like banking and global shipping (Verhoef et al., 2021, p. 889).

In the hyper-connected business environment, retailers have no choice but to invest in systems and tools to compete with other competitors (Anica-Popa et al., 2021, p. 121). As technology change continues to accelerate, retailers wanting to remain competitive and survive in an ever-changing diversified customer market are looking towards AI to alleviate some of the challenges mentioned above. As a result, AI is earmarked to transform the retail industry (Kietzmann et al., 2018, p. 265), and retailers such as Walmart are using big data, the internet of things (IoT) and Artificial Intelligence (AI) to transform their retailer operations and customer experience (Marr, 2017).

As new digital technologies continue to transform the retail industry (Hagberg et al., 2016, p. 695; Romero & Martínez-Román, 2015, p. 659; van Esch et al., 2019, p. 35), the retail value chain needs to evolve with it (Fiorito et al., 2010, p. 887). However, the majority of retailers still employ the traditional value chain or variations thereof (like the introduction of multiple channels to serve customer needs)—the traditional value chain inherent the following four risks. First, increasing stakeholders adds complexity to the value chain, inhibiting retailers from understanding and swiftly responding to customer demand (Hagel et al. 2016, p. 702). Second, various stakeholders likely use their platforms and software, making it difficult to integrate systems and manage data across the value chain. Third, the more complex and extended the value chain is, the longer it takes for products to reach the customer. Finally, overly complex value chains leave organisations vulnerable to digital disruption from smaller, more agile firms that leverage new technologies to reduce costs and scale up quickly (Gupta, 2018, p. 100; Verhoef et al., 2019, p. 889).

Authors argue that the retail value chain needs revisiting because of new technologies such as AI (Hagel et al., 2016, p. 705; Reinartz et al., 2019, p. 352), yet limited empirical literature are available to guide practitioners on how the retail value chain should change.

1.2.2 Artificial intelligence (AI) in Business

AI dominates conversations (Kaplan & Haenlein, 2020, p. 38; Shankar, 2018, p. 6), and it is changing the world around us (Deloitte, 2021). However, there are many misconceptions about AI's role and its potential and threat to business (Kaplan & Haenlein, 2020, p. 38). This is partly due to movies such as iRobot or the matrix creating unrealistic expectations for the technology. This study uses Poole and Mackworth (2010, p. 3) definition of AI as "computational agents that act intelligently". In the simplest sense, AI uses big data, algorithms, and programs to provide a specific goal or output (Paschen et al., 2019, p. 149; Shankar, 2018, p. 6) (see Chapter 2, in particular, Section 2.2 for detailed discussion). However, all AI that exists today are narrow, meaning the technology can only perform specific tasks and not learn anything from the narrow domain it is programmed to operate in (De Bruyn et al., 2020, p. 92; Yao et al., 2019, p. 19). For instance, AI can be programmed to recognise patterns in big data (De Bruyn et al., 2020, p. 95), provides answers to specific questions (Ameen et al., 2021, p. 4) and personalised product recommendation online (Alexander & Kent, 2021). The AI industry covers a wide range of intelligent applications under the umbrella term AI. For instance, computer vision, deep learning (DL), digital assistants, chatbots, machine learning (ML), natural language processing (NLP), and augmented intelligence, to name a few (see Chapter 2, in particular, Section 2.2.3 for a detailed discussion of what AI is and the applications that it incorporates).

AI, in particular, receives significant attention due to its positive impact on the modern business environment (Cao, 2021, p. 1). AI could provide businesses and customers with numerous opportunities such as improved efficiency, providing shorter lead times (Dogru & Keskin, 2020, p. 72), predicting future trends, processing and interpreting data (Anica-Popa et al., 2021, p. 122), and offering personalised services and products (Riegger et al., 2021, p. 140). However, despite the promise of AI, most AI investments are failing to deliver on their promised returns (Fountaine et al., 2019, p. 4). Numerous scholars have highlighted the benefits of AI (Davenport & Ronanki, 2018; Duan et al., 2019; Dwivedi et al., 2021; Manyika & Bughin, 2018b; Shechtman et al., 2018; Zhang et al., 2021), however transforming a business with AI is not as straightforward (Burström et al., 2021, p. 85).

Businesses need to overcome a few challenges to get the most out of AI investments. For instance, the complexity of understanding and interpreting AI results to use in the business (Barredo Arrieta et al., 2020; Dogru & Keskin, 2020; Jin & Shin, 2020; Lee & Shin, 2020; Preece, 2018), the data and technical infrastructure required to run AI systems (Dwivedi et al., 2021; Kaplan & Haenlein, 2020; Lee, 2017; Lee & Shin, 2020), the impact on the workforce and the new skills required to work alongside AI (Barredo Arrieta et al., 2020; Dogru & Keskin, 2020; Dwivedi et al., 2021; Frey & Osborne, 2017; Kaplan

& Haenlein, 2020; Manyika et al., 2017), and the businesses internal readiness and capability to work with AI systems (Dwivedi et al., 2021; Lee & Shin, 2020). In addition, as AI disseminates into business, it is crucial to understand how to integrate AI into the organisation. Nevertheless, limited research describes what is required to gain total value from AI investments.

1.2.3 AI in the retail value chain

Various scholars agree that the retail landscape is changing due to rapidly evolving technologies such as AI (Alexander & Kent, 2021; Ameen et al., 2021, p. 1; Gauri et al., 2021, p. 42; Grewal et al., 2017, p. 1; Jin & Shin, 2020, p. 301; Pillai et al., 2020; Shankar, 2018; Wadhawan & Seth, 2016, p. 60; Weber & Schütte, 2019, p. 264). AI is touted as one of the critical technologies set to transform both the retail experience and the retailer operating model. Expectations for the commercial application of AI in business, particularly in retailing, are significant (Ransbotham et al., 2017, p. 1). In the retail value chain, in particular, AI can be used to automate processes, reduce complexities, and offer real-time analytics, leading to smaller, agile value chains (Hagel et al., 2016; Oosthuizen et al., 2020, p. 2).

AI represents retailers with various opportunities to evolve and innovate their retail value chain through digitising in-store experience through interactive mirrors (Alexander & Kent, 2021), offering personalised services and product recommendations (Ameen et al., 2021, p. 113), enhancing the customer experience (Gauri et al., 2021, p. 42), automating forecasting activities (Weber & Schütte, 2019, p. 264), recognising patterns and providing insights into customer and sales data (Acharya et al., 2018, p. 95; Ameen et al., 2021, p. 1; Gupta, 2018, p. 19), creating automated checkouts in-store (Pillai et al., 2020, p. 57), providing 24-hour customer service (Roy et al., 2017, p. 257; Y. Xu et al., 2020, p. 2952), collecting, curating and analysing data (Shankar, 2018), and automating manual tasks (Kaplan & Haenlein, 2020, p. 23). Thus, AI presents retailers with various options to improve the consumer experience, enhance profitability and streamline business processes through the value chain. Many authors agree that AI can transform various stages within the retail value chain, yet none have looked at its impact. Therefore, while authors broadly discussed the opportunities retailers could experience with AI technologies (Grewal et al., 2017; Hagberg et al., 2016; Jain & Gandhi, 2021; Shankar, 2018), these studies are predominately conceptual. Other authors focused on specific applications or use cases of specific AI technologies in retail (Ameen et al., 2021; Pillai et al., 2020; Pizzi et al., 2021; van Esch et al., 2021).

While retailers have several opportunities to invest in AI, navigating the AI landscape remains complicated. Various specific use cases are available for retailers, yet many applications focus on single business processes and do not cover multiple aspects of the value chain. While several retailers are pilot testing AI possibilities, navigating the AI landscape remains complicated. Many applications are once-off initiatives within confined business units and do not cover multiple aspects of the retail value chain. Retailers, for example, overlook the collective benefits of AI across the entire retail value chain (Davenport & Ronanki, 2018; Standish & Ganapathy, 2020). Therefore, there is no clear indication of AI's role in the extended retail value chain (Oosthuizen et al., 2020).

1.2.4 Current literature on AI in the retail value chain

To better understand the literature available, research constructs, namely, artificial intelligence or AI; Retail; and Value chain, were investigated. A bibliometric map was created to understand the potential gap in the literature. Bibliometric analysis helps researchers analyse current trends in literature and motivates future research work (Muhuri et al., 2019, p. 218). The bibliometric map was created to understand better the literature available for the research constructs (see Appendix B outlining more detail on the process followed). Figure 1.2 shows the bibliometric map of the author’s keywords found during the identification process for all returned results for AI in retail literature. The keywords are from author-supplied keyword lists (van Eck & Waltman, 2014, p. 4).

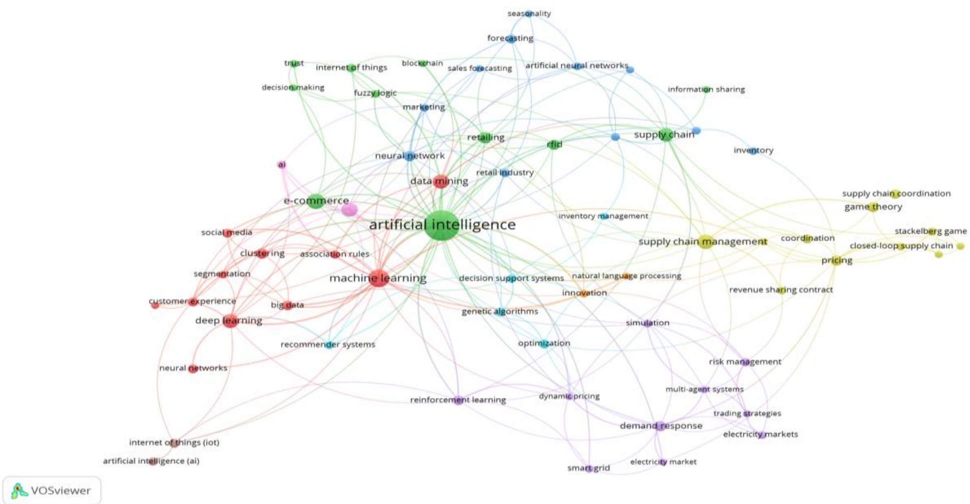


Figure 1.2: Bibliographic map from authors-supplier keywords

The leading studies summarised in Table 1.1 are based on the number of citations dealing with AI in retail (see Appendix A for all the reviewed studies).

Table 1.1: Most influential studies dealing with AI and retail

No	Title	Authors	Citations as of 29 June 21	Theoretical focus	Research Focus	Link to the retail value chain stage	Customer or Business Facing	Link to Leavitt Diamond Model	AI technology mentioned
1	The future of employment: How susceptible are jobs to computerisation?	(Frey & Osborne, 2017)	8403	Occupational choice, Skill demand; Technological change	Changing occupations with computerisation and AI technologies	No link	No link	Technology, People	Computeri sation in general
2	The Future of Retailing	(Grewal et al., 2017)	961	Retail; Future technologies	The article focuses on the future of retail by highlighting five key areas, Technology, Visual display, Consumption and engagement, extensive data collection and analytics	Customer use and support	Customer-facing	Technology	AI in general
3	Siri, Siri, in my hand: Who is the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence	(Kaplan & Haenlein, 2019)	738	Internet of things; Big data; AI	Discussion on AI application	No link	No link	Technology	AI in general
4	The digitalisation of retailing: an exploratory framework	(Hagberg et al., 2016)	478	Retail; Digitalisation	This article addresses a significant and ongoing transformation in retailing and develops a framework	Store operations and sales	Customer-facing	Technology; Tasks	Technology in general
5	A Brief History of Artificial Intelligence: On the Past, Present, and Future of Artificial Intelligence	(Haenlein & Kaplan, 2019)	296	AI; Big data; Strategy	Review of AI history	No link	No link	Technology	AI in general
6	Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy	(Dwivedi et al., 2021),	285	AI, Research agenda	This article focuses on emerging AI challenges and opportunities across a variety of sectors, including retail	Store operations and sales; Customer support and end-use	Customer-facing	Structure, Technology, People and Tasks	AI in general
7	Value co-creation with the Internet of things technology in the retail industry	(Balaji & Roy, 2017)	215	Marketing; retail management	Customers experience shopping with IoT technology	Customer use and support	Customer-facing	Technology	IoT, AI
8	Artificial Intelligence in Advertising How Marketers Can Leverage Artificial Intelligence Along the Consumer Journey	(Kietzmann et al., 2018)	111	AI; Marketing	AI application along the customer journey	Customer use and support	Customer-facing	Technology; Tasks	Multiple AI types

9	How Artificial Intelligence (AI) Is Reshaping Retailing	(Shankar, 2018)	103	AI; Retail	Resents a framework for understanding AI. This article also outlines how AI can be applied in retail.	Link to all stages	Link to all stages	Structure, Technology	AI in general
10	The future of in-store technology	(Grewal et al., 2020)	100	Retail; Future technologies	A conceptual framework for understanding new and futuristic in-store technology infusions	Store operations and sales	Customer-facing	Technology	None
11	The Evolution and Future of Retailing and Retailing Education	(Grewal et al., 2018)	95	Retail, Future Education	The article outlines retail innovations and how retail has evolved. Calls out new retail technologies that should be included in retail education, AI, Service robots, IoT, Blockchain,	No link	No link	Technology	AI in general
12	Applications of artificial intelligence in the apparel industry: a review	(Guo et al., 2011)	84	AI, Apparel industry	Review of AI literature in apparel	Design; Sourcing/ Procurement; Manufacturing and assembly	Business-facing	Technology	Various AI types
13	Rulers of the world, unite! The challenges and opportunities of artificial intelligence	(Kaplan & Haenlein, 2020)	76	AI; Business	Analysis of AI using PESTEL	No link	No link	Economical	AI in general
14	A human-centric perspective exploring the readiness towards smart warehousing: The case of a large retail distribution warehouse	Mahroof, 2019)	68	Artificial Intelligence, Logistics; Technical readiness	The research explores the barriers and opportunities of AI within the warehouse of a major retailer.	Inventory Management and Distribution	Business-facing	People; Technology; Tasks	AI in general
15	Artificial intelligence (AI) and its implications for market knowledge in B2B marketing	(Paschen et al., 2019)	67	Marketing; AI	describes the foundational building blocks of any artificial intelligence system and their interrelationships	No link	No link	Technology	AI in general
16	A GA-based optimisation model for big data analytics supporting anticipatory shipping in Retail 4.0	(Lee, 2017)	57	Retail, Big data	Optimisation model using Big data to support anticipatory shipping	Fulfilment	Customer-facing	Technology	Genetic Algorithm (GA)-based optimisatio n mode
17	Artificial intelligence: Building blocks and an innovation typology	(Paschen et al., 2019)	51	AI, Information systems	AI building blocks	No link	No link	Technology	Multiple AI types
18	Autonomous Shopping Systems: Identifying and Overcoming Barriers to Consumer Adoption	de Bellis & Venkataramani Johar, 2020)	46	Artificial Intelligence; Consumers; Retail	Examining the barriers to adoption of autonomous systems	Store operations and sales; Customer support and end-use	Customer-facing	People; Technology; Tasks	Virtual assistants

19	State-of-the-art and adoption of artificial intelligence in retailing	(Weber & Schütte, 2019)	32	Artificial Intelligence; Retail	The article shows the application of AI to different value-added core tasks depending on the area you apply it to	Link to all stages	Link to all stages	Tasks	AI in general
20	Indian shopper motivation to use artificial intelligence: Generating Vroom's expectancy theory of motivation using grounded theory approach	(Chopra, 2019)	29	Artificial intelligence; Consumer motivation; Retail	The findings indicate that Vroom's expectancy theory of motivation can explain young consumers' motivation to use AI tools to aid in making shopping decisions.	Store operations and sales; Customer support and end-use	Customer-facing	Technology, People	Chatbot, Augmented reality, Voice assistant
21	Shopping intention at AI-powered automated retail stores (AIPARS)	(Pillai et al., 2020)	24	Technology readiness; Consumers; Retail	The study's outcome reveals that Innovativeness and Optimism of consumers affect the perceived ease and usefulness.	Store operations and sales; Customer support and end-use	Customer-facing	Technology, People	RFID, AR systems
22	Changing the game to compete: Innovations in the fashion retail industry from the disruptive business model	(Jin & Shin, 2020)	23	Business innovation disrupting the fashion retail industry	The study analyses how business-model innovations have disrupted the fashion retail industry	Inventory Management and Distribution	Business-facing	Technology	AI in general
23	Taking the fiction out of science fiction: (Self-aware) robots and what they mean for society, retailers and marketers	(Gonzalez-Jimenez, 2018)	22	Artificial Intelligence; Consumer; Retail	The article outlines examples of how human-robot interactions can be shaped with AI	No link	No link	People/Environment	AI; Robots
24	Rising with the machines: A sociotechnical framework for bringing artificial intelligence into the organisation	(Makarius et al., 2020)	21	Artificial Intelligence; Organisational socialisation; Sociotechnical	Organisational socialisation approach to build an understanding of integrating AI into the organisation.	No link	No link	All	AI in general
25	Chatbots in retailers' customer communication: How to measure their acceptance?	(Rese et al., 2020)	20	Artificial Intelligence; Consumers Acceptance	The study measured the customer acceptance of a chatbot at an online retailer	Customer use and support	Customer-facing	Technology, People	Chatbots

The current research focused on providing theoretical contributions in exploring the relationships between AI and digital marketing (Kietzmann et al., 2018; Mogaji et al., 2020), advancing knowledge on AI-enabled customer experiences and service (Ameen et al., 2021; Balaji & Roy, 2017; Pillai et al., 2020), researching customer adoption of AI-enabled technologies (Chen et al., 2021; Jain & Gandhi, 2021; Pitardi & Marriott, 2021; Pizzi et al., 2021; Rese et al., 2020), and consumer patronage towards AI-enabled checkouts (van Esch et al., 2021). A literature review showed that most of the research in AI in retail-focused on customer-facing value chain stages (see Figure 1.3).

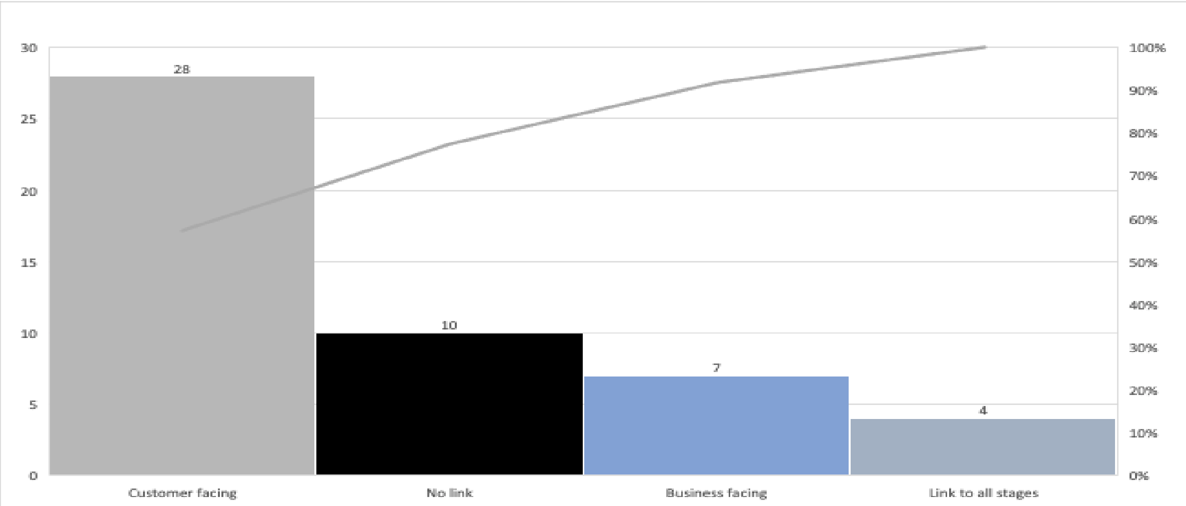


Figure 1.3: Count of reviewed AI in retail literature: Customer vs Business-facing

The difference between customer-facing value chain stages (i.e., the store operations and sales, customer support and end-user) and business-facing value chain stages (i.e., design, sourcing/procurement, manufacturing and assembly, inventory management and distribution, and fulfilment) are that customer-facing stages serve customers and business-facing serve the internal business environment. The customer-facing stages, for example, are the AI technologies used to support customers and the sales process, the store checkout process, in-store customer experience management, payments process, personalisation or product recommendations, and customer service. The business-facing value chain stages, for example, are all the AI technologies used to procure, manage, and move products to the customer. Most studies present the customer-facing value chain stages examining how retailers could enhance customer service and shopping experience through different applications of AI technologies. However, few studies focused on the role of AI in the earlier stages of the value chain (e.g., manufacturing), and none on the role of AI across the whole value chain. This is a gap in current literature that this study aims to fill.

In the customer-facing value chain stages, authors argued that AI could (i) improve customer experience and satisfaction (Ameen et al., 2021; Chen et al., 2021; Jain & Gandhi, 2021; Tupikovskaja-Omovie & Tyler, 2020), (ii) enhance customer service (Rese et al., 2020), (iii) aid shopping decisions for consumers through AI-enabled application (Chopra, 2019; Pizzi et al., 2021; van Esch et al., 2021), (iv) change the consumers' shopping behaviour by using autonomous shopping (de Bellis & Johar, 2020), connected devices (Balaji & Roy, 2017), and AI-enabled mobile applications (Stanciu & Rîndașu, 2021). There are multiple roles for AI to improve the customer-facing value chain stages. While improving the customer experience can render financial benefits and improve customer satisfaction for retailers, it is essential to address how AI can also benefit the business-facing value chain stages.

The literature review revealed few studies that focused on business-facing value chain stages. For example, procurement of products, demand planning, inventory management, distribution and logistics, and order placement. Some authors argued that using AI models to simulate various inventory processes could improve inventory management in retail by (i) reducing product out of stocks (Bottani et al., 2019), (ii) creating a more accurate demand forecast (Priyadarshi et al., 2019), (iii) generating anticipatory shipping plans (Lee, 2017), and (iv) determining the best merchandise locations to allocate inventory (Cruz-Domínguez & Santos-Mayorga, 2016). While studies on business-facing value chain stages can help retailers apply specific use cases of AI, it is essential to address how AI can create value in the entire retail value chain.

Few studies focus on the value and benefits AI could create for retailers that have a possible link to all of the value chain stages. Weber and Schütte (2019) argued that applying AI to value-added core retail processes depends on the technology's function areas. Shankar (2018) focused on the possible application of AI to different dimensions of retail. However, they noted that more research is required in this domain, and Cao (2021) study focuses on the strategic choices retailers should consider for AI-related data management. While some scholars have indicated AI applications in various retail value chain stages (Cao, 2021; Grewal et al., 2017; Kaur et al., 2020; Schmitt, 2020; Shankar, 2018; Weber & Schütte, 2019), it is unclear to ascertain from the literature the relationship between AI and the retail value chain.

In summary, when comparing the studies to the possible link to the retail value chain, most authors focused on specific use cases of AI in the customer-facing value chain stages rather than the entire retail value chain. It is essential to address how AI will change and transform the retail value chain. However, it is yet to be clarified. Jin and Shin (2020) argued that traditional retail business models face disruption from retailers that offer more innovative business models, and retailers need to do more than only implement new technologies. No studies have looked at AI across the retail value chain to the author's knowledge. Therefore, our primary or overall research question for this study is:

How is AI transforming the retail value chain?

This research question is the primary question of this study and guides the development of the subsequent research questions for the articles. This study broadens our understanding of how new technologies impact value chains in general and retail value chains in particular.

To remain competitive and survive in an ever-changing and diversified customer market, retailers have started adopting various AI-powered solutions. AI can significantly improve speed, cost, and flexibility across the retail value chain (Liang et al., 2020, p. 4). Major retailers (i.e., Walmart, Home Depot and Amazon) that have invested in AI are generating economic wins with AI by reinventing design, merchandising, marketing and customer service (Kaplan, 2020; Liang et al., 2020, p. 4; Weber & Schütte, 2019, p. 272). Nevertheless, no studies have investigated how AI transforms the retail value chain. The following sections detail the literature to ascertain how AI changes the retail value chain.

1.2.4.1 How is AI transforming the retail value chain?

An early study by Guo et al. (2011) suggested that AI algorithms such as fuzzy logic, neural networks, and generic algorithms could aid various retail processes and emphasises that future research is required on the topic. A review of the literature revealed that many authors discussed AI influence on retail as a technology in general without focusing on the specific application of the technology (Anica-Popa et al., 2021; Dwivedi et al., 2021; Jain & Gandhi, 2021; Jin & Shin, 2020; Mahroof, 2019; Makarius et al., 2020). Current research discussing a specific AI technology type, i.e., chatbots, focused on applying the technology to enhance the customer shopping experience. The authors highlighted various AI aiding retail such as chatbots (Chen et al., 2021; Pizzi et al., 2021), virtual assistants (de Bellis & Venkataramani Johar, 2020), voice assistants (Purcărea et al., 2021), internet of things (IoT) (Balaji & Roy, 2017; Chan et al., 2020), deep neural networks (DNN) (Bottani et al., 2019; Cruz-Domínguez & Santos-Mayorga, 2016; Priyadarshi et al., 2019), Machine Learning (ML) (Rodgers et al., 2021; Stanciu & Rîndașu, 2021), robots (Gonzalez-Jimenez, 2018; Guha et al., 2021) and radio frequency identification (RFID) (Pillai et al., 2020). The literature highlights specific AI types to improve areas in the retail value chain; however, no studies assessed the various types of AI's role in the retail value chain.

AI encompasses many different intelligent technologies and can serve multiple purposes across the retail value chain. However, many AI applications, already available or under development, contribute to retailers' confusion and frustration regarding which AI technologies to invest in. While authors argue that the retail value chain needs revisiting because of new technologies (Hagel et al., 2016; Reinartz et al., 2019), limited empirical literature, to the author's knowledge, have suggested what the role of AI is in the retail value chain and how the retail value chain should change. Therefore, it is essential to understand where AI applications can improve efficiencies, automate processes, and drive insights in the retail value chain. However, it is yet to be clarified. Therefore, to assess the potential application of AI-enabled solutions across the various retail value chain activities, research question one was developed:

Research question 1: What role does AI play in the retail value chain?

It is essential to understand AI's role in the retail value chain and the different tasks AI can perform across the retail value chain. Therefore, research question two was developed:

Research question 2: What are retailers using AI technologies for in the retail value chain?

In the same way, before retailers invest in AI, they need to understand the potential benefits from the investment to maximize a positive business outcome. Various authors discussed the benefits of AI (Adapa et al., 2020; Ameen et al., 2021; Dogru & Keskin, 2020; Manyika et al., 2017; Shechtman et al., 2018). For instance, Dogru and Keskin (2020) noted that AI improves productivity in operations through robotics and Manyika et al. (2017) noted that AI enhances employees productively through automating manual tasks. While, Shechtman et al. (2018), Adapa et al. (2020), and Ameen et al. (2021) noted that AI Improves the way employees interact with customers and improves customer satisfaction. Although there are many benefits AI can provide retailers, a further benefit is garnered through understanding business outcomes (Zolkiewski et al., 2017, p. 174). However, the outcomes of applying AI in the retail value chain is unfamiliar, leading to the development of research question three:

Research question 3: What business outcomes can AI drive in the retail value chain?

Despite AI being earmarked to transform retail, there is limited research into how to integrate the technology into the value chain. Authors Stanciu and Rîndașu (2021), Anica-Popa et al., (2021), and Purcărea et al. (2021) all discussed AI challenges from a customer shopping perspective. The authors discussed some barriers to adopting AI in retail throughout the literature. Authors noted users acceptance of AI systems to be necessary for the adoption of the technology in retail (Pitardi & Marriott, 2021; Rese et al., 2020; van Esch et al., 2021), and Mahroof (2019) argued the challenges for adopting AI by warehouse staff are caused by a shortage of skills and their mindset to change. In contrast, de Bellis and Johan (2020) argued that customers' culture or psychology barriers hinder adopting autonomous shopping systems in a retail environment. While understanding the user acceptance challenges can assist with the customer adoption of AI applications in retail, it is only one element of the overall adoption of AI in retail.

Multiple authors argued that a significant challenge for adopting AI is the technologies impact on retail jobs (Adapa et al., 2020; Ammanath et al., 2020; Begley et al., 2018; Dogru & Keskin, 2020; Dwivedi et al., 2021; Kaplan & Haenlein, 2020). In comparison, Kaplan and Haenlein (2020)and Sohn et al. (2020) argue that jobs will need to evolve to work with AI models and systems. Nevertheless, the change in roles will require a change in how retailers operate. For example, Kaur et al. (2020) argued that organisations are not embracing new ways of doing business or changing business processes as a challenge for successfully adopting technology. Similarly, Shankar (2018) argued that it is also crucial for retailers to understand when and how AI will benefit their customers and business rather than blindly applying it to siloed processes.

There seems to be a challenge with implementing and adopting AI into the retail value chain. However, there is limited research regarding AI's adoption challenges or implementation challenges into the retail value chain. While authors note some challenges for adopting AI in retailers, these often come from managerial recommendations and future research suggestions. Very few studies research the challenges empirically. Many challenges come with implementing and adopting AI into the retail value chain. However, it is yet to be clarified by scholars. For retailers to successfully integrate AI into the retail value chain, it is vital to understand the challenges retailers experience when implementing AI into their business. Therefore, research question 4 was developed.

Research question 4: What are the challenges retailers experience when integrating AI into their value chain?

Recently there has been a growing body of knowledge for AI in retail literature, especially particular AI technology itself. The following section investigates which theoretical approaches these studies used.

1.2.4.2 Theoretical approaches to examine adopting AI in the retail value chain

Multiple models, theories, and frameworks are available to delineate technology and organisational acceptance. For instance, the technology acceptance model (TAM) field and the unified theory of acceptance (Davis, 1985) and use of technology (UTAUT) is a widely accepted model for examining user acceptance and adoption in the Information Systems (IS) (Mahroof, 2019, p. 181; Pitardi &

Marriott, 2021, p. 628). AI in retail studies by Chen et al. (2021) and Liang et al. (2020) examined customer acceptance of AI chatbots and AI-enabled shopping assistants by applying TAM as a theoretical lens. Loske and Klumpp (2021) applied UTAUT as a theoretical lens to test truck drivers' use of AI technologies. Although these models are widely recognised, it was less relevant for this study to examine AI’s influence in retail and business, as successfully implementing AI requires more than only adopting the technology.

A model that represents the entire organisation is the Leavitt Diamond Model (Leavitt, 1965). Leavitt (1965) notes that when organisations change any task, technology, structure or people variable, it results in compensatory changes in one or more of the other variables. This study uses the Leavitt Diamond Model to examine how AI transforms the value chain as a theoretical lens to investigate the subsequent research questions. The Leavitt Diamond Model is an important model to explore the impacts of organisational change by considering the interrelated social (i.e., human and structure) and technical (i.e., tasks and technology) variables (Hartmann & Lussier, 2020; Leavitt, 1965). Various scholars have used Leavitt’s model to examine a variety of organisational change topics applying it in numerous contexts, including the COVID pandemic shock on B2B organisations (Hartmann & Lussier, 2020), to information systems in the Organisational environment (Lyytinen & Newman, 2008), management challenges associated with analytics (Vidgen et al., 2017), marketing and supply chain management (Jüttner et al., 2007), and the use of information technology and the effectiveness of human resource function(Haines & Lafleur, 2008).

Multiple studies in AI in retail literature only focus on technology variable of the Leavitt Diamond Model (Balaji & Roy, 2017; Bottani et al., 2019; Grewal et al., 2017, 2020; Guo et al., 2011; Jin & Shin, 2020; C. K. H. Lee, 2017; Wadhawan & Seth, 2016), which is a limitation in research. All variables, especially people, should be considered when integrating AI or any digital projects into retail. Therefore, this study uses all the variables (structure, technology, people and tasks) in the Leavitt Diamond Model to access AI in the retail value chain. To the author's knowledge, no other studies have used the Leavitt Diamond Model in the context of AI in the retail value chain before. Understanding the complexities of integrating AI successfully is critical to retail theory and practice.

1.3 SUMMARY OF RESEARCH QUESTIONS

The primary and overarching research question for this study is:

How is AI transforming the retail value chain?

It is evident that AI plays a role in transforming the retail value chain; hence the following research questions are proposed:

- Research question 1: what role does AI play in the retail value chain?
- Research question 2: What are retailers using AI technologies for in the retail value chain?
- Research question 3: What business outcomes can AI drive in the retail value chain?
- Research question 4: What are the challenges retailers experience when integrating AI into their value chain?

These research questions are investigated through the lens of the Leavitt Diamond Model, which considers the impact of the technology on the organisation and how the technology impacts people, processes/tasks, and the organisational infrastructure. The remainder of this chapter focuses on the individual articles used to answer the respective research questions, followed by the research methodology used for this study.

1.4 LAYOUT OF THE INDIVIDUAL ARTICLES

Four articles were developed to answer the research questions to understand the primary research question. Figure 1.4 outlines the articles and the research question associated with each article.

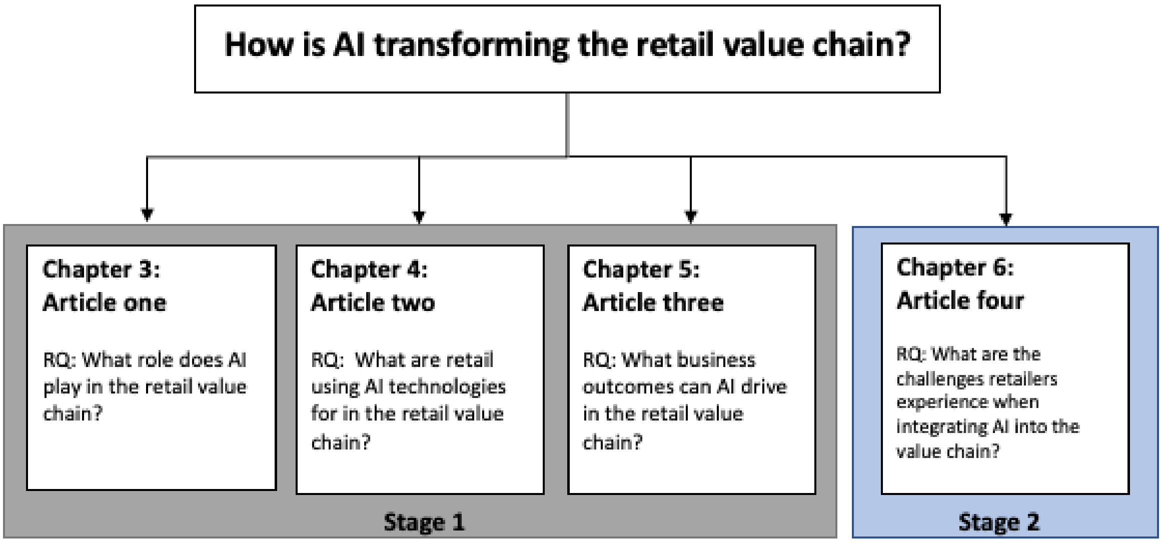


Figure 1.4: Article layout and research questions

Four articles investigate how AI transforms the retail value chain. Each article links back to the components of the Leavitt Diamond Model variables, i.e., structure, people, technology and tasks. First, article one investigates AI in the retail value chain, linking to the structure variable in the Leavitt Diamond Model. Second, article two investigates the tasks variable in the Leavitt Diamond Model by examining how AI technologies are used in the value chain. Third, article three investigates the outcomes obtained with AI by focusing on the technology variable in the Leavitt Diamond Model. Last, article four investigates the challenges for implementing AI across all Leavitt Diamond Model variables. The following sections details how each article was used to address their relevant research questions.

1.4.1 Article one: Artificial intelligence in retail: The AI-enabled value chain

Article one introduced a conceptual framework to understand AI's role in the retail value chain proposing (Assarroudi et al., 2018; Burkett, 2013; Moher et al., 2009; O'Reilly, 2009; Parida et al., 2015; Snyder, 2019; Vargo & Akaka, 2009; Vargo & Lusch, 2004) an alternative: the AI-enabled value chain. Research question 1 asks *what role does AI play in the retail value chain*. All the AI activities in the retail value chain were classified using a jobs-to-be-done approach into four categories: knowledge and insight management, inventory management, operations optimisation and customer engagement, to answer the research question.

The article illustrates that some AI technologies can serve multiple purposes across the retail value chain. The article shows that retailers apply AI technologies across the different value chain stages and proposes an AI-enabled value chain. Therefore, an AI-enabled retail value chain moves away from a linear and siloed approach to the value chain to a real-time iterative approach based on knowledge management. Using this framework, retailers can prioritise their investment in AI or diversify their current application of AI across the value chain.

This article provides two essential contributions to the emerging literature on AI and its implementation in marketing and retailing. First, we show how AI technologies can be used across various retail value chain activities. While several authors have addressed the relevance of AI to business in general (Kietzmann et al., 2018; J. Paschen et al., 2019; Poole & Mackworth, 2017; Ransbotham et al., 2017), the strategic role and implementation of AI in retailing organisations have been subject to limited critical scrutiny (van Esch et al., 2019). Furthermore, by mapping specific AI technologies against the retail value chain, we provide retail managers with some guidance regarding which AI technology investments to prioritise or how to leverage current AI investments.

Second, while authors argue that the retail value chain needs revisiting because of new technologies (Hagel et al., 2016; Reinartz et al., 2019), limited empirical literature, to the author's knowledge, have suggested precisely how the retail value chain should change. Guided by the job-to-be-done approach in innovation (Christensen et al., 2016), we identify four key roles for AI solutions in the retail value chain: knowledge and insight management, inventory management, operations optimisation, and customer engagement. This approach is customer-centric (Bettencourt & Ulwick, 2008), not tayloristic and process-driven and, therefore, better suited to the complex nature of business amidst new technologies (McChrystal et al., 2015). Contrary to the more traditional silo-mentality and linear view of the value chain, we argue that AI solutions can perform multiple roles simultaneously, thus establishing interconnectivity between the different value chain activities.

1.4.2 Article two: Artificial intelligence in retail: Simplifying tasks by using AI in the retail value chain

Following an improved understanding of AI's role in the retail value chain, the following article attempts to understand research question two, *what retailers are using AI technologies for in the retail value chain*. We reviewed retailers currently using AI in the value chain using a content analysis approach to answer the research question.

This article illustrates a detailed review of AI's different tasks across the retail value chain. However, when retail tasks are replaced with AI, it has a necessary knock-on effect on the people and structure, creating business implications for retail managers. Understanding the tasks AI can perform will help retailers' leaders focus the technology on specific business problems the technology can solve. Through AI, simplifying the value chain can help retailers create value, automate, and streamline relationships between people, processes, and technology.

This article contributes to the emerging literature on AI and its application in retail. Guided by the Leavitt Diamond Model, focusing on the *dimension of the task* of the model (Leavitt & Bahrami, 1989), we identify the tasks AI can perform across the retail value chain. Current research focuses on specific applications of AI in retail (Ameen et al., 2021; Pillai et al., 2020; Pizzi et al., 2021; van Esch et al., 2021) and limited empirical literature to the author's knowledge have suggested and outlined the different tasks AI can perform across the whole retail value chain. This comprehensive view of the role of AI across the value chain will increase the ROI of the technology as it extends its use beyond isolated siloed use cases. One of the main reasons current AI applications fail is their narrow applications within a business (Davenport & Ronanki, 2018; Standish & Ganapathy, 2020).

Building on the insights gained on articles one and two. Article three investigates the business outcomes of applying AI in the retail value chain.

1.4.3 Article three: Applying service-dominant logic to artificial intelligence investment in retail: The outcome of an AI-enabled value chain

Before retailers invest in AI, they need to understand the potential benefits from the investment to maximize a positive business outcome. However, investment in AI has primarily been made from a product-dominant, input-output perspective (Vargo & Akaka, 2009, p. 32). Article three aimed to answer research question 3 *what business outcomes can AI drive for retailers.* This article used a content analysis approach to understand the outcomes of applying AI in the retail value chain.

This article applies service-dominant logic (Vargo & Lusch, 2004) to present the business value of AI in the retail value chain. Four key outcomes AI can deliver in the retail value chain: cost-saving and efficiency, enabling revenue, customer experience improvements, and improved decision-making. Insights on the relationship between benefits and retail value chain stages were presented, and the association between the application of AI and its outcomes.

Article three contributes to the emerging literature on AI by first providing a comprehensive view of AI technologies deployed across the retail value chain by major retailers. Second, using service-dominant logic shows how retailers can use AI to attain their business goals using an outcomes-based approach. Finally, insight is provided into how these outcomes relate to where AI is applied in the retail value chain, helping retailers identify where best to apply AI to attain specific outcomes.

Article four focuses on challenges retailers experience when integrating AI into their business.

1.4.4 Article four: Artificial intelligence in retail: The challenges retailers experience when integrating AI into their business

No other new technologies have garnered more attention than AI, and companies are scrambling to adopt the technology (Rimol, 2020). Similarly, a majority of retailers have started to implement AI into their organisations. However, many AI projects fail to realize the intended benefits or remain once-off proof of concepts. This article aims to understand the challenges retailers experience when implementing AI, using Leavitt's Diamond Model (Leavitt, 1965). The Leavitt Diamond Model considers not only the technology for understanding organisational challenges but also the people, tasks, and structure necessary for its successful integration of AI.

Article four aimed to answer research question 4: *What are the challenges retailers experience when integrating AI into their value chain?*. To understand the challenges retailers experience when integrating AI, semi-structured interviews were conducted with twenty experts working or implementing AI in retail. To ensure a rounded view of the challenges, the participants were from various backgrounds; seven AI/technology platform experts, eight retailer participants from various international retailers (who have implemented AI) and five business consultants working with AI in retail.

Article four contributes to the emerging literature on AI by first providing a structure, tasks, technology, and people review of the literature concerning the challenges retailers experience when implementing AI. Further, the Leavitt Diamond Model is applied to classify this research according to whether the mentioned challenges concern people, tasks, structures, or AI itself. Current research typically looks at only one of these aspects of AI integration in retail, rendering an incomplete view of the challenges associated with implementing AI in retail. Therefore, the second contribution of this article was to provide a comprehensive look at the challenges presented by implementing AI. Better understanding all the possible tasks, structures, technology, and people-related challenges associated with implementing AI provides retailers with a better chance of integrating the technology successfully. Finally, we provide recommendations for retailers regarding how to increase their chances of successfully implementing AI.

1.5 RESEARCH METHODOLOGY

To remain competitive and survive in an ever-changing and diversified customer market, retailers need to become leaner (Campbell et al., 2020), more agile (Goworek, 2014), and innovate their value chain by adopting AI (Lee et al., 2018). Nevertheless, while there is great excitement about AI, it has yet to fully deliver its promise (Ransbotham et al., 2017). In addition, section 1.1.3 showed limited empirical research focusing on AI in the retail context, specifically with regards to how it transforms the retail value chain. Therefore, this study followed an exploratory research design. Exploratory research is concerned with discovering, generating or building theory (Davies, 2011) and endeavours to clarify or discover potential business opportunities (Zikmund, 2010, p. 54). Exploratory research is conducted in the early stage of decision making and follows an unstructured approach. When looking into specific research methodology textbooks, the exploratory design is the most appropriate selection to investigate this study's research questions (Creswell, 2012; Zikmund, 2010). This approach reflects that of other researchers in this field. Table 1.2 considers previous empirical research focused on AI and summarises the research design and method used.

Similar studies focusing on AI in retail (Table 1.2) used exploratory research to generate theory and clarify business opportunities (Zikmund, 2010, p. 54). Exploratory research was used by similar qualitative studies discovering AI across retail (Alexander & Kent, 2021; Ameen et al., 2021; Balaji & Roy, 2017).

Table 1.2: Similar research previously conducted

Title	Authors	Research design	Research method
Customer experiences in the age of artificial intelligence	(Ameen et al., 2021)	Exploratory research	Quantitative/Online survey
Tracking technology diffusion in- store: a fashion retail perspective	(Alexander & Kent, 2021)	Exploratory research	Qualitative/direct observation
Value co-creation with the Internet of things technology in the retail industry	(Balaji & Roy, 2017)	Exploratory research	Quantitative/ Questionnaire
Constituents and consequences of smart customer experience in retailing	(S. K. Roy et al., 2017)	Exploratory research	Multi-phased research approach
The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI	(Shin, 2021)	Exploratory research	Quantitative/ Survey
Cobots in knowledge work Human – AI collaboration in managerial professions	(Sowa et al., 2021)	Exploratory research	Qualitative/Semi-structured interviews
Marketing AI recruitment: The next phase in job application and selection	(van Esch et al., 2019)	Exploratory research	Quantitative/ Survey

Consequently, this study followed suit and used an exploratory research design for this study (Thyer, 2010; Zikmund, 2010). The research design for this study is discussed in the following section.

1.5.1 Research design

This study used a two-stage research design for the development of each article. Two-stage research designs entail “the application of two or more sources of data or research methods to the investigation of a research question or different but highly linked research questions” (Bryman, 2004, p. 678). Due to the limited empirical literature available, the two-stage design is deemed most appropriate for the following reasons. First, this approach addresses different sub-topics sequentially using qualitative and quantitative approaches to provide a complete understanding of a phenomenon (DeCuir-Gunby & Schutz, 2017, p. 92). Second, the two-stage design allows the researcher to investigate a phenomenon from a macro perspective to gain insights (Sowa et al., 2021). Third, by using a two-stage design, the process can uncover “diverse perspectives, to better understand a phenomenon or process that is changing as a result of being studied” (Creswell, 2014, p. 213). Fourth, the initial stage (either quantitative or qualitative), followed by a second stage (either qualitative or quantitative), builds on the earlier stage; in other words, the data collection approach informs the findings from one stage to another (Creswell, 2014, p. 212). Therefore, the two-stage design suited this study well as it used two separate phases to address the various research questions, the findings from the first stage of the research informing the design of the second stage. Figure 1.5 outlines a summary diagram of the two-stage design for the process followed for this study.

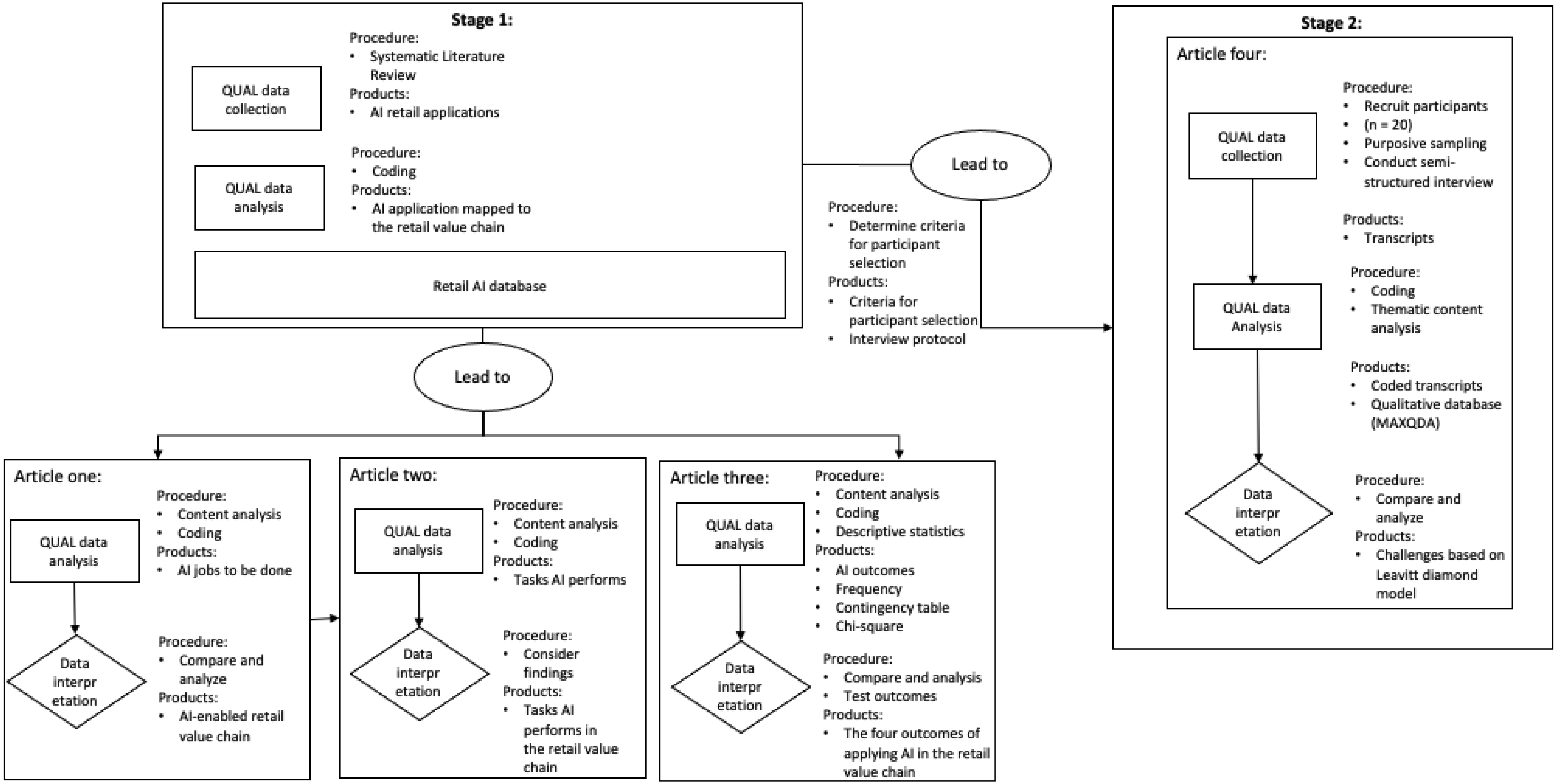


Figure 1.5: Two-stage design for this study

1.5.1.1 Stage one: data collection

To identify relevant scientific journal articles that have dealt with the application of AI in retail, a search was conducted on a major database, namely EBSCOhost, to collect and identify secondary data for this study. The database was suitable as it included reputable resources from multiple sources, including academic journals, news, magazines, trade publications, and reports. Furthermore, typical to integrative literature reviews, in addition to academic articles, other published texts such as company press releases and news articles were included in the analysis (Snyder, 2019, p. 336). Boolean logic was used to include or exclude search terms to identify articles available on the databases. Table 1.3 depicts how the search process prescribed by Moher *et al.* (2009) was followed.

Table 1.3: Application of the PRISMA process for systematic review

Stage	Process	Checklist item	Process
1	Identification	Identify the articles via keyword search (n =4304)	"Artificial intelligence" OR "AI" AND "retail*" OR ("retail industry" AND "retailers"). Focused period: 2015 – 2020.
		Add to keywords to search (n=1319)	use case OR ("application" AND "Implement*" AND "Deploy*" AND "applied").
2	Screening	Identify the source	Currently trading retailers. The technology used should be AI technology. The retailer should already use AI technology.
3	Eligibility	Number of records available (n=201)	Identify the retailer and software vendor in the case. Then, supplement the information with technology vendor press releases, retailer press releases; retail-related news articles; technology vendor white articles, retail industry reports and technology news platforms.
		Remove duplicates (n=84)	Removal of duplicates.
4	Included	Collect and capture retail AI use cases (n=117)	Record the data.

First, a total of 4,304 records were identified in the initial search. Most of the records found with the initial search did not focus on retailers using AI technology, and the search had to be narrowed. A second search included keywords use case OR ("application" AND "Implement*" AND "Deploy*" AND "applied"). This search had a higher concentration of possible retailers using AI technology in the 1,319 records identified. The 1,319 articles were reviewed to determine if they were suitable for analysis.

Second, the screening process required each record to meet all selection criteria for inclusion (refer to Table 1.3). It was confirmed that the retailer was currently trading by identifying the retailer through its website and online news platforms to ensure the validity of the selected record. Where insufficient information was found in the primary article, the data was supplemented by searching for further information to enrich the original information to decide on inclusion or exclusion. The supplementary information was obtained from software vendor press releases, retailer press releases, retail-related news articles, technology vendor white articles, retail industry reports, and technology news platforms.

Third, 201 records meeting the selection criteria were identified using the eligibility protocol. Fourth, the coding of the retailer, technology provider and summary of the AI application led to the identification of 84 duplicate use cases. Last, once removed, a final sample of 117 unique records were recorded for coding and analysis.

A coding process followed the identification of common themes to prepare the data for analysis. First, the data was coded into its relevant value chain stage to identify where the AI was applied in the retail value chain (see section 2.1.2). Second, once retail use cases databases were collated, the technology mentioned in each article was compared to predefined AI types code (see section 2.2.3) to determine the AI type. The objective was to ascertain which areas in the retail value chain retailers used AI. Either to drive internal business activities (design, sourcing and procurement, manufacturing, inventory, and distribution) or to support customer-facing activities (sales and operations, fulfilment, customer use and support).

The data formed the database for articles one, two and three. In the following section, each article's data analysis is discussed in more detail.

1.5.1.2 Data analysis for each article

1.5.1.2.1 Article one: Content analysis

Article 1 used qualitative techniques to analyse the retail AI database, using a grounded theory content analysis approach. Content analysis has been applied to investigate many studies, for instance, to investigate AI-enabled recruiting systems (Black & van Esch, 2019), to investigate big data in the fashion industry (Acharya et al., 2018) and to investigate human and AI collaboration (Sowa et al., 2021). Content analysis “conventional, directive or summative “ (Hsieh & Shannon, 2005, p. 1277) nature was deemed the most suitable to address the research question, “what role does AI play in the retail value chain?”. The database was coded using Christensen et al.’s (2016) jobs-to-be-done approach to analyse all the AI activities in the retail value chain. Christensen et al. (2016) argue that people “hire” products and services to get jobs done, and companies can innovate by doing those jobs better. Each “job” can be broken down into various steps, stages of execution, and validating questions (Bettencourt & Ulwick, 2008, p. 2). The coding for article one was approached with the following question: what “job” does this AI do in the retail value chain? From this perspective, four “jobs” emerged: knowledge and insight management, inventory management, operations optimisation, and customer engagement. The jobs-to-be-done approach assisted with developing an AI-enabled value chain.

1.5.1.2.2 Article two: Content analysis

With this study's exploratory design, article 2 used a qualitative content analysis approach to analyse the retail AI application database. A systematic review "is the process of collating the best available evidence in answer to specific questions" (Lewis-Beck et al., 2004, p. 1111). The purpose of the approach was to "identify categories of meaning" (Cho & Lee, 2014, p. 3) for the different tasks AI can perform across the retail value chain. Content analysis was deemed the most appropriate as it blends objectivity and participant observation to identify themes in the data (Neuendorf, 2017) and used "descriptive knowledge and understanding" (Assarroudi et al., 2018, p. 42) to identify the tasks AI performs. First, to assess the tasks AI-enabled solutions perform across the various retail value chain activities, we reviewed the type of AI technology used and asked what the AI was used for in the retail value chain. Second, with the research question lens "what are retailers using AI technologies for in the retail value chain", the AI use cases were coded to specific tasks to understand the various activities AI technologies perform in the retail value chain. Coding and synthesizing the AI tasks assisted with understanding the various tasks AI can perform in the retail value chain.

1.5.1.2.3 Article three: Content analysis

Article three used a content analysis approach to understand the outcomes of applying AI in the retail value chain. Second, statistical methods were used to test the results to understand where the outcomes apply in the retail value chain. This approach was deemed the most appropriate as we wanted to test our coding results to explain our findings further (Creswell, 2012, p. 528). Other studies by Pitardi and Marriott (2021) and Adapa et al. (2020) followed similar approaches. First, an integrative literature review was performed to critique and synthesize the database's application of AI in retail value chains. Second, the analysis was aimed to result in a taxonomy of outcomes (Snyder, 2019, p. 334). Analysing the outcomes of the AI application in retail revealed themes about the primary outcome that each retailer may gain from applying AI in their value chains. While certain AI technologies can allow retailers to obtain more than one of these outcomes, the coding was done for the primary outcome for each unique use case. Consequently, four potential outcomes emanated from applying AI in the retail value chain, and each AI use case was classified according to the primary outcome obtained for that retailer.

This was followed by testing the results statistically to help understand how the outcomes relate to *where* AI is applied within the value chain. Next, the dataset was analysed and reviewed. Thereafter, statistical tests were used to test the outcome assumptions and conclude the data. Table 1.4 summarises the statistical test used to test the outcomes assumptions.

Table 1.4: Summary of statistical tests

Type of test required	Type of data	Statistical test used	Assumptions of the test
Distribution between two constructs	Grouping variable = nominal data + Dependent variable = interval / ratio data	Frequency distribution	Test the distribution of the observations
Relationship between two constructs	Both variables are normal	Chi-square	None
Predicting the outcome	All variables are measured using an interval/ratio scale	Regression	Test for the desired outcome

Once all the use cases were identified for further analysis, each case was coded using predetermined codes for the types of AI specified, the type of retailer, and the seven potential stages where AI can be positioned in the value chain. During the iterative review process, the focus was on emerging themes that would inform the outcomes obtained from applying the technology within the retail value chain.

1.5.2 Stage two

Stage two of the research followed the findings of the first stage and an exploratory research design to examine the AI challenges retailers experience when implementing the technology into their organisations. Again, a qualitative research method was employed to discover insights into the research question: *"what are the challenges retailers experience when integrating AI in their value chains?* Semi-structured interviews were conducted to collect data to create a robust conclusion of AI challenges retailers experience when implementing AI in the retail value chain.

1.5.2.1 Stage two: Research design

Semi-structured interviews will be used to gain insights into how retailers are transforming to an AI-enabled retail value. Semi-structured interviews "seek to address several predetermined questions" (Barlow, 2010, p. 469) and open-ended questions to discover their insights on a particular subject (Firmin, 2012). Semi-structured interviews were deemed the most suitable as the researcher develops more significant insights into the AI phenomenon (Firmin, 2012). Also, semi-structured interviews are appropriate for business research where limited empirical studies are available. Other studies also used semi-structured interviews to collect data regarding AI or technology in retail or business

(Acharya et al., 2018; Burström et al., 2021; Chopra, 2019; de Bellis & Johar, 2020; Duan et al., 2019; Mahroof, 2019).

1.5.2.2 Stage two: Target population

1.5.2.2.1 Description of the target population

Recent studies in AI focused on a specific area of AI applications in retail (see section 1.2.3.2). For example, a study by Alexander and Kent (2021) focused on in-store technology innovation and identified the importance of in-store technology integration. In addition, artificial intelligence in retail research often deals with customer-facing technologies. Consequently, the target population is usually in-store specific AI systems or customers using the systems.

The purpose of stage two was to understand the challenges retailers experience when integrating AI into the retail value chain. To do so, the target population needed to focus on a group with the relevant expert knowledge. A target population consists of people, objects, groups or events that share a particular characteristic (Boslaugh, 2008, p. 1030). The target population for this study was experts with knowledge in consulting, developing, working with, or implementing AI applications in the retail industry. A search on LinkedIn for the size of the target population with relevant AI and retail experience rendered about 79 000 experts (LinkedIn, 2021). The target population focused on three groups, namely, (i) technology experts developing artificial intelligence systems for retailers, (ii) retail managers that have implemented AI technologies, and (iii) AI business consultants working with AI in retail.

1.5.2.2.2 Sampling

Purposive sampling was used to identify relevant participants to investigate AI in retail. Morse (2011) explains that purposive sampling deliberately seeks out participants with a specific characteristic. Purposive, also referred to as judgement sampling, is “a nonprobability sampling technique in which an experienced individual selects the sample based on his or her judgment about some appropriate characteristics required of the sample member” (Zikmund, 2010, p. 369). Purposive sampling was deemed the most appropriate to identify participants who would “most likely yield rich information about their experiences” (Patton, 1990, p. 40) and provide the ability to achieve a specific objective (Zikmund, 2010, p. 396).

The social media platform, LinkedIn, was used to identify relevant participants to be interviewed. A search (using a keyword search Artificial Intelligence, AI, Retail, Digital Transformation and AI implementation) was conducted in July 2020 to source participants on the platform. The search rendered 78 possible participants suitable for the semi-structured interviews. The suitable candidates were contacted via LinkedIn direct message service to seek their participation in the study. After initial contact was made, 28 participants responded, and 20 agreed to participate in the interviews for the study. Table 1.5 shows the initial contact, response, and interviews. Once the participant agreed to participate in the study, individual consent was shared via email. Once consent was obtained, an interview was scheduled.

Table 1.5: Participant roles

Expert	Initial contact	Initial contact percentage	Responded	% Responded to initial contact	Actual interviewed	% Interviewed to initial contact
AI Technology Vendor	23	29.5%	5	21.7%	4	17.4%
Management Consultant	16	20.5%	7	43.8%	5	31.3%
Platform Technology Vendor	10	12.8%	3	30.0%	3	30.0%
Retailer	29	37.2%	13	44.8%	8	27.6%
Total	78	100.0%	28	35.9%	20	25.6%

The 20 participants were from a variety of backgrounds, all shaping AI in retail, namely:

i. four technology experts developing artificial intelligence systems for retailers,
ii. eight retail managers that have implemented AI technologies from various retailers across the world,
iii. five management consultants working with AI in retail, and
iv. three platform technology vendors were implementing technologies embedded with AI for retailers.

1.5.2.3 Stage two: Data collection

Stage two focused on the challenges retailers experience when integrating AI into their business. Thus, 20 semi-structured interviews were conducted with experts working with AI in retail. Table 1.6 highlights the variety of roles and seniority of the participants.

Table 1.6: Stage two research participants

Participant number	Role	Country	Grouped coding	Date interviewed (Australian Eastern time)
Participant 1	Chief Technology Officer	Singapore	AI Technology Vendor	Monday 2 Nov 12.30pm
Participant 2	Global Head of Retail Business Unit	Germany	Platform Technology Vendor	Thursday 3.30 pm 27 Aug
Participant 3	Retail and Consumer Industries Lead	United Arab Emirates	Management Consultant	Sunday 6 Sep 5 pm
Participant 4	Group VP Information Technologies	United States of America	Retailer	Thursday 7 am 20 August
Participant 5	Retail Innovation Head	Germany	Platform Technology Vendor	Friday 5 pm 21 August
Participant 6	SVP Merchandise Planning	United States of America	Retailer	Monday 7 Sep 7 am
Participant 7	Product Manager	Australia	Retailer	Friday 4 Sep at 13.30
Participant 8	Data Scientist	Australia	Retailer	Friday 4 Sep at 13.30
Participant 9	Chief Strategy and Customer officer	Australia	Retailer	Monday 7 Sep 3 pm
Participant 10	Head of Retail - APJ	Singapore	Platform Technology Vendor	Thursday 12.30 pm 10 Sept
Participant 11	Founder and Director	Australia	AI Technology Vendor	Monday 21 Sep 10.30 am
Participant 12	Retail Solution Architect Consultant	United States of America	Management Consultant	Tuesday 27 Oct 9 am
Participant 13	SVP Information Technology	United Arab Emirates	Retailer	Monday 9 November 18.30
Participant 14	Retail Solutions Director ANZ	Australia	Management Consultant	Friday 23 Oct 12.30 pm
Participant 15	Merchandise Systems Manager	Australia	Retailer	Friday 28 August 3 pm
Participant 16	Head of Country	Australia	AI Technology Vendor	Monday 19 Oct 4 pm
Participant 17	Vice President Technology	United States of America	AI Technology Vendor	Thursday 2 pm 5 Nov
Participant 18	Customer Experience Director	South Africa	Management Consultant	Wednesday 21 Oct 4.30 pm
Participant 19	Solution Architect	South Africa	Management Consultant	Tuesday 10 November 6 pm
Participant 20	Head of Retail Systems	South Africa	Retailer	Wednesday 18 Nov 5 pm

The interviews followed an interview protocol developed from stage one's data analysis and the findings from article one's AI-enabled retail value chain framework. The interview protocol is available in Appendix F. The interviews used a combination of 1) semi-structured interviews "to address several predetermined questions" (Barlow, 2010, p. 496), 2) open-ended questions to discover their insights on a particular subject, and 3) probing techniques to "generate further explanation from participants" (Roulston, 2012, p. 682). Effective and efficient probing required the interviewer to actively listen to the participants' responses and ask for further explanation, clarification, or elaboration of their responses. Ethical approval was granted by Stellenbosch University ethical clearance committee on 7 August 2020 (see Appendix E).

All the interviews were formal, semi-structured, and conducted using Zoom teleconference software from August 2020 to November 2020. Teleconference software was the most appropriate due to the geographical locations of participants and the worldwide COVID-19 pandemic. The interviews lasted between 60 minutes and 75 minutes. After a short preliminary talk, the researcher explained the confidentiality at the start of the interview and asked the participants' consent to be recorded. Once the participant agreed to consent, the recording started. The voice recordings were downloaded and saved for analysis.

1.5.2.4 Stage two: Data Analysis

A three-step process was followed to prepare the text data for analysis. First, the interview transcripts were coded iteratively using computer-aided qualitative data analysis software (CAQDAS) MAXQDA, using a grounded theory approach suggested by Lewins & Silver, 2011 and Bryant et al., 2007. The grounded theory approach comprises a systematic, inductive, and comparative approach for conducting an inquiry to construct theory (Bryant et al., 2007). Second, the grounded theory process involved a critical review of the responses to determine appropriate coding.

Qualitative thematic analysis was used to analyse the data to explore the research question, allowing for further insights from the data. Thematic analysis was deemed the most appropriate due to its "flexible approach to analysis qualitative data" and a method that searches for themes (Braun & Clarke, 2006, p. 77). The text data coding was conducted in three cycles to answer the research questions. First, the coding followed an open coding method to identify and categorize the text data. Second, once data was labelled into codes, the *challenges of implementing AI* followed a refining and grouping phase. Third, the multiple AI challenges were coded into the four Leavitt Diamond Model variables.

1.5.3 Research ethics

Research ethics provides guidelines for the responsible conduct of research. This study followed ethical practices and was of paramount importance during the study. In stage two of the study, human participants were involved in the data collection process. Therefore, before the commencement of stage two data collection, the research first obtained ethical clearance. To ensure an appropriate ethical standard for this research, the following practices were in place (i) followed informed consent rules, (ii) respecting confidentiality and privacy of participants, (iii) anonymising all participants information, and (iv) data management plan in place to ensure data ethics. In addition, the study adhered to the ethical requirements of the University of Stellenbosch Business School's ethics committee, and their ethical clearance for the study is provided in Appendix E.

1.6 POTENTIAL CONTRIBUTION OF THE STUDY

Knowledge generation is the process of phenomenon-exploring whereby the phenomenon is solved and/or explored defined by four parameters, namely "problem or phenomenon, theory, method and context" (Berthon et al., 2002, p. 421). Berthon et al. (2002) developed a framework (Table 1.7) to assess and evaluate the possible contribution of a study for MIS research.

Table 1.7: Potential research space: Studies of zero to three degrees of freedom

Type of study	Degrees of freedom	Theory	Method	Context
Pure replication	0		r (Validation)	
Content extension	1		r	g (Generalization)
Method extension	1	r	g (Method triangulation)	r
Theory extension	1	g (Theoretical extension)	r	r
Theory/Method	2	g (Theory/Method extension)		r
Method/Context	2	r	g (Method/Context extension)	
Theory/Context	2	g (Theory/		Context extension)
Pure generation	3	g (Generation)		

Source (Berthon et al., 2002, p. 422)

This study provided theoretical contributions in exploring the relationships between AI and the retail value chain. Current research mainly focuses on the technology (AI) and neglect the human, process/tasks, and structural component of the deployment of AI. Therefore, this study broadens our understanding of how new technologies impact value chains and retail value chains in particular. Moreover, it considers the impact on the business in general and on critical factors in the organisation:

structure, technology, tasks, and people. Using Leavitt's Diamond Model as the theoretical foundation of this study allows for the simultaneous consideration of these factors.

This study also departs from previous studies on AI in retail literature, which are predominantly conceptual (Grewal et al., 2017, 2020; Hagberg et al., 2016; Jain & Gandhi, 2021; Shankar, 2018). Despite AI's increasing popularity, empirical inquiry into AI in the retail value chain is still limited. Therefore, this study's potential contribution is addressing this gap in the literature.

The study employed existing theory (value chain; application of jobs theory; Leavitt Diamond Model) to investigate AI in retail in a new context (AI in the retail value chain). Compared to Berthons et al., (2002) framework, this study's possible contribution lies in employing AI in retail with existing methods in a new context using the Leavitt Diamond Model.

While authors argue that AI has transformed retailing (Guha et al., 2021, p. 28; Kietzmann et al., 2018, p. 265; Shankar, 2018, p. 6), no studies show what this transformation should resemble. Therefore, this study has three potential contributions to the body of knowledge. First, by examining AI's purpose in the retail value chain and how the iterative nature of AI could potentially change the traditional retail value chain. Second, by applying the application of jobs theory and outcomes-based innovation (Ulwick, 2016, p. 58) in the context of AI in the retail value chain to understand the jobs and outcomes AI can provide in the value chain.

Third, this study used the Leavitt Diamond Model (Leavitt, 1965) variables (i.e. structure, technology, tasks and people) to examine how AI transforms the retail value chain. All articles focus on each component of the Leavitt Diamond Model individually, and the final chapter is used to draw an overall conclusion considering all four factors at once. Therefore, providing a more comprehensive understanding of implementing AI in the retail value chain. The following section discusses how these contributions might benefit different stakeholder groups.

1.6.1 Possible contribution to stakeholders

Many consulting practitioners are articulating the importance of AI in retail. However, few frameworks, guidelines or mechanisms support retailers with adopting AI to deliver the greatest return on investment by transforming with the technology.

Table 1.8: Potential contributions to stakeholders

<table>
<tr><th>Potential contribution</th><th>Scholars</th><th>Retail IT managers/ Retail business leaders</th><th>Technology vendors (platform and AI)</th><th>Management consultants</th></tr>
<tr><td>The updated shape of the retail value chain</td><td>Moving from linear to circular retail value chain</td><td>Role of AI technology in the retail value chain</td><td>AI systems could solve their business problems could help retailers achieve their benefits</td><td>AI can be implemented to perform four roles in the retail value chain</td></tr>
<tr><td rowspan="2">Application of jobs theory, outcomes-based innovation</td><td rowspan="2">Extension of future research in the application of jobs theory and outcomes-based innovation through the lens of AI</td><td>Use cases of AI technology in the retail value chain</td><td>AI types that can be applied to specific tasks</td><td>AI can be used to solve business problems</td></tr>
<tr><td colspan="3">Articulation of business benefits for AI investments</td></tr>
<tr><td rowspan="2">Leavitt Diamond Model</td><td rowspan="2">The Leavitt Diamond Model in a new context</td><td>Mitigate the challenges for integrating AI into the retail business</td><td colspan="2">Guidelines to retailers for successful integration of AI in the business</td></tr>
<tr><td>All the elements required to transform with AI</td><td></td><td></td></tr>
</table>

This study aimed to understand how AI is transforming the retail value chain. Nevertheless, for retailers to transform, the transformation will require support from various stakeholders. As outlined in Table 1.8, the stakeholders could benefit from this study's contribution by applying the frameworks provided to practice to guide AI projects and implementations of AI in retail.

1.7 SCOPE AND DELIMITATION

This study focused on how AI is transforming the retail value chain by investigating the current application, implementation, use of and challenges of AI in the retail value chain. This study did not cover a futuristic viewpoint of AI in retail. Four articles were developed to investigate the primary RQ. A two-stage research design was used for data collection to uncover insights into the research questions. First, this study data collection was limited to relevant scientific journal articles that have dealt with the application of AI in retail only; all other applications of AI were excluded from the data collection process. Second, this study's targeting and sampling were limited to three groups, namely, 1) technology experts developing artificial intelligence systems for retailers, 2) retail managers that have implemented AI technologies, and 3) AI business consultants working with AI in retail. The experts needed to either have AI knowledge in consulting, developing, working with or implementing AI applications in the retail industry to meet the targeting requirements.

This study's analysis limited the research questions to understanding how AI transforms the retail value chain. No consideration was given to other factors that could transform retail or any criticism towards AI. Although various authors (Dwivedi et al., 2021; Feuerriegel et al., 2020 Kaplan & Haenlein, 2020, Lee & Shin, 2020) noted the ethical challenges of AI, the chosen research methodology did not address the application of ethics in retail. Thus, this study does not address AI in retail in its entirety. Nevertheless, it provides (i) articulation of how AI can be applied across the value chain, helping understand where AI can solve business problems, (ii) business case developed for AI by the articulation of the outcomes associated with applying AI, and (iii) an updated diamond model with considerations to minimise the impact of integrating AI into the retail business.

The following were excluded from this study:

i. the future viewpoint of how AI could change retail,
ii. ethical considerations for the implementation of AI in retail
iii. articles that did not mention the retailer's name or were options of how AI could transform retail, and
iv. other experts who work in AI with no experience in the retail industry.

The objective of this study was to determine how AI is transforming the retail value chain. Four articles were used to investigate the research questions. Figure 1.6 outlines the structure of this study.

1.8 CONCLUSION

This chapter explored the current gaps in AI in retail literature and developed an overall research question and individual research questions for each article. It was identified that extant literature covers a wide variety of research subjects. Most of the literature focuses on customer-facing value chain stages and not on the entire retail value chain. Despite that AI being earmarked to transform retail, none of the studies addressed how AI is transforming the retail value chain.

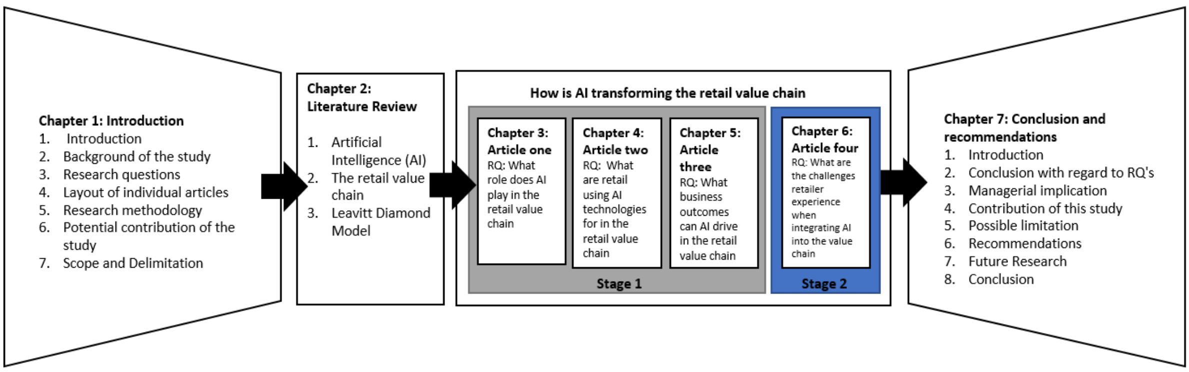


Figure 1.6: Structure of this study

Figure 1.6 outlines the structure of the study. The next chapter deals with the literature review focusing on three constructs: AI, the retail value chain, and the Leavitt Diamond Model. This is followed by the four articles developed across chapters 3, 4, 5 and 6 to understand how AI transforms the retail value chain. Chapter 3 focuses on article one, exploring the roles AI can fulfil in the retail value chain, proposing an AI-enabled retail value chain using the jobs-to-be-done approach. Chapter 4 focuses on article two to identify the tasks AI performs across all the retail value chain stages, using the Leavitt Diamond Model. Chapter 5 focuses on article three to understand AI's outcomes in the value chain. Chapter 6 focuses on article four to provide insights into the challenges retailers experience when integrating AI into their business. Finally, chapter 7 concludes with the research questions, managerial implications and recommendations, the study’s contribution, possible limitations, future research, and the conclusion.

The following chapter focuses on the literature review for this study.

Chapter 2: LITERATURE REVIEW

2.1 CHAPTER INTRODUCTION

This chapter provides an in-depth literature review of the key constructs of concern in this study (i.e. AI and the retail value chain) and the theoretical lens used (i.e. the Leavitt Diamond Model). Figure 2.1 shows the outline of the chapter, and it follows from chapter 1, which presented the background of the study and articulated the research questions.

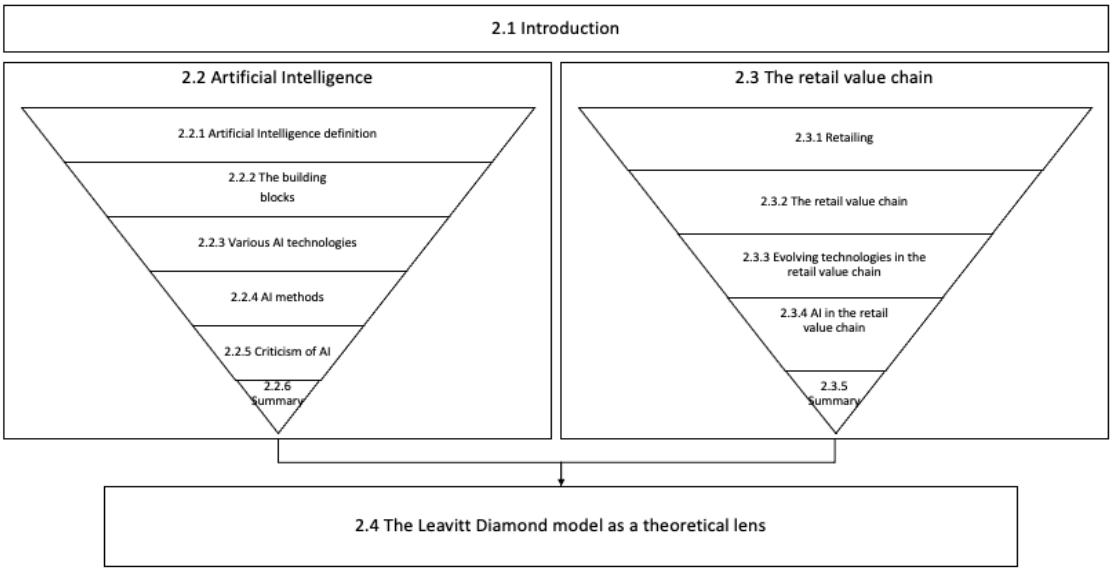


Figure 2.1: Literature layout

To understand AI in more detail, the first section discusses the (i) definition of AI (section 2.2.1), (ii) the building blocks of AI (section 2.2.2), (iii) the various AI technologies (section 2.2.3), (iv) closes with the AI methods (section 2.2.4) and (v) closes with the criticism of AI (section 2.2.5). There are illustrative examples of retailers used throughout this section to ground it in this study. We then move on to a discussion of retailing, which includes a section on retailing in general (section 2.3.1), followed by an explanation of the retail value chain (section 2.3.2), then the technological disruption of the retail value chain (section 2.2.3). The final section discusses the Leavitt Diamond Model used as a theoretical model in this study (section 2.4).

2.2 ARTIFICIAL INTELLIGENCE (AI)

This section focuses on a discussion of AI's definition, the methods AI systems use, the various AI technologies, an explanation of AI building blocks, and a conclusion on AI.

2.2.1 Artificial intelligence definition

Most extant conceptualizations of AI refer to computer systems with human-like intelligence (Wierenga, 2010, p. 2), which encompasses these systems' abilities "to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Kaplan & Haenlein, 2019, p. 17). In their definition, the Oxford Dictionary includes tasks such as visual perception, speech recognition, decision-making, and the translation between languages, with the Merriam-Webster Dictionary emphasizing that AI imitates intelligent human behaviour. Poole and Mackworth (2010, p. 3) offer a slightly nuanced explanation by framing AI as "computational agents that act intelligently". This definition describes AI as agents capable of perceiving an environment to take action, with the goal being to maximize the likelihood of achieving success (U. Paschen et al., 2019, p. 150). It also implies a rational view of AI, where an AI system would, given what it knows, act to achieve the best possible outcome (U. Paschen et al., 2019, p. 148).

For this study, we adopt the definition by Poole and Mackworth (2010), highlighting two conceptual delineations. First, it highlights the different evolutionary stages of AI (Haenlein and Kaplan, 2019). What might have been considered intelligent behaviour displayed by a machine five years ago is now hardly noteworthy? Three stages of AI are differentiated: artificial *narrow* intelligence (applied, below human-level AI, e.g., Siri voice recognition), artificial *generalized* intelligence (strong, human-level AI, e.g., Siri developing the ability to perform tasks like driving a car autonomously), and artificial *superintelligence* (conscious/self-aware, above human-level AI, e.g., Siri developing superhuman capabilities to solve complex problems instantaneously). Most of the commercial AI technologies available today are classified as "narrow", and almost all of the AI technology to be integrated into business in the next ten years will be "narrow" or "applied" (Kelly, 2017, p. 50; Yao et al., 2019, p. 18). For example, the use of AI to create personalised music recommendations on Spotify (Candelon et al., 2020).

The second defining characteristic of the Poole and Mackworth (2010) definition is the notion that AI represents knowledge, expertise, and intuition to solve problems. This definition is relevant to this study because AI, as computational agents, perceives and acts within the environment. It is programmed to solve business problems in practice, as supposed to in principle (J. Paschen et al., 2019, p. 1411). AI requires tailored knowledge to be built into a "carefully constructed system" (Kaplan, 1984, p. 52), where the storage of past knowledge should reflect experiences that would inform subsequent intelligent behaviour (U. Paschen et al., 2019, p. 148). Regardless of the definition of AI, our understanding thereof can greatly be enhanced through an understanding of both the building blocks of AI and the technologies available to AI. These are discussed in the following section.

2.2.2 The building blocks of AI

For AI systems to present knowledge from past experiences, the systems require specific components to perform optimally. Many authors have discussed the building blocks or components AI requires to perform and process information (Campbell et al., 2020; Canhoto & Clear, 2019; Gerbert et al., 2017; Hwang, 2019; A. Kaplan & Haenlein, 2019; J. Paschen et al., 2019; U. Paschen et al., 2019; Wozniak & Polap, 2020). Table 2.1 summarises the studies that outline authors that have discussed AI building blocks or components.

Table 2.1: AI building blocks

Article	Authors	Input data	Processing	Output - Actions
Artificial intelligence and machine learning as business tools: A framework for diagnosing value destruction potential	Canhoto & Clear, 2019)	Input data - Historical, Real-time, Knowledge. Connectivity	Processing algorithm - Supervised ML Unsupervised ML, Reinforced learning	Output decision - Results, Selection of results, Action
Artificial intelligence: Building blocks and an innovation typology	(U. Paschen et al., 2019b)	Input -Structured data, Unstructured data	Pre-processing; NLU - interpretation of human speech and written language. Computer Vision transforms images Problem solving - selecting a solution to achieve a goal. Reasoning - to come up with conclusions on the data. Machine Learning - lets AI systems enhance performance	Meaningful information for human decision making or as inputs into other information systems
From data to action: How marketers can leverage AI	(Campbell et al., 2020)	ML algorithms detect patterns	Supervised ML, Unsupervised ML, Reinforcement ML, Hybrid ML	New insights into customer behaviour
Putting Artificial Intelligence to work	(Gerbert et al., 2017)	Data - Structured data, speech, text, optical patterns, objects	Machine vision - Detecting faces and objects in images, Speech recognition - transforming spoken words into text, Natural language processing - detecting a text-based command, Machine Learning - learning from data, Information processing - search, knowledge extractions and processing unstructured text	Big data analytics to enable data, processing, and action
Intelligent Home Systems for Ubiquitous User Support by Using Neural Networks and Rule-Based Approach	(Wozniak & Polap, 2020)	Raw data and public database	Processing data by using a neural network. The data gets modified by a sensor so that it can be used by a training algorithm and Face recognition	Information, user need and identification
A network clock model for time awareness in the Internet of things and artificial intelligence applications	(Hwang, 2019)	Data - collected from connected devices	Data preparation and cleaning, sorting, analysing, and making sense of data.	Visualisation
Collaborative intelligence: How human and artificial intelligence create value along with the B2B sales funnel	(J. Paschen et al., 2020)	Data - structured data such as web clicks Unstructured data - non-numerical data such as text, audio, images	Pre-processing using natural language understanding and computer vision. Processing three main processes, problem-solving, reasoning and machine learning (ML)	Information that feeds into business applications
Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence	(Kaplan & Haenlein, 2019)	Data sets characterised by massive amounts of volume, velocity and variety	Supervised learning, unsupervised learning, reinforcement learning	Finding a relationship that explains an existing set of data points

For AI technologies to perform optimally, three components are required: input data, processing, and outputs or actions. The component will be discussed in more detail in the following section.

2.2.2.1 Input data

For AI to learn from past experiences, it requires input data. Data is fundamental to the functioning of any AI application. Data can be described as units of information (often numeric) relating to products, items or a person, and the values can either be qualitative or quantitative variables (J. Paschen et al., 2020, p. 405). Data characterised can be described by volume (the amount), velocity (frequency of update) and variety (numeric, textual or images) (Acharya et al., 2018; A. Kaplan & Haenlein, 2019). AI systems utilised different types of input data, either structured (i.e., historical sales data, customer data, or product information) or unstructured data (i.e., video, images, or text data) (U. Paschen et al., 2019). The AI data requirements are dependent on the output goal. For instance, if the output goal is to increase the number of units for online orders, the data requirement could be companion products or similar products customers shop together. It is important to emphasise that AI requires quality non-bias data to provide accurate outputs, as the AI model will only be as good as the trained data.

2.2.2.2 Processing

Following the input data requirements, the AI systems need to clean, transform and prepare the unstructured data to structured data for further processing (Hwang, 2019; J. Paschen et al., 2020; U. Paschen et al., 2019; Wozniak & Polap, 2020). The pre-processing of qualitative data uses natural language understanding (NLU) and computer vision to transform the images, written, text and spoken language into structured data (J. Paschen et al., 2019; U. Paschen et al., 2019). Once the data are in the correct format, the data gets processed using learning processing algorithms (Hwang, 2019; J. Paschen et al., 2019). To focus on the different learning processes, we focus on Machine Learning (ML), as it underpins most AI functions (Campbell et al., 2020). ML systems are the most widely used AI applications in business and society (Yao et al., 2019). There are three types of ML used during processing: supervised ML, unsupervised ML, and reinforcement learning.

First, supervised machine learning (ML) requires humans to provide training data sets, with inputs and correct outputs, so that the algorithm can learn patterns and develop rules to apply to future scenarios to the same task (Canhoto & Clear, 2019; J. Paschen et al., 2020). Supervised ML is the most widely used ML method in business (Campbell et al., 2020). For instance, the system learns the difference between a dog and a cat image and then distinguishes the difference when presented with the same image. Chatbots are trained on a similar approach to identifying common customer queries (Campbell et al., 2020).

Second, unsupervised machine learning (ML) works a little differently than supervised, here the system is given data, and the algorithm is tasked to infer the underlying structure for the data (Canhoto & Clear, 2019; Kaplan & Haenlein, 2019). The goal of unsupervised is to discover useful representations and observations in the data. For instance, unsupervised ML could identify what products customers regularly buy or cluster stores together based on sales and/or customer similarities. Third, in Reinforcement Learning (RL), the algorithm receives training data and an output variable to simulate a series of decisions to maximize the reward (Canhoto & Clear, 2019; Kaplan & Haenlein, 2019). Reinforcement learning must observe the success of their choices to improve the learning speed. Reinforcement learning (RL) can be applied "where an existing data set does not exist" (Campbell et al., 2020, p. 4). The reinforcement learning algorithm finds the best combinations by taking different actions while building data and continually evaluating the results based on the success or failure of the output variable (Campbell et al., 2020; Canhoto & Clear, 2019; Kaplan & Haenlein, 2019). For instance, RL can be applied to optimise retail prices by constantly monitoring and adjusting how customers react to the new prices. When creating the processing phase, it is possible for organisations to "blend or stack" the different learning algorithms to improve their predictions (Campbell et al., 2020, p. 4).

2.2.2.3 Output and action

After the learning process has been completed, the AI system generates an output or action, depending on the goal (Campbell et al., 2020; Canhoto & Clear, 2019; Hwang, 2019; Kaplan & Haenlein, 2019; Paschen et al., 2019). For example, the system could produce outputs for further action by humans (Canhoto & Clear, 2019), generate outputs for feeds into other business applications (J. Paschen et al., 2020), produce visualizations for decision analysis (Hwang, 2019), perform tasks autonomously (de Bellis & Venkataramani Johar, 2020). For AI technologies to perform the functions discussed above, it uses various intelligent technologies. The following section discussed the various AI technologies available.

2.2.3 Various AI technologies

AI is an umbrella term, and it encompasses various intelligent technologies in different stages of value creation (Sicular et al., 2019, p. 3). Furthermore, the term AI encompasses different intelligent technologies under the AI banner (Kaplan & Haenlein, 2019). To develop an awareness of the current AI technologies available, we utilised the Gartner (2019) hype cycle for the artificial intelligence report for this study. The report examines trends and innovations in the AI sector (Sicular et al., 2019). The focus was on the AI technologies predicted to reach mainstream adoption within the next five years. A brief explanation of each AI application, the benefit, most common application, and most common application in retail are provided in Table 2.2. With so many AI technologies available, selecting the best AI can be challenging for business leaders wanting to benefit from the technology. Instead, leaders should focus on the business problems AI can solve (see Section 6.8) rather than the technology itself (Chui et al., 2018). Therefore, investing in AI requires a clear business purpose. While there are various AI technologies to be integrated into business and society, to apply AI into business successfully, there are various methods the technology uses. The following section discusses the methods in more detail.

2.2.4 AI methods

Kaplan and Haenlein (2019, pp. 18–20) classified the AI methods into three types, namely, "analytical, human-inspired AI and humanized AI"; the method depends on the intelligence the AI exhibits. The role of the various AI methods is to perform specific tasks to solve business problems. Figure 2.2 show a breakdown of the AI methods.

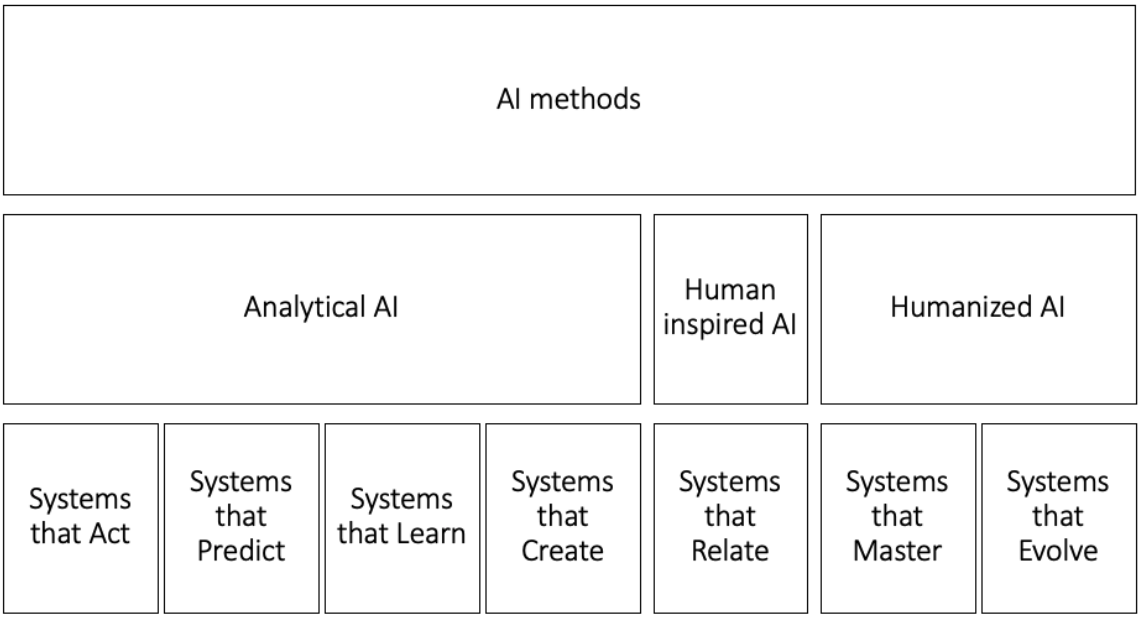


Figure 2.2: AI methods (Kaplan & Haenlein, 2019; Yao et al., 2019)

First, *Analytical AI* learns from past experiences to inform future decisions. Analytical AI displays only traits consistent with cognitive intelligence (Kaplan & Haenlein, 2019, p. 18) by extracting meaning from collected data by learning past experiences and enabling analytics, recognizing patterns and extracting meaning, helping decision making.

Table 2.2: Various AI technologies and common applications

AI Technology	Brief Description	Predicted to mainstream adoption	Benefit	Most common applications in general	Most common application in retail
AI-related C&SI Services	Artificial intelligence related consulting, and system integration is services offered by third-party vendors to process, analyse, and automate specific tasks	2 - 5 years	Transformational	Ideation, proof of concepts, defining data strategies and designing business or IT processes	Automation of marketing campaigns and/or data services
Augmented Intelligence	Augmented intelligence is a human-centred partnership between AI and humans to help people perform tasks easier.	2 - 5 years	Transformational	The use of AI to compensate for human limitations and enables people to expand the possibilities	Virtual products try on; product demonstration; interactive dressing rooms
AutoML	Automated machine learning (AutoML) is the capability of automating the process of building, deploying and/or managing machine learning models.	2 - 5 years	Emerging	ML programming assistance	Assist data scientists with data reprocessing, algorithm selection, model management
Chatbots	Domain-specific conversation interface that simulates human conversation through voice commands or text, or both. The interface uses an app, messaging platform, social network, or chat solutions for its conversations	2 - 5 years	Transformational	Social media, service desks, HR and self-service (dependent on natural language understanding (NLU)	24/7 Customer interactions; Answering questions
Computer Vision	Computer vision is a process involving the capturing, processing, and analysing of images and videos to allow machines to extract meaningful	2 - 5 years	High	Platforms as Amazon Web Services, Microsoft Azure	Finding similar products; New product discovery; Virtual stylist
Data labelling and Annotation services	Data annotation and labelling services support enterprises labelling/annotating data for artificial intelligence (AI) projects. These services and associated platforms route and allocate this work to internal staff and external third-party knowledge workers.	2 - 5 years	Emerging	Labelling and classification of data	Assist with calibrating and continually training chatbot or recommendation engines
Deep Learning (DL) or Deep neural network (DNN)	DL is a subset of ML. Deep neural networks (DNNs) are large-scale neural networks, often with many processing layers. They underpin most recent advances in AI by enabling computers to process much better complex data, such as video, image, speech, and textual data.	2 - 5 years	Transformational	Process complex data, such as video, image, speech and textual data	Monitoring foot traffic in-store; master data creation
Edge AI	Edge AI refers to the use of AI techniques embedded in IoT endpoints, gateways, and edge devices, in applications ranging from autonomous vehicles to streaming analytics. While predominantly focused on AI inference, more sophisticated systems may include a local training capability to optimise the AI models.	2 - 5 years	Transformational	Visual inspection in manufacturing, Enhancing customer experience Remote monitoring, data-intensive	Automated check-out; Inventory visibility
Insight engines	Insight engines apply relevancy methods to describe, discover, organise and analyse data to enable existing or synthesized information to be delivered proactively or interactively in the context of digital workers, customers or constituents at timely business moments.	2 - 5 years	High	Search and insight technology - IBM, Microsoft	Analysing product and customer data; Generating customer profiles

Intelligent applications	Intelligent applications are enterprise applications with embedded or integrated AI technologies to support or replace manual human-based activities via intelligent automation, data-driven insights, and guided recommendations to improve productivity and decision making	2 - 5 years	Transformational	ERP, Back office enterprise and customer applications. Human capital management	Order placement; Workforce planning; Financial planning
Machine learning (ML)	Machine learning is an AI discipline that solves business problems by utilising mathematical models to extract knowledge and patterns from data. Three major sub-disciplines relate to the types of observation provided: supervised learning, where observations contain input/output pairs (also known as “labelled data”); unsupervised learning (where labels are omitted); and reinforcement learning (where evaluations are given of how good or bad a situation is).	2 - 5 years	Transformational	Automation, Customer Engagement, Supply Chain Optimisation, Operational effectiveness, Workforce effectiveness	Personalisation; Product recommendations; Price management and Optimisation
Natural Language Processing (NLP)	NPL allows AI systems to extract and derive meaning from human language or text	2 - 5 years	Transformational	Text analysis to improve Virtual assistants and chatbots interaction, transcription services, Keyword tagging	Customer service by answering queries, Analysis of online product reviews, Twitter feeds, or Facebook posts
Robotic Process Automation (RPA)	RPA mimics a human's mouse clicks and key stores using screen and keyboard to drive applications and execute system-based work.	Less than two years	High	Business process outsourcing, Manual rule-based processes.	Order placement; Scheduling deliveries
Smart robots	Smart robots work autonomously in the physical world, learning in short-term intervals from human-supervised training and demonstrations or by their supervised experiences on the job.	5-10 years	Emerging	Logistics and warehousing, Product picking and packing, e-commerce order fulfilment. Manufacturing: product assembly, stock replenishment	Managing assembly; Picking and packing orders; movements of goods
Virtual assistants (VAs)	Virtual assistants (VAs) or digital assistants is an application that understands voice commands to complete tasks	2 - 5 years	Transformational	Apple Siri, Google Assistant, Amazon Alexa, bots	Contactless pick up; Navigation assistance in-store; customer interactions
VPA-Enabled Wireless Speakers	Conversational user interface (CUI) is a high-level design model in which the user and machine interactions primarily occur in spoken or written natural language. Therefore, the sophistication of the CUI can vary from understanding just simple verbal utterances to handling complex multi-turn interactions.	2 - 5 years	Transformational	Smart Home and speaker applications such as Amazon Echo, Siri, Google home	Customer interactive voice response and ability to automatically order products through voice

Source: adapted from (Baird, 2019; Pitardi & Marriott, 2021; Rese et al., 2020; Schmelzer, 2020; Sicular et al., 2019)

Analytical AI methods are used to automate processes, create personalised recommendations at scale, ensure the correct inventory are stocked in stores, and customers stay safe by using a contactless check out in stores (Dogru & Keskin, 2020; Riegger et al., 2021; Wadhawan & Seth, 2016). There are four AI approaches within analytical AI: systems that act, predict, learn, and create (Yao et al., 2019, pp. 29-32). The majority of AI systems used by retailers fall into the analytical AI group (Kaplan, 2020). The first analytical AI system, i.e. systems that act according to a predefined script, such as robotic process automation (RPA) (Sicular et al., 2019), includes automating repetitive tasks such as placing orders or matching invoices suppliers. The second analytical AI system, i.e. systems that predict, such as insight engines, require big data, data mining, statistical modelling, machine learning (ML) and mathematical processes to produce an outcome (Edwards, 2019). An example is using predictive models to manage shipping schedules in retail. Third, systems that learn, such as machine learning (ML) and deep learning (DL), are similar to predictive systems. However, they can function at a human or better than human level to solve business problems and learn tasks without explicitly being programmed (Yao et al., 2019, p. 29). These systems learn from past experiences to produce an outcome. The AI processes vast amounts of data, reducing the shortcomings of manual efforts today (Chen et al., 2016; Gupta, 2018; Sivarajah et al., 2017). An example of a retailer that uses systems that learn is Burberry, which used data to generate customer profiles and segments to guide sales assistants in-store to recommend items to customers based on similar profiles (Marr, 2019) and online retailers Zalando using an AI personal stylist to recommend personalised digital outfits based on searches by the customer (Marr, 2019). Finally, systems that create, such as neural networks (NN), are capable of creativity by producing writing, images, music and even other AI software (Simonite, 2017). Systems that create are transforming the design phase by providing designers with recommendations of new products design, product discovery, prototypes and customised designs. For instance, Tommy Hilfiger used an AI system to recommend new product designs based on historical colours, silhouettes and prints, streamlining new product development and reducing time (Arthur, 2018).

After analytical AI, we also get human-inspired *AI* systems, which are AI systems with elements of cognitive and emotional intelligence. The systems can understand human emotions and consider them in their decision-making (Kaplan & Haenlein, 2019. p. 18). An excellent example of these systems is digital assistants. There is an AI approach within human-inspired AI, namely, systems that relate (Yao et al., 2019, p. 32-34). Systems that relate are emotionally aware and could improve customer service, customer interaction, marketing and communications (Yao et al., 2019, p. 33). These systems use sentiment analysis to extract meaning from visual elements, such as faces, images, text, voice and activities (Ammanath et al., 2020; Yao et al., 2019), recognizing human emotions such as happiness, anger and surprise, sometimes better than employees (Kaplan, 2020). An example of a retailer that uses a system that relates is Uniqlo, which used a booth to detect human emotion by showing customers digital images of particular t-shirts, detecting customers' emotions and then recommending the best t-shirt to purchase. Similarly, Walmart developed facial recognition software to identify customers' emotions at check-out, hoping the technology would help reduce customer complaints (Kaplan, 2020).

Finally, *humanized AI* systems show characteristics of all types of human competencies and could potentially be the most human-like (Kaplan & Haenlein, 2019, p. 18). Systems that master and evolve would be capable of constructing abstract concepts and adapting to a changing environment (Yao et al., 2019, p. 34). Unfortunately, no modern AI system with human-like intelligence exists today. While advances in AI have come a long way, building AI systems that master and evolve to display human-like intelligence are still far into the future. Views from experts collated by Müller and Bostrom (2016) estimate that AI could reach human-level ability by 2075. Nevertheless, some experts believe superintelligence AI would be bad for humanity (Barrat, 2013). Although AI systems today can only complete narrow tasks, the possibility of human-level AI is a possibility in the distant future. The following section discusses the criticisms of AI.

2.2.5 Criticisms of AI

Developing ethical and safe AI is a complex and evolving topic for businesses to consider (Yao et al., 2019, p. 165), creating many criticisms for the technology. The criticisms noted by authors are the lack of fairness in AI applications (Feuerriegel et al., 2020), bias in the AI results (Dwivedi et al., 2021; Lee & Shin, 2020), privacy concerns (Ameen et al., 2021; Dwivedi et al., 2021; Kaplan & Haenlein, 2020; Lee & Shin, 2020,), the interpreting the AI results (Barredo Arrieta et al., 2020; Dogru & Keskin, 2020; Lee & Shin, 2020; Preece, 2018; Shin, 2021), job displacement (Dogru & Keskin, 2020; Dwivedi et al., 2021; Frey & Osborne, 2017; Kaplan & Haenlein, 2020; Manyika et al., 2017) and the lack of government policy and regulations for the ethical use of AI (Dogru & Keskin, 2020; Dwivedi et al., 2021).

2.2.5.1 Bias in the results leading to a lack of fairness in AI application

The prevalence of biases in AI is well documented (Dwivedi et al., 2021). Part of the challenge is that models are opinions embedded in mathematics and any AI bias reflects the judgements and priorities of its creators (O'Neil, 2016). The models may be biased from the beginning. As mentioned in section 2.2.2.1 above, AI interprets data and learns from it. Suppose the AI's trained data is biased (e.g., the data does not represent a particular community of people). In that case, such bias can be integrated into the AI system (Kaplan & Haenlein, 2020, p. 44). For instance, facial recognition AI trained with, e.g., Google images only representing white persons, are more likely to misidentify or ignore images of black persons (Feuerriegel et al., 2020, p. 380). AI can thus lead to unintended consequences of discrimination based on social biases of gender, race, and ethnicity (Dwivedi et al., 2021, p. 26). For example, Latanya Sweeny, a professor at Harvard, uncovered that online searches associated with the black community were 25 percent more likely to be targeted by ads that implied the person had a criminal record (Yao et al., 2019, p. 41). Therefore, to mitigate biases in AI results, an organisation should ensure the models have trained responsibility with quality data representative of the community.

2.2.5.2 Privacy concerns

The increasing demand for personalised services requires businesses to collect, store and process vast amounts of identifiable personal data, creating AI privacy concerns and criticisms for using specific data (Lee & Shin, 2020, p. 72). The increased use of AI in business amplifies the privacy risks of customers (Dwivedi et al., 2021, p. 17). Data is critical for AI systems to understand the customer journey. However, a challenge for organisations is accessing the correct data on which personalisation AI is based without negatively affecting a customer's privacy (Ameen et al., 2021, p. 5). The vast amount of data organisations collect and store can be vulnerable to data theft due to weak security controls (Dwivedi et al., 2021, p. 28). Similarly, privacy challenges can create legal challenges due to strict requirements like the General Data Protection Rule (GDPR), which impacts how companies handle and store personal data (Kaplan & Haenlein, 2020, p. 41). Therefore, ensuring the correct processes are in place to maintain privacy and keep collected data secure and safe should be considered as AI systems integrations into the organisation.

2.2.5.3 The interpretation of AI results

A long-standing criticism of AI is the increasing complexity of understanding and interpretation of AI systems. Some authors noted that the continuously evolving algorithms in AI, such as machine learning and neural networks, reduce the capability of users to examine the outputs, making it impossible for users to explain the outcome (Dwivedi et al., 2021; Preece, 2018). In addition, various authors noted interpretability, and transparency of results challenges, causing AI to operate in "black boxes" (Barredo Arrieta et al., 2020; Dogru & Keskin, 2020; Lee & Shin, 2020; Preece, 2018; Shin, 2021). Authors Feuerriegel et al. (2020), Kaplan and Haenlein (2020), and Shin (2021) argued that testing and validating the results could be left to employees with specialised expertise and knowledge. However, explanations on the inner workings of the algorithms used are challenging to describe, creating a lack of trust amongst users.

2.2.5.4 Job displacement

Automating tasks through AI could improve businesses performance and quality by reducing errors. However, many authors argue that AI automation could harm jobs by displacing or changing jobs, especially in low skilled work activities (Barredo Arrieta et al., 2020; Dogru & Keskin, 2020; Dwivedi et al., 2021; Frey & Osborne, 2017; Kaplan & Haenlein, 2020; Manyika et al., 2017). Frey and Osborne (2017, p. 265) argued that 47% of U.S. employment is at risk of automation. Manyika et al. (2017) estimated that a third of current work activities could be impacted by 2030. In contrast, Kaplan & Haenlein (2020) argued that job displacement would be dependent on the industry. A challenge for organisations is the need to upskill their current employees to enable them to work with the new AI applications, thereby protecting certain employees from job displacement (Dogru & Keskin, 2020; Simon et al., 2020).

2.2.5.5 Regulations for the ethical use of AI

Inadequate regulation regarding the ethical use of AI is another criticism. Despite the benefits of AI, AI systems are operating in a legal grey area that has not been regulated well, and AI could hold risks for society. For instance, AI may develop biases in favouring a specific political orientation or reinforcing undesired practices without regulation (Dwivedi et al., 2021, p. 35). The lack of regulation and policy creates challenges for customers harmed by automated technology to find the necessary legal representation (Dogru & Keskin, 2020, p. 71). Therefore, governance of AI systems is needed to understand how connected AI systems influence human decision making, as without this, AI technologies can cause harm or biases towards consumers (Dogru & Keskin, 2020; Dwivedi et al., 2021).

As AI is integrated into business and society, organisations need to ensure adequate data control processes, governance, and processes to minimise the risk to customers and/or employees.

2.2.6 Summary: AI

A large number of authors have discussed the benefits of implementing AI into organisations (Adapa et al., 2020; Ameen et al., 2021; Björkdahl, 2020; Dogru & Keskin, 2020; I. Lee & Shin, 2020; Manyika et al., 2017; Shechtman et al., 2018). For example, AI enables organisations to transform their manual processes into automated intelligent processes, freeing employees to focus on higher-value tasks, such as improving customer service (Lee & Shin, 2020); AI improves productivity in operations through robotics (Dogru & Keskin, 2020); and AI enhance employees productivity through automating manual tasks (Manyika et al., 2017). While, Shechtman et al. (2018), Adapa et al. (2020) and Ameen et al. (2021) noted that AI Improves the way employees interact with customers and improves customer satisfaction. Wadhawan and Seth (2016) noted that AI improves forecasting and reduces the overall cost of inventory. Nevertheless, implementing AI into a business is not as straightforward as one might think (Burström et al., 2021).

Businesses need to overcome some challenges to gain total value from AI investments. For instance, the complexity of understanding and interpreting AI results to use in the business (Barredo Arrieta et al., 2020; Dogru & Keskin, 2020; Jin & Shin, 2020; I. Lee & Shin, 2020; Preece, 2018), the data and technical infrastructure required to run AI systems (Dwivedi et al., 2021; Kaplan & Haenlein, 2020; Lee, 2017; Lee & Shin, 2020), the impact on the workforce and the new skills required to work alongside AI (Barredo Arrieta et al., 2020; Dogru & Keskin, 2020; Dwivedi et al., 2021; Frey & Osborne, 2017; Kaplan & Haenlein, 2020; Manyika et al., 2017), and the businesses internal readiness and capability to work with AI systems (Dwivedi et al., 2021; Lee & Shin, 2020). As AI disseminates into business, it is essential to understand how to integrate AI into the organisation. Organisations wishing to capture value through integrating or adopting AI into their business should focus on embedding the technology into their operations (Tarafdar et al., 2019). Nevertheless, limited research describes what is needed to get the most out of AI.

AI has been implemented into multiple industries, including retail, and affects how businesses operate (Daugherty & Wilson, 2018; Davenport & Ronanki, 2018; Hoffman & Freyn, 2019; Ransbotham et al., 2017; Tarafdar et al., 2019). However, although many organisations have begun to adopt AI, the pace of implementation and adoption across industries seems to be a challenge (Chui et al., 2018). Similarly, AI adoption within the retail industry remains low, even though AI has been shown to provide significant value in this industry(Dogru & Keskin, 2020, p. 69).

With AI's potential to transform businesses and disrupt traditional sectors (Kerzel, 2021; Lee & Shin, 2020), retailers need to evolve with the technology. The following section discusses the evolution of the retail and retail value chain.

2.3 THE RETAIL VALUE CHAIN

New technologies are challenging the traditional retail value chain; for example, there has been a shift away from purely operating in traditional store formats to integrated omnichannel environments (Lee, 2017, p. 593). Today, most customer shopping journeys involve a digital channel, making the delineation between physical and digital channels even more blurry and hard to predict. This section discusses retailing, the retail value chain, the evolution of the retail value chain, followed by a discussion of AI in the retail value chain.

2.3.1 Retailing

Retailing is one of the world's biggest industries, with global sales projected to be around 26.7 trillion U.S. dollars by 2022 (Statista, 2020). Retailing is exchanging goods and services with customers through physical and digital channels (Gauri et al., 2021; Wadhawan & Seth, 2016). Table 2.3 illustrates the different formats in more detail.

Table 2.3: Different retail formats

Retail format	**Description**	**Type of merchandise**	**Retailer examples**
Big Box Retailer	Big-box retailers are retailers with large free-standing stores that sell various products, usually meant to be a one-stop-shop for customers	A general mix of product categories	Walmart, Ikea, Home Depot, Sam's club
Convenience store	A small store with extended opening hours selling a limited range of groceries and household goods	The mix of food products and consumable household products	7eleven, Speedway LLC,
Department store	Department store retailers typically sell a wide variety of products, and the stores are generally divided into small speciality areas within the store	Multiple products across a vast amount of categories	Macy's, Bloomingdales
Digital marketplace	Online website or mobile applications that connects buyers and sellers	Multiple products across a vast amount of categories	eBay, Etsy, Gumtree, Facebook Marketplace
Fast fashion	Fast fashion retailers move quickly from the catwalk to stores to meet new trends. They are specialist clothing retailers with a quick stock turnaround whose business model relies on selling high volumes (usually) at inexpensive price points	Category-specific, such as footwear or clothing	Zara, H&M, Forever 21
Off-Price Retailer	Retailers who provide high-quality goods at low prices	Inconsistent assortment of brand and fashion orientated items	TJ Maxx, Burlington, Marshalls
Online retailers	Online retailers are retailers that primarily operate, if not entirely, online.	Multiple products across a vast amount of categories	Amazon, Farfetch
Speciality	A retailer that carries a deep assortment within a relatively narrow category	Category-specific, such as footwear, outdoor or clothing	Nike, Lululemon, Apple, Sephora, Uniqlo
Supermarket	Supermarket retailers mainly sell grocery products and various fresh and packaged food items	Consumer products such as food, grocery and household products	Carrefour, Aldi, Morrisons, Tesco, Spar

Adapted from (Goworek, 2014; Hayes, 2019; Jindal et al., 2020; Zentes et al., 2012)

For retailers to exchange goods and services, retailers operate through various formats. A format can be described as a specific configuration to satisfy the retailer's target customers (Gauri et al., 2021; Reinartz et al., 2019; Zentes et al., 2012). Similarly, formats are differentiated by a combination of assortment offered, services offered, price band, type of store, geographical footprint, relationship with suppliers, and customer segments (Cao, 2014; Reinartz et al., 2019; Shi & Yan, 2017). Traditionally, retailers existed through physical stores (Reinartz et al., 2019, p. 350), and the move to omnichannel environments have significantly evolved the formats (Gauri et al., 2021, p. 42).

Retail encompasses many different functions, for example, procuring and building of customer assortments, the physical movement of products, transacting with customers, marketing to customers, managing inventory, retail operations and customer service (Gauri et al., 2021; Goworek, 2014; Grewal et al., 2018; Reinartz et al., 2019). The combination of these functions is referred to as the retail value chain. The role of retail is to transfer possession of a physical item to a consumer, from one part of the retail value chain (i.e. raw materials) into the consumer's hands and after that (i.e. customer service) (Reinartz et al., 2019, p. 350). The following section discusses the retail value chain in more detail.

2.3.2 The retail value chain

In 1985 Michael Porter introduced the concept of the "value chain". He describes the value chain as a strategic framework for thinking about the activities involved in any business (Porter, 1998, Location. 1011). The value chain plays a fundamental role in "identifying sources of competitive advantage" (Porter, 1998, Location. 1013). The value chain describes a set of activities performed to design, produce, market, deliver and support products within businesses (Hagel et al., 2016, Porter, 1998). The value chain includes the set of processes that deliver value across primary activities (like inbound logistics, operations, outbound logistics, marketing and sales, and service) and secondary activities (including firm infrastructure, human resource management, technology development and procurement). The activities are distinct from the business's physical and technological activities (Porter, 1985). The activities in the traditional value chain move in a sequence of linear steps and facilitate information and product flow between design, manufacturer, suppliers, shipping agents, warehouses, shelves, consumers and retailers to the point of consumption (Reinartz et al., 2019). The purpose is to exchange products and services for a profit by offering to customers and exchanging them for payment (Fiorito et al., 2010; Wadhawan & Seth, 2016).

In retailing, the value chain encompasses all the stakeholders and processes needed for retailers to deliver an end product (or service) to a customer (Reinartz et al., 2019, p. 352). Retailers play a fundamental role in the value chain by offering a wide range of product options to customers, responding to customer demand and disseminating information to suppliers or manufacturers (Lai et al., 2010). In addition, retailers link customers to manufacturers by providing channels for the customer to interact. The retail value chain (see Figure 2.2) has multiple interconnected activities through each stage and are the phases the retailer must go through to get products to their customers. The retail value chain includes information and product flow between design, manufacturer, suppliers, shipping agents, warehouses, shelves, consumers and retailers to the point of consumption (Hübner et al., 2018; Reinartz et al., 2019).

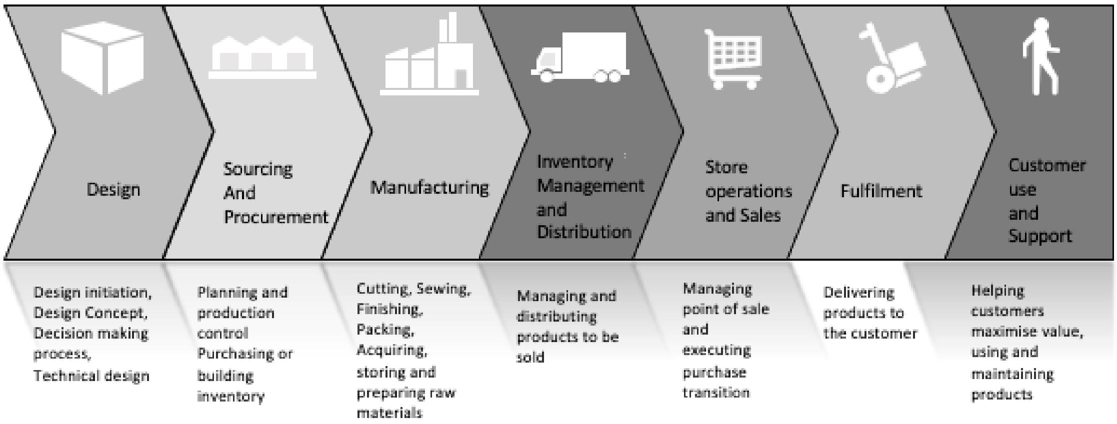


Figure 2.3: The retail value chain

Adapted from: (Hagel et al., 2016; Reinartz et al., 2019; Rieple & Singh, 2010)

Suppliers, manufacturers, and retailers play a fundamental role in delivering value to the end customer through the retail value chain. First, the supplier's role is to connect retailers with agents or manufacturers to aid in producing the required product assortments for the retailer's customers (Cammett, 2006). Second, suppliers such as Li and Fung manage multiple products for retailers and brands worldwide, enabling them to select, price and buy designs with confidence (Li & Fung, 2019). Suppliers consolidate and disseminate the retailer's order information to producers and streamline production times by adhering to the retailer's anticipated delivery date (Lai et al., 2010). It is crucial for retailers to constantly provide suppliers with updated information on orders or customer sales information to ensure on-time delivery of products.

Manufacturers are responsible for making products using raw materials, labour, machinery, and tools to create a final output (Zentes et al., 2012). Manufacturers market their finished products through suppliers or wholesalers to respond to customer demand. Manufacturers usually focus their resources on producing single product types, such as sneakers or homeware (Sternbeck & Kuhn, 2014; Zentes et al., 2012). However, manufacturers have extended lead times, adding pressure to retailers to replenish merchandise, forcing retailers to anticipate future demand months before products are sold (Cammett, 2006).

Finally, retailers play a fundamental role in the value chain by offering a wide range of product options to customers, responding to customer demand and disseminating information to suppliers or manufacturers (Lai et al., 2010). Retailers link customers to manufacturers by providing channels for the customer to interact. Their purpose is to exchange products and services for a profit by offering customers and exchanging them for payment (Fiorito et al., 2010; Wadhawan & Seth, 2016). Some retailers, like Zara, choose to vertically integrate many of the value chain activities traditionally performed by manufacturers to have greater control of the final product, improving efficiencies and reducing lead time to customers.

Information technology plays a fundamental role in the value chain; the systems disseminate information flow across all value chain stages and stakeholders (Rieple & Singh, 2010). Therefore, various technologies and software are needed to enable the retail value chain ecosystem. For example, computer-aided design (CAD) software is used to design products (Guo et al., 2011, p. 1873), enterprise resource planning (ERP) systems to place orders (Xu et al., 2018, p. 2955), point-of-sale (POS) to enable the sales transaction (Suriyantphupha & Bourlakis, 2019, p. 98), customer relationship management (CRM) systems to manage relationships with customers (Grewal et al., 2017, p. 4), sales forecasting systems to manage customer demand (Guo et al., 2011, p. 1879,) and analytics to make informed decisions to name a few.

Technology forms the backbone to the successful operations of the retail value chain. Nevertheless, various stakeholders are likely to use their platforms and software, making integrating systems and managing data difficult. Moreover, legacy systems often inhibit organisations' agility from responding to changing customer needs (Westerman et al., 2014). Also, when any change occurs to technology in the retail value chain, it could affect the competitive business advantage (Porter, 1985). Therefore, for retail value chains to move and share information optimally, technologies need to enable the flow of goods, services and information to transition between the stages seamlessly. The following section discusses the evolving technologies in the retail value chain.

2.3.3 Evolving technologies in the retail value chain

Multiple advances in the technologies that retailers use, and evolving customer behaviours, played a major role in retail's transformation (Grewal et al., 2017; Oh & Polidan, 2018). When technology was first introduced in the seventies, retail started evolving more rapidly. For example, the introduction of the universal product code (UPC) in 1974 assisted with speeding up checkout processes in stores and simplifying stock takes (Weightman, 2015). In addition, the introduction of the UPC helped retailers more accurately account for inventory in their stores, provide tracking on order deliveries and systematically account for sales. In 1985 the evolution continued when a new retail format, the home shopping network, brought television and shopping together, giving customers the ability to shop products from the comfort of their homes (Gauri et al., 2021).

In 1989, computer scientist Tim Berners-Lee released code for the world's first web browser, giving internet access to millions (History.com, 2020). The emergence of the internet transformed the retail industry in the nineties (Wadhawan & Seth, 2016). Being connected to the internet provided essential tools to internationalise retail operations, leading to the global acceleration of retail as European and US retailers expanded their products and services into new markets across the world. Similarly, the emergence of the internet and management technologies exposed traditional retailers to global manufacturers expanding their sourcing networks globally (Wrigley & Lowe, 2010). The adoption of the internet also saw the development of new online stores, with Amazon, an online bookstore at the time, starting to sell books online in 1995 (Gauri et al., 2021). The technology disruption in the nineties started shifting the buying power from retailers to consumers by giving consumers the ability to view, compare prices and purchase items online.

In the 2000s, online retailing started to take shape with online marketplace Alibaba starting to trade online (Alibaba, 2021) and major brick and mortar retailer Walmart adding an online channel to their business (Walmart, 2021). As more brick and mortar retailers also expanded their own online channels, creating multichannel retailers. It also saw new direct to consumer competitors emerging. Manufacturers (i.e., Nike) started utilising online platforms to interact directly with their customers (Reinartz et al., 2019). Fast forward to today, where the technology evolution brought internet connectivity to millions of mobile devices. The evolution has reduced entry barriers, making the retail landscape more competitive (Oh & Polidan, 2018). In addition, digital devices have changed the way customers interact with retailers, shifting the relationship from retailer to customers (Fiorito et al., 2010). Figure 2.4 shows the shift from retailers to consumers.

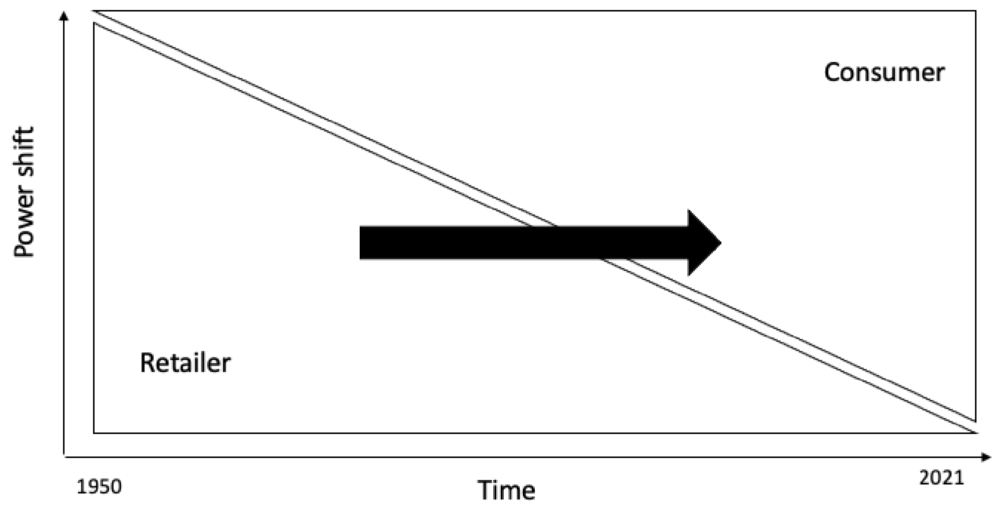


Figure 2.4: Powershift from retailer to customer

In recent years, the retail market landscape has changed from purely operating in stores to omnichannel environments, disrupting traditional retail businesses and significantly altering the customer purchase journey (Bolton et al., 2019, p. 15; Carlsson, 2018, p. 424). Customers interact with retailers through physical stores and a wide range of digital platforms (Fiorito et al., 2010, p. 879) and transactions often involve a rapidly increasing number of (often digital) customer journey touchpoints (Verhoef et al., 2019, p. 889). In addition, market segments of younger and technologically-proficient customers are growing in buying power fuelled by 24/7 mobile connectivity and demand seamless and complete integration across all purchasing channels to enhance their shopping experience (Hagberg et al., 2016, p. 695; Lee, 2017, p. 593; Oh & Polidan, 2018, p. 32).

The transformation from store to omnichannel retailing has elevated the service expectations of the average customer (Oh & Polidan, 2018, p. 31) and is creating several challenges for the retail industry. For example, multiple channels create complexities in inventory management and demand uncertainty by reshaping supply and demand (Jin & Shin, 2020), and logistics and fulfilment of products become complicated (Cai & Lo, 2020, p. 7). Omnichannel retailing creates new business opportunities and changes how retailers provide products and services to customers (Pantano & Pizzi, 2020, p. 298), yet requires a different strategy than a traditional one (Cai & Lo, 2020). In addition, changing customer expectations cause challenges with outdated legacy operations as new infrastructure is required to meet customer needs (Kaur et al., 2020). Also, brick and mortar stores need to be integrated with digital capabilities to provide cross channel experiences for customers (Capgemini, 2018) and manage price consistency across all channels (Grewal et al., 2018 p. 87). Similarly, omnichannel environments generate more data and more opportunities for data insights, but such analyses and forecasting tasks are complex and often require advanced analytical skills not available inside the organisation (Anica-Popa et al., 2021; Dwivedi et al., 2021; Grewal et al., 2018). Moreover, misguided analysis and forecasts profoundly impact the downstream value chain process – in essence, destroying value instead of creating it.

The retail sector will continue to evolve as ‘digital’ embeds into the retail industry (Romero & Martínez-Román, 2015, p. 656). Multiple authors agree that the transformation in retail technology and evolving customer demands have forced retail companies to rethink their traditional approaches and embrace technologies to capture value and market share (Bieniek & Lobaugh, 2015; Gupta, 2018; Hagel et al., 2016; Oh & Polidan, 2018; Shrivastava, 2017; Simon et al., 2020; Simpson et al., 2017; Yrjölä et al., 2018). Retailers have no choice but to transform their businesses with technology and adopt new business models or become irrelevant (Burström et al., 2021; Valenduc & Vendramin, 2017; Verhoef et al., 2021; L. D. Xu et al., 2018). Elevated customer expectations and technological pressures add complexities to the retailers' value chains and create many challenges (Acharya et al., 2018; Adapa et al., 2020; Ardolino et al., 2018; Cai & Lo, 2020). Retailers are utilising new technologies to address changing customer needs and the other complexities of the current market. Of the new technologies impacting the retail industry, AI has been earmarked as the most transformative (Kietzmann et al., 2018; Lee et al., 2018; Silva et al., 2019). AI in the retail value chain is discussed in the next section.

2.3.4 AI in the retail value chain

Traditional retailers value chain models face disruptions by new entrants who can deliver value to the customers effectively and efficiently (Lee & Shin, 2020). Many traditional retailers have been surpassed by innovative, fast-growing digital entrants (Verhoef et al., 2019, p. 889), such as Warby Parker, Stitch Fix and Rent the Runway (Jin and Shin pg. 308). To remain competitive and survive in an ever-changing and diversified customer market, retailers have started adopting various AI-powered solutions. AI can significantly improve speed, cost, and flexibility across the retail value chain (Liang et al., 2020, p. 4). Major retailers (i.e., Walmart, Home Depot and Amazon) that have invested in AI are generating economic wins with AI by reinventing design, merchandising, marketing and customer service (Kaplan, 2020; Liang et al., 2020, p. 4; Weber & Schütte, 2019, p. 272).

The influence of AI in the retail value chain is projected to be substantial (Guha et al., 2021, p. 28; Kietzmann et al., 2018, p. 265; Shankar, 2018, p. 6) for various reasons. First, retailers interact directly with customers throughout the entire customer journey, leading to *increased data* on the consumer and creating complexities for retailers (Grewal et al., 2018; Lee, 2017, p. 593). Understanding the customer touchpoints increases complexity for retailers (Kietzmann et al., 2018, p. 263). AI can provide retailers with insights to reduce shortcomings in data analysis by recognising patterns and providing insights into customer and sales data (Acharya et al., 2018, p. 92; Ameen et al., 2021, p. 1; Gupta, 2018, p. 170). When AI is used in retail, it can provide retailers with real-time data and personalised customer recommendations (Guha et al., 2021, p. 29). For example, a grocery retailer, Kroger, has an in-house analytics department that combines AI and advanced analytics to personalise customer communications (Weber & Schütte, 2019, p. 273).

Second, omnichannel retailing has *elevated the service expectations of the average customer* (Oh & Polidan, 2018, p. 31), and managing customer interaction across all the retail channels can be complex. AI helps retailers by providing an improved customer experience by offering intelligent applications across the customer journey for customers to interact with retailers (Chopra, 2019; Pillai et al., 2020; Rese et al., 2020; Roy et al., 2017; Y. Xu et al., 2020). For example, Amazon go stores uses AI to automate the in-store check-out process (Guha et al., 2021, p. 39, Shankar, 2018, p. 16).

Third, in the retail value chain, many stakeholders are involved through each value chain stage, adding complexity and manual activities to the value chain. Overly *complex retail value chains generate inefficiencies in operations*. AI can streamline operations by automating manual tasks and reducing costs (Gupta, 2018, p. 21; Manyika & Bughin, 2018; Verhoef et al., 2021, p. 891). For example, Waitrose, a grocery retailer, uses AI to automatically process, capture and place orders for their items (Blueprism, 2019).

Fourth, AI creates opportunities for manufacturers, wholesalers and third parties to *engage with customers directly*, shortening the value chain (Reinartz et al., 2019) and creating new competition for traditional retailers. For example, Under Armour, a sports apparel and footwear wholesaler, connects with customers through their AI-enabled apps and uses the data to provide new products and services (Leighton, 2018).

AI can play a role in the value chain by changing interactions with customers, automating manual tasks through the value chain, maintaining relationships with suppliers and how profits are tracked (Alexander & Kent, 2021; Ameen et al., 2021, p. 1; Gauri et al., 2021, p. 42; Grewal et al., 2017, p. 1; Jin & Shin, 2020, p. 301; Pillai et al., 2020; Shankar, 2018; Wadhawan & Seth, 2016, p. 60; Weber & Schütte, 2019, p. 264). Various scholars agree AI is revolutionising retail by changing the way customers interact with retailers (Ameen et al., 2021), by (i) providing personalised services and product recommendations (Tupikovskaja-Omovie & Tyler, 2020, p. 388), (ii) enhancing the in-store shopping experience (Grewal et al., 2020; Pillai et al., 2020), (iii) analysing images and videos to assist designers (Liang et al., 2020), (iv) automating various routine or manual tasks (Kaplan & Haenlein, 2020, p. 46), (v) answering customer queries 24 hours a day (Roy et al., 2017, p. 150; Xu et al., 2020, p. 190), (vi) recognising patterns, and (vii) providing insights into customer and sales data (Acharya et al., 2018, p. 92; Ameen et al., 2021, p. 1; Gupta, 2018, p. 170). Thus, AI presents retailers with various options to improve consumer insights, enhance profitability and streamline their business processes in the value chain.

2.3.5 Summary: the retail value chain

As new AI continues to transform the retail industry (Hagberg et al., 2016; Romero & Martínez-Román, 2015; van Esch et al., 2019), the retail value chain needs to evolve with it (Fiorito et al., 2010, p. 887). However, the majority of retailers still employ the traditional value chain, or variations thereof, as the introduction of multiple channels to serve customer needs.

The traditional value chain inhibits the following four risks. First, increasing stakeholders in the form of channel members add complexity to the value chain, inhibiting retailers from understanding and swiftly responding to customer demand (Hagel et al., 2016). Second, various stakeholders likely use their platforms and software, making it difficult to integrate systems and manage data across the value chain. Third, the more complex and extended the value chain is, the longer it takes for products to reach the customer. Finally, overly complex value chains leave organisations vulnerable to digital disruption from smaller, more agile firms that leverage new technologies to reduce costs and scale up quickly (Gupta, 2018; Verhoef et al., 2019).

Retailers willing to invest in AI technologies could benefit due to its contribution to productivity growth in the value chain by automating repetitive tasks (Lee & Shin, 2020), increasing profit by understanding the customer requirements (Ameen et al., 2021), growing market share by giving companies the opportunities to enter new markets (Bolton et al., 2019) and driving actionable insight via big data analytics (Lee, 2017). While there is great excitement about AI, it has yet to fully deliver on its promise (Ransbotham et al., 2017, p. 1). Capgemini's (2018, p. 16) report calculated that a $300 billion opportunity exists for retailers investing in AI. However, it noted that only 30% of retailers use AI for some business processes. AI adoption seems limited to siloed processes (Fountaine et al., 2019, p. 6), and businesses are finding it challenging to integrate AI into their “people, process and systems” (Makarius et al., 2020, p. 262).

Few theoretical frameworks are used to test the adoption and integration of AI into retail. Some have investigated customer acceptance of AI applications using the technology acceptance model (TAM) (Chen et al., 2021, Liang et al., 2020) or used UTAUT (the unified theory of acceptance and use of technology) to test truck drivers' use of AI (Loske & Klumpp, 2021). Although these models are widely recognised, it was less relevant for this study to examine AI’s influence in retail and business, as successfully implementing AI requires more than only adopting the technology.

Investments into AI must be applied to the best use cases within the value chain to ensure retailers get the most out of AI (Elliot & Andrews, 2017). Nevertheless, implementing AI into business is complicated, and success depends on integrating the technology into the structure, people, and tasks. A model that represents the entire organisation is the Leavitt Diamond Model (Leavitt, 1965), to be discussed in the next section.

2.4 THE LEAVITT DIAMOND MODEL AS A THEORETICAL LENS

Organisations operate in an increasingly volatile competitive environment consisting of other organisations, suppliers, and customers. In addition, organisations are influenced by the broader environmental forces, such as new competitors, government legislations, the pace of technological change, and economic factors, making it hard for managers to navigate the complex changing environment (Leavitt, 1965; Porter, 1998). For an organisation to be effective and competitive, it requires the effective use of both people and systems (Bostrom & Heinen, 1977; Davis et al., 2014; Leavitt, 1965). However, organisations operate in an increasingly volatile competitive environment. Furthermore, technological advances have changed how organisations operate and play a significant role in introducing organisational complexities and challenges. Various approaches have been suggested to help managers make sense of the “complex structures of interrelated systems” in an organisation (Boella & van der Torre, 2006), including the McKinsey 7-S framework, the Leavitt Diamond Model and Social-technical systems (STS). All the models are essential tools to help understand the complexity in organisations.

The McKinsey 7S model depicts how effectiveness could be achieved by interacting with seven elements: structure, strategy, skills, staff, style, system, and shared values. However, it takes a more organisational design approach (McKinsey, 2008; Peters & Waterman, 2012). Instead, the Leavitt Diamond Model and STS considers the importance of the four interrelated social (i.e., people and structure) and technical (i.e., tasks and technology) variables when examining organisational change (Hartmann & Lussier, 2020). The Leavitt Diamond Model recognises that when a change in one of the four interrelated variables (structure, tasks, people and technology) occur, change can be predicated upon the other variables causing organisational challenges (Hartmann & Lussier, 2020; Leavitt, 1965). The Leavitt Diamond Model of organisational change forms part of the Socio-technical systems (STS) theory.

The Socio-technical systems (STS) theory, extends and builds onto Leavitt’s Diamond Model, assumes an organisation is a working system “made up of two jointly independent but correlative interacting systems, social and technical” and emphasises that if any redesign occurs in the work system, the focus should be given to both social or technical systems in the organisation (Bostrom & Heinen, 1977). Socio-technical systems (STS) theory has been in development for over 60 years (Davis et al., 2014, p. 171). It describes the interrelated relationship between social (humans) and technology (machines) in an organisation work system. Researchers have applied Socio-technical systems (STS) thinking to various studies, namely, to study smart work systems (Bednar & Welch, 2020), knowledge transfer practices for the implementation of electronic patient records (Masri et al., 2017), information technology implementation (Davis et al., 2014), the relationship between sustainable practices and systems (Seidel et al., 2013), and organisational interaction (Wigand, 2017). Furthermore, socio-technical systems (STS) stressed the effectiveness of an organisation (Bednar & Welch, 2020) by how the social and technological aspects “interact with and influence each other” (Bostrom et al., 2009, p. 186).

For this study, the Leavitt Diamond Model is preferred. Leavitt's Diamond model provides an explanatory framework for understanding AI's impact on the interdependencies between four key variables, structure, technology, people and tasks. Using the Leavitt Diamond Model as a framework for analyses could assist with appreciating the impact of AI on management and technology practice in the retail organisation. In addition, few studies on AI and retail link empirical AI research to theory (see. Section 1.2.4). Scholars have used Leavitt's Diamond Model to examine a variety of organisational change topics applying it in numerous contexts, including applying the model to assist B2B sales forces to better respond to COVID-19 or other crises (Hartmann & Lussier, 2020) to information systems in the organisational environment (Lyytinen & Newman, 2008), management challenges associated with data analytics (Vidgen et al., 2017); demand chain management by combining marketing and supply chain management (Jüttner et al., 2007) and the use of information technology and the effectiveness of human resource function (Haines & Lafleur, 2008).

In 1965, Harold J Leavitt designed a model to manage change in an organisation. The model indicates that organisations are complex structures of interrelated systems designed for a particular purpose (Boella & van der Torre, 2006; Leavitt, 1965), and subsequently developed the Leavitt Diamond Model. He argues that to compete in an ever-growing volatile environment, organisations can manipulate one of four interrelated sets of task, structural, technological, or human variables to improve performance (Leavitt & Bahrami, 1989). Describing such, Leavitt (1965) notes that when organisations change any task, technology, structure or people variable, it sometimes results in compensatory changes in one or more of the other variables. Thus, when the interdependencies are not managed at critical times during the change process, problems can occur within the business (Leavitt & Bahrami, 1989; Paghaleh et al., 2011; Smith et al., 1992). Figure 2.5 shows the relationships and interplay between four elements: structure, tasks, people and technology (Leavitt & Bahrami, 1989, p. 252).

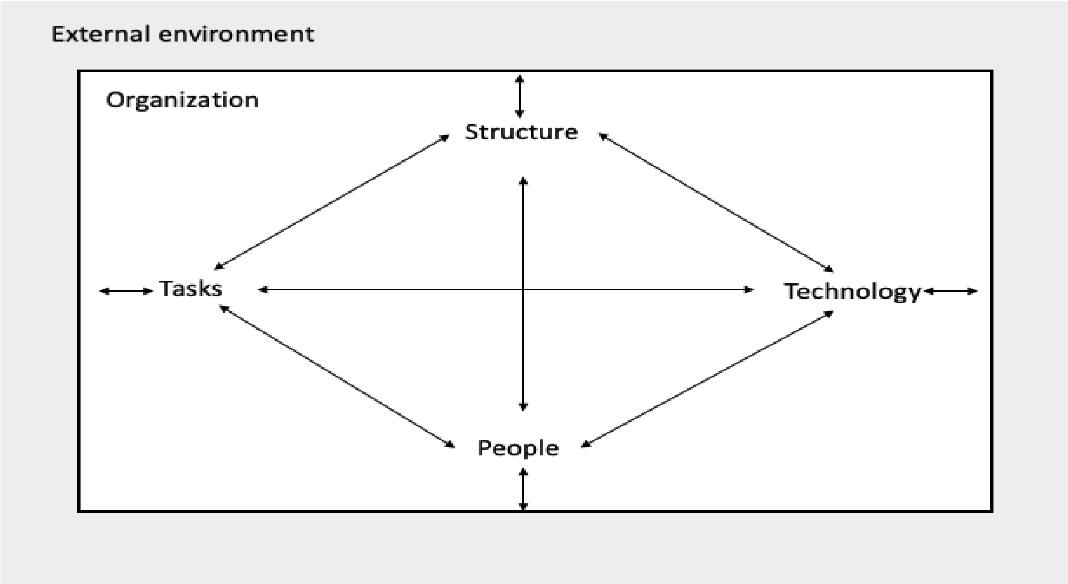


Figure 2.5: The Leavitt Diamond Model (Leavitt & Bahrami, 1989, p. 252)

The interaction between the four variables determines any organisation's result as everything is connected. The four variables are highly interdependent, and when organisations manipulate or change any of the variables, it is likely to cause significant effects in the others (Leavitt, 1965). Organisational change cannot occur in isolation, and when change is not managed at critical times during the manipulation of one of the variables, problems can occur within the organisation (Leavitt & Bahrami, 1989; Paghaleh et al., 2011; Smith et al., 1992). Table 2.4 details the four variables presented in the Leavitt Diamond Model, their definition, purpose and impact a technology change has the other variables. In Table 2.4, the *impact of change to the technology variable* refers to, in general, the impact any technology implementation has on the other variables in an organisation.

The Leavitt Diamond Model is an important model to examine the impacts of organisational change by considering the interrelated social (i.e., human and structure) and technical (i.e., tasks and technology) variables (Hartmann & Lussier, 2020). The Leavitt Diamond Model represents a balanced and rational view towards the complexities of implementing AI technologies. Technology directly relates to tasks, people, and structure in the model. Therefore, from this perspective, when retailers implement AI only focusing on the technology, the AI creates a knock-on effect on other variables, tasks, people, and structures within the retail organisation. As AI technologies are integrated into the retail value chain, it changes the way retailers operate in the retail value chain (Oosthuizen et al., 2020). However, few studies consider the impact of implementing AI on these organisation factors, and none, to the author's knowledge, considers the impact of AI on all four of these factors at once. Retail leaders must understand how AI will change their organisations to successfully scale AI across their organisations. Therefore, this study aims to understand how AI transforms the retail value chain using the Leavitt Diamond Model as the theoretical lens for this inquiry.

Table 2.4: The four Leavitt Diamond Model variables

Variables	**Structure**	**People**	**Tasks**	**Technology**
Definition	The structure is the activities and authority divided, organised and coordinated to achieve the goals of the organisation	People refer to the work executed by people at some time or place; it includes sub-variables such as skills, the readiness of people, people knowledge and resources	Task variable is the activities performed inside the organisation, including many subtasks that exist within an organisation such as manufacturing of products, selling goods and services, procurement of supplies and finance of operations	The technology variable is the systems, tools and mechanisms that turn inputs into business outcomes. This includes hardware (e.g., computers, mobile devices, servers), software (e.g., application software), and websites
Purpose	Structure divides employees' tasks into duties and responsibilities to facilitate decision making and how information flows between different company levels (Kenton, 2020).	People are responsible for performing tasks within their organisational structure.	A task purpose is to produce a specific output within a particular time	Technologies enable employees and organisations to perform tasks more efficiently and effectively.
Impact of change to Technology variable (Impact in general)	Requiring new structure to support the technology, removing silos by improving communication; management and measuring productivity	Requires new skills, extensive training and changing job roles. automating processes making previous roles redundant and a change in workforce competencies	Requires a change in the way work is done, change in the way employees work	Requires the skills and competencies to enable the technology to work at its best. Processing capacity

Adapted from:(Ahmady et al., 2016; Bostrom & Heinen, 1977; Hartmann & Lussier, 2020; Leavitt, 1965; Leavitt & Bahrami, 1989; Paghaleh et al., 2011)

A survey by Gartner 2019 estimates that 30 % of businesses are using some form of AI technologies (Hare & Andrews, 2019, p. 3). However, less than half of AI proof of concepts gets integrated and scaled into business (Davis, 2020, p. 3). Similarly, AI adoption rates remain low in retail, even though AI can provide significant value (Dogru & Keskin, 2020, p. 69). Therefore, as AI disseminates into the retail value chain, it is essential to understand how AI transforms it.

2.5 CONCLUSION

This chapter provided an in-depth literature review of the key constructs of concern for this study (i.e. AI and the retail value chain) and the theoretical lens used (i.e. the Leavitt Diamond Model). To examine how AI transforms the value chain, this study uses the Leavitt Diamond Model as a theoretical lens to investigate the subsequent research questions. Major studies in AI in retail literature only focus on the technology variable of the Leavitt Diamond Model (Balaji & Roy, 2017; Bottani et al., 2019; Grewal et al., 2017, 2020; Guo et al., 2011; Jin & Shin, 2020; Lee, 2017; Wadhawan & Seth, 2016), which is a gap in current research. Therefore, this study uses all the variables (structure, technology, people and tasks) in the Leavitt Diamond Model to understand the impact of AI on the retail value chain. To the author's knowledge, no other studies have used the Leavitt Diamond Model in the context of AI in the retail value chain before. Understanding the complexities of successfully integrating AI into the retail value chain is critical to retail theory and practice. Four articles are used to understand this research question, each with its accompanying research question. The following chapter investigates research question one - what role does AI play in the retail value chain.

Chapter 3: WHAT ROLE DOES AI PLAY IN THE RETAIL VALUE CHAIN?

3.1 CHAPTER INTRODUCTION

AI encompasses many different intelligent technologies and can serve multiple purposes across the retail value chain. However, many AI applications, already available or under development, contribute to retailers' confusion and frustration regarding which AI technologies to invest in. Therefore, it is essential to understand where AI applications can improve efficiencies, automate processes, and drive insights in the retail value chain. While authors argue that the retail value chain needs revisiting because of new technologies (Hagel et al., 2016; Reinartz et al., 2019), limited empirical research, to the author's knowledge, have suggested exactly what the role of AI is in the retail value chain and how the retail value chain should change. Therefore, article one was developed to assess the potential application of AI-enabled solutions across the various retail value chain activities.

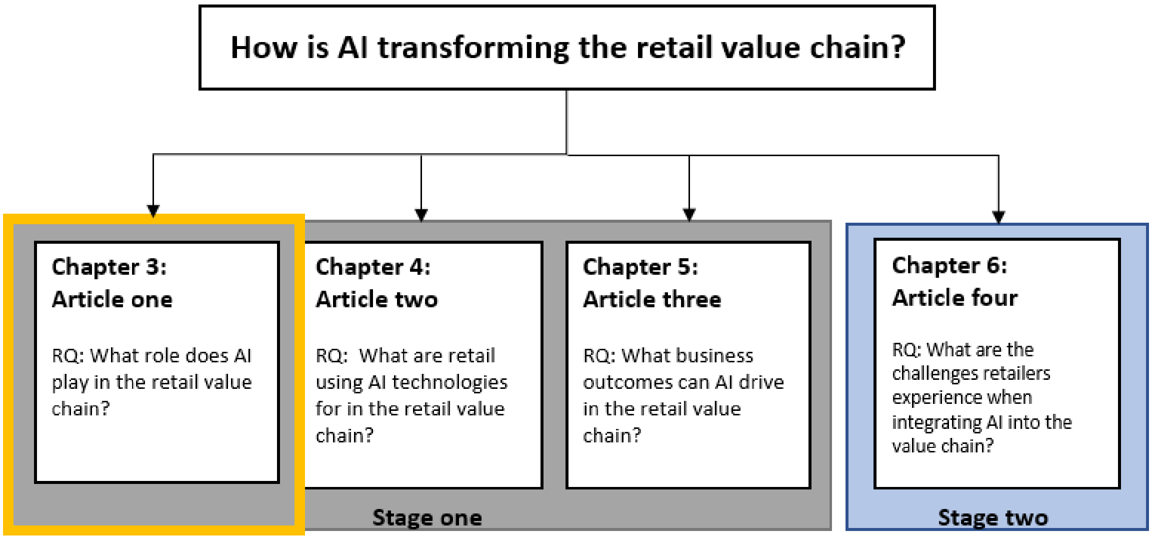


Figure 3.1: Article layout and the research questions

Article one introduced a conceptual framework to understand AI's role in the retail value chain proposing an alternative: the AI-enabled value chain. Article one asks *what role does AI play in the retail value chain*. To answer the research question, all the AI activities in the retail value chain were classified using a jobs-to-be-done approach into four categories: knowledge and insight management, inventory management, operations optimisation and customer engagement. The following section covers the published article Artificial Intelligence in retail: The AI-enabled value chain.

3.2 ARTICLE ONE: ARTIFICIAL INTELLIGENCE IN RETAIL: THE AI ENABLED VALUE CHAIN

3.3 INTRODUCTION

Traditional retailers' business models face disruption by new entrants who can deliver greater value to customers more efficiently. In recent years, authors have argued that the "traditional" value chain drives inefficiencies (Begley et al., 2018, p. 2) and that the value chain is shortening as manufacturers, third parties, and customers are increasingly engaging with customers directly (Reinartz et al., 2019). These inefficiencies and the inability to adapt to a changing competitive landscape leave traditional retailers vulnerable to disruption from market entrants. To remain competitive and survive in an ever-changing and diversified customer market, retailers need to become leaner (Campbell et al., 2020), more agile (Goworek, 2014), and innovate their value chain by adopting new technologies (Lee et al., 2017). Of the new technologies impacting the retail industry, AI has been earmarked as the most transformative (Kietzmann et al., 2018; Lee et al., 2018; Silva et al., 2019). Nevertheless, while there is great excitement about AI, it has yet to fully deliver on its promise (Ransbotham et al., 2017, p. 1), and academics and practitioners are in the early stages of understanding the application of AI (van Esch et al., 2019, p. 36). This article introduces a conceptual framework to understand AI's role in the retail value chain by proposing an AI-enabled retail value chain.

As a starting point, we provide a brief overview of the traditional retail value chain and the activities, stakeholders, and technology involved at each stage. The disruption of the retail industry is then explained, followed by a particular focus on the role that AI has played in disrupting this industry. We then map various AI technologies (based on Gartner's (Sicular et al., 2019) to each stage in the value chain and show that some AI technology investments can serve multiple purposes in the value chain. Then, we use Christensen's jobs-to-be-done approach (Christensen & Raynor, 2013; Christensen et al., 2016) better to understand the value of AI in the retail industry. Therefore, this article aims to understand better what an AI-enabled retail value chain should resemble.

This article provides two important contributions to the emerging literature on AI and its implementation in marketing and retailing. First, we show how AI technologies can be used across various retail value chain activities. While several authors have addressed the relevance of AI to business in general (Kietzmann et al., 2018; Paschen et al., 2019; Poole and Mackworth, 2010; Ransbotham et al., 2017), the strategic role and implementation of AI in retailing organisations have been subject to limited critical scrutiny (van Esch et al., 2019). By mapping specific AI technologies against the retail value chain, we provide retail managers with some guidance regarding which AI technology investments to prioritise or how to leverage current AI investments.

Second, while authors argue that the retail value chain needs revisiting because of new technologies (Hagel et al., 2016; Reinartz et al., 2019), limited empirical literature, to the author's knowledge, have suggested precisely how the retail value chain should change. Guided by the job-to-be-done approach in innovation (Christensen et al., 2016), we identify four key roles for AI solutions in the retail value chain: knowledge and insight management, inventory management, operations optimisation, and customer engagement. This approach is customer-centric (Bettencourt & Ulwick, 2008), not Tayloristic and process-driven and, therefore, better suited to the complex nature of business amidst new technologies (McChrystal et al., 2015). Contrary to the more traditional silo-mentality and linear view of the value chain, we argue that AI solutions can perform multiple roles simultaneously, thus establishing interconnectivity between the different value chain activities. First, however, the digital disruption of the traditional retail value chain is discussed.

3.4 DIGITIAL DISRUPTION IN THE TRADITIONAL VALUE CHAIN

In his seminal work, Michael Porter (1998) used the term value chain to describe a set of activities performed to design, produce, market, deliver and support products within businesses (Hagel et al., 2016). The value chain is a set of processes that deliver value across primary activities (for example, inbound logistics, operations, outbound logistics, marketing and sales, and service) and secondary activities (including firm infrastructure, human resource management, technology development and procurement). The activities in the traditional value chain move in a sequence of linear steps, which facilitates the process from product design to the point of consumption (Reinartz et al., 2019, p. 352). In retailing, the value chain encompasses all the stakeholders and processes needed for retailers to deliver an end product or service to a customer (Hagel et al., 2016, p. 4). From supplier to manufacturer to retailer, each stakeholder in the value chain adds value to the customer. Table 3.1 details the stages involved in the traditional retail value chain, including each stage's objectives and typical activities (Hagel et al., 2016; Rieple and Singh, 2010). The stakeholders and technologies typically involved in each stage have been included.

Table 3.1: Traditional retail value chain stages, objectives and activities

Retail Value Chain Stages	Activities	Stakeholders	Key Driver	Decision	Outcome	Current Technology Application Examples
Design	Design initiation, Design Concept, Decision-making process, Technical design	Retail, Manufacturer, Suppliers, Customers	Product trends, customer needs, bring a new product to market quicker, Market research, Product quality	Which products to design. Product specification. Materials.	Pattern Design and specifications. Production planning and control. Garment evaluation.	CAD system, Fabric quality checking, Online product searches
Sourcing/ Procurement	Planning and production control Purchasing or building inventory	Retailer, Manufacturer, Suppliers	Tailoring assortment for customer needs, understanding customer segments, product selection, price negotiation, liaising with suppliers	Which products will fulfil customer needs? When is the product needed in store? Buy quantity. Aligned to Budget. Which supplier or manufacturer.	Sales budget planning, Merchandise Strategy, Merchandise Financial Planning, Assortment Planning, Supplier/Manufacturer selection, order placement	Assortment Planning, Merchandise financial planning, Size profile Optimisation, Excel
Manufacturing and assembly	Cutting, Sewing, Finishing, Packing, Acquiring, storing, and preparing raw materials	Manufacturer, Supplier, Shipping	Accurate forecasting, One-time ordering, Product flow visibility, Product quality	Cutting, Sewing, finishing and distribution. Production scheduling and factory management. Quality checking	Cutting quantity, Job Scheduling, Assembly line, Fabric Laying, cutting, overall handling. Workforce planning	ERP systems, Assembly, Workforce Scheduling, Materials management
Inventory management and distribution	Managing and distributing products to be sold	Retail, Suppliers, Logistics, Distribution	End to End Inventory visibility, Consistent, accurate Sales & Inventory forecasting, monitoring product deliveries	Monitoring deliveries, monitoring inventory, scheduling DC to Store deliveries	Movement of Products from manufacturer to DC or Store Sales forecasting, Allocation to stores, forecasting, determining replenishment information, controlling inventory levels.	Product information management, Order processing, demand planning, Product allocation
Store operations and Sales	Managing point of sale and executing purchase transition	Retail, Suppliers, Logistics, Customer, competitors	Performance management, Price & Markdown optimisation, monitoring stock levels	Maximising sales, minimising markdowns, managing product life cycle, price point management, customer service	Promotions and Markdown planning. Reordering, Key products, reverse logistics, Repairs, returns and maintenance support, Traffic management.	Pricing management, promotional planning, Product lifecycle management, POS system
Fulfilment	Delivering products to the customer	Retail, Suppliers, Manufacturer	Matching demand to product supply	Managing out of stocks, maximising sales, managing inventory, reorder negotiation	Product replenishment, Logistics management, Movement of products to stores, forecast accuracy, Inventory placement optimisation for Omni fulfilment, Workforce planning	Demand prediction, inventory management, ordering items
Customer use and support	Helping customers maximise value, using and maintaining products	Retail, Customer, Logistics	Offering customers personalised offerings	Identify high-value customers and products, Supporting Customer queries.	Satisfied customers, personalised offerings and product recommendations	Online platform, POS systems, CRM management

SOURCE: Adapted from Cammett, 2006; Hagel et al., 2016; Lee et al., 2018; Porter, 1998; Reinartz et al., 2019; Rieple & Singh, 2010

However, new digital technologies have disrupted the traditional retail business model by changing marketplaces from brick and mortar only to omnichannel, which significantly alter the customer purchase journey (Bolton et al., 2019; Carlsson, 2018; Van Esch et al., 2019). Customers are more connected than ever (Kietzmann et al., 2011), and the transformation from store to omnichannel retailing has elevated their service expectations (Oh and Polidan, 2018). Moreover, as the rate with which these new technologies enter the market increases (Brynjolfsson et al., 2013; Gupta, 2018), it blurs the market boundaries and holds unpredictable consequences for retailers (Day and Schoemaker, 2019). For instance, innovative and fast-growing digital entrants like Alibaba and Amazon have already adversely affected traditional retailers like Toys 'R'Us and RadioShack by using their digital resources to not only disrupt the retail industry but also seemingly unrelated industries, like banking and global shipping (Verhoef et al., 2019).

As new digital technologies continue to transform the retail industry (Hagberg et al., 2016; Romero and Martínez-Román, 2015; Van Esch et al., 2019), the retail value chain needs to evolve with it (Fiorito et al., 2010). However, the majority of retailers still employ the traditional value chain, or variations thereof (like the introduction of multiple channels to serve customer needs), which holds the following four risks. First, while each stage of the retail value chain adds value, it also adds complexity by increasing the number of stakeholders and their accompanying support structures involved. Complicated value chains inhibit retailers from understanding and swiftly responding to customer preferences (Hagel et al., 2016). Second, various stakeholders are likely to use their platforms and software, making integrating systems and managing data difficult. Legacy systems often inhibit organisations' agility from responding to changing customer needs and using the data for competitive advantage (Westerman et al., 20). The ability to manage mass amounts and different data sources are critical to a company's success (DalleMule and Davenport, 2017; Sankaran et al., 2019), and data-driven decisions are becoming increasingly important in value chains (Sankaran et al., 2019). Third, the more complex and extended the value chain is, the more expensive products and services become, and the longer it takes to reach customers. Finally, overly complex value chains leave organisations vulnerable to digital disruption from smaller, more agile firms that leverage new technologies to reduce costs and scale up quickly (Gupta, 2018; Verhoef et al., 2019).

According to Ransbotham et al. (2017), expectations for the commercial application of AI in business, particularly in retailing, are sky-high. However, while there are existing analytical tools for managers to gauge AI's influence on retail and other industries (U Paschen et al., 2019), creating and leveraging AI's value for commercial advantage in the value chain still seems complex to most. To assist in this delineation, the following section explicates what exactly AI is and how it is currently applied in retailing.

3.5 ARTIFICIAL INTELLIGENCE IN THE RETAIL VALUE CHAIN

3.5.1 The definition of Artificial intelligence

Most extant conceptualizations of AI refer to computer systems with human-like intelligence (Wierenga, 2010, p. 2), which encompasses these systems' abilities "... to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Kaplan and Haenlein, 2019, p. 17). In their definition, the Oxford Dictionary includes tasks such as visual perception, speech recognition, decision-making, and the translation between languages, with the Merriam-Webster Dictionary emphasizing that AI imitates intelligent human behaviour. Poole and Mackworth (2010, p. 3) offer a slightly nuanced explanation by framing AI as "computational agents that act intelligently". This definition describes AI as agents capable of perceiving an environment to take action, with the goal being to maximize the likelihood of achieving success (U. Paschen et al., 2019, p. 150). From a systems perspective, the definition also implies a rational view of AI, where an AI system would, given what it knows, act to achieve the best possible outcome (U. Paschen et al., 2019, p. 148).

For this article, we adopt the definition by Poole and Mackworth (2010), as it highlights two conceptual delineations. First, it highlights the different evolutionary stages of AI (Haenlein and Kaplan, 2019). What might have been considered intelligent behaviour displayed by a machine five years ago is now hardly noteworthy? Three stages of AI are differentiated: artificial narrow intelligence (applied, below human-level AI, e.g., Siri voice recognition), artificial generalized intelligence (strong, human-level AI, e.g., Siri developing the ability to perform tasks like driving a car autonomously), and artificial superintelligence (conscious/self-aware, above human-level AI, e.g., Siri developing superhuman capabilities to solve complex problems instantaneously). Most of the commercial AI technologies available today are classified as "narrow", and almost all of the AI technology to be integrated into business in the next ten years will be "narrow" or "applied" (Kelly, 2017, p. 50; Yao et al., 2019, p. 18). For example, the use of AI to create ads (Kietzmann et al., 2018). This applies to retailing as well.

The second defining characteristic highlighted in the Poole and Mackworth (2010) definition is the notion that AI represents knowledge, expertise, and intuition to solve problems. AI requires tailored knowledge to be built into a "carefully constructed system" (Kaplan, 1984, p. 52), where the storage of past knowledge should reflect experiences that would inform subsequent intelligent behaviour (U. Paschen et al., 2019, p. 148). In AI systems, these knowledge representations could include inputs (structured and unstructured data); processes (machine learning); or self-generated AI-output (robotics) (U. Paschen et al., 2019). As AI continuously advances, our understanding of its various applications needs to develop quickly. The following section focuses on AI technologies in retail and their role in the retail value chain.

3.5.2 AI in retail

AI technologies have advanced in recent years. However, it remains in its infancy (Bughin et al., 2017). A vast majority of retailers have started testing the possibility of AI, yet many retailers are missing the full benefit of scaling the technology throughout the value chain (Standish and Ganapathy, 2020). Furthermore, many AI applications, already available or under development, contribute to retailers' confusion and frustration regarding which AI technologies to invest in. This section first provides an overview of where AI is *currently* being applied in retail to assess the potential application of AI-enabled solutions across the various retail value chain activities.

To develop an understanding of the *current* application of AI technologies used in retailing, we first reviewed the 2019 Gartner hype cycle for artificial intelligence report (Sicular et al., 2019), focusing on the AI technologies predicted to reach mainstream adoption in the next five years. Next, the report examines trends and innovations in the AI sector and classifies the different AI applications (Sicular et al., 2019). These include speech recognition, graphic processing unit (GPU) accelerators, robotic process automation software, artificial intelligence (AI)-related consulting and system integration (C & SI) services, augmented intelligence, chatbots, machine learning, deep learning, edge AI, intelligent applications, virtual personal assistant (VPA)-enabled wireless speakers, virtual assistants, field-programmable gate array (FPGA) accelerators, computer vision, insight engines, data labelling and annotation services, and automated machine learning (AutoML) (Sicular et al., 2019).

Using the retail value chain presented in Table 3.1 to better understand the possible role of AI therein, we identified retailers who currently apply AI technologies in their value chain. Table 3.2 illustrates examples of retailers applying various AI technologies throughout the value chain.

Table 3.2: Example applications of Retailers' AI Technology in the value chain

Value Chain Stage	**Retailer**	**AI Technology (Gartner Hype Cycle)**	**Detail of Technology Use**
Design	Adidas	Machine learning	Using Machine learning Adidas is using a "speed factory" to help customers design their own personalised shoes and make them in 24 hours, and shipping to customers
Sourcing/Procurement	Simons	Insight engines	Simons implemented analytics for improved insight on projected demand and inventory Optimisation recommendations that get the right product to the right store proactively
Manufacturing	Mohammedi Fashion Sweaters	Intelligent applications	AI-enabled sewing machines that knit sweaters
Inventory management and distribution	ThredUp	Deep learning	Scanning close to 100 million unique inbound items via image recognition enabling automated visual tagging of products and assigning a unique item code
Fulfilment	The Home Depot	Edge AI	Home Depot Inc. is connecting in-store robotics with an intelligent enterprise approach. It is using drones and robotics to create an efficient in-store experience that delights customers and provides faster order fulfilment
Store operations and Sales	Sephora	Augmented Intelligence	The app allows customers to try products virtually via augmented reality. The tool scans a customer's face, figures out their lips and eyes match colours and suggests buying products.
Customer use and support	Ikea	Augmented Intelligence	The augmented reality helps the customer virtually "place" true to scale 3D furniture in their home.

SOURCE: Adapted from Araujo, 2019; de Leon, 2019; Emont, 2018; Galer, 2018; Ikea, n.d.; RIS, 2020; Sephora, 2017

Retailers are already beginning to apply AI applications in parts of the value chain (Bughin et al., 2017). However, both researchers and practitioners are only in the early stages of fully understanding the application of AI (Van Esch et al., 2020). In addition, and as is evidenced in Table 3.2 above, some AI applications were used for more than one value chain activity. For example, Augmented Intelligence was used for store operations and sales by one retailer and customer use and support by another. This prompted the authors to take a broader view of where each AI technology can be applied in the retail value chain.

While understanding the current application of AI in retail can help identify gaps in its use, it does not provide insight into its most effective use in the retail value chain. To further develop our understanding of the opportunities and address this gap, we next use Clayton Christensen's (2003) jobs-to-be-done approach as a guideline to identify four conceptual dimensions which highlight how AI can best be applied to the retail value chain.

3.5.3 Reimagining AI in the retail value chain: A jobs-to-be-done approach

Using a customer-centric innovation approach to understanding value (Bettencourt and Ulwick, 2008), the jobs-to-be-done approach was developed by Clayton Christensen in his 2003 book, *The Innovator's Solution*, and later expanded upon in *Competing Against Luck* (Christensen et al., 2016). The theory proposes a group of principles that explain how to make marketing more effective and innovation more predictable by focusing on the customer's jobs to be done**.** Christensen et al.'s (2016) approach is based on the idea that companies should focus on the key goals of a product or service to stimulate the effective development and implementation of innovation. For example, when considering how to improve a razor blade best, companies should be less concerned with improving the product itself (e.g., adding more blades) and more concerned with what "job" the razor blades do (e.g., quick and easy grooming). For example, Philips recently presented their One Blade range of razor blades, which shaves and trims and styles any length of hair for multiple looks (Philips, 2020). In essence, Christensen et al. (2016) argue that people 'hire' products and services to get jobs done, and companies can innovate by doing those jobs better. Each job can be broken down into various steps or stages of execution, with validating questions to assess the best job fit at each stage (Bettencourt and Ulwick, 2008).

Following the job mapping approach by Bettencourt and Ulwick (2008), the authors iteratively followed a customer-centric validation process, guided by the retail value chain processes as a reference point, to conceptually cluster what jobs AI can perform in the retail value chain. We argue that this approach can successfully be applied to final products and services and the application of technology like AI in the workplace. Furthermore, better understanding the jobs-to-be-done by AI technologies will increase its value to the company. From this perspective, four job dimensions emerged discussed in greater depth in the following sections:

1. *Knowledge and insight management AI technologies* refer to the ability to provide insights by managing, sharing, using, creating and processing information.
2. *Inventory management AI technologies* refer to those that assist in the process of balancing demand to supply over large assortments to meet customer needs and financial objectives.
3. *Operations optimisation AI technologies* help retailers operate effectively and efficiently by minimising cost and maximising operational capabilities.
4. *Customer engagement AI technologies* enable retailers to build relationships with their customers.

Table 3.3 details current AI technologies that fulfil these four 'jobs-to-be-done dimensions set against the traditional stages of the retail value chain. Each of these four dimensions of AI applications in the retail value chain is now discussed in the following section.

3.5.3.1 Knowledge and insight management

Knowledge and insight management AI technologies provide insights throughout the value chain by managing, sharing, using, creating and processing information. Data is one of the foundations of AI (Haenlein et al., 2019), and the effective translation of that data into knowledge is key to its success. This dimension includes the process of transforming structured and unstructured data inputs into outputs that contribute to the organisation's knowledge base. Paschen et al. (2019) refer to this as the building blocks of AI. Current examples include deep learning, intelligent applications, and insight engines, amongst others. The importance of transforming data into knowledge has been stressed by various authors (Black & van Esch, 2019; U. Paschen et al., 2019). Although more data is available than ever before, only a fraction is integrated and analysed within businesses (Chen et al., 2016). While some companies use data to create a competitive advantage, many businesses fall short of gaining real insights from their data. This can mainly be ascribed to big data requiring powerful technologies, computer processing power, skilled personnel and predictive models to crunch enormous amounts of data (Djafri et al., 2018; Gupta, 2018).

Table 3.3: AI jobs-to-be-done in the Retail Value Chain

		Current applications of AI in the retail value chain						
Jobs to be done area of application	**Objective**	**Design**	**Sourcing/ Procurement**	**Manufacturing and assembly**	**Inventory management and distribution**	**Store operations and Sales**	**Fulfilment**	**Customer use and support**
Customer engagement	To build customer trust through personalisation	Machine Learning	Deep learning			AI-related C&SI Services Augmented Intelligence Chatbot Computer Vision Deep learning Intelligent applications Machine Learning Virtual Assistant		Augmented Intelligence Chatbot Computer Vision Deep learning Edge AI Insight engines Machine Learning Speech recognition Virtual Assistant
Inventory Management	Predict demand close to supply by anticipating customer needs and achieving financial objectives		Intelligent applications		Intelligent applications Machine Learning.	Chatbot Virtual Assistant	Insight engines Intelligent applications Machine Learning	
Operations optimisation	Operating efficiently and effectively by minimising cost and maximising operational capabilities		Robotic process automation software	AI-related C&SI Services Deep learning Intelligent applications.	Deep learning Edge AI Robotic process automation software	AI-related C&SI Services Computer Vision Edge AI Intelligent applications Machine Learning Robotic process automation software Virtual Assistant	Edge AI	
Knowledge and insight management	Ability to provide insights by managing, sharing, using, creating and processing information	Deep learning Insight engines	Deep learning Insight engines		Insight engines	Deep learning Edge AI GPU Accelerators Insight engines		AI-related C&SI Services Insight engines Intelligent applications

The analysis, processing and interpretation of data is a time-consuming activity in the retail value chain; thus, more sophisticated AI technologies can be utilised to reduce the shortcomings of human efforts (Chen et al., 2016; Gupta, 2018; Sivarajah et al., 2017). Furthermore, insight engines can anticipate future customer product needs and assist retailers in optimal sourcing assortments for their customers. Therefore, gaining knowledge and insights from value chain data should be a key motivator to implement AI technologies in the retail value chain. However, siloed legacy IT systems should be replaced with robust and scalable technology (Wirth, 2018). Therefore, the current linear approach to the retail value chain is not conducive to advanced knowledge and insight management of AI technologies.

3.5.3.2 Inventory management

Retailers have two main inventory management objectives: first, to buy products to fulfil customers' requirements, and second, to plan the inventory flow to maximise profit for their company (Fairhurst and Fiorito, 1990). As retailers always try to match supply to demand, they continually revise their sales forecasts to anticipate demand throughout the value chain (Goworek, 2014). To achieve the required forecasting capabilities, they need particular sources of knowledge and insight. AI technologies can assist in the process of balancing demand and supply over large assortments to meet the customers' needs and the company's financial objectives. Current AI applications in this category can drive lower inventory levels, anticipate future demands and create localised assortments leading to reduced working capital for retailers (Chao et al., 2019; Chuprina, 2019; Marr, 2018). These AI solutions include chatbots, insight engines, intelligent applications, machine learning and virtual assistants.

AI can furthermore assist retailers in streamlining inventory management by predicting demand, keeping popular items stocked on shelves, and using clustering technologies to anticipate future customer requirements. Machine learning, deep learning and intelligent applications could match supply to demand by using multiple data sources and adjusting demand accordingly (Bughin et al., 2017). Predictive inventory management could drive improvements in forecast accuracy and optimise the inventory throughout the retail value chain, leading to increased profits and cost-saving for the retailer (Petropoulos et al., 2018). The eCommerce retailer, Otto Group, has, for example, reduced their out-of-stock rate by 80% by using predictive machine learning applications, which also boosted revenue, increased margins and assisted in responding to market shifts (Trotter, 2018).

3.5.3.3 Operations optimisation

AI applications assisting with operations optimisation are designed to improve operations efficiently and effectively by minimising cost and maximising operational capabilities (Li et al., 2017). However, inefficient operations slow down the movement of products through the value chain, moving the customer further away from a successful purchase (Rieple and Singh, 2010). AI applications for this purpose include AI-related C&SI services, computer vision, deep learning, Edge AI, intelligent applications, machine learning robotic, process automation and virtual assistants, which all shorten the value chain by improving production speed and managing inventory flow to the customer.

Various authors agree that streamlining operational processes creates efficiencies throughout the retail value chain (Bughin et al., 2017; Li et al., 2017; Marr, 2019; Daugherty and Wilson, 2018). For example, JD.com, one of China's largest retailers, has introduced AI to drive efficiencies in their operations (Marr, 2019). The introduction of the AI applications allowed the retailer to deliver 92% of their orders on the same or the next day (Trotter, 2018). In addition, Nike implemented augmented intelligence to design customised shoes for its customers, and the end-to-end process only takes two weeks from design to customer delivery (Chao et al., 2019). Thus, optimising operations can offer unexpected benefits by increasing operational efficiency, increasing agility and speed across the retail value chain. These improvements should be the driving force behind implementing AI in retail operations.

3.5.3.4 Customer engagement

The value of using AI in customer-facing activities is well documented. Xu et al. (2020) recently defined AI in the context of customer service as "a technology-enabled system for evaluating real-time service scenarios using data collected from digital and/or physical sources to provide personalised recommendations, alternatives, and solutions to customers' enquiries or problems" (Xu et al., 2020, p. 189). To create a customer-centric value chain, retailers need to exceed customer expectations to survive in a competitive market. Furthermore, to deliver seamless shopping experiences across all channels, retailers need to build connections with their customers (Araujo, 2019). Therefore, AI technologies for customer engagement in the retail value chain predominantly focus on the customer journey, enabling customer engagement, enhanced customer service, and sales support functions (Kaplan and Haenlein, 2019). As per Table 3.3, most retailers currently focus on AI applications to facilitate customer engagement. Retailers are utilising AI applications to connect with and build relationships with customers by personalising their product recommendations and purchases, helping them find their way around the store, and answering product-related questions in real-time using apps (Morgan, 2019; Standish & Ganapathy, 2020; Weber & Schütte, 2019). A typical example of such personalisation is chatbots to reduce customer service costs and speed up customer response time to queries (Reddy, 2017).

Current AI technologies that assist retailers in engaging with customers across the retail value chain (and not only in the final stages of the value chain) include speech recognition, robotic process automation, AI-related C&SI services, augmented intelligence, chatbots, computer vision deep learning, Edge AI, insight engines, intelligent applications, machine learning, speech recognition and virtual assistants. At retailer Sephora, for example, in-store employees are equipped with handheld devices to scan a customer's face, creating a personalised cosmetic shade to match the customer’s complexion. The shade matching creates a unique code enabling the customer to personalise purchases across all channels (Milnes, 2016). Likewise, the North Face, a retailer of technical outerwear, utilizes augmented intelligence to help consumers find clothing and apparel suited to specific weather conditions (Trotter, 2018). These customer engagements AI applications build customer loyalty through personalisation, moving away from purely transactional towards a customer-centric approach.

3.6 THE AI-ENABLED RETAIL VALUE CHAIN FRAMEWORK

In the previous section, we used the jobs-to-be-done approach (Christensen et al., 2016) to understand better how AI can be successfully applied to the retail value chain. We conceptually proposed four AI technology dimensions, which fulfil most of the roles in the “traditional” retail value chain. The majority of current AI applications are narrow (Marr, 2017) and implemented in some offerings and processes (Ransbotham et al., 2017). However, we suggest that various AI applications, such as machine learning, intelligent applications, Edge AI and deep learning, can undertake multiple tasks across the retail value chain. Retail managers would therefore get the greatest return on investment in investing in these AI technologies.

When applied more generally to the retail value chain, the four dimensions identified in section 3.5 can be represented as an improved value chain (Figure 3.2) that stands in contrast to the silo mentality and linear process proposed in many traditional retail value chains (see Figure 2.3). The process within the AI-enabled retail value chain framework is iterative and agile, enabling real-time data flows.

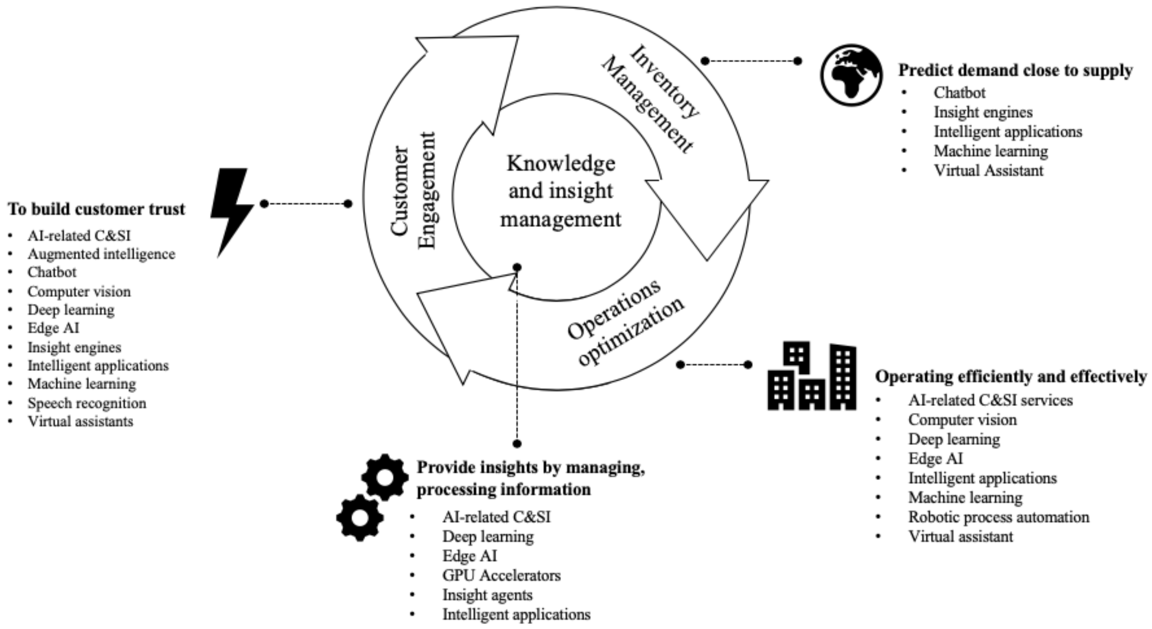


Figure 3.2: The AI-enabled retail value chain

The dimensions in the AI-enabled retail value chain framework are not mutually exclusive. Its objective is to generate knowledge and insights supporting all value chain activities. As the backbone of any AI implementation, knowledge and insight management provides insights throughout the value chain by managing, sharing, using, creating and processing information. The appropriate use of AI technologies provides responsive R&D, dynamic price recommendations, and extensive transactional data processing. In addition, AI applications can anticipate future product and customer needs by collecting and analysing data across various data sources.

AI-enabled *customer engagement* retail activities include a myriad of functions geared toward Optimising customer interactions and building customer relationships. For example, these functions include supporting customers to navigate the store, answering questions and creating personalised product recommendations. As a result, retailers investing in customer-facing AI technologies create a unique competitive advantage in the market. In addition, technological innovations such as AI help new entrants seamlessly move through the value chain stages in the design, manufacture, commercialization, distribution and support of products - enabling them to connect with their customers.

In *inventory management*, AI can assist retailers in matching supply and demand by using multiple data sources and adjusting demand accordingly through the implementation of machine learning, deep learning, and other AI intelligent applications. Predictive inventory management could improve forecasting accuracy and optimise inventory throughout the retail value chain, leading to increased profits and cost-saving for the retailer. Retailers that want to benefit from this category of AI applications must identify employees' capability to work alongside intelligent applications (Black and Van Esch, 2020).

Optimising operational efficiencies by streamlining processes with AI applications can remove silos throughout the value chain. Major manufacturers and retailers are already using AI-based technologies throughout their distribution centres to streamline operations (Grewal et al., 2017).

3.7 CONCLUSION AND MANAGERIAL IMPLICATIONS

Research asserts that the traditional retail value chain is experiencing a metamorphosis, yet, literature offering managerial guidance on responding to these changes is limited (Araujo, 2019; van Esch et al., 2019). With added pressure to remain competitive, many retailers have started to embrace various digital technologies to engage with their customers (Grewal et al., 2017). Many are utilising AI applications to establish this connection (Morgan, 2019). To bridge this gap, the application of current AI technologies to the retail value chain was reviewed, and four dimensions of AI applications were conceptualised. AI can best be employed in the retail value chain by serving one of the following purposes: knowledge and insight management, inventory management, operations optimisation and customer engagement. These four categories of AI technologies in the value chain enabled us to propose a revised AI-enabled retail value chain.

Although extant literature suggests that most AI applications over the next decade will remain narrow or applied (De Bruyn et al., 2020, p. 92; Yao et al., 2019, p. 19), we propose that these narrow applications of AI can be extended to multiple functions in the retail value chain. Therefore, retailers should invest in classes of AI technologies (e.g. deep learning capability) and not just specific applications, thereby ensuring that these technologies be used for multiple functions across the value chain. In addition, this framework provides retailers with a list of priorities for investing in AI: Start with knowledge and insight management at the foundation. Using this framework, single AI applications can be applied to multiple tasks. Therefore, the framework (in combination with Tables 3.3) provides retailers with insight into how to best leverage current AI investments.

Retail managers need to focus on scaling AI technologies to reap the full long-term benefits across the value chain. Broadening their horizons, retailer management should move away from a narrow focus on technology investments for distribution channels and customer-facing technologies only (Olanrewaju and Willmott, 2013). The suggested conceptual framework can help retailers transform their value chains to compete and thrive in the changing retail landscape for increased and sustained competitive advantage.

3.8 FUTURE RESEARCH

Future research could further build on the four identified value-adding dimensions that AI solutions can play in the retailers' value chain. Future research could explore how these different AI dimensions contribute to organisations' competitive advantage in different product-market contexts. Furthermore, as many global industries gear up for the widespread adoption of AI technologies, demand and competition will grow for scarce skilled employees who can implement, manage and work alongside the new technology (Butler-Adam, 2018; van Esch et al., 2019). Therefore, it will be crucial for organisations to have a skilled workforce to support the implementation of AI, and there will be an even higher demand for skilled professionals (Van Esch and Black, 2019). While companies face external competition in finding skilled employees, low skilled workers could find it challenging to compete with machines and struggle to be employable in the future (Frey and Osborne, 2017). Therefore, future research can focus on the skills and competencies necessary for the organisation to implement the AI-enabled retail value chain.

An AI-enabled retail value chain relies heavily on skilled employees who supply high-quality data at each touch point in the value chain. If the data is less than optimal, this may create vulnerabilities and areas of risk, as organisations may unintentionally create biases with accompanying adverse outcomes through the data provided for intelligent automation. Future research could assess how organisations can address these vulnerabilities and avoid potential biases. Finally, scaling AI applications across the retail value chain will require the right platforms to be in place, data to be available, and employees to support the initiatives in the long term. Future research should examine the technological and organisational platforms necessary for successfully implementing an AI-enabled value chain. As the technology, most likely to reshape the retail landscape, retailers that embrace AI are poised to enhance every link in their value chain.

3.9 CONCLUSION: ARTICLE ONE

This article illustrated that some AI technologies can serve multiple purposes across the retail value chain and found that retailers are applying AI technologies across the different value chain stages. Article one argues that AI can be best employed in the retail value chain by serving one of the following purposes: knowledge and insight management, inventory management, operations optimisation, and customer engagement.

Article one suggested that the retail value chain needs to be updated within the improved AI-enabled retail value chain framework. An AI-enabled retail value chain moves away from a linear and siloed approach to the value chain to a real-time iterative approach. The AI-retail value chain framework is iterative and agile, enabling real-time data flows, in contrast to the traditional silo-mentality and linear view of the traditional value chain. Using this framework, retailers can prioritise their investment in AI or diversify their current application of AI across the value chain. The article-specific references are available in Appendix J. The following chapter investigates research question two – What are retailers using AI technologies for in the retail value chain?

Chapter 4: WHAT ARE RETAILERS USING AI TECHNOLOGIES FOR IN THE RETAIL VALUE CHAIN

4.1 CHAPTER INTRODUCTION

The previous chapter illustrated that AI technologies could serve multiple purposes throughout the retail value chain. However, most retail implementations are experimental and deployed to siloed business processes (Ganapathy et al., 2020). One reason is that retailers are hesitant to scale investments into AI, citing a lack of understanding of which tasks AI could perform in the retail value chain (Ganapathy et al., 2020; Himmelreich, 2020; Olanrewaju & Willmott, 2013). To address this concern, article two was developed to understand what retailers are using AI technologies for in the retail value chain by reviewing retailers current application of the technology.

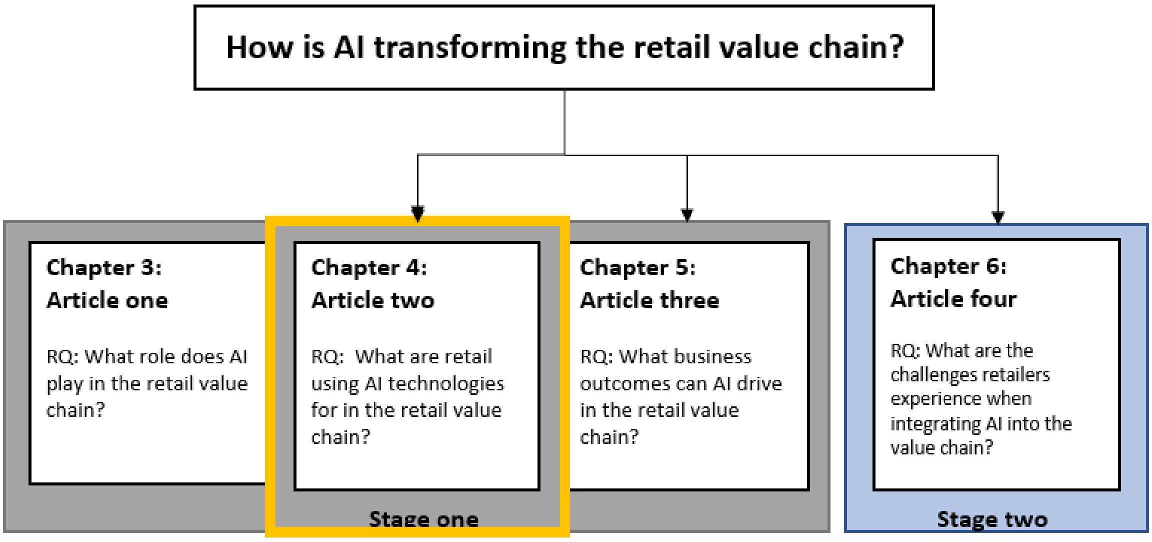


Figure 4.1: Article layout and the research questions

Article two attempts to understand research question two, *what retailers are using AI technologies for in the retail value chain*. Guided by the Leavitt Diamond Model, focusing on the *dimension of the task* of the model (Leavitt & Bahrami, 1989), we identify the tasks AI performs across all the retail value chain stages. First, we show the various AI technologies used to automate tasks across the retail value chain. Second, this is followed by a detailed discussion of how AI can be used to manage, operate and complete specific tasks in the retail value chain. The following section covers article two, Artificial Intelligence in Retail: Simplifying tasks by using AI in the retail value chain.

4.2 ARTICLE TWO: ARTIFICIAL INTELLIGENCE IN RETAIL: SIMPLIFYING TASKS BY USING AI IN THE VALUE CHAIN

4.3 INTRODUCTION

Artificial Intelligence (AI) is an important technology to transform retail (Guha et al., 2021, p. 28; Kietzmann et al., 2018, p. 265; Shankar, 2018, p. 6). As such, many retailers are excited about the possibilities of the technology (Guha et al., 2021, p. 28). AI offers retailers the ability to transform their operations by enhancing the in-store shopping experience (Ameen et al., 2021; Chen et al., 2021; Jain & Gandhi, 2021; Tupikovskaja-Omovie & Tyler, 2020), aiding shopping decisions for customers (Chopra, 2019; Pizzi et al., 2021; van Esch et al., 2021), improving supply chain efficiency (Shankar, 2018; Weber & Schütte, 2019), and automation of tasks across the retail value chain (Oosthuizen et al., 2020). AI is set to transform both the retail experience and the retailer operating model, and expectations for the commercial application of AI in business, particularly in retailing, are significant (Ransbotham et al., 2017, p. 1). In the retail value chain, AI can be used to automate tasks to reduce complexities and manual effort, moving retailers away from the traditional way of doing business (Oosthuizen et al., 2020, p. 2). When retailers adopt AI to automate tasks across the retail value chain, it could unlock unprecedented value, transforming their businesses and optimising day-to-day operations (Balchandani et al., 2020; Standish & Ganapathy, 2020; Weber & Schütte, 2019).

A survey by Gartner 2019 estimates that 30 % of businesses are using some form of AI technologies (Hare & Andrews, 2019, p. 3). However, less than half of AI proof of concepts gets integrated and scaled into business (Davis, 2020, p. 3; Fountaine et al., 2019, p. 4). Similarly, in retail, AI adoption rates remain low (Dogru & Keskin, 2020, p. 69). Most retail implementations are experimental and deployed to siloed business processes (Ganapathy et al., 2020). One reason is that retailers are hesitant to scale investments into AI, citing a lack of understanding of which tasks AI could perform in the retail value chain (Ganapathy et al., 2020; Himmelreich, 2020; Olanrewaju & Willmott, 2013). While there are existing analytical tools for managers to gauge AI's influence on retail and other industries (J. Paschen et al., 2019), navigating the AI landscape can be complicated for any retailer. Therefore, retailers willing to invest in AI need to understand the best tasks AI could automate in their value chain. To address this concern, this article aims to understand what retailers are using AI technologies for in the retail value chain by reviewing retailers current application of the technology. Therefore this article's research question is: *What are retailers using AI technologies for in the retail value chain?*

To review the different tasks AI can perform across the value chain, we propose using Leavitt's Diamond Model. Leavitt (1965) suggested that everything in an organisation is connected, and no change can occur in isolation. When implementing AI to perform and automate tasks across the retail value chain, the technology can assist retailers in becoming more efficient and effective. However, when manual tasks are replaced with AI, it has a necessary knock-on effect on the people and structure involved, creating business implications for retail managers. Therefore, implementing AI requires retail leaders to think differently about how the day-to-day activities should be performed, requiring organisational change.

This article provides an important contribution to the emerging literature on AI and its application in retail. Guided by the Leavitt Diamond Model, focusing on the *dimension of the task* of the model (Leavitt & Bahrami, 1989), we identify the tasks AI can perform across the retail value chain. Current research focuses on specific applications of AI in retail (Ameen et al., 2021; Pillai et al., 2020; Pizzi et al., 2021; van Esch et al., 2021) and limited empirical literature to the author's knowledge have suggested and outlined the different tasks AI can perform across the whole retail value chain. This comprehensive view of the role of AI across the value chain will increase the ROI of the technology as it extends its use beyond isolated siloed use cases. One of the main reasons current AI applications fail is their narrow applications to business processes (Davenport & Ronanki, 2018; Standish & Ganapathy, 2020).

As a starting point, we provide an overview of the Leavitt Diamond Model (Leavitt & Bahrami, 1989) and its importance within any organisation. Thereafter the application of AI in the retail value chain is discussed by first defining AI and then mapping out the various AI technologies (based on Gartner's Hype cycle (Sicular et al., 2019) to each AI application. This is followed by classifying each application into the relevant value chain stage. Finally, the tasks AI performs in the retail value chain are discussed in detail, followed by how retailers work with the technology.

4.4 LITERATURE REVIEW

4.4.1 The Leavitt Diamond Model

Organisations are complex systems in which four interacting variables loom: task, structural, technological, and human (Leavitt, 1965, p. 1144). In 1965, Harold J Leavitt designed a model to manage change in an organisation. The model indicated that organisations are complex structures of interrelated systems designed for a particular purpose (Boella & van der Torre, 2006; Leavitt, 1965)and subsequently developed the Leavitt Diamond Model. In the model, the arrows represent a direct and robust relationship between tasks, technology, structure, and people (Paghaleh et al., 2011) (see Section 2.4, in particular, Figure 2.5).

Describing such, Leavitt (1965) noted that when organisations change any task, technology, structure or people variable, it sometimes results in compensatory changes in one or more of the other variables. Thus, changing the task variable in an organisation directly impacts people, structure, and technology in the organisation. When the interdependencies are not managed at critical times during the change process, problems can occur within the organisation (Leavitt & Bahrami, 1989; Paghaleh et al., 2011; Smith et al., 1992).

In the Leavitt Diamond Model, the *task* variable can be defined as the activities performed inside the organisation, including many subtasks that exist within an organisation such as manufacturing of products, selling goods and services, procurement of supplies and finance of operations (Leavitt, 1965; Leavitt & Bahrami, 1989). The purpose of a task within an organisation is to produce a specific output within a particular time (Hartmann & Lussier, 2020). To perform tasks across an organisation, technology, people, and structure are required to complete and manage the activities. For example, in the retail value chain, tasks are the set of activities performed to design, produce, market, deliver and support products within businesses (Hagel et al., 2016). The activities encompass all the processes needed for retailers to deliver an end product (or service) to a customer (Reinartz et al., 2019, p. 352).

New technologies are challenging the traditional value chain. For example, omnichannel environments generate more data (Lee, 2017, p. 593), adding complexities and manual workload to current tasks in the retail value chain.

As technologies continue to advance exponentially, inefficiencies will drive complexities across the value chain over time, burdening employees with low value-added work (Oosthuizen et al., 2020). McKinsey (2018) study found that over half of all retail work activities could be automated by using AI that exists today (Manyika & Bughin, 2018). It is estimated that by 2030, 30% of the current retail tasks will be automated (Balchandani et al., 2020, p. 1), shifting some of the tasks from employees to AI, impacting the retailer's internal process, people, and structure. The following section discusses the role of AI in the retail value chain.

4.4.2 AI in the retail value chain

4.4.2.1 Defining AI

We employ Poole and Mackworth (2017, p. 3) definition of AI as "computational agents that act intelligently" by taking actions to find the best choices within the boundaries of its environment, experiences and limitations. The definition differs from the hyped versions of AI displaying human-like intelligence (U. Paschen et al., 2019, p. 148). The definition involves the learning and processing capacity embedded in AI to enable interaction with humans, such as interpreting meaning, analysing records and helping solve business problems (Gupta et al., 2018, p. 78; U. Paschen et al., 2019, p. 148). AI technologies have limitations as the technology can only take actions based on its availability of data and the output goal defined (Canhoto & Clear, 2019; J. Paschen et al., 2020). Nevertheless, AI enables machines to perform tasks usually done by humans, such as generating outputs for feeds into other business applications (J. Paschen et al., 2020) produce visualizations for decision analysis (Hwang, 2019), performing tasks autonomously (de Bellis & Venkataramani Johar, 2020). Various AI technologies are available to perform tasks, discussed in the next section.

4.4.2.2 AI enablers and types

AI is an umbrella term, and it encompasses various intelligent technologies in different stages of value creation (Sicular et al., 2019, p. 3). The term AI is used to market different intelligent technologies under the AI banner (Kaplan & Haenlein, 2019). The assembly of systems can all perform specific tasks by interpreting and processing large volumes of data to complete a particular activity (Canhoto & Clear, 2019, p. 4; Kaplan & Haenlein, 2019, p. 18-19). Most of the AI technologies available today for business are classified as narrow AI, meaning the AI can only perform a specific goal or output. In the next ten years, almost all AI technology to be integrated into business and society will be narrow AI (De Bruyn et al., 2020, p. 92; Yao et al., 2019, p. 19). Figure 4.2 outlines the enablers, type of AI technologies, and goals to understand the various AI technologies available and their actions.

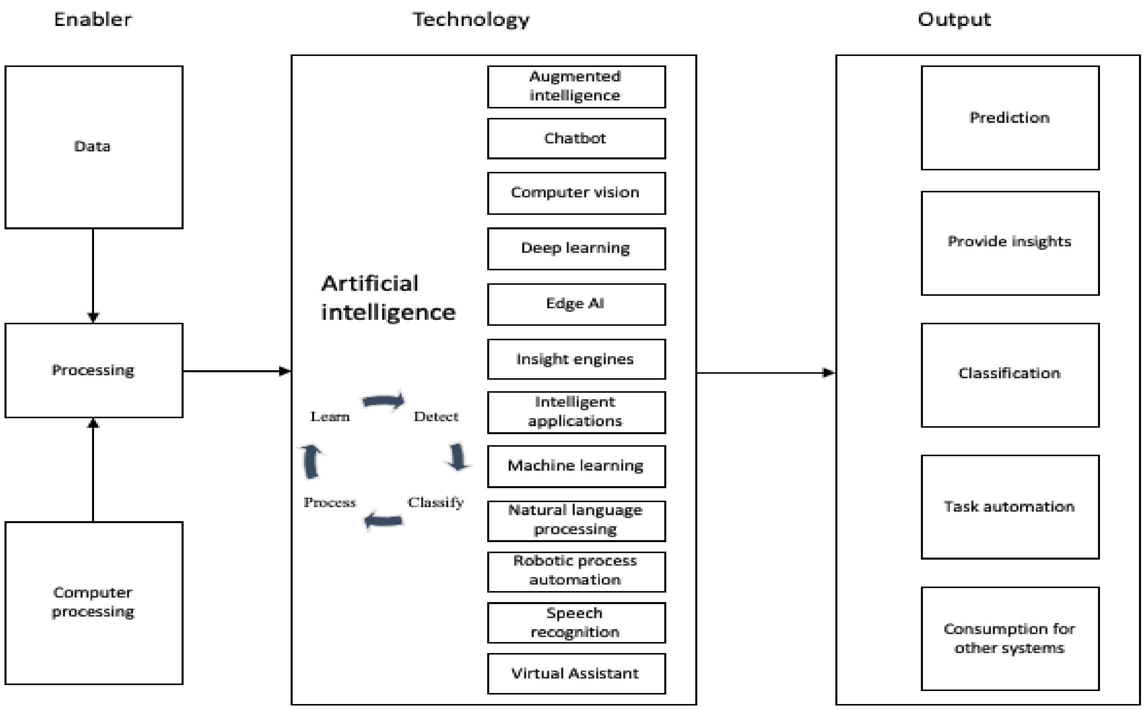


Figure 4.2: AI enablers

Adapted from (Chen et al., 2016; P. R. Daugherty & Wilson, 2018; Marshall & Lambert, 2018; U. Paschen et al., 2019; Sicular et al., 2019)

AI systems utilised different types of input data, either structured (i.e., historical sales data, customer data, or product information) or unstructured data (i.e., video, images, or text data) (U. Paschen et al., 2019). The data requirements of the AI system are dependent on the output goal. For example, the data required will be different for a forecasting model vs customer service response, where a forecasting model requires historical sales data, and text data with specific keywords are required for customer service responses.

AI encompasses many different technologies, with each technology responsible for performing a specific task. For instance, a Chatbot can reply to customer messages by processing text data, interpreting the keywords using a pattern matching approach, and then providing an output reply (Rese et al., 2020, p. 3). After the learning process has been completed, the AI system generates an output or action, depending on the goal (Campbell et al., 2020; Canhoto & Clear, 2019; Hwang, 2019; Kaplan & Haenlein, 2019; Paschen et al., 2019). In addition, the system could perform tasks for further action by humans (Canhoto & Clear, 2019), generate outputs for feeds into other business applications (J. Paschen et al., 2020), produce visualizations for decision analysis (Hwang, 2019) or perform tasks autonomously (de Bellis & Venkataramani Johar, 2020) to name a few. The following section discussed AI opportunities in the retail value chain further.

4.4.2.3 AI's application in the retail value chain

AI represents retailers with various opportunities to automate tasks in the retail value chain. Shankar (2018, p. 7) argues that AI can be used in retail to influence customer-facing activities in shopping behaviour, customer service, payment management and supply activities such as inventory optimisation. To complete tasks in the retail value chain, AI can be used to:

i. digitising in-store experience through interactive mirrors (Alexander & Kent, 2021),
ii. offering personalised services and product recommendations (Ameen et al., 2021, p. 113),
iii. enhancing the customer experience (Gauri et al., 2021, p. 42),
iv. providing insights into customer and sales data (Acharya et al., 2018, p. 95; Ameen et al., 2021, p. 1; Gupta, 2018, p. 19), and
v. collecting, curating and analysing data (Shankar, 2018).

Current research suggests that AI has the potential to:

i. automate various activities such as the store check-out process without the need for any employees (Pillai et al., 2020, p. 57),

ii. providing 24-hour customer service (Roy et al., 2017, p. 257; Y. Xu et al., 2020, p. 2952),
iii. providing personalise services and product recommendations to customers (Tupikovskaja-Omovie & Tyler, 2020, p. 388),
iv. assisting designers through analysing images and videos (Liang et al., 2020),
v. automatically forecasting customer demand (Weber & Schütte, 2019, p. 264), and
vi. provide insights into data analysis (Acharya et al., 2018, p. 92; Ameen et al., 2021, p. 1; Gupta, 2018, p. 170).

Various authors agree that AI can perform and automate tasks in retail (Anica-Popa et al., 2021; Cao, 2021; Chopra, 2019; Gonzalez-Jimenez, 2018; Weber & Schütte, 2019). Nevertheless, these studies focus on single-use cases and not on the entire retail value chain; limited empirical literature has suggested and outlined the different tasks AI can perform across the entire retail value chain.

Many retailers are experimenting with AI, yet some retailers are still hesitant to scale investment in AI. Retailers are hesitant to scale investments into AI, citing a lack of understanding of which tasks AI could perform in the retail value chain (Ganapathy et al., 2020; Himmelreich, 2020; Olanrewaju & Willmott, 2013). However, when retailers adopt AI to automate tasks across the retail value chain, it could unlock unprecedented value, transforming their businesses and optimising day-to-day operations (Balchandani et al., 2020; Standish & Ganapathy, 2020; Weber & Schütte, 2019). To understand what retailers use AI technologies for in the retail value chain, we reviewed retailers currently using AI in their value chain. The research methods are discussed in more detail next.

4.5 RESEARCH METHODOLOGY

This article uses a qualitative content analysis approach to analyse the retail AI application database to explore how AI can eventually diminish some tasks, expand others, and create new ones in the value chain. The purpose of the approach was to "identify categories of meaning" (Cho & Lee, 2014, p. 3) for the different tasks AI can perform across the retail value chain. A qualitative content analysis approach was used to analyse data previously collected by the authors to address the research question. Content analysis was deemed the most appropriate as it blends objectivity and participant observation to identify themes in the data (Neuendorf, 2017, p. 10) and uses "descriptive knowledge and understanding" (Assarroudi et al., 2018, p. 42) to identify the tasks AI performs. The retail AI application database reviewed 117 retailers currently using AI in their value chain (see Section 1.5.2). The data analysis process will be discussed in more detail.

4.5.1 Data analysis

First, to assess the tasks AI-enabled solutions perform across the various retail value chain activities, we reviewed the type of AI technology used, followed by what the AI is used for in the value chain. To review the AI technologies used in retailing, we utilised the Gartner hype cycle for an artificial intelligence report that provides trends and innovations in the AI sector (Sicular et al., 2019). We focused on AI technologies currently in use. These include augmented intelligence, chatbots, computer vision, deep learning, edge AI, insight engines, intelligent application, machine learning, robotic process automation software, smart robots and virtual assistants (Sicular et al., 2019). For instance, a visual search tool allows customers to upload their photos and provide similar items coded to *Computer vision*. Table 4.1 shows the different AI types coded in the AI in a retail dataset.

Table 4.1: Different AI types applied by retailer coded

AI technology	Number of retailers
Augmented Intelligence	11
Chatbot	7
Computer Vision	11
Deep learning	7
Edge AI	15
Insight engines	15
Intelligent applications	15
Machine Learning	15
Robotic process automation software	5
Smart robots	5
Virtual Assistant	11
Total	117

Second, to establish the tasks AI performs in the value chain, we analysed each retail use case and classified it into its activity. A task is the activities performed inside the organisation, including many subtasks that exist within an organisation such as manufacturing of products, selling goods and services, procurement of supplies and finance of operations (Leavitt, 1965). The AI use cases were coded to specific tasks to understand the various activities. For instance, H&M, a fast-fashion retailer, uses AI technology to predict precise demand to ensure the correct quantities are produced. This use case was coded to task *optimising inventory.* Table 4.2 outlines the coded AI tasks in the retail value chain.

Table 4.2: Coded AI tasks in the retail value chain

Retail value chain stage	Coded Task	Number of retailers	% Frequency
Customer use and support	Customer service	6	5.13%
	Virtually try products	5	4.27%
	Virtual stylist	4	3.42%
	Customised product suggestion	3	2.56%
	Finding similar items	3	2.56%
	Build personalised relationships	2	1.71%
	Product features demonstration	2	1.71%
	Personalised product recommendation	2	1.71%
	Virtual try-on	2	1.71%
	Customer data collection	2	1.71%
	Interactive dressing room	2	1.71%
	Automatic checkout	2	1.71%
	Track orders	1	0.85%
	Share relevant information	1	0.85%
	Checking stock availability	1	0.85%
	Contactless pick up service	1	0.85%
	Optimise inventory	1	0.85%
	Automated checkout	1	0.85%
Total: Customer use and support		40	34.19%
Store operations and Sales	Optimise inventory	4	3.42%
	Automate marketing campaigns	3	2.56%
	Build personalised relationships	3	2.56%
	Customised product design	3	2.56%
	Fraud detection	2	1.71%
	Price management	2	1.71%
	Matching customers to deals and offers	2	1.71%
	Customer service	2	1.71%
	Virtually try products	2	1.71%
	Automated checkout	2	1.71%
	Price checks vs competitor	1	0.85%
	Automated workforce scheduling	1	0.85%
	Dynamic price management	1	0.85%
	Combating counterfeits	1	0.85%
	Personalised product recommendation	1	0.85%

	Customer data collection	1	0.85%
	Automated task management	1	0.85%
	Interactive dressing room	1	0.85%
	Collecting customer data	1	0.85%
	Foot traffic monitoring	1	0.85%
Total: Store operations and Sales		35	29.91%
Inventory management and distribution	Optimise inventory	3	2.56%
	Automated warehouse management	3	2.56%
	Predicting customer demand	2	1.71%
	Inventory visibility	2	1.71%
	Order fulfilment and scheduling deliveries	2	1.71%
	Automated workforce scheduling	1	0.85%
	Automatic master data creation	1	0.85%
	Price management	1	0.85%
	Moving and packing products for transportation	1	0.85%
	Automated returns transfers	1	0.85%
Total: Inventory management and distribution		17	14.53%
Sourcing/Procurement	Customised assortments by location	3	2.56%
	Predicting customer product needs	2	1.71%
	Inventory visibility and optimisation	2	0.85%
	Order processing, capturing and placement	1	0.85%
	Integrating planning process	1	0.85%
	Predicting customer demand	1	0.85%
Total: Sourcing/Procurement		10	8.55%
Manufacturing	Automatic garment sewing	2	1.71%
	Managing quality	2	1.71%
	Managing assembly	2	1.71%
Total: Manufacturing		6	5.13%
Fulfilment	Order fulfilment	4	3.42%
	Optimise inventory	1	0.85%
Total: Fulfilment		5	4.27%
Design	New product design	2	1.71%
	Product curation and discovery	1	0.85%
	Customised product design	1	0.85%
Total: Design		4	3.42%
Grand Total		**117**	**100.00%**

Based on the coding of the AI tasks retail use cases (Table 4.2), most of the use cases are in the customer use and support (34.19%) and store operations and support (29.91%) value chain stages. The remaining use cases are inventory management and distribution (14.53%), sourcing and procurement (8.55%), manufacturing (5.13%), fulfilment (4.27%), and design (3.42%) value chain stages. Thus, various AI tasks (Table 4.2) can be applied to manage, operate, and complete specific retail value chain tasks, changing how daily activities are performed. The following section discusses the tasks identified above to understand the tasks AI could perform and possibly substitute people's current tasks.

4.6 DISCUSSION: THE TASKS RETAILERS ARE USING AI FOR IN THE RETAIL VALUE CHAIN

A retail value chain is a series of activities performed to deliver new products and services to customers (Hagel et al., 2016, Porter, 1998). The retail value chain includes information and product flow between design, manufacturer, suppliers, shipping agents, warehouses, shelves, consumers and retailers to the point of consumption (Hübner et al., 2018; Reinartz et al., 2019). The processes consist of products and information flows across different organisational processes until the final product is delivered to the customer. Figure 4.3 shows the various AI technologies used by retailers to perform tasks across the value chain.

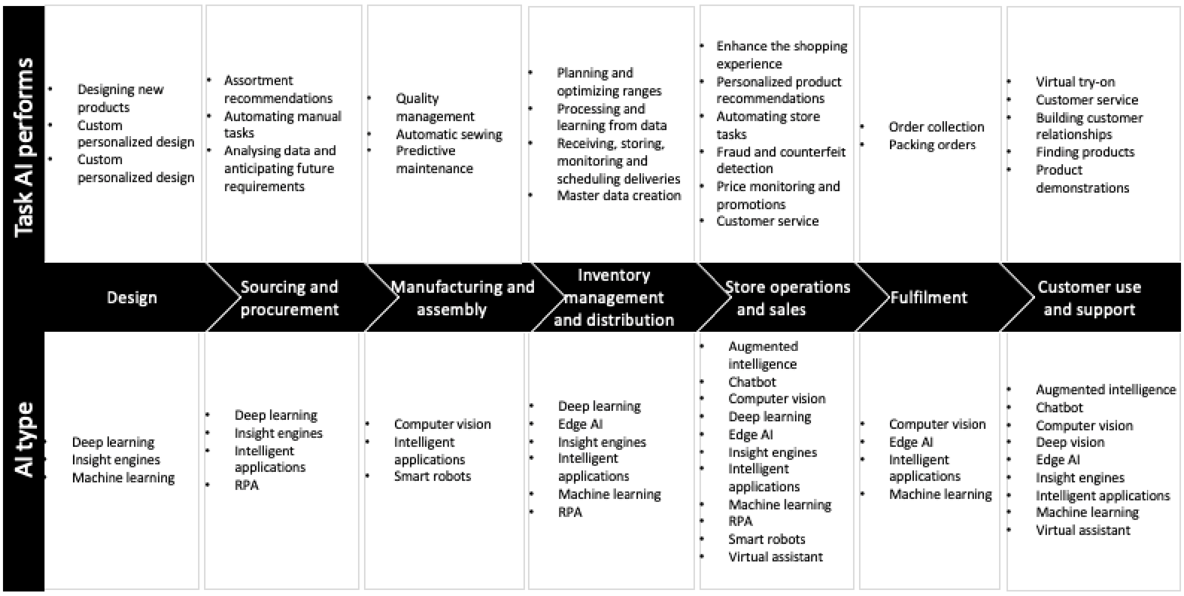


Figure 4.3: What AI is used for in the retail value chain

By deploying AI in the retail value chain, retailers could automate and streamline specific retail value chain tasks. The following section describes how and what retailers use AI for across the various retail value chain stages.

4.6.1 Design

Creating and designing new products is the starting point for any product development journey. The design phase is when products are designed, developed and prototyped (Rieple & Singh, 2010). Retailers and brands must continuously design and create new products that will hopefully create customer excitement (Chao et al., 2019, p. 7). During the design phase, consideration for products are based on a high-level financial budget, new trends, customer needs and historical data with the ultimate goal of offering value to the customers the design is for (Grewal et al., 2017, p. 2). Nevertheless, the design process can take months (Berg et al., 2018, p. 4), and multiple iterations for products to come to fruition, slowing down the value chain. AI is transforming the design phase by providing designers with recommendations of new products design, product discovery, prototypes and customised designs. AI combines customer data, thousands of product images and runway video analysis to complement the design process, making it easier for designers to select or develop new products.

4.6.1.1 AI for designing new products

Tommy Hilfiger, an American lifestyle retailer, teamed up with IBM and the Fashion Institute of technology to show how AI capabilities can give retailers the edge when designing new products. The developed platform uses AI deep learning capabilities to analyse, process and learn from fifteen thousand stored product images, sixty thousand runway images and one hundred thousand patterns from fabric sites (Arthur, 2018). The processed data recommends new product designs based on colours, silhouettes and prints, assisting design by streamlining new product development and reducing time.

4.6.1.2 AI for custom personalised designs

Another design use case of AI during the design phase is to personalise customer products at mass by interacting directly with customers getting their feedback regarding product design choices. For example, Ikea, a big-box furniture retailer, uses insight engines to send surveys to customers to understand how and which products to develop in the future (Ikea, 2020).

4.6.1.3 AI using customer data to design new products

StichFix, an online styling service, uses AI insight engines to create new product collections from customer data and opinions (Lake, 2018). AI extends human ability through the design stage by processing, learning and recommending new designs, simplifying the design process.

In summary, AI can guide and support the creative design process by analysing large product information databases and generating suggestions for new designs helping designers find new design options quickly.

4.6.2 Sourcing and procurement

The sourcing and procurement process is purchasing and building inventory that will satisfy customer demand at a given time yet meet the retailer's financial objectives (Rieple & Singh, 2010, p. 2293). The primary goal of sourcing and procuring products is to offer customers a balanced and targeted assortment by selecting, negotiating, and liaising with suppliers. The process requires analysing and considering multiple data sources, including historical information, market trends, industry trends, supplier information, quantities needed, financial objectives and future demand requirements. The demand decisions should be based on the anticipated customer demand. Anticipating what products and when customers want them can be challenging for any retailer. AI applications modernise activities in the planning process by utilising customer information to develop product plans and creating clusters to recommend localized assortments (Spicer, 2020).

4.6.2.1 AI for product assortment recommendations

Intermarché, a French grocery retailer, uses AI to process customer and store data to suggest product assortments to customise each location (Standish & Ganapathy, 2020), boosting the planning activity productivity. Myer, an Australian department store, uses an intelligent application with machine learning to analyse current trends to anticipate future customer demand by suggesting relevant localized assortments transforming the planning process (Ambrogio, 2019).

4.6.2.2 AI for ensuring correct quantities is produced

H&M, a fast-fashion retailer, uses AI technology to help make an informed decision about raw materials used in the production process. The system predicts precise demand to ensure the correct quantities are produced, reducing waste and making the retailer more sustainable (Cosgrove, 2020).

4.6.2.3 AI for predicting customer requirements

Avenue stores, an apparel retailer, integrate all data across multiple customer touchpoints, including store and market trends, to learn customers' future product requirements. As a result, they predict demand when they require it, helping the retailer improve its product sourcing process (Chao et al., 2019).

In summary, AI technologies enrich the sourcing and procurement process by predicting customer product requirements by processing large data volumes using predictive analysis and recommending buying products. In addition, the technology provides a 360-degree view of the customer and anticipates future customer product needs and expectations across channels.

4.6.3 Manufacturing and assembly

The manufacturing process involves cutting, sewing, packing and preparing raw materials to complete finished goods for retailers. Today, the process still involves many human workers to stitch, quality check and assemble products, slowing the manufacturing process down. To avoid downtime, manufacturers need to understand their equipment's performance in factories to reduce downtime and increase efficiency. AI for manufacturing is expected to reach U$3.7 trillion by 2035 (Schaeffer et al., 2018, p. 5), and there are multiple activities that AI can transform.

4.6.3.1 AI for quality management

Products are checked for quality during the assembly to meet retailers' expectations, yet relying on humans to compare quality can be risky and costly for manufacturers. AI applications can assist by managing the quality process during assembly by inspecting fabric and colour quality. A sweater factory Cognex Corp uses computer vision to automatically examine fabric weaving, knitting and printing during the manufacturing process to flag any quality issues (Bharadwaj, 2019).

4.6.3.2 AI for sewing garments

Smart robots are also helping shorten the assembly process by automatically sewing garments based on designs and different patterns. For example, another sweater factory Mohammedi Group uses AI-enabled sewing machines to knit sweaters, producing clothing faster than human hands (Emont, 2018).

4.6.3.3 AI for predictive maintenance

Further to the assembly of products, AI can provide predictive maintenance into equipment by processing large volumes of data (audio and visual) to identify abnormalities during the production process preventing breakdowns (Schaeffer et al., 2018).

In summary, AI technologies streamline the manufacturing process by making it safer, more efficient and helping track products throughout the production process.

4.6.4 Inventory management and distribution

The inventory management process refers to forecasting, ordering, storing and distributing inventory across the retailer's network. The process requires constant monitoring and adjusting to ensure the correct items are available for customers to purchase when they need them. However, end to end inventory management is complicated, creating many retailers' challenges. Inventory management spans the entire product lifecycle and value chain. Nevertheless, retailers still rely on old, disconnected legacy systems to monitor their inventory movements, leading to poor management decisions. AI is helping retailers manage processes in the back office and distribution centres. Within the inventory management and distribution stage, AI assists retailers in improving forecasting, optimising distribution centres and generating inventory insights.

4.6.4.1 AI for planning and Optimising ranges

Retailers are using AI to help generate recommendations on assortments and which locations they would best be suited for, allowing the retailers to buy better and reduce wastage through the value chain. Morrisons, a grocery retailer, uses an AI intelligent demand forecasting and replenishment solution to predict customer demand accurately. The solution reduced manual replenishment efforts by ordering the correct stock level and reducing product waste (Robinson, 2018).

4.6.4.2 AI for processing and learning from data

The AI applications at Co-op, a grocery retailer, assist with operations and create insights for managing inventory in near real-time by processing and analysing multiple data points. H&M, a clothing retailer, uses big data and AI to analyse returns, receipts and loyalty card data to create localized ranges for each store (Marr, 2018). The AI insights help the retailer invest in the correct products and remove unwanted items, improving customer preferences.

4.6.4.3 AI for receiving, storing, monitoring, and scheduling deliveries

AI systems are improving safety in retail distribution centres by managing inventory movements. For example, gap, an apparel retailer uses AI material handling systems in their distribution centres to receive, sort, and pick customer orders (Vargo, 2020), helping the retailer scale to fulfil capabilities to unexpected changes in the value chain. RPA technology is also helping remove inefficiencies by automating repetitive tasks. For example, Waitrose, a grocery retailer, uses robotic process automation (RPA) to schedule deliveries to each store from their distribution centre, whilst John Lewis, a department store, uses the technology to transfer returned items from store to distribution centre (Blueprism, 2019).

4.6.4.4 AI for master data creation

Master data is the foundation for all future product analyses in retail. Therefore, accurate master data creation is essential for any retailer and aids with data governance. For example, the online, second-hand retailer, ThredUp needs to manage millions of different items for resale. To streamline the product listing process, they turned to AI to manage their listing process. The AI generates listing information by scanning close to 100 million unique items and visually tagging each product, assigning resale value and creating a unique code for each item (de Leon, 2019). Generally, creating product listing records would require multiple employees to load the information, now automated and managed by AI, helping speed the loading process.

In summary, the area where AI can benefit the retail value chain most is the inventory management and distribution process by removing inefficiencies and improving forecasting accuracy, reducing unnecessary costs, increasing margin and removing waste through the retail value chain.

4.6.5 Store operations and sales

The store operations and sales phase are the first stages where the customer interacts directly with the retailer. To ensure stores' optimum operations, retailers need to keep shelves stocked, understand the customer needs, and deliver a unique customer experience.

4.6.5.1 AI to enhance the shopping experience

AI technologies let retailers create unique experiences for their customers by seamlessly integrating digital and physical experiences. Burberry, a luxury retailer, has transformed its in-store and online shopping experience with AI technologies. Using big data and AI to enhance sales and customer relationships by engaging with 51 million social media followers globally, across 13 unique platforms, 24 accounts, and 11 languages. Burberry goes one step further by offering personalised luxury services through product recommendations tailored to customer preferences, using the data to ensure dynamic online customer engagement by personalising homepages (Roy, 2019). In addition, Burberry bridges the gap between online and in-store, allowing customer flexibility over payment and delivery options and letting customers switch seamlessly between physical and digital.

4.6.5.2 AI for personalised product recommendations

Sephora, a cosmetics retail store associate, can use a handheld device to scan a customer's face. The device captures a person's exact skin tone and creates a "shade library". Each customer's library is unique and can be used for future purchases. Ebag, an online retailer, allows customers to place a virtual product in real-life environments to help shoppers gauge the size and scale before purchasing. The AI-driven marketing platform assists RealReal, an online retailer, create real-time personalised messaging for customers abandoning their products at check out. The platform generates a personalised informational message about the product or similar products. The recommendations helped the retailer focus on advertising spending and boost sales by increasing conversion rates by 58%.

4.6.5.3 AI for automated payments

Retailers recognizing customers' desire for convenience and limited contact have started embracing AI (Grewal et al., 2020, p. 97). AI technologies create a convenient environment for customers to purchase items without standing in long queues. Sobeys, a grocery retailer, uses AI-powered smart shopping carts to allow customers to skip checkout lines. The shopping carts armed with deep learning and computer vision AI identifies items added to the trolley, automatically creating a digital cart for seamless payment.

4.6.5.4 AI for keeping shelves stocked in store

To assist sales associates in large stores to keep shelves stocked and price tags updated, some retailers use bots armed with computer vision to roam isles. For example, Walmart and Lowes use shelve scanning robots in some stores to ensure shelves are fully stocked and to update price tags. When the robots are roaming the isles and notice an empty shelf or wrong price, it will send a notification to store associates to address (Heater, 2019).

4.6.5.5 AI for fraud and counterfeit detection

Walmart uses computer vision technology to scan more than a thousand stores to monitor self-checkout kiosks to ensure all items are scanned and paid for, deterring potential theft during the checkout process (Grill-Goodman, 2019).

4.6.5.6 AI for price monitoring and promoting

Lovethesales.com, an online market price, uses AL to suggest the price of over one million items. As a result, it is helping the marketplace promote over one million products at incredible speeds. A task that would have taken a team of staff over four years to complete only took the machine learning system eight hours (Hardaker, 2017).

4.6.5.7 AI for customer service

Lowe's, a home improvement retailer, uses a chatbot called LoweBot to help customers find products in-store by providing customers with a map of the products they want to purchase. The bot can understand and answer questions in multiple languages (Lowe's, 2020.).

In summary, there are many AI applications to enable the store operations and sales value chain stage. AI technologies facilitate improved operations, customer engagement and inventory management during the sales process. The technologies can serve as an essential touchpoint for customers and support frontline employees (Grewal et al., 2020).

4.6.6 Fulfilment

The fulfilment process in the value chain refers to preparing, picking and delivering customer's orders. Optimal management of the fulfilment process leads to customer satisfaction. However, fulfilling items to ensure quick processing and delivery of customer orders to delight customers can be overwhelming for retailers. AI technologies are helping streamline the last mile process.

4.6.6.1 AI for order collection

JD.com is using AI to verify customers at delivery. Once customers are verified using facial recognition, automated delivery agents hand over their packages at their doorsteps (Marr, 2019, location. 1677).

4.6.6.2 AI for packing orders

ThredUp, an online retailer, uses machine learning to improve order fulfilment and packing process. The AI algorithm helps stylists fulfil orders by remembering each customer preference by creating a second-hand clothing product list tailored to each customer's style (de Leon, 2019). Ocado uses AI robotics to steer thousands of bins filled with products to pick stations for human packers to pack. The robots connected to a central system are used to lift, move and sort items 24 hours a day, speeding up the fulfilment process (Vincent, 2018).

In summary, the technology embedded with edge AI can steer products on conveyor belts to make it easy for human packers to fill shopping bags. Other AI technologies enable customers to collect orders without the interaction of a sales associate.

4.6.7 Customer use and support

One of the broadest use cases of AI applications in the value chain is the customer use and support stage. Retailers would not exist without customers buying their products and services. It is no surprise that most AI applications available today assist and support customers in the retail value chain.

4.6.7.1 AI for virtual try-on

To enhance the online shopping experience, retailers have invested in applications to assist customers in trying products before purchase. Retailers Nike, Gucci, Ikea, The Home Depot, Warby Parker, and Sephora use augmented intelligence tools to enhance the customer shopping experience. For example, Sephora and Ultra Beauty allow customers to try makeup and hair colours virtually before purchasing the product (Berthiaume, 2019; Milnes, 2016). In addition, Ikea and the Home Depot use the 3D augmented reality technology to measure and place products within the customer's home (Home Depot, 2018; Johnston, 2017).

4.6.7.2 AI for customer service

Retailers use chatbots, robots and virtual assistants as real-time communicators for their customer customers. For example, Walmart uses speech recognition/chatbot software to assist customers in asking Alexa about their orders' status. Sam's Club lets the customer use their scan and go mobile app to use voice search capabilities to help them navigate and find products around their stores. The app also allows customers to view product stories about products (Blair, 2018). Lowe's and Home Depot use navigation AI to help their customers find products and navigate their large stores (Home Depot, 2018; Lowe's, 2020). The North Face uses AI to help customers find the perfect jacket through conversational Q&A, assisting the retailer in achieving a 75% sale conversion rate (Medeiros, 2018).

4.6.7.3 AI for building customer relationships

AI helps sports retailers build a unique customer experience by using product and performance data to help customers improve their fitness. Under Armour offers customers connected shoes that collect data on the customer running style via their UA MapMyRun app. As data is collected, the app starts coaching the runner on improving their running technique. Nike uses an AI-powered assistant to help customers reach their exercise goals by virtually training users. The connected app generates exercise plans and sends motivational messages to help achieve users' goals (Nike, 2020).

4.6.7.4 AI for finding similar products

AI-enabled mobile applications assist customers ``snap find shop" to visually find items at their retailers by uploading or taking photos of things they are interested in buying. For example, retailers Neiman Marcus and Zalando enable customers to visually search for items through their apps. Customers upload images onto the app, and AI algorithms search the retailer's databases for similar items recommending them for purchase (Marr, 2019). In addition, retailers West Elm and Target collaborated with social media platform Pinterest to enable customers to upload their Pinterest boards onto their websites or apps, creating an easier way to explore, discover and buy products (Pinterest, 2017; Target, 2017).

4.6.7.5 AI for product demonstrations

Sam's club and the Home Depot use AI technology to educate customers on how best to use items. Sam's Club uses a mobile-enabled shopping app, sharing product stories and details of where products were sourced (Blair, 2018). Conversely, The Home Depot uses machine learning to help customers with home improvement projects, recommending products and services required to complete the project (Home Depot, 2018).

In summary, AI technologies are helping customers find the right product for a specific need, answering customer queries through chatbots or virtual assistants and helping customers complete their home projects. AI applications are benefiting retailers' customer use and support in many ways. The following section discusses the conclusion and recommendations.

4.7 CONCLUSION AND RECCOMENDATIONS

AI represents retailers with various opportunities to automate tasks in the retail value chain. The benefits of AI are automating many processes in the value chain and improving efficiency, enabling people and machines to work together more collaboratively (Daugherty & Wilson, 2018). There are many benefits for retailers wanting to scale AI across the retail value chain. When AI supports the retail value chain tasks, manual non-value-added tasks can be replaced by AI and support the interplay between people and tasks. AI has the potential to automate certain activities fully, for instance, harnessing volumes of data, analysing patterns and interpreting findings in a fraction of the time that a human counterpart can complete the task (Acharya et al., 2018, p. 95; Ameen et al., 2021, p. 1; Chen et al., 2016; Gupta, 2018, p. 19). This article found that AI could change how retail employees perform their day-to-day tasks by substituting and automating specific tasks in the retail value chain.

AI simplifies many activities in the retail value chain through automation. When retailers adopt AI to automate tasks across the retail value chain, it could unlock unprecedented value, transforming their businesses and optimising day-to-day operations (Balchandani et al., 2020; Standish & Ganapathy, 2020; Weber & Schütte, 2019). Also, AI technologies are substituting specific tasks in the retail value chain, previously carried out by people, freeing workers to focus on new activities, changing the organisations' core skills (World Economic Forum, 2018). Therefore, when AI replaces tasks in the value chain, it has a necessary knock-on effect on the people that previously performed the tasks creating business implications for retail managers. Automating tasks with AI will require retailers to change their structure and work practices around how work is performed in the retail value chain.

Simplifying the retail value chain through AI would require retailers to focus on activities that benefit their operations. Nevertheless, applying AI to current business process tasks would not render transformation benefits. Therefore, retailers should move away from fitting new technologies into their current operations and focus on adopting a new way of working to accommodate AI in the retail value chain. Similarly, AI should be seen as an enabler to simplifying the value chain, not only technology. Retailers that are serious about streamlining the retail value chain with AI technology need to get the "basics right and build AI use cases that the business wants and can use to improve" (Ransbotham et al., 2020). Simplifying the retail value chain with AI requires new behaviours across people, processes and technology.

As more AI enters the retail business, we believe that today's employees with manually orientated tasks are at risk of replacement by AI. More than fifty percent of retail activities can be automated by AI that exists today (Simon et al., 2020). An example of such a change is the drive to automate the checkout process, requiring fewer cashiers. There are varied opinions on the impact AI will have on employment. A study conducted by Freddi, 2017, suggests that digital technology will positively affect work; as organisations introduce processes and become more productive, they can extend their markets, growing faster and increasing jobs. However, other studies conducted by Frey and Osborne (2013), World Economic Forum (2016) and Salento (201) argued that 30-40% of jobs would be at risk of automation in the next 15-20 years. We believe AI has an increasing impact on the retail value chain workforce by eliminating specific tasks, redefining roles, and creating new jobs generating the need for a different type of employee to work alongside AI. To get the most out of AI, retailers require a workforce with the ability to implement and work alongside the technology. The future skills retailers require would differ from the people skills required today. For retailer leaders to prepare, retailers must access their current employee's skill sets throughout the value chain to understand the capabilities required to work alongside the technology.

4.8 LIMITATIONS AND FUTURE RESEARCH

Whilst this article highlighted the tasks retailers are using AI technology for in the retail value chain, the current use cases are limited to retailers current application of the technology and do not focus on future use cases of AI in the retail value chain. Therefore, this article aimed to understand what retailers are using AI for in the retail value chain. To do so, a qualitative method was followed. Qualitative methods are not without limitations. The most notable limitation is generalising the findings (Eriksson & Kovalainen, 2008, p. 158; Leung, 2015, p. 327). The purpose of this article was not intended to generalise the findings but rather on gaining a firm grasp into the phenomenon of artificial intelligence in the retail value chain by investigating what retailers are using AI technology for in the retail value chain.

This study noted the various tasks AI can automate in the retail value chain. Future research could compare the tasks people currently perform versus AI can automate in the retail value chain. The research should focus on ascertaining the possible percentage of job losses due to automating tasks in the retail value chain. When AI automated tasks in the retail value chain, there could be an emergence of new tasks people need to complete. For instance, a chatbot automates responses to customer queries, yet, a new task emerging could be a software engineer maintaining the chatbot's responses. Future research could focus on the new people role (i.e., ML data manager or virtual assistant engineer) that could emerge due to the introduction of AI into business.

4.9 CONCLUSIONS: ARTICLE TWO

Article two illustrated a detailed review of AI's different tasks across the retail value chain. Guided by the Leavitt diamond model, focusing on the *dimension of the task* of the model (Leavitt & Bahrami, 1989), we identify the tasks AI can perform across the retail value chain. This is followed by a detailed discussion of how AI can be used to manage, operate and complete specific tasks in the retail value chain. Furthermore, AI can automate multiple tasks in the retail value chain.

Article two found that AI can be used to automate multiple activities the across retail value chain. For instance, AI could aid customer use and support by building relationships with customers, demonstrating a product, and detecting counterfeit products. The technology could also enhance the shopping experience by tailoring product recommendations to each customer preference and automating the scheduling of customer orders. The article-specific references are available in Appendix K. Building on the insights gained in articles one and two, the following chapter investigates the business outcomes of applying AI in the retail value chain.

Chapter 5: WHAT BUSINESS OUTCOMES CAN AI DRIVE IN THE RETAIL VALUE CHAIN

5.1 CHAPTER INTRODUCTION

Before retailers invest in AI, they need to understand the potential benefits from the investment to maximize a positive business outcome. Various authors discussed the benefits of AI (Adapa et al., 2020; Ameen et al., 2021; Dogru & Keskin, 2020; Manyika et al., 2017; Shechtman et al., 2018). For instance, Dogru and Keskin (2020) noted that AI improves productivity in operations through robotics and Manyika et al. (2017) noted that AI enhances employees productively through automating manual tasks. While, Shechtman et al. (2018), Adapa et al. (2020), and Ameen et al. (2021) noted that AI improves the way employees interact with customers and improves customer satisfaction. Although there are many benefits AI can provide retailers, a further benefit is garnered through understanding business outcomes (Zolkiewski et al., 2017, p. 174). However, little is known about the outcomes of applying AI in the retail value chain. Therefore, article three was developed to understand the outcomes of applying AI in the retail value chain.

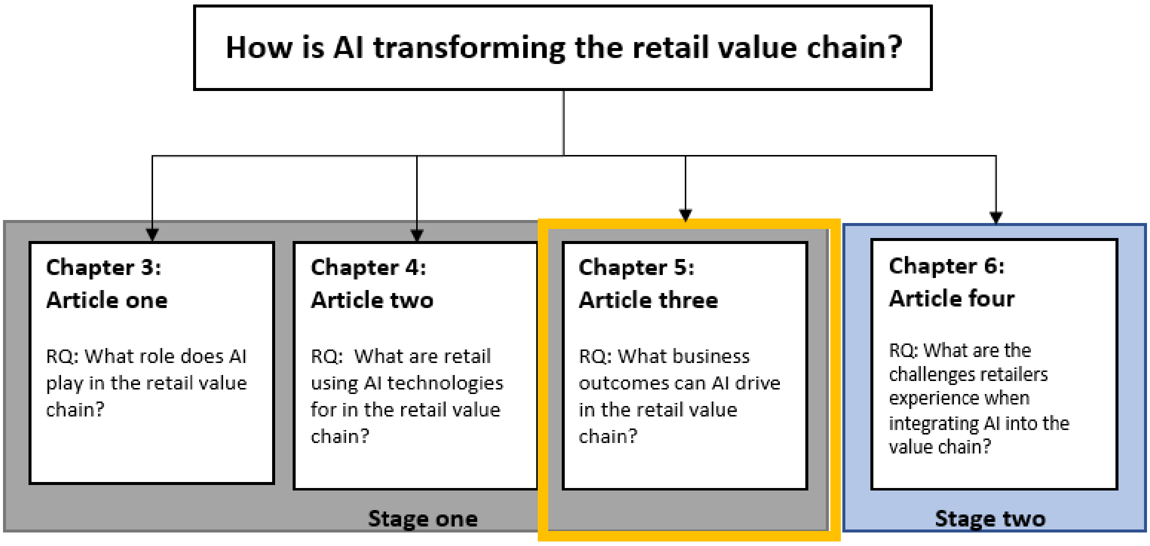


Figure 5.1: Article layout and the research questions

Article three aimed to answer research question three *what business outcomes can AI drive in the retail value chain.* This article applies service-dominant logic (Vargo & Lusch, 2004) to present the business value of AI in the retail value chain and found four key outcomes AI can deliver in the retail value chain: cost-saving and efficiency enabling revenue, customer experience improvements, and improved decision-making. The following section covers article three, titled Applying Service-Dominant logic to AI investments in retail: The outcomes of an AI-Enabled value chain

5.2 ARTICLE THREE: APPLYING SERVICE-DOMINANT LOGIC TO AI INVESTMENTS IN RETAIL: THE OUTCOMES OF AN AI-ENABLED VALUE CHAIN

5.3 INTRODUCTION

The rate at which new technologies enter and alter the market has exponentially increased (Nadkarni & Prügl, 2020). Combining these technologies has unpredictable consequences and blurred market boundaries (Day & Schoemaker, 2019, p. 4). For example, manufacturers, third parties, and consumers increasingly engage with customers, shortening the value chain (Reinartz et al., 2019, p. 352). In retailing, the value chain encompasses all the stakeholders and processes needed for retailers to deliver an end product (or service) to a customer (Reinartz et al., 2019, p. 352). Moreover, traditional retailers' value chains face disruption by new entrants who deliver value to customers more effectively and efficiently through the use of technology.

In particular, Artificial Intelligence (AI) receives significant attention due to its positive impact on the modern business environment (Cao, 2021). Poole and Mackworth (2017, p. 3) define AI as "computational agents that act intelligently" and include many applications from machine learning and chatbots to robotic process automation. AI is touted as one of the critical technologies set to transform both the retail experience and the retailer operating model. Expectations for the commercial application of AI in business, particularly in retailing, are significant (Ransbotham et al., 2017, p. 1), with retail spending on AI technologies expected to reach $19.9 billion by 2027 (Meticulous Research, 2020). In the retail value chain, in particular, AI can be used to automate processes, reduce complexities, and offer real-time analytics, leading to smaller, agile value chains (Hagel et al., 2016; Oosthuizen et al., 2020).

While several retailers are pilot testing AI possibilities, navigating the AI landscape remains complicated. Many applications are once-off initiatives within confined business units and do not cover multiple aspects of the value chain. Retailers, for example, overlook the collective benefits possible across the entire operations (Davenport & Ronanki, 2018; Standish & Ganapathy, 2020). Therefore, beyond single-use cases and varied success stories, there is no clear indication of AI's role in the extended retail value chain (Oosthuizen et al., 2020).

In addition, there is currently no clear understanding of the outcomes associated with implementing AI in the retail value chain. Outcomes-based measures have become increasingly important (Burkett, 2013, p. 84) and stem from service-dominant logic (Vargo and Lusch, 2004, p. 2) and digital servitisation (Sklyar et al., 2019, p. 450) research. With an outcomes-based approach, companies are less concerned with the investment in the product, infrastructure, or technology and more concerned about how these investments will allow them to attain their goals (Zolkiewski *et al.,* 2017, p. 177). An outcomes-based approach shifts the focus away from the input (i.e. technology or infrastructure investment) to a more strategic service-centric metric (i.e. how is this investment helping the organisation achieve its goals). Outcomes-based measures prompt questions beyond infrastructure investments and consider why the investment was needed in the first place.

Moreover, taking an outcomes-based approach, while sometimes more complex, can "better support strategic conversations" and "enable [the] parties to focus on critical activities" (Zolkiewski et al., 2017, p. 174). However, the outcomes of applying AI in the retail value chain have yet to be elucidated. Therefore, there is a gap in current literature regarding understanding the outcomes obtained by applying AI in retail and how these outcomes relate to *where* AI is applied within the value chain. This article consequently has the following three aims:

- To determine how major retailers are currently using AI.
- To identify the outcomes obtained by retailers from investing in AI.
- Furthermore, to determine whether there is an association between the AI outcomes and where they are applied within the retail value chain.

This article contributes to the emerging literature on AI by first providing a comprehensive view of AI technologies currently deployed across the retail value chain by major retailers. Second, how retailers can use AI to attain their goals are explored by using service-dominant logic—using an outcomes-based approach and presenting a framework of the four outcomes of applying AI in the retail value chain. Finally, insight is provided into how these outcomes relate to where AI is being applied in the retail value chain, helping retailers identify where best to apply AI to attain specific outcomes.

The article starts by reviewing AI technologies and discussing the retail value chain stages. Then, the research design and our process of collecting data are articulated. Thereafter the results are presented. The results section presents our framework of AI outcomes in retail and further analyses their relationship with the retail value chain. Finally, in the discussion and implications sections, we argue that complexity in implementing AI in earlier stages of the value chain impedes the outcomes retailers obtained from investing in AI. The article concludes by suggesting how retailers can better apply AI to obtain the desired outcome within their value chain.

5.4 LITERATURE REVIEW

5.4.1 The retail value chain

The retail industry operates in widely differing formats to satisfy the demand of the customers (Gauri et al., 2021; Reinartz et al., 2019; Zentes et al., 2012). Retailers are differentiated by a combination of characteristics, such as assortment offered, services offered, price band, type of store, geography, footprint, relationship with suppliers, and customer segments (Cao, 2014; Reinartz et al., 2019; Shi & Yan, 2017). Retailing consists of a variety of different formats. Big-box retailers are retailers with large free-standing stores that sell various products, usually meant to be a one-stop-shop for customers (Hayes, 2019) (i.e., Walmart). Department store retailers typically sell a wide variety of products, and the stores are generally divided into small speciality areas (i.e., Macy's) (Goworek, 2014, p. 761). Fast fashion retailers move quickly from the catwalk to stores to meet new trends. They are specialist clothing retailers with a quick stock turnaround whose business model relies on selling high volumes (usually) at inexpensive price points (i.e., Zara) (Choi et al., 2014, p. 84). Online retailers use an online channel to sell their products or services to customers (i.e., Amazon) (Fan et al., 2020). Supermarket retailers mainly sell grocery products and various fresh and packaged food items (i.e., Waitrose). However, the distinction between these formats is becoming blurred with the current drive towards omnichannel retailing. In this study, retailers were classified according to their major retail outlet function, and when in doubt, the group consensus was obtained before moving ahead.

Porter (1998) used the term value chain to describe a set of activities performed to design, produce, market, deliver and support products within businesses. The value chain activities are a sequence of linear steps and facilitate information and product flow between design, manufacturer, suppliers, shipping agents, warehouses, shelves, consumers, and retailers to the point of consumption (Reinartz et al., 2019). In retailing, the value chain encompasses all the stakeholders and processes needed for retailers to deliver an end product or service to a customer (Reinartz et al., 2019, p. 352). The retail value chain can be split into primary business drivers (design, sourcing, and procurement; manufacturing; inventory and distribution) and customer-facing activities (sales and operations; fulfilment; customer use and support). Business activities are the stages responsible for business success, while customer-facing activities involve direct interaction with a customer.

Retailers play a crucial role in the retail value chain by offering a wide range of product options to customers, responding to customer demand, and disseminating information to suppliers or manufacturers (Lai et al., 2010, p. 6). In addition, retailers link customers to manufacturers by providing channels for customer interaction, providing products and services in exchange for payment (Fiorito et al., 2010; Wadhawan & Seth, 2016).

5.4.2 AI in the retail value chain

Retailers have adopted new technologies, including various AI-powered platforms, to remain competitive and survive in an ever-changing and diversified customer market. AI accelerates the retail value chain by automating processes, reducing complexities, and offering real-time analytics, leading to shortened and agile value chains (Oosthuizen et al., 2020). AI technologies such as predictive platforms, insight engines, and personalised recommendations help retailers move seamlessly through the value chain stages, enabling them to connect with their customers at scale.

Gartner's hype cycle report for AI examines trends and innovations in the AI sector (Sicular *et al.*, 2019). The research focused on the 19 AI applications predicted to reach mainstream adoption in the next five years. During analysis of the use cases, evidence of 13 applications was identified that is presented in Table 5.1 together with an application identified from the analyses.

While understanding current AI applications in retail can help identify future investments, it does not provide insight into how AI can create business value. Although there are existing measures for managers to gauge AI's influence, navigating the AI landscape to gain business value remains complex. Understanding how to deploy AI to create business value in the value chain remains complicated.

AI technologies have advanced in recent years, yet their widespread adoption in the retail industry remains limited (Bughin et al., 2017, p. 6) due to the complexity in building clear business cases that define the benefits throughout the value chain (Standish & Ganapathy, 2020). In addition, a further benefit is garnered through understanding business outcomes (Zolkiewski et al., 2017, p. 174), and little is known about the outcomes of applying AI in the retail value chain.

Table 5.1: Description and examples of the types of AI

AI Technology	Brief Description	The example application in retail
AI-related consulting and integration services (C&SI)	AI-related C&SI are services offered by third-party vendors to process, analyse and automate specific tasks.	RealReal uses a vendor-managed AI marketing platform to help the brand build relationships with its customers (Zeta, 2020).
Augmented intelligence	Augmented intelligence is a human-centred AI-human partnership to help people perform tasks easier.	Sephora employees use a handheld device to scan customers' faces to capture a person's exact skin tone to match cosmetic shades (Milnes, 2016).
Chatbots	A chatbot simulates human conversation through voice commands or text, or both.	Lowe's uses a chatbot to answer simple customer questions regarding product availability (Trotter, 2018).
Computer vision	Computer vision involves capturing, processing, and analysing images and videos to allow machines to extract meaning from data.	Walmart uses computer vision technology to monitor checkouts to ensure all items are scanned to deter potential theft during the checkout process (Grill-Goodman, 2019).
Deep learning	Deep learning enables computers to process complex data, such as video, image, speech and textual data.	Zalando's visual search helps customers find similar items from social media on their app. Then, a deep learning algorithm locates items online for customers to purchase (Marr, 2019).
Edge AI	Edge AI are connected devices that use AI algorithms to process data at the closest point of interaction.	Gap uses edge AI to automatically receive, store, pick and pack products in their fulfilment centres (Vargo, 2020).
Insight engines	Insight engines apply relevancy methods to describe, discover, organise and analyse data.	StitchFix uses insight engines to create a collection of clothing items created from customer data (Lake, 2018).
Intelligent applications	Intelligent applications support or replace human-based activities via intelligent automation, data-driven insights, and guided recommendations to improve productivity and decision–making.	Morrison's uses a demand forecast and replenishment solution powered by AI to accurately predict customer demand, order stock, and reduce waste (Robinson, 2018)
Machine learning (ML)	ML solves business problems by utilising mathematical models to extract knowledge and patterns from data.	The Otto Group is automating daily price updates by applying ML learning algorithms to monitor thousands of products, leading to optimised revenue and profit (Chuprina, 2020)
Robotic process automation (RPA)	RPA is a recognition and workflow execution technology that mimics human actions to drive applications and execute system-based work automatically.	John Lewis uses a connected RPA to automate and accelerate the inter-branch transfer process for product returns (Blueprism, 2019).
Smart robots	Smart robots work autonomously in the physical world, learning in short-term intervals from human-supervised training and demonstrations or by their supervised experiences on the job.	Walmart uses autonomous shelf scanning robots to ensure shelves are restocked and updated price tags (Heater, 2019).
Virtual assistants (VA)	VA is an AI that understands voice commands to complete tasks.	Sam's Club has an app that uses customers' voice commands to show them the best route to navigate around the store (Blair, 2018).

5.4.3 Moving from inputs-outputs measures to outcomes-based measures

Moving from inputs-outputs measured to outcomes-based measures stems from work in servitisation research (Smith et al., 2014) and service-dominant logic (Vargo and Lusch, 2004), where companies move away from a product-dominant focus towards a more customer-centric service focus. Vargo et al.'s (Vargo & Akaka, 2009; Vargo & Lusch, 2004) service-dominant (S-D) logic is an alternative to the traditional goods-dominant paradigm and is based on the idea that service (i.e. the application of competence for the benefit of another) is the basis of all exchange. One foundational premise of the service-dominant logic is that all goods (both durable and non-durable) derive their value through use, i.e. the service they provide (Vargo & Akaka, 2009, p. 35). Thus the focus should be less on the goods themselves and more on the service (or outcome) they provide. While S-D logic originated in customer research, it has evolved to inform various organisation and business model parts. Notably, digitization research typically goes "hand in hand with adopting a servitisation strategy" (Parida et al., 2015, p. 41). D*igital servitisation* refers to using digital tools, like AI, for "the transformational process whereby a company shifts from product-centric to a service-centric business model and logic" (Sklyar et al., 2019, p. 450). Nevertheless, issues in organizing specifically for servitisation remain underexplored (Sklyar et al*.,* 2019).

In an outcomes-based approach, companies are less concerned with the investment in the product, infrastructure, or technology and more concerned about how these investments will allow them to attain their goals (Zolkiewski et al., 2017). In service research, this means a shift away from asking "did they like it?" towards asking "what difference did it make?" (Burkett, 2013). Therefore, an outcomes-based approach takes a broader and more strategic view of technology investments by the firm. An inputs-outputs approach to measuring the performance of technology investments would centre on critical indicators like cost, schedule, and compliance with technical specifications.

In conclusion, using the two classifications of the retail value chain and AI technologies discussed in section two, this article aims to understand which outcomes are being obtained through the implementation of AI across the retail value chain. First, it was needed to understand how major retailers are currently applying AI and where AI is implemented in the retail value chain to obtain outcomes. The following section details how we went about answering these research questions.

5.5 RESEARCH METHODOLOGY

5.5.1 Research design

The first step was understanding the current application of AI technologies in the value chain using Moher et al.'s (2009) Preferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA) approach. An exploratory, qualitative research design was followed. In particular, an integrative literature review was conducted as the article's purpose was to critique and synthesize the application of AI in retail value chains, and our analysis aimed to result in a taxonomy of outcomes (Snyder, 2019, p. 334). Each step of the research process is described in detail in the following section.

5.5.2 Research process

The EBSCOhost research database was used to identify the resources for analysis. This database was suitable as it includes reputable resources from multiple sources, including academic journals, news, magazines, trade publications, and reports. Typical to integrative literature reviews, in addition to academic articles, other published texts like company press releases and news articles were included in the analysis (Snyder, 2019, p. 334). Boolean logic was used to include or exclude search terms to identify the articles available on the database. Table 5.2 depicts how the search process prescribed by Moher *et al.* (2009) was followed.

A total of 4,304 records were identified in the initial search. However, most records were not focused on retailers using AI technology, and the search had to be narrowed. Therefore, a second search included keywords use case OR ("application" AND "Implement*" AND "Deploy*" AND "applied"). This search had a higher concentration of possible retailers using AI technology in the 1,319 records identified.

Next, the articles were reviewed to determine if they were suitable for analysis. The screening process required each record to meet all selection criteria for inclusion (refer to Table 5. 2). First, to ensure the validity of the selected record, it was confirmed that the retailer was currently trading by identifying the retailer through its website and online news platforms. Secondly, the technology mentioned in each article was compared to the predefined AI types code (Table 5.1) to ensure the retailer applies AI, rather than how they intend to apply it in future.

Table 5.2: Application of the PRISMA checklist for systematic review

Stage	Process	Checklist item	Process
1	Identification	Identify the articles via keyword search (n =4304)	"artificial intelligence" OR "AI" AND "retail*" OR ("retail industry" AND "retailers"); Focused time period: 2015 – 2020.
		Add to keywords to search (n=1319)	use case OR ("application" AND "Implement*" AND "Deploy*" AND "applied").
2	Screening	Identify the source	Currently trading retailers. The technology used should be AI technology. The retailer should already use AI technology.
3	Eligibility	Number of records available (n=201)	Identify the retailer and software vendor in the case. Then, supplement the information with technology vendor press releases, retailer press releases; retail-related news articles; technology vendor white articles, retail industry reports and technology news platforms.
		Remove duplicates (n=84)	Removal of duplicates.
4	Included	Collect and capture retail AI use cases (n=117)	Record the data.

Where insufficient information was provided in the primary article to decide on inclusion or exclusion, the data was supplemented by searching for further information to enrich the original information. This was obtained from software vendor press releases, retailer press releases, retail-related news articles, technology vendor white articles, retail industry reports, and technology news platforms. Using the eligibility protocol, 201 records that met all the selection criteria were identified, and coding of the retailer, technology provider and summary of the AI application led to the identification of 84 duplicate use cases. Once removed, a final sample of 117 unique records was used for coding and analysis.

5.5.3 Data Analysis

We used a deductive coding method to develop an initial coding scheme, focusing on finding insights by analysing the retail AI dataset (O'Reilly, 2009, p. 36). We followed a predetermined coding process to review 117 retailers currently using AI in their value chain to address the research questions. First, to understand where in the retail value chain AI is used, the retail value chain's stage was coded into the relevant stages (see Figure 2.3). Second, the objective was to ascertain in which areas in the retail value chain retailers were using AI technology to drive internal business activities (design, sourcing and procurement, manufacturing, inventory, and distribution) or to support customer-facing activities (sales and operations, fulfilment, customer use and support).

Second, to identify the type of retailer in the database, we coded the retailer into their respective format (see section 2.3.1). For instance, Walmart stores generally trade in large warehouse store locations and offer various products. Walmart was coded as a big-box retailer. The authors recognise that the distinction between these formats is becoming blurred with the current drive towards omnichannel retailing. Retailers were classified regarding what most of their retail outlets function as, and where in doubt, inter-rater reliability was obtained.

Third, the type of AI technologies applied in the dataset was coded using Gartner's hype cycle report for AI that examines trends and innovations in the AI sector (Sicular et al., 2019). The research focused on the 19 AI applications predicted to reach mainstream adoption in the next five years. During analysis of the use cases, evidence of 13 applications was identified that is presented in Table 5.1 together with an application identified from the analyses. Last, during the iterative review process, the focus was on emerging themes that would inform the outcomes obtained from applying the technology within the retail value chain.

5.5.4 Content analysis

A content analysis approach and statistical techniques were used to understand the outcomes of applying AI in the retail value chain. The analysis considered “conventional, directive and summative approaches” to describe the phenomenon (Assarroudi et al., 2018, p. 42). First, an integrative literature review was performed to critique and synthesize the database’s application of AI in retail value chains. Second, the analysis was aimed to result in a taxonomy of outcomes (Snyder, 2019, p. 334). Analysing the outcomes of the AI application in retail revealed key themes about the primary outcome that each retailer may gain from applying AI in their value chains. While certain AI technologies can allow retailers to obtain more than one of these outcomes, the coding was done for the primary outcome for each unique use case. Consequently, four potential outcomes emanated from applying AI in the retail value chain, and each AI use case was classified according to the primary outcome obtained for that retailer. This was followed by statistical methods to understand how the outcomes relate to *where* AI is applied within the value chain.

5.6 RESULTS

5.6.1 How retailers are currently using AI

The study's descriptive statistics coded (Table 5.3) included the type of retailer using AI, the value chain AI was applied, and the type of AI used. Each is now discussed in turn.

The most widely applied AI application was for speciality retailers (40%). Speciality retailers focus on specific product categories such as beauty products, clothing, electronics, or footwear. Examples of speciality retailers are Sephora, Lululemon, and Levi's. Speciality retailers use AI technologies to optimise inventory across their stores, recommend new product assortments, predict customer demands, and offer customers the ability to try on products virtually. For example, a speciality retailer used insight engines as an interactive data map to inform customers where the flu is recurring across the US, helping customers schedule their flu vaccinations.

Online retailers were the next biggest cohort of retailers using AI (17%), closely followed by supermarkets (14.5%) and big-box retailers (12%). Online retailers use AI technology to offer customers virtual try-on solutions, optimise order fulfilments in distribution centres, automatically list products, and personalise recommendations at scale. For example, one online retailer used a chatbot to help customers find the best deals on items spanning over one billion listings. Customers can text, talk, or take pictures to tell the bot what they are looking for. Supermarket retailers used AI technology to enhance the customer shopping experience by answering questions on item availability, managing inventory in real-time, creating automatic checkouts in-store, and scheduling deliveries. One supermarket retailer used an intelligent demand forecast, and replenishment AI to accurately predict customer demand, order the correct stock level, and reduce overall product waste. Big-box retailers used AI technologies to assist with customer service in-store or online, help customers fit products in their homes through virtual placement, and prevent theft at checkouts. For example, a big-box home improvement retailer used a chatbot to provide customer service by answering simple product questions.

AI is less frequently applied by department stores (7%), fast-fashion retailers (6%), and factories (4%). The few applications of AI observed in these retail settings included price checks, automating product returns, contactless pickup service in-store, monitoring customer movements in-store, and product assembly. For example, RPA was used to perform price checks to ensure the most competitive price was available for its customers in one department store. In contrast, a speciality retailer uses AI to match demand with the supply by using data analytics, where the AI application ensures the correct products are in the correct store.

Table 5.3: Descriptive statistics for retailer type, retail value chain stage and type of AI application

Descriptive Variable		**Frequency**	**Percentage**
Retailer type n=117	Big-box retailer	14	12.0%
	Department store	7	6.0%
	Factory	5	4.3%
	Fast fashion retailer	7	6.0%
	Online retailer	20	17.1%
	Speciality retailer	47	40.2%
	Supermarket	17	14.5%
Retail value chain stage n=117	Design	4	3.0%
	Customer use and support	40	34.0%
	Fulfilment	5	4.0%
	Inventory management and distribution	17	15.0%
	Manufacturing	6	5.0%
	Sourcing and procurement	10	9.0%
	Store operations and sales	35	30.0%
Type of AI technology N=117	AI-related C&SI services	3	2.6%
	Augmented intelligence	11	9.4%
	Chatbots	7	6.0%
	Computer vision	11	9.4%
	Deep learning	7	6.0%
	Edge AI	15	12.8%
	Insight engines	15	12.8%
	Intelligent applications	15	12.8%
	Machine Learning	12	10.3%
	Robotic process automation (RPA)	5	4.3%
	Smart robots	5	4.3%
	Virtual Assistants	11	9.4%

When looking at where in the retail value chain stages AI was being applied, the majority of AI applications were either in customer use and support (34%), store operations and sales (30%), or inventory management and distribution (15%). That means that almost 80% of AI applications were used in the latter half of the value chain. On the other hand, relatively few applications were used in the front end of the value chain, for example, design (3%) and sourcing/procurement (9%).

Multiple types of AI were used within the retail value chain, and edge AI (12.8%), insight engines (12.8%) and intelligent applications (12.8%) were the most prominent applications. For example, one speciality retailer used edge AI to automatically receive, store, pick and pack products in their fulfilment centres. One online retailer used an insight engine to utilize customer data to create personalised clothing collections for each customer, thus creating personalisation at scale. Finally, demand forecast and replenishment AI solutions were used to accurately predict customer demand, order the correct stock level, and reduce waste.

The next biggest group of AI types used was machine learning (10.3%), augmented intelligence (9.4%), computer vision (9.4%), and virtual assistants (9.4%). Examples of machine learning use cases include an online retailer automating daily price updates by applying machine learning algorithms to monitor thousands of products. A speciality retailer uses augmented intelligence to let employees use a handheld device to scan a customer's face to capture the person's exact skin tone and match cosmetic shades to the customer. A big-box retailer used computer vision technology in more than 1,000 stores to monitor checkouts, ensure all items were scanned, and deter potential theft during the checkout process. Finally, a virtual assistant use case was a big-box retailer app that recognised voice commands to show customers the best route to navigate around the store.

There were fewer use cases for chatbots (6%) and deep learning (6%). An example of a chatbot use case was a big-box retailer using a chatbot to answer customer questions regarding product availability in-store. One retailer used a deep learning application, particularly the visual search capability, to help customers find similar items. The customers could upload images from social media onto the app, then the AI located relevant items online to purchase.

Lastly, the fewest use cases were found for smart robots (4.3%), robotic process automation (4.3%), and AI-related C&SI services (2%). For example, one big-box retailer used shelf-scanning smart robots to ensure shelves were restocked and price tags were updated. Finally, as an example of robotic process automation by a retailer, one department store used a connected RPA to automate and accelerate the inter-branch transfer process for product returns. Next, we analysed which outcomes these retailers gained from applying AI in their value chains.

5.6.2 Retail outcomes that are met when applying AI

The importance of approaching technology investments from an outcomes-based perspective has been established above. Although understanding AI applications in retail are the first step, it is also required to understand the business value created. Analysing the outcomes of the AI application in retail revealed vital themes about the primary outcome that each retailer may gain from applying AI in their value chains. Consequently, the reviewers identified four potential outcomes emanating from applying AI in the retail value chain. Each AI use case was classified according to the primary outcome obtained for that retailer. While certain AI technologies can allow retailers to obtain more than one of these outcomes, the coding was done for the primary outcome for each unique use case.

Figure 5.2 illustrates that the four identified outcomes are interactive and reinforce one another. Although the outcomes are not mutually exclusive, for example, cost-saving and efficiency practices can support revenue generation, AI technologies should be directed at one of these outcomes, and implementation performance should be measured accordingly.

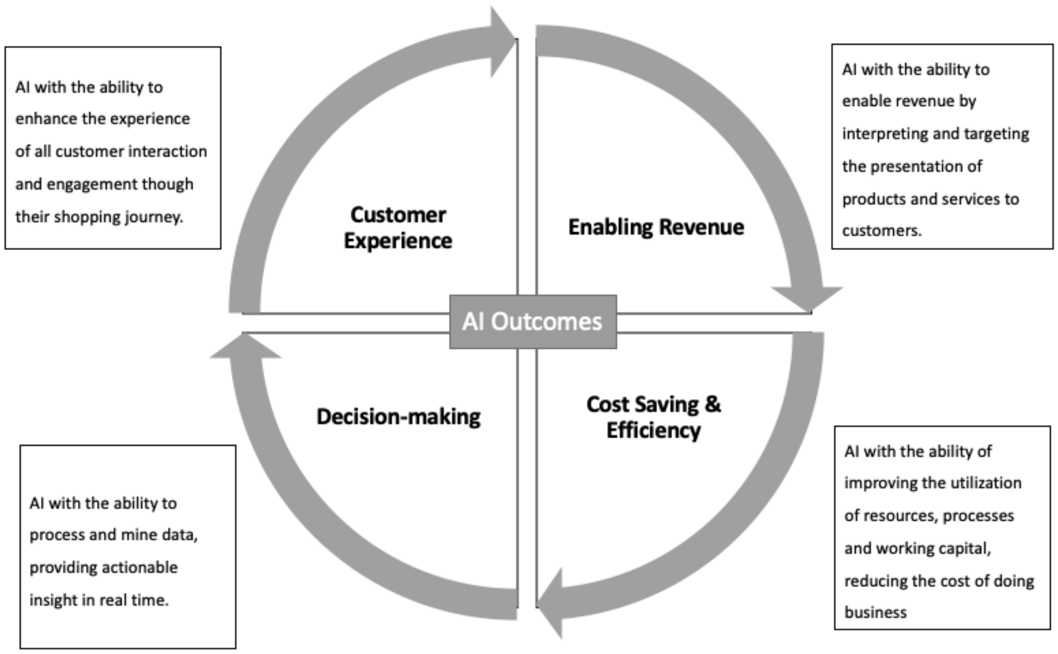


Figure 5.2: The four outcomes of applying AI in the retail value chain

AI bridges the digital and offline world gap by seamlessly integrating the customer journey across devices. Retailers are using AI to enhance the ***customer experience*** by:

- allowing customers to customise and design products,
- allowing customers to try on or place products virtually in their home,
- recommending products or services,
- connecting customers to use devices to enhance the in-store experience, and
- enabling customers to use voice search through retail-specific mobile apps to access additional information about products in-store.

However, retailers are not only using AI for the customer, but they are also using AI to equip employees with knowledge through handheld devices filled with product information to enhance customer intimacy in-store.

Augmented intelligence, chatbots, computer vision, deep learning, edge AI, and VAs can be implemented throughout the retail value chain to support customer decision-making, decrease customer pain points, and improve employees' knowledge about the customers. All efforts are geared towards building a closer relationship with the customer (Ameen et al., 2021; Hollebeek et al., 2021). Therefore, the application of AI for customer experience can be defined as applying *AI technologies to enhance all customer interactions throughout the shopping journey.*

AI technologies improve the retailer's capability to ***enable revenue*** by creating personalisation at scale, targeting customers through connected devices, dynamically managing prices or promotions, and monitoring inventory in real-time to ensure shelves are always stocked. In addition, ML, insight engines, and intelligent applications can be implemented throughout the retail value chain to enable revenue by connecting employees to the customer through decision support notifications, pricing recommendations, and real-time decision-making. Therefore, AI for enabling revenue can be defined as *AI with the ability to enable revenue by interpreting and targeting the presentation of products and services to customers.*

The appropriate application of AI can lead to substantial ***cost savings and improvements in efficiency*** across the value chain. For example, AI can improve assortments in-store by anticipating future demand so that the correct quantity of stock can be ordered at the right time, thus reducing product wastage. AI vendors claim the implementation of AI can reduce the overall cost by 49% (Chuprina, 2020). Throughout the retail value chain, insight engines, computer vision, intelligent applications, deep learning, edge AI, and smart robots enable retailers to monitor the store checkout process and improve efficiency by automatically scheduling deliveries and, for example, sewing or assembling garments in the production process. Therefore, AI technologies geared towards generating cost reductions and efficiencies are defined as the application of *AI to improve the utilization of resources, processes, and working capital, thus reducing the cost of doing business*.

Retailers are also applying AI to ***enhance decision-making*** across the value chain by relying on insights drawn from real-time data. AI analytics support retailers to uncover insights by processing and mining large information databases, which may be time-consuming or impossible for employees to perform (Elliot & Andrews, 2017; Shechtman et al., 2018). Retailers use AI to discover trends in large datasets to generate customer profiles and segments, create customer recommendations at scale, and monitor inventory and price information in real-time. Up to 40% of AI vendors believe the use of AI in retail decision-making is the main benefit of the technology (Chuprina, 2020). Thus, AI technologies for the primary purpose of enhanced decision-making can be defined as applying *AI to discover trends and visualize data for human consumption, thus improving decision cycle time*.

After identifying the four emergent outcome themes retailers attain from investing in AI, the final question was whether an investment in AI in different value chain stages would render different outcomes.

5.6.3 Outcomes and the retail value chain

Table 5.4 was constructed to show the multivariate frequency distribution of the AI outcomes and the retail value chain stages to test the association between the outcome of AI investment and the value chain stage, the contingency.

Table 5.4: AI outcome*retail value chain stage contingency table

Retail value chain stage (% within AI application outcomes)	**Cost-saving & efficiency**	**Customer experience**	**Decision-making**	**Enabling revenue**	**Total**
Design	0 (0%)	1 (0.9%)	3 (2.6%)	0 (0%)	4 (3.4%)
Sourcing/Procurement	5 (4.3%)	0 (0%)	1 (0.9%)	4 (3.4%)	10 (8.5%)
Manufacturing	6 (5.1%)	0 (0%)	0 (0%)	0 (0%)	6 (5.1%)
Inventory management and distribution	11 (9.4%)	0 (0%)	4 (3.4%)	2 (1.7%)	17 (14.5%)
Store operations and sales	4 (3.4%)	9 (7.7%)	10 (8.5%)	12 (10.3%)	35 (29.9%)
Fulfilment	1 (0.9%)	1 (0.9%)	3 (2.6%)	0 (0%)	5 (4.3%)
Customer use and support	1 (0.9%)	30 (25.6%)	4 (3.4%)	5 (4.3%)	40 (34.2%)
TOTAL	28 (23.9%)	41 (35.0%)	25 (21.4%)	23 (19.7%)	117 (100%)

Most AI use cases investigated applications were found in customer use and support (34.5%) and store operations and sales (29.9%). Thus, almost 70% of the AI use cases were customer-facing or geared towards sales, fulfilment, or support. Nevertheless, only 35% of these improved the customer experience, hinting at a disparity between where AI is being applied in the value chain and the outcome obtained. Conversely, most cost-saving and improvements in efficacy resulted from the application of AI in manufacturing (21.4%) and inventory management (39%).

There was a relatively uniform distribution of the four different outcomes obtained through AI applications, with the majority in customer experience improvements (35%), followed by cost-saving and efficiency (24%), AI used for decision-support (21%), and AI geared towards revenue generation

(20%). Most of the AI technologies geared towards revenue generation were applied in-store operations and sales (52.2%). The AI outcome of customer experience was mainly centred on applications within customer use and support (73%). AI for better decision-making was distributed across the value chain, yet no use cases were found of AI being applied in manufacturing. Despite the multiple AI technologies directed at these phases, design (3.4%) and manufacturing (5.1%) were the two stages with the fewest applications of AI.

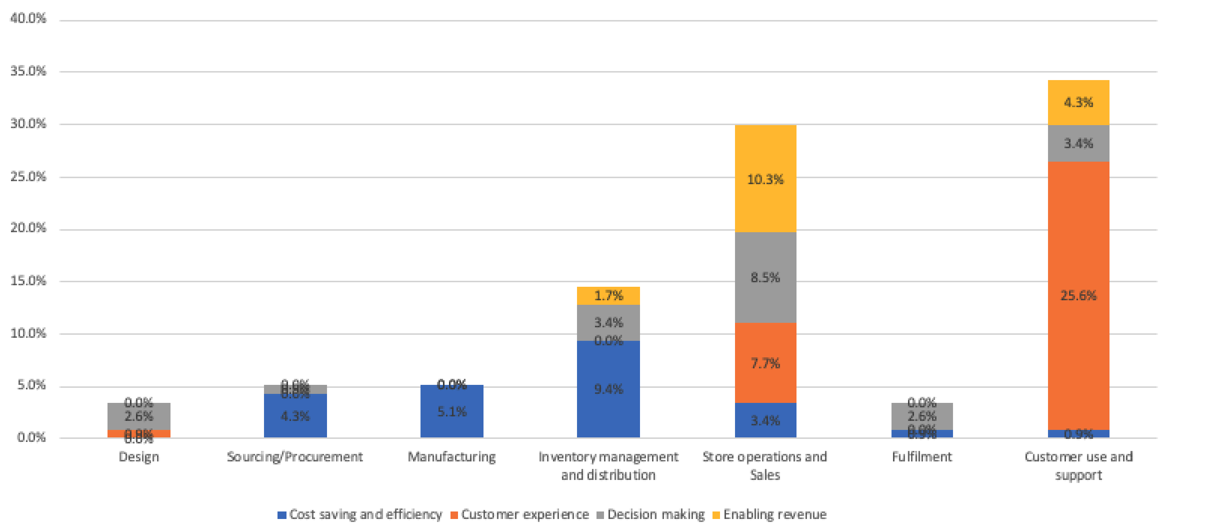


Figure 5.3: AI outcome*retail value chain stage clustered bar chart

It is evident from Figure 5.3 that AI applications are more prevalent in the latter stages of the retail value chain and that there is less evidence that AI outcomes are realized in the early stages of the retail process from the use cases. This could contrast with authors (Oosthuizen et al., 2020; Standish & Ganapathy, 2020), who argued that the highest return on investment in AI was found in the earlier stages of the value chain. However, Table 5.2 and Figure 5.2 represents the frequency of value against use cases, not the normative value of the return. Thus, it is plausible that the magnitude of returns may be substantially different.

While Table 5.4 provides insight into the association between the stage in the retail value chain and the outcome observed, no inferences can be made from this analysis as some assumptions of the Chi-square test were not met in creating the frequency distribution. In particular, the contingency Table 5.4 had structural zeros, and more than 20% per cent of the expected values were smaller than five (Agresti, 2009). Instead, log-linear models can describe association patterns among a set of categorical variables (Agresti, 2009). Multinomial logistic regression was used because the dependent variable outcomes had more than two categories (see Table 5.5).

Table 5.5: Multinomial log-linear analysis

Model fit						
	Chi-square	Sig		Cox & Snell	Nagelkerke	McFadden
Likelihood ratio test	77.95	0.00	Pseudo R-square	0.49	0.52	0.25
		Chi-square	Sig		Chi-square	Sig
Goodness of fit	Pearson	0.00	.	Deviance	0.00	.
Indicator						
	AIC of a reduced model	BIC of a reduced model	2 Log-likelihood of a reduced model	Likelihood ratio tests		
				Chi-square	df	Sig.
Retail value chain stage	114.38	122.67	108.38	77.95	9	0.00
Classification						
	Cost-saving & efficiency	Customer Experience	Decision-making	Revenue generating*	Overall percentage	
Classification	78.6%	73.2%	52%	0%	55.6%	

The model was significant (p=0.00, Chi-square=77.95), indicating that the entire model presents a significant improvement in fit over the null model. The pseudo-R-square values can be treated as rough analogues to R-square values in OLS regression, which in this case (bar McFadden) indicates that the indicator could explain a fair percentage of the variance in the dependent variable. However, there is no strong guidance in the literature on how these should be used or interpreted (Smith & McKenna, 2013). Using the conventional 5% likelihood threshold, it can be seen that the retail value chain stage was a significant predictor in the model. This confirms an association between the retail value chain stage and the AI outcome obtained in that stage (Likelihood Ratio Test: p=0.00, Chi-Squared=77.95, df=9).

Finally, the classification statistics provide insight into which model best predicted AI outcomes. For example, Cost-saving and efficiency were correctly predicted 78.6% of the time; customer experience was correctly predicted 73.2% of the time; and decision-making, 52%. The model was particularly limited in predicting the AI outcome of enabling revenue, but this variable was also the reference category in the model. Overall, the model accurately predicted 55.6% of the AI outcomes.

5.7 DISCUSSION

Using service-dominant logic, this article aimed to 1) identify the AI applications used by retailers, 2) understand the types of outcomes retailers obtain from investing in AI and 3) investigate whether there was an association between these AI outcomes and where they were being applied in the value chain.

The types of AI applications covered 13 of the 19 most prominent AI technologies from leading industry classifications indicating the deployment of rich sets of AI technologies across the retail value chain. A service approach to AI investments by retailers can identify which retailer outcomes are met through the use of AI, and four outcomes emerged. The analysis that the outcomes obtained from applying AI in the retail value chain, and the retail value chain stage in which it was used, are not independent of one another.

Applying AI across the retail value chain has four key outcomes that are not mutually exclusive, and some AI applications can fulfil multiple roles. The outcome obtained by AI technology is significantly influenced by where the technology is applied in the value chain. Two retailers investing in the same AI technology in different value chain stages may achieve different outcomes. Retailers need to be clear on what outcome they aim to achieve through their AI investment and implement it in the appropriate value chain stage.

More than 70% of all AI applications manifest in the last three stages of the value chain (see Figure 5.4). This may be because retailers' investment in customer-facing AI is more visible to both customers and competitors. However, while this provides evidence of their AI investment, they may not be gaining key benefits that AI technology can offer, such as assisting them with decision-making across the value chain, cost-saving and efficiency improvements, and enabling revenue.

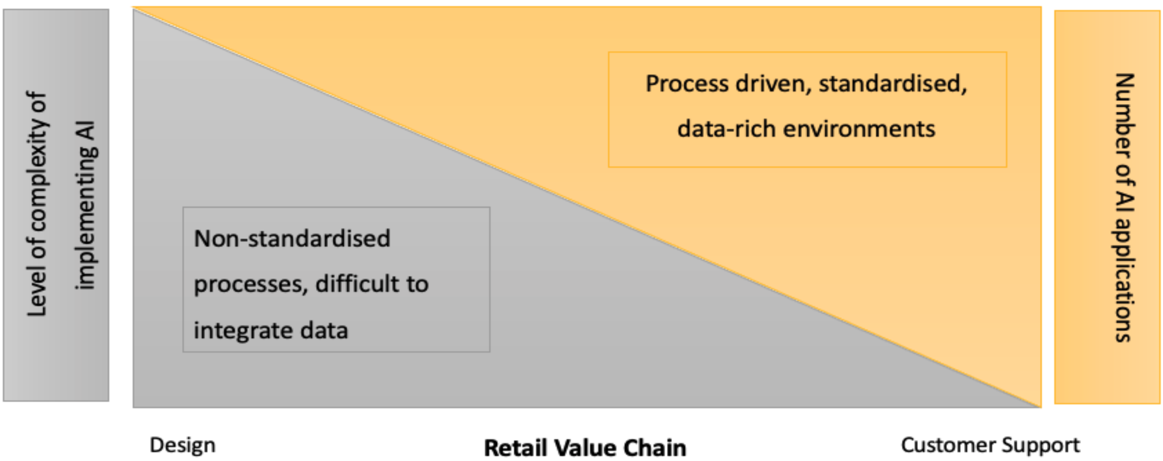


Figure 5.4: Complexity and AI in the retail value chain

The reality is probably more multifaceted as the implementation of AI is becoming increasingly complex in the earlier stages of the value chain. The earlier stages in the retail value chain (like design, sourcing, and procurement) are often characterized by non-standardized processes, legacy systems, and weakly integrated data. On the other end of the spectrum, store, sales, and support systems are typically more process-driven and standardized. With customer experience technology breakthroughs and various customer relationship management systems widely adopted, overlaying AI on top of rich data is more feasible to implement. This is indicated in Figure 5.4, which illustrates that the greater complexity in the earlier stages of the retail value chain has resulted in a potential imbalance in the application of AI across the value chain.

Idealistically, AI technologies would have resulted in a uniform and widespread application across the retail value chain. However, researchers believe the most significant impact of AI is not in its customer-facing applications but rather in its ability to reduce costs and increase efficiencies in the value chain (Begley et al., 2018; Chao et al., 2019).

With an evolving customer demand and increasingly competitive market, historical data is no longer sufficient to interpret customer needs. Therefore, retailers need to predict future trends more accurately to remain relevant to their customers. Investing AI in the early stages of the value chain can drive business value by improving inventory management, leading to more efficient and streamlined operations (Oosthuizen et al., 2020; Standish & Ganapathy, 2020).

5.8 MANAGERIAL IMPLICATIONS

Retailers should be clear about the benefits of an AI investment, where they want to apply AI in their value chain, and how they will monitor and manage their investment. This study identified four key outcomes that AI delivers in the retail value chain that should form the basis of an AI implementation business case.

AI improves the *customer experience* by enhancing the experience of all customer interaction and engagement throughout their shopping journey. Retailers are applying AI to enhance the customer experience by allowing customers to try or place products virtually, using digital stylists to recommend outfits to customers, and enabling customers to use voice search through retail-specific mobile apps to access additional information about products in-store.

AI *enables revenue* by interpreting and targeting the presentation of products and services to customers. Retailers are applying AI to enable revenue by creating personalisation at scale, targeting customers through connected devices, dynamically managing prices or promotions, and monitoring inventory in real-time to ensure shelves are always stocked.

The appropriate application of AI can lead to significant *cost savings and efficiency improvements* across the value chain by improving the utilization of resources, processes, and working capital, thus reducing the cost of doing business. For example, retailers are applying AI to optimise the cost of goods by improving assortments in-store by anticipating future demand, which leads to ordering the correct quantity of stock at the right time to reduce product wastage.

Retailers are also applying AI to *enhance decision-making* processes and mine data, providing actionable insight in real-time across the value chain. AI analytics support retailers to uncover insights by processing and mining large databases of information created by existing systems within the business environment. The large datasets in modern organisations are highly complex or impossible to analyse by traditional human-intrinsic methods.

Retailers need to be clear about where they want to apply AI in the retail value chain. Ideally, retailers have the integrated and circular retail value chain proposed by Oosthuizen *et al.* (2020). However, most value chains are linear and siloed, plagued by legacy systems and incomplete data. This article shows that some outcomes are more likely when AI is applied in particular value chain stages. Therefore, once retailers have decided which outcome they want to attain through the application of AI, both the type of AI and the value chain stage in which they want to apply the technology. Their options are reduced significantly, and managerial decision making and business case development become easier.

Finally, the ROI of any technology investment can only be realized if that investment is being appropriately measured and monitored. The four AI outcomes provide retailers with a guideline on measuring return on investment. If retailers are clear about the outcome they want to achieve with their AI investment, they can measure accordingly.

5.9 CONCLUSION: ARTICLE THREE

This article applied service-dominant logic (Vargo & Lusch, 2004) to present the business value of AI in the retail value chain. Four key outcomes were identified that AI could deliver in the retail value chain: cost-saving and efficiency, enabling revenue, customer experience improvements, and improved decision-making. Insights on the relationship between benefits and retail value chain stages were presented. An association between where retailers are applying AI technologies and their outcomes from it were presented. Although the outcomes are not mutually exclusive, for example, cost-saving and efficiency practices can support revenue generation, AI technologies should be directed at one of these outcomes, and implementation performance should be measured accordingly.

Second, article three argues that the outcome obtained by AI technology is significantly influenced by where the technology is applied in the value chain. For instance, two retailers investing in the same AI technology in different value chain stages may achieve different outcomes. Therefore, retailers need to be clear on what outcome they aim to achieve through their AI investment and implement it in the appropriate value chain stage. For this reason, retailers should instead approach AI investments from a more strategic service-centric perspective and understand the outcomes that can be achieved through the use of AI in the retail value chain. The article references are available in Appendix M. The following chapter investigates the challenges retailers experience when integrating AI into their business.

Chapter 6: WHAT ARE THE CHALLENGES RETAILERS EXPERIENCE WHEN INTEGRATING AI INTO THE RETAIL VALUE CHAIN?

6.1 INTRODUCTION

Despite the promise of AI, most AI investments are failing to deliver on their promised returns (Fountaine et al., 2019). Only 50% of AI proof of concepts move into business (McCormick, 2020; Press, 2019). In contrast, 47% of companies found it difficult to integrate AI into existing processes, workflows and systems (Deloitte, 2017), rendering its benefits to isolated business processes (Fountaine et al., 2019; Ganapathy et al., 2020). Many challenges come with integrating and adopting AI into the retail value chain. However, it is yet to be clarified by scholars. It is essential for retailers to successfully integrate AI into the retail value chain to understand the challenges retailers experience when integrating AI. Therefore, article four was developed to understand why retailers struggle to integrate AI into their business.

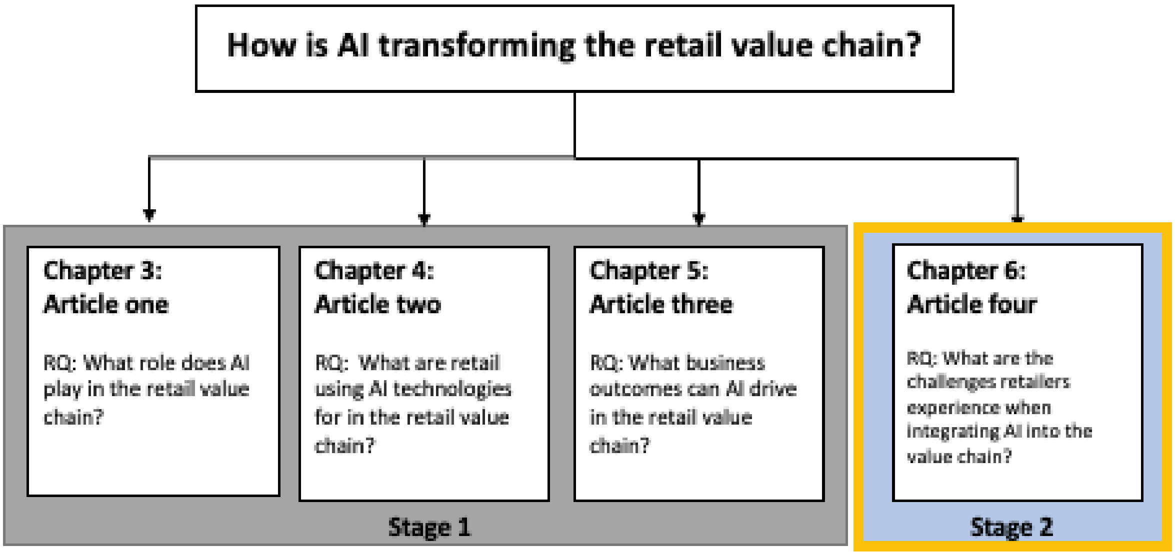


Figure 6.1: Article layout and research questions

Article four aimed to answer research question four: *What are the challenges retailers experience when integrating AI into their value chain?*. Article four used two steps to understand the challenges of the retail experience. First, semi-structured interviews were conducted to understand retailers' experiences when implementing AI. The interviews were conducted with twenty experts developing, working, implementing, and using AI in retail.

Second, the Leavitt Diamond Model was used to understand what causes AI implementation challenges for retailers. The Leavitt Diamond Model considers the technology for understanding organisational challenges and the people, tasks, and structure necessary for its successful integration of AI. Leavitt (1965) suggested that everything in an organisation is connected, and no change can occur in isolation. Therefore, using the Leavitt Diamond Model, this article aimed to understand the possible *structure*, *technology*, *task* and *human-related* challenges of integrating AI in the retail value chain. The following section covers article four, Artificial Intelligence in retail: The challenges retailers experience when integrating AI into the value chain.

6.2 ARTICLE FOUR: ARTIFICIAL INTELLIGENCE IN RETAIL: THE CHALLENGES RETAILERS EXPERIENCE WHEN INTEGRATING AI INTO THE VALUE CHAIN

6.3 INTRODUCTION

The competitive landscape is shifting for retailers, and many are scrambling to stay ahead of the competition by investing in new technologies like AI, automation, robotics and blockchain. Of these new technologies, AI has received the lion share of investment by retailers, with major retailers like Levi, Walmart and Home Depot boasting its benefits (Weber & Schütte, 2019, p. 271). AI refers to "computational agents that act intelligently" (Poole & Mackworth, 2017, p. 3) and covers a broad assembly of different technologies that are continuously evolving (Elliot & Andrews, 2017). AI systems can interpret, comprehend and learn from large data volumes (Lee, 2017, p. 593) and mimic tasks performed by humans (i.e. text or voice) (Canhoto & Clear, 2019; U. Paschen et al., 2019).

AI technologies are associated with lowering product or service costs, automating routine tasks, increasing customer personalisation, and improving customer service across the retail value chain (Kaplan & Haenlein, 2020; Lee & Shin, 2020; Oosthuizen et al., 2020). AI can benefit retailers by creating efficiencies, automating processes, creating inventory visibility, providing insights on customers and products and reducing lead times across the value chain (Campbell et al., 2020; Canhoto & Clear, 2019; Dogru & Keskin, 2020; U. Paschen et al., 2020).

Despite the promise of AI, most AI investments are failing to deliver on their promised returns (Fountaine et al., 2019, p. 4). Only 50% of AI proof of concepts move into business (McCormick, 2020; Press, 2019). In contrast, 47% of companies found it difficult to integrate AI into existing processes, workflows and systems (Deloitte, 2017), rendering its benefits to isolated business processes (Fountaine et al., 2019; Ganapathy et al., 2020).

Authors suggest various reasons for these failings, including leader's misconception about the goal of AI within their business (J. Paschen et al., 2019), the complexity of explaining the output of AI (Preece, 2018, p. 65), data quality issues (Vidgen et al., 2017, p. 631), the need for skilled experts to implement the AI (Dwivedi et al., 2021, p. 36), and employees' inability to work with the technology (Makarius et al., 2020, p. 263). Considering that AI often costs millions of dollars to implement, retailers cannot afford not to integrate AI successfully. AI has become a business imperative and is no longer considered a competitive advantage investment for retailers but a competitive necessity. AI can provide many benefits for retailers to operate more effectively and efficiently across the value chain. Therefore, retailers must understand the challenges of implementing AI to circumvent them.

Nevertheless, most studies investigating the challenges associated with implementing AI only focus on the technology itself (e.g., data quality and complexity) or the people responsible for implementing the technology (e.g. interpretation of results). However, competing in the age of AI is not only about technology (Sanders & Wood, 2020). When AI is implemented focusing purely on the technology, the technology change can create a knock-on effect on other variables, tasks, people, and structure within the organisation (Leavitt & Bahrami, 1989, p. 252). Therefore, to more fully understand the challenges of AI in retailing, we propose using Leavitt's Diamond Model. Leavitt (1965) suggested that everything in an organisation is connected, and no change can occur in isolation, and therefore also considers tasks, people and structure in addition to the technology. Therefore, using the Leavitt Diamond Model to investigate the organisational challenges retailers experience when integrating AI into their business, the following research question was developed: *"What are the challenges retailers experience when integrating AI in their value chains?*

This article contributes to the emerging literature on AI by first providing a structure, tasks, technology, and a people review of the literature concerning the challenges retailers experience when implementing AI. Few studies use established theories and frameworks to better understand this phenomenon because of the exploratory and relatively new nature of empirical research in AI. Therefore, we explore the use of the Diamond Model better to understand the implementation of AI in retail organisations. In addition, current research typically looks at only one of these aspects of AI integration in retail, rendering an incomplete view of the challenges associated with implementing AI in retail. Therefore, the second contribution of this article is to provide a comprehensive look at the challenges presented by implementing AI. Better understanding all the possible tasks, structures, technology, and people-related challenges associated with implementing AI provides retailers with a better chance of integrating the technology successfully. Finally, we then provide recommendations for retailers regarding how to increase their chances of successfully implementing AI.

The article starts by reviewing the Leavitt Diamond Model with the interdependent variables and AI challenges. Then, the research design and data collection are discussed in detail. After that, the findings are discussed, presented, and followed by the managerial implications.

6.4 LITERATURE REVIEW

This section reviews the Leavitt Diamond Model and the four interconnected variables that define the model, then discusses the AI challenges from the Leavitt Diamond Model perspective.

6.4.1 The Leavitt Diamond Model

Organisations operate in an increasingly volatile competitive environment consisting of other organisations, suppliers, and customers. They are also influenced by the broader environmental changes, such as new competitors, government legislations, the pace of technological change, and economic factors, making it hard for managers to navigate the complex changing environment (Leavitt, 1965; Porter, 1998). Various approaches have been suggested to help managers understand the "complex structures of interrelated systems" in an organisation (Boella & van der Torre, 2006, p. 4), including the McKinsey 7-S framework and the Leavitt Diamond Model. Both models are important tools to help understand the complexity in organisations. The McKinsey 7S model depicts how effectiveness could be achieved by interacting with seven elements: structure, strategy, skills, staff, style, system, and shared values. However, it takes a more organisational design approach (McKinsey, 2008; Peters & Waterman, 2012). While the Leavitt Diamond Model recognises that when a change in one of the four interrelated variables (structure, tasks, people and technology) occur, change can be predicated upon the other variables causing organisational challenges (Hartmann & Lussier, 2020; Leavitt, 1965).

In 1965, Harold J Leavitt designed a model to manage change in an organisation. The model indicates that organisations are complex structures of interrelated systems designed for a particular purpose (Boella & van der Torre, 2006; Leavitt, 1965), and subsequently developed the Leavitt Diamond Model. He argues that to compete in an ever-growing volatile environment, organisations can manipulate one of four interrelated sets of variables: task, structural, technological and human variables to improve performance (Leavitt & Bahrami, 1989). Describing such, Leavitt (1965) notes that when organisations change any task, technology, structure or people variable, it sometimes results in compensatory changes in one or more of the other variables. Scholars have used Leavitt's model to examine various organisational change topics. This model has subsequently been applied in numerous contexts, including applying the model to assist B2B sales forces to better respond to COVID-19 or other crises (Hartmann & Lussier, 2020) to information systems in the organisational environment (Lyytinen & Newman, 2008), management challenges associated with data analytics (Vidgen et al., 2017); demand chain management by combining marketing and supply chain management (Jüttner et al., 2007) and the use of information technology and the effectiveness of human resource function (Haines & Lafleur, 2008).

The Leavitt Diamond Model is an important model to examine the impacts of organisational change by considering the interrelated social (i.e., human and structure) and technical (i.e., tasks and technology) variables (Hartmann & Lussier, 2020). The four variables are defined as; first, the *tasks* variable are the activities performed inside the organisation, including many subtasks that exist within an organisation such as manufacturing of products, selling goods and services, procurement of supplies and finance of operations (Hartmann & Lussier, 2020). Second, the human variable refers to *people (actors)* and the work executed by people at some time or place. It includes sub-variables such as skills, the readiness of people, people knowledge and resources (Leavitt, 1965). Third, *technology* is the systems, tools and mechanisms that turn inputs into business outcomes. This includes hardware (e.g., computers, mobile devices, servers), software (e.g., application software), and websites. The last variable *structure* is the activities and authority divided, organised and coordinated to achieve the organisation's goals (Leavitt, 1965). Figure 6.2 shows the relationship and interplay between the four variables, tasks, people, technology, and structure.

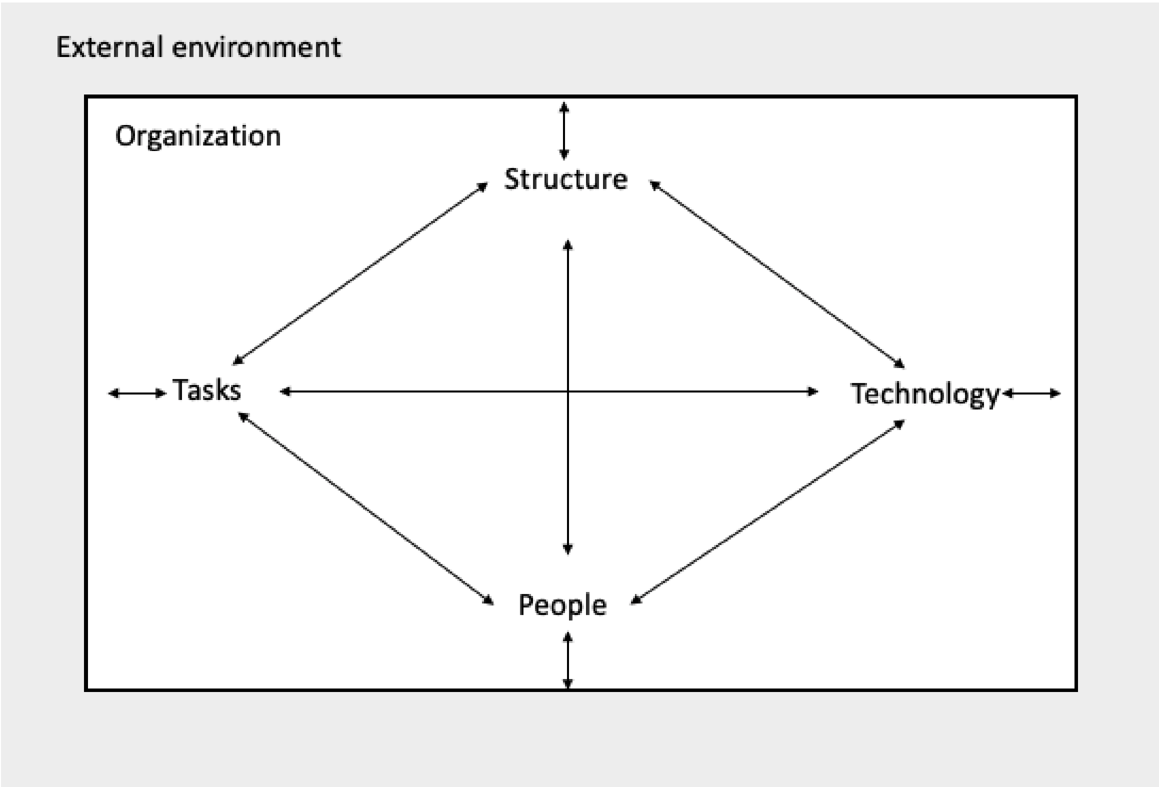


Figure 6.2: The Leavitt Diamond Model (Leavitt & Bahrami, 1989, p. 252

The four variables are highly interdependent, and when organisations manipulate or change any of the variables, it is likely to cause significant effects in the others (Leavitt, 1965). Organisational change cannot occur in isolation, and when change is not managed at critical times during the manipulation of one of the variables, problems can occur within the organisation (Leavitt & Bahrami, 1989; Paghaleh et al., 2011; Smith et al., 1992).

The Leavitt Diamond Model represents a balanced and rational view towards the complexities of implementing AI technologies. Technology directly relates to tasks, people, and structure in the model. When retailers only focus on the technology, the AI creates a knock-on effect on other variables, tasks, people, and structure within the retail organisation. As AI technologies are integrated into the retail value chain, it changes the way retailers operate in the retail value chain (Oosthuizen et al., 2020). Retail leaders must understand how AI will change their organisations to successfully scale AI across their organisations. Similarly, AI can change how employees interact with technology and require training or skilled personnel to work with the technology, affecting the organisational structure and creating new complexities.

6.4.2 The challenges of implementing AI from a Diamond Model perspective

While there is an abundance of research and popular press about the benefits of implementing AI, an increasing number of authors write about the challenges of implementing this technology. This might be because the implementation of AI differs from other technical implementations, creating a new set of challenges (Dwivedi et al., 2021).

Table 6.1 summarises the key studies investigating the challenges of implementing AI. As a further layer of analysis, we apply the Leavitt Diamond Model lens to these studies to better understand where there are current gaps in the research (i.e., from a people, technology, structure, or/and task perspective). To do this, we had to either classify the findings as explicitly mentioned or implied. If a finding was classified as *implicit* in Table 6.1, either people, technology, structure or tasks were suggested but not directly expressed in the article. If it was classified as *explicit,* meaning that either people, technology, structure or tasks were directly expressed in the article.

Table 6.1: Challenges of AI from a Structure, Technology, People and Task Perspective

Title	Authors	AI challenges discussed	Structure	Technology	People	Tasks	External
AI in operations management- applications, challenges and opportunities	(Dogru & Keskin, 2020)	Re-calibration of tasks between human and machine				Implied	
		Lack of internal readiness	Implied				
		Lack of technical infrastructure or technical environments		Explicit			
		Hard to explain the AI output - black box		Explicit			
		Job displacement			Implied		
		Lack of governmental policy and regulations					Explicit
		Managing privacy concerns		Explicit			
		Trust in the output result			Implied		
Artificial intelligence (AI) and its implications for market knowledge in B2B marketing	(J. Paschen et al., 2019)	What AI can be used for, and what it can/cannot do		Explicit			
		Creating, organizing, and sharing knowledge through the organisation	Implied				
		Human/user interaction with AI					
Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice, and policy	(Dwivedi et al., 2021)	AI implementation is different to other technical implementations		Explicit			
		AI understanding issue			Explicit		
		Ethical challenges due to bias results		Explicit			
		Complex to implement		Explicit			
		Cost vs benefit	Explicit				
		Data quality		Implied			
		Lack of technical infrastructure or technical environments		Implied			
		Hard to explain the AI output - black box		Explicit			
		Job displacement			Explicit		

		Human/user interaction with AI			Explicit		
		Interpretation and accuracy of the AI results		Implied			
		Lack of internal readiness	Implied				
		Lack of governmental policy and regulations					Explicit
		People need reskilling			Explicit		
		Privacy concerns		Explicit			
		Lack of governmental policy and regulations					Explicit
		Organisationally, who is responsible for the AI output results	Explicit				
		Selecting the best AI use case				Implied	Implied
		Shortage of skilled resources			Implied		
		Lack of trust in results			Implied		
		What problem to solve	Explicit				
Asking 'Why' in AI-Explain ability of intelligent systems – perspectives and challenges	(Preece, 2018)	Hard to explain the black box		Explicit			
		Interpretation and accuracy of the AI results		Explicit			
		Requirement of skilled resources with domain knowledge			Explicit		
Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI	(Barredo Arrieta et al., 2020)	Interpretation and accuracy of the AI results		Implied			
		Hard to explain the black box		Explicit			
		Human/user interaction with AI			Implied		
		Lack of trust in results			Implied		
Fair AI: Challenges and Opportunities	(Feuerriegel et al., 2020)	Ethical challenges due to bias results		Explicit			
		Lack of governmental policy and regulations					Explicit

		Selecting the best AI use case				Explicit	
		Lack of trust in results			Implied		
Rulers of the world, unite! The challenges and opportunities of artificial intelligence	(Kaplan & Haenlein, 2020)	AI understanding issue			Explicit		
		Ethical challenges due to bias results		Implied			
		Cost vs benefit	Implied				
		Data quality		Implied			
		Job displacement			Explicit		
		Interpretation and accuracy of the AI results		Explicit			
		Misconception about what AI is			Explicit		
		Privacy concerns		Explicit			
		Processing capacity limit		Implied			
		Lack of governmental policy and regulations					Explicit
Machine learning for enterprises: Applications, algorithm selection, and challenges	(I. Lee & Shin, 2020)	Cost vs benefit	Explicit				
		Data quality		Explicit			
		Ethical challenges due to bias results		Explicit			
		Hard to explain the AI output - black box		Explicit			
		Interpretation and accuracy of the AI results		Explicit			
		Selecting the best ML algorithm		Explicit			
		Shortage of skilled resources			Explicit		
		What problem to solve	Implied				
Sustainable Supply Chains in the Age of AI and Digitization:	(Sanders et al., 2019)	How to use AI to unlock value in data		Explicit			

Research Challenges and Opportunities		Connectivity of connected devices (i.e. RFID)		Explicit			
The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI	(Shin, 2021)	AI understanding issue			Implied		
		Hard to explain the AI output - black box		Explicit			
		Human/user interaction with AI			Explicit		
		Interpretation and accuracy of the AI results			Implied		
		Lack of trust in results			Explicit		
FREQUENCY			9	31	19	3	6
PERCENTAGE OF TOTAL			13.2	45.6	27.9	4.4	8.8

The literature offered various current and emerging challenges for implementing AI into business or society. Nevertheless, only one article by Dwivedi et al., 2021 explicitly mentioned AI challenges that could apply across all diamond model variables, and none of the other studies discussed all the variables. In contrast, none of the studies applied the Leavitt Diamond Model to assess the AI challenges. The literature mainly focused on the technology variable (45.6%), followed by the people variable (27.9%), structure variable (13.2%), external environment variable (8.8%) and tasks variable (4.4%). The major challenge mentioned by these studies can be categorized into five themes: the complexity of understanding and interpretation, people challenge for implementing AI, governmental policy and privacy, technical infrastructure, cost and data, and the internal organisation capability. Each of these is now discussed in turn.

6.4.2.1 Complexity of understanding and interpretation

A long-standing challenge of AI is the increasing complexity of understanding and interpretation of AI systems. These studies include a technological view of AI challenges, including the complex algorithm machine learning use, the black-box nature of AI, the importance of explainable AI, and the complexity of interpretation. Studies by Dwivedi et al. (2021) and Preece (2018) noted that the continuously evolving algorithms in AI, such as machine learning and neural networks, reduce the capability of users to examine the outputs, making it impossible for users to explain the outcome (Dwivedi et al., 2021; Preece, 2018). In addition, various authors noted challenges of interpretability, explainability and transparency of results, causing AI to operate in “black boxes” (Barredo Arrieta et al., 2020; Dogru & Keskin, 2020; Lee & Shin, 2020; Preece, 2018; Shin, 2021). Authors Feuerriegel et al. (2020), Kaplan and Haenlein (2020), and Shin (2021) argued that testing and validating the results could be left to employees with specialized expertise and knowledge. However, explanations on the inner workings of the algorithms used are challenging to describe, creating a lack of trust amongst users.

6.4.2.2 Data quality and technical infrastructure

Data quality measures the accuracy, completeness and consistency of an organisation's data. Data is essential for organisations wanting to create value and insights from data. Studies reviewed mentioned data quality as a challenge for implementing AI applications (Dwivedi et al., 2021; Kaplan & Haenlein, 2020; Lee, 2017; Lee & Shin, 2020). Low-quality data leads to poor decision-making ability and can derail AI projects (Vial et al., 2021, p. 47). Moreover, data quality affects how AI interprets the data, and poor quality could lead to bias in the result, causing ethical challenges for businesses (Feuerriegel et al., 2020, p. 383). In a business analytics study, Vidgen et al. (2017) noted managing data quality as a significant challenge identified by managers.

The management of AI systems requires relevant technical infrastructure. The technical infrastructure is the platforms, environments, software, data and processing capacity needed for AI to process its output. For example, Dogru and Keskin (2020) stated that organisations require a considerable amount to ensure proper data storage and security. In contrast, Sanders et al. (2019) noted that connectivity across connected devices is challenging in monitoring across supply chain networks.

6.4.2.3 People challenge of implementing AI

The people challenges raised in the studies associated with AI implementation included job displacement, shortage of skilled resources, and the interaction between humans and AI. Many authors argue that AI automation could harm jobs by displacing or changing jobs, especially in low skilled work activities (Barredo Arrieta et al., 2020; Dogru & Keskin, 2020; Dwivedi et al., 2021; Frey & Osborne, 2017; Kaplan & Haenlein, 2020; Manyika et al., 2017). In Frey & Osborne, (2017) study “the future of employment”, they argued that AI might automate 47% of US jobs, changing the nature of work, and Manyika et al. (2017) estimated that a third of current work activities could be impacted by 2030. In contrast, Kaplan & Haenlein (2020) argued that job displacement would be dependent on the industry. Studies by authors Acharya et al. (2018), Araujo et al. (2020), and Dogru & Keskin (2020) stated that the growing complexity of AI and the use of AI would require employees with new skills creating a shortage of qualified, skilled AI experts. The lack of skilled resources creates a challenge for organisations implementing and working with AI systems. A challenge for organisations is the need to upskill their current employees to enable them to work with the new AI applications (Dogru & Keskin, 2020; Simon et al., 2020).

6.4.2.4 Governmental regulations and privacy

Other challenges raised for organisations implementing AI are the lack of governmental policy and privacy concerns. For example, Dogru and Keskin (2020) and Feuerriegel et al. (2020) discussed the lack of inadequate governmental policy regarding the deployment and use of AI creating challenges for transparent use of automated technology. In addition, an inadequate policy can develop biased results, such as reinforcing undesirable practices, reinforcing historical discrimination, or resulting in unanticipated outcomes (Dwivedi et al., 2021).

Privacy concerns raised are customers providing their personal information to companies (Dogru & Keskin, 2020, p. 72), salespeople worrying that their customers' details could be poached by competitors (Dwivedi et al., 2021, p. 17), and organisations worried about AI’s use of external data causing legal privacy issues (Kaplan & Haenlein, 2020, p. 44). Another challenge for implementing AI is strict privacy rules (i.e., General Data Protection Rule) regarding the storing and use of personal information (Kaplan & Haenlein, 2020). In addition, the increasing demand for customised products or services requires large volumes of identifiable data to be collected, stored, and processed, creating an increased privacy risk for organisations (Dogru & Keskin, 2020).

6.4.2.5 Internal capability and readiness

Another challenge raised was the internal readiness of the organisation when deploying AI applications. Dwivedi et al. (2021) noted that organisations lack the internal readiness to adopt AI, mainly due to the required change management processes to adapt and work alongside the new automated AI technology (Capgemini, 2018). The introduction of AI in business requires changes to work practices and prioritises the required investment. Nevertheless, Lee and Shin (2020) argued that senior managers struggle to quantify the benefits associated with AI investment required, leading to AI applications getting lesser priority on the IT roadmaps of organisations (Capgemini, 2018).

To the best of our knowledge, scholarly research has not yet been applied using the Leavitt Diamond Model to assess the AI challenges in retail. The discussion above shows that, while broad themes have emerged from current literature, there is no comprehensive view of how AI affects organisational structures, people, processes and tasks. This study aimed to address this gap to understand the people, task, structural, and technological challenges retailers experience to integrate AI into their value chains. The following methodological approach was used to answer this research question.

6.5 RESEARCH METHODOLOGY

The research methodology followed an exploratory research design. In particular, a qualitative research method was employed to discover insights into the research question. To gain insights, semi-structured interviews were used. Semi-structured interviews were deemed the most suitable as the researcher develops more significant insights into the AI phenomenon (Firmin, 2012). Also, semi-structured interviews are appropriate for business research where limited empirical studies are available. Other studies also used semi-structured interviews to collect data regarding AI or technology in retail or business (Acharya et al., 2018; Burström et al., 2021; Chopra, 2019; de Bellis & Johar, 2020; Duan et al., 2019; Mahroof, 2019). The interviews were conducted with experts developing, working, implementing, and using AI in retail. All interviews were recorded, transcribed, and coded for analysis.

6.5.1 AI in retail expert interviews

The target population for the study focused on participants in three groups, namely, technology experts developing artificial intelligence systems for retailers. These retail information technology managers have implemented AI technologies and business consultants working with AI in retail. The selection process used purposive sampling where participants either had the expertise for consulting, developing, implementing or using AI technologies within the retail industry. Participants were sourced using purposive sampling and targeted via the social media platform LinkedIn. The search was conducted during July 2020 and identified 78 individuals (Table 6.2) deemed suitable for participation. All individuals were contacted via LinkedIn message to seek their participation in the study. After the initial contact, 28 responded, and 20 agreed to participate in the interviews.

Table 6.2: Identified individuals deemed suitable for participation

Expert	Initial contact	Initial contact percentage	Responded	% Responded to initial contact	Actual interviewed	% Interviewed to initial contact
AI Technology Vendor	23	29.5%	5	21.7%	4	17.4%
Management Consultant	16	20.5%	7	43.8%	5	31.3%
Platform Technology Vendor	10	12.8%	3	30.0%	3	30.0%
Retailer	29	37.2%	13	44.8%	8	27.6%
Total	78	100.0%	28	35.9%	20	25.6%

The semi-structured interviews were conducted through teleconference software Zoom from August 2020 to November 2020. Teleconference software was the most appropriate due to the geographical locations of the participants and the worldwide COVID-19 pandemic. The interviews lasted between 60 minutes and 75 minutes. The interviews focused on the respondents' experienced while implementing and scaling AI across the retail value chain.

The 20 participants were from multiple locations across the world. They included management consultants, thought leaders, technology vendors and developers, and retailers working with AI technology, all of whom play a role in shaping AI in retail. Appendix A shows a breakdown of the participants’ roles and country.

6.5.2 Analysis

6.5.2.1 Preparing the transcripts

To prepare the interviews for analysis, a three-step process was followed. First, all recorded interviews were orthographically transcribed using computer-assisted transcription software Otter.ai. Second, all audio files and transcripts were revisited to correct any language errors in the transcripts. Third, to ensure confidentiality of the participants, the researcher anonymized all identifying information in the transcripts and classified the respondent’s information into participants with a number, i.e., participant 1. Finally, each completed transcript was downloaded into a Microsoft Word document and imported into MAXQDA as a single document for coding. MAXQDA is a software package for qualitative and mixed-method research (MAXQDA, 2020).

6.5.2.2 Coding

The interview transcripts were coded iteratively in MAXQDA using a grounded theory approach suggested by Lewins and Silver (2011) and Bryant et al. (2007). The grounded theory approach comprises a systematic, inductive, and comparative approach for conducting an inquiry to construct theory (Bryant et al., 2007). The grounded theory approach seeks to find themes and topics to answer the research question. The text data coding was conducted in three stages to answer the research questions. First, the coding followed an open coding method to identify and categorize the text data. Second, once data was labelled into codes, the *challenges of implementing AI* followed a refining and grouping stage. Third, the multiple AI challenges were coded into the four Leavitt Diamond Model variables. The coding stages will be discussed in more detail.

6.5.2.2.1 Stage one: Identify and categorize data

The initial coding stage of the data followed an open coding method. Open coding is an interpretive process by which raw research data are first systematically analysed and categorized (Mills et al., 2010). Then, the data was conceptually labelled based on phrases, words and concepts represented in the transcripts. Finally, the codes were conceptually identified and categorized based on the answers provided during the interviews.

For instance, “cost will always play a factor and retail is tough these days, you know, we are fighting for every dollar” were coded into code *challenges for implementing AI* and “I think the building blocks are your data and your goal, your hardware and your cloud infrastructure” was coded into code *starting an AI project*. Table 6.3 shows the first 25 codes developed during the initial coding stage.

Table 6.3: Stage 1: Opening coding code structure

Codes	**Code frequency**
Challenges for implementing AI	130
AI Benefits	63
AI for inventory management	61
AI driving insights for retails	55
Starting an AI project	54
AI in the value chain	50
AI for operation optimisation	48
Retail challenges	46
AI for customer engagement	41
Type of data AI use	39
What is needed	38
AI-enabled value chain	29
Current skills	25
AI understanding issue	24
Retail Use case example	22
AI challenges	20
Recommendation for implementation	19
Know what the problem is	18
How to change retail	16
Understanding where to apply AI	7
Are current Inventory equipped with AI?	7
What is AI?	3
Covid changing the way	2
Make the UI easier	1
Summary write up	1
TOTAL	819

6.5.2.2.2 Stage two: Refining and grouping the codes

The open coding method produced many concepts. The axial coding process relates categories to their subcategories, the outcomes of open coding (Mills et al., 2010). The researcher analysed the open codes and grouped the data into categories to rationalise the initial coding structure. For instance, code *challenges for implementing AI* and *retail challenges* were grouped into *overall challenges.* The process facilitated making sense of the various types of AI challenges retailers experience.

Second, during the interactive analysis of the coded dataset, specific observations started to emerge from the data. It was prominent that various challenges (247) were raised during the interviews. Various challenges were coded challenges for implementing AI (130), retail challenges (46), current skills (25), AI understanding issue (24) and AI challenges (20). However, the coding was too broad to investigate the detail behind the challenges and to require further coding. Therefore, codes were rearranged, and new subcodes were created to understand the different types of challenges. For instance, "I do not think the medium-sized guys do not have a team" was coded into *lack of resources* and "I think you could put that right up against cost because the cost is going to be huge" was coded into the *cost.* By the end of the second stage, the overall challenges code system expanded from 6 to 35 codes. Table 6.4 shows the challenge codes with their corresponding quotes.

Table 6.4: AI challenges code structure

Challenge code	**Quote**	**Frequency**	**Percentage**
AI understanding issue	"In business in general, that is a general problem, not just for AI, but for most things is you get a buzzword, and you are going to do this, and you go right, so what does that mean?"	32	10.56
Know what the problem is	"The problem is always going to be the starting point and then building the solution around the problem rather than saying I have an AI"; "It is the combination of setting the goal and then being able to interpret the outputs of the data to achieve that goal is quite an obstacle."	18	5.94
Struggle to quantify the benefits	"We struggle to paint the benefits case of it"; "the company does not have enough budget to pump in and expanded right, so they lose."	8	2.64
Not knowing where to start	"The challenge was one understanding where we needed to start [with AI] and focus our efforts needed."	5	1.65
Not understanding the use case	"That is really hard to [understand the] use cases with AI it is kind of sophisticated."	8	2.64
Sometimes it is cheaper to keep human resources	"The workforce costs today in India, it is still lower than the artificial intelligence I could implement."	2	0.66
Hard to explain AI output	"The [way] machine learning works and where it gets to [the] decisions [from]. No one really knows because it is just too complicated to do understand."	5	1.65
Narrow in its focus	"When you dig into what they are actually talking about, it is just an algorithm. Or it is machine learning."	5	1.65
Technically difficult	"From a technical point of view is extremely complicated, because you need to worry about security and people are not accessing your data feeds."	4	1.32
Cost vs benefit	"You could put that right up against cost, because the cost is going to be huge" ". It is difficult to articulate its benefit."	18	5.94
Trust issue	"The trust in the system, that is the biggest one."	11	3.63
Lack of change management	"a lack of recognition around the amount of change management that's required to make it successful"	11	3.63
Worried about job security	"The biggest obstacle, I think, especially in operations that I faced, was the perception of job security. And the robots are going to come and take my work."	9	2.97

Changing the way of working	"A big issue around the world, particularly if you are looking at a lot of industries outside retail. There is a lot of automation taking jobs away and changing how work is done."	7	2.31
letting go of control	"Because I think you know, [people has been doing the same job] for ten years, and they have always been right, and the predictions always come true, and why would I give it to a system."	5	1.65
People not willing to change adapt to a different way of working	"I think that the literacy probably at the root cause, because a lot of people have been working in companies for a long time, and they know the stuff and do not want to work [differently]."	5	1.65
Automation to replace current tasks	"I think a lot a large part of this whole process is going to be automated by the technologies that we have available today."	5	1.65
Lack of correct data	"AI is only as good as the data that's given"; "Because very often, you can take a dirty set of data, apply some cleaning methodologies to it, and you end up with data that is actually not represented From what the truth was."	11	3.63
Disconnected Legacy systems	"Major obstacles definitely is that their current systems are just not prepared to cope with them within simulation or with some optimisation."	15	4.95
Lack of technical infrastructure	"So data processing of that data transferring that data can take a long time."	7	2.31
Needs to be integrated into system processes	"So the machine learning capabilities must cope with this kind of complexity and must integrate into the overall framework. And it's something that is kind of sometimes challenging because you cannot just do what you are what you want to do".	7	2.31
Can be unstable	"I think that is a bit of a where the technology is still a bit unstable."	2	0.66
Managing privacy	"a huge amount of this dataset is related to data privacy topics that we see are seen relevant more and more. I mean, of course, camera surveillance is a huge topic, especially in Europe."	2	0.66
Conflicting goals	"Probably just prioritisation of where it sits on their roadmap."	10	3.3
Retail is slow to adapt to new tech	"As a retailer. We are early, all of us early. There are other businesses I think that is way further ahead than us. But then retail, but that is the nature of retail.".	7	2.31
Lack of resources	"Implementation skills, depending on the platform that you select, specific skills for that platform, and the budget and the resources"; "People with the ability to clearly articulate what the value of what we are doing is, how is it working, and kind of have a relationship with the users is important rather than just pure skills."	30	9.9
Inadequate capability in current people	"I have got the people to manage it, and I have got to be able to capture it all and put it in a system"; "People that do not have an analytical background."	12	3.96
Not very analytical in nature	"People that do not have an analytical background."	9	2.97
Lack of leadership	"It could be just anchored leadership. And we are human. Right? Every leader is human. So I have been really good at this for 40 years. It is actually myself worth that is tied up with that."	3	0.99
Very traditionally focused. Buy product then sell	"Retail is a relationship business. I mean, that is what it is all about, right? It is about relationships."	9	2.97
Best way for people and AI to work together	"I would still say that it is not like everything; we can leave everything for the machine to decide or an algo, you put forward, and the algo decides everything. It is not, and there is a human part associated as well."	6	1.98
Integrating AI into the business	"So the biggest challenge for retailers is unless you have open standards, sharing of ways of working, sharing that data, and then you can see data changes and data is just stand-alone".	5	1.65

Complex issues to solve	"One of the things is kind of inventory management is actually a very complex problem, because, like, depending upon the depth to which you want actually to solve, the solution also varies."	4	1.32
Managing AI projects incorrectly	"There is a bit of a disconnect between project management and how they expect to see a project run and how they expect to see milestones delivered. Versus if you are embarking on one of these things, you have to kind of be agile and learn".	2	0.66
Lacking the correct processes	"I would say, immature retailer or a very dynamic retailer, they do not have proper processes."	4	1.32
TOTAL		303	100
PERCENTAGE FREQUENCY			

6.5.2.2.3 Stage 3: Coding into the Leavitt Diamond Model

The challenges retailers face when implementing AI technologies are plentiful. To assess the challenges in a retail organisational setting, we use the Leavitt Diamond Model to code the AI challenges into four variables, structure, technology, people, and tasks. For instance, *changing the way of working* was coded into *structure* variable, and *lack of resources* was coded into *people.* Table 6. 5 shows the AI challenges coded in the relevant diamond model variable.

Table 6.5: AI challenges coded to Leavitt Diamond Model variable

Leavitt Diamond Model variable	**AI challenge code**
Structure variable i.e., the activities and authority divided, organised and coordinated to achieve the goals of the organisation	Know what the problem is Cost vs Benefit Conflicting goals Very traditionally focused. Buy product then sell Retail is slow to adapt to new tech The best way for people and AI to work together Not knowing where to start Integrating AI into the business Complex issues to solve Lack of leadership Managing AI projects incorrectly
Technology variable i.e., the systems, tools and mechanisms that turn inputs into business outcomes	Disconnected Legacy systems Lack of correct data Needs to be integrated into system processes Lack of technical infrastructure Narrow in its focus Hard to explain AI output Technically difficult Managing privacy Can be unstable
People variable i.e., the work executed by people at some time or place, it includes sub-variables such as skills, the readiness of people, people knowledge and resources	AI understanding issue Lack of resources Inadequate capability in current people Trust issue

	Lack of change management Worried about job security Changing the way of working letting go of control
Tasks variable i.e., the activities performed inside the organisation, including many subtasks that exist within an organisation	Not understanding the use case Automation to replace current tasks Lacking the correct processes

The coding procedure identified multiple AI challenges across the structure, technology, people, and tasks variables. The following section will discuss the findings associated with the Leavitt Diamond Model challenges.

6.6 FINDINGS: THE CHALLENGES RETAILERS EXPERIENCE WHEN IMPLEMENTING AI

Drawing on Leavitt's diamond model to assess the challenges retailers' experience when implementing AI into their organisations. The analyses revealed a variety of challenges retailers experience whilst integrating AI into their businesses. As the challenges are discussed below, the complex, interrelated systems become notable. Following the order of aggregated themes in the coding structure, we describe AI challenges retailers experience based on the Leavitt Diamond Model below as per Table 6.6

Table 6.6: Summary of AI challenges retailer experience based on the Leavitt Diamond Model

	Total		**Structure**		**Technology**		**People**		**Tasks**	
Challenge code	**Count**	**%**	**Count**	**%**	**Count**	**%**	**Count**	**%**	**Count**	**%**
AI understanding issue	32	10.56					32	24.43		
Lack of resources	30	9.90					30	22.90		
Cost vs Benefit	26	8.58	26	27.37						
Inadequate capability in current people	21	6.93					21	16.03		
Know what the problem is	18	5.94	18	18.95						
Disconnected Legacy systems	15	4.95			15	25.86				
Changing the way of working (people not willing to adapt)	12	3.96					12	9.16		
Trust issue	11	3.63					11	8.40		
Lack of correct data	11	3.63			11	18.97				
Lack of change management	11	3.63					11	8.40		
Conflicting goals	10	3.30	10	10.53						
Worried about job security	9	2.97					9	6.87		
Very traditionally focused. Buy product then sell	9	2.97	9	9.47						

Not understanding the use case	8	2.64							8	42.11
Retail is slow to adapt to new tech	7	2.31	7	7.37						
Needs to be integrated into system processes	7	2.31			7	12.07				
Lack of technical infrastructure	7	2.31			7	12.07				
Best way for people and AI to work together	6	1.98	6	6.32						
Not knowing where to start	5	1.65	5	5.26						
Narrow in its focus	5	1.65			5	8.62				
letting go of control	5	1.65					5	3.82		
Integrating AI into the business	5	1.65	5	5.26						
Hard to explain AI output	5	1.65			5	8.62				
Automation to replace current tasks	5	1.65							5	26.32
Technically difficult	4	1.32			4	6.90				
Lacking the correct processes	4	1.32							4	21.05
Complex issues to solve	4	1.32	4	4.21						
Lack of leadership	3	0.99	3	3.16						
Sometimes it is cheaper to keep human resources	2	0.66							2	10.53
Managing privacy	2	0.66			2	3.45				
Managing AI project incorrectly	2	0.66	2	2.11						
Can be unstable	2	0.66			2	3.45				
TOTAL FREQUENCY & PERCENTAGE TO TOTAL	303	100	95	31.35	58	19.14	131	43.23	19	6.27

Table 6.6 shows that AI challenges related to people (43.23%) and structure (31.35%) were the most prominent when implementing and scaling AI into the retail organisation, followed by technology (19.14%) and tasks (6.27%). Participants mentioned regarding each of these elements are discussed in greater depth in the following sections.

6.6.1 People

When retailers are implementing AI, barriers are caused by retailers' lack of focus on the people variable (42.23%). The people variable is the ability, capability, and knowledge of the people in the organisation to perform the tasks assigned to them. It includes skills, the readiness of people, knowledge held by employees and resources. The findings indicated the most prominent people challenges are 1) the knowledge about AI, i.e., understanding what AI is (24,4%), 2) a shortage of relevant skilled resources with the skills to implement AI (22.9%), 3) inadequate capability in current people to use AI (16.03%), 4) user’s trust in AI systems output (8.4%) and 5) lack of change management (8.4%).

6.6.1.1 Knowledge about AI

The first most common people complaint was related to people in retail not having the relevant knowledge about AI (24.4%). This concerns issues regarding people’s ability to perform their assigned tasks. Participants noted that people use AI as a catchphrase with limited knowledge of the technology’s role and its capability in the value chain. People use “*buzzwords, like machine learning and artificial intelligence, but all they want to do is sell products on a website, and that is not AI”* (Participant 19). In addition, there are misconceptions about AI’s capability as “*people will hear this magical term being thrown around and they will think that it does everything for them”* (Participant 17). Adding to people’s confusion, vendors selling the technology do not clearly explain the technology purpose, or when they do, they present the wrong retail stakeholders, not the systems' users.

6.6.1.2 Shortage of relevant skills

The second most common people complaint was that retailers have a shortage of relevant skills (22.9%), which concerns people’s ability to implement and adopt AI technology. Participants stressed the importance of needing employees with relevant skills such as knowledge about the algorithms, data modelling and programming, the ability to analyse and interpret results and business knowledge. Retailers require technical skills such as “*data modelling people that can do python programming, or whatever tool you have, a lot of the modern tools have AI built-in''* (Participant 18). On the business side, retailers require non-technical business people who can communicate and discuss the data. The need for *“interpersonal skills of the analysts can be quite important to demystify output decisions'' (*Participant 8). However, retailers lack the relevant people as *“[retailers] do not have the skill set or the talent either on the technical side or its business side to be able to leverage the power of tools like that*” (Participant 4). The importance of both technical and business skills was emphasised amongst the participants for implementing and adopting AI. Yet, in retail, AI-talent is hard to come by and most “*retailers just do not have the people''* (Participant 1) to implement AI successfully.

6.6.1.3 Inadequate capability in current employees

The third most frequently people-related challenges were current retail employees with inadequate capability (16.3%), which concerns issues regarding AI technologies. The challenge participants noted was that some retailers employees have worked in the same position for many years, creating a capability gap. In addition, long term employees do not recognise the importance of reskilling, “*many people have been working in companies for a long time, and they know their stuff, and do not want to change to AI as they can work out the answer in excel*” (Participant 18). This creates a challenge for retailers as retraining people is not solely the retailer's responsibility. Therefore, employees need to be willing to reskill and learn a new skill. The overriding message from participants was a lack of mathematical skills in current retail employees, "*I do think there is a gap in skills. We definitely saw a gap in skills in terms of people not necessarily having a mathematical background" (*Participant 17). While others noted retail employees "lack analytical background" (participant 10) and "use a lot of gut feel" (Participant 7) when anticipating results.

6.6.1.4 User trust

The fourth most frequently people-related challenge was users trust in AI (8.4%) output, causing concern for retailers integrating the technology into their business. Participant 14 mentioned trust in the system as the most significant challenge retailers face, stating that "*it takes time for users to trust the outcome of the data*". Trust plays an integral part in adopting AI in retail as "*you need trust from the people who are going to be using the solutions, in order for them to be used and to be embedded*" (Participant 7). Participant 8 noted it is essential for retailers to manage the change messages and articulate the value of the AI clearly, how it works and how users interact with the technology. Therefore, where trust in AI is concerned, the technology itself needs to be trusted, trust in the data AI systems use, trust in the outputs, and trust in the people implementing it.

6.6.1.5 The lack of change management

The fifth most frequently mentioned people-related challenge was that retailers are not doing enough change management (8.4%) when implementing AI technologies, and there seems to be "*a lack of recognition around the amount of change management that's required to make [AI] successful*" (Participant 9). Retail is a traditional industry rooted in legacy systems and operations: "*the corporate immune system of these organisations is resistant to change, which makes the adoption of these kinds of technologies quite protracted*" (Participant 19). Nevertheless, without a proper change management practice in place to articulate the benefit of working with AI, employees start to distrust and resist working with the technology: "*When people do not know why the new technology is needed, they start to feel threatened by the technology as they have known the old system and why would they want to adopt a new system"* (Participant 18). Participant 15 emphasised that "*one thing that let us down was that change as a function was not understood",* and people need to be taken on a journey rather than getting a communication.

Therefore, when considering the *people* challenges that retailers face when implementing AI, greater emphasis should be placed on building AI knowledge in people, ensuring employees with the relevant technical and business skills are in place, and recognizing the readiness of the current employees.

Without appropriate change management, too much reliance is placed on AI technology and is required to integrate AI and people successfully.

6.6.2 Structure

When retailers implement AI technologies, it causes challenges to the structure variable (31.35%). The structure is associated with how tasks in the organisation are divided, organised, and coordinated to achieve the goals. The findings indicated the structure challenges are 1) difficulty articulating the cost vs benefit of investing in AI (27.4%), 2) retailers not knowing the problem AI can solve (18.9%), 3) conflicting priorities (10.5%) and 4) the integrating AI into the current traditional way of working (9.5%).

6.6.2.1 Articulating the cost vs benefit

The most frequently mentioned structure related challenge was retailers finding it difficult to articulate the cost vs the long-term benefit of AI, causing concern for retailers requiring the capital investment to start AI projects. Articulating the intended benefits of AI is challenging as AI can take years to reap a return on investment. Participants indicated that it is challenging for retailers to articulate the value of AI to finance teams or other decision-makers, leading to AI not getting the investment priority it is needed. However, participant 18 mentioned that budgets are granted for pilot AI projects to prove the technology, yet full-scale implementation falls flat when it comes to the investment needed. Retailers need to weigh up the cost of AI investments vs other investments: "*cost is all always playing a factor and retail is tough these days, we are fighting for every dollar, and we struggle to [quantify] the benefits of AI. Especially when you are talking about some of these bigger solutions that are costly to implement*" (Participant 4). Also raised was that retailers underestimate the cost of all the elements (i.e., infrastructure, resources, processing capacity) needed to implement and scale AI.

6.6.2.2 Determining the problem for AI to solve

The second most frequent structure related challenge was retailers not knowing the business problem AI can solve (18.95), causing concern for capital investments into the technology. Participants noted that retailers need to deliberate about how AI applications can drive business results. Retailers should "*know what you are solving for; you cannot use ML for the sake of using ML*" (Participant 13). Another respondent noted, "*what they should be trying to solve with AI technology, knowing about what it is and how it works is great*" (Participant 17). The participants emphasised the importance of defining a business problem upfront for AI to solve; however, defining the problem is challenging for retailers: *"[the challenge is] coming up with a well-defined commercial problem that is big enough to solve"*

(Participant 7). Therefore, understanding what problem to solve within retail is critical for any AI implementation and should be the starting point to selecting, building, or implementing any solution.

6.6.2.3 Conflicting priorities

The third most frequent structure related challenge was conflicting priorities (10.5%), causing concern for prioritising AI on the retailer's strategic roadmap. Participants noted a challenge for AI is "*prioritisation of where it sits on [retailers] roadmap is a challenge* (Participant 16). Participants also noted that AI competes amongst other retail investments priorities, such as an investment into a new store. Participant 6 indicated that an AI investment could be equivalent to an investment into one big store and found the payback period of the store to be quicker than AI, where AI takes years to pay back the return on investment.

6.6.2.4 Integrating AI into the way of working

The fourth most frequent structure related challenge was integrating AI into the current traditional way of working (9.5%), causing concern to adopt and work alongside the new automated AI technology. Participants found that integrating AI into business to be a challenge for retailers, "*unless [retailers] have open standards, sharing of ways of working, sharing that data, AI is just stand-alone*" (Participant 13). A challenge indicated by the participants were retailers are applying AI applications to a single business process, citing that implementation across retail "*are very much siloed*" (Participant 5), leading to retailers missing out on the benefit of integrating AI into the way of working. Also, a single business process view causes integration and scale challenges where retailers are "*trying out things here with a very small scope*" (Participant 20) without the complete end to end process in mind, causing retailers to underestimate the future investments required by the technology.

Participant 18 indicated they worked with a retailer to implement an AI model to predict employee churn rate with accurate results. However, the retailer never did anything with the information it provided. To integrate AI into the way of working, participant 15 noted that the business users need to define the outcome, not the IT team, as they are disconnected from the business goals. Integrating AI into the way of working improves the "*utilisation of people in operational areas*" (Participant 2) and can assist with embedding AI into the retail organisation.

Therefore, when considering the *structure* challenges retailers face when implementing AI, retailers need to establish what problem they will solve with AI. Once the problem is defined, it can assist retailer leaders to articulate the benefits associated with implementing AI and assisting with roadmap prioritisation and relevant capital investments. When considering changing the way of working to accommodate AI, retailers should focus on the process handoff between AI and their employees in specific roles, possibly focusing on re-engineering organisational structures to accommodate AI in the way of working.

6.6.3 Technology

When retailers implement AI, challenges are caused when retailers do not have adequate technology (19.14%) foundations in place. Technology is associated with all the systems, tools and mechanisms required to turn inputs into business outcomes. The findings indicated the technology challenges are 1) old, outdated, disconnected legacy systems (25.9%), 2) lack of correct data (19.0%), 3) inadequate technical infrastructure and integration methods (12.1%) and 4) explaining the output of AI (8.6%).

6.6.3.1 Outdated legacy systems

The most frequent technology-related challenge was retailers' outdated current legacy systems (25.9%), causing concern for integrating AI applications current systems. Participants noted an integration challenge as "largely due to [retail being a] traditional sector that is deeply rooted in legacy operations" (Participant 19). Participants also commented on disconnected retail systems creating technical integration challenges: "*they fractured across multiple systems, and they do not connect*" (Participant 8). Another challenge with legacy systems is that they do not have the processing capacity to cope with AI simulations. Participant 5 noted, "*current systems are just not prepared to cope with them within simulation or with some optimisation* (Participant 5).

6.6.3.2 Lack of quality data

The second most frequent technology-related challenge was the lack of correct or quality data (19.1%), causing concern for the accuracy and interpretation of the AI output. Participants indicated that retailers struggle to provide data accessibility and good data quality for AI applications to consume. Also, participants noted that retailers underestimate the time and effort required to provide the correct data for AI to work, leading to complexities and delays to AI projects. Retailers have "*an inherent lack of data across the retail landscape, and there is a massive inconsistency in the type of data that's available*" (Participant 1). Participants added the inaccuracy of data, accessibility issues, lack of use case-specific data, dirty and inconsistent data, and specific challenges faced while implementing AI in retail.

6.6.3.3 Inadequate technical infrastructure

The third most frequent technology-related challenge was inadequate technical infrastructure (12.1%), causing concern for the performance and integration of AI applications. Participants noted that AI applications require relevant technical infrastructure to manage, store, retrieve and replicate information. For example, AI requires technical infrastructure with the adequate processing and storage capacity to access, process and learn from large data volumes to provide an output. Ideally, before commencing any AI projects, "foundational basics should be in place" (Participant 12). Nevertheless, participants noted retailers have been slow to update theirs on-premise technical infrastructure needed to run AI applications optimally, "*largely due to the investments it required*" (Participant 7). Participant 12 experienced data processing and transferring challenges, taking a long time at retailers where AI was implemented. Participants also noted technical challenges for integrating AI into current systems. Participant 5 noted that retailers need to consider how AI will integrate into their existing processes. It can lead to wasted effort and hinder the ability to scale the technology without doing so. Participant 1 noted, "*hardware such as cloud computing is needed to run the AI applications*", helping retailers scale their processing capacity without the need to invest in on-premise technical infrastructure.

6.6.3.4 Interpreting the AI output

The fourth most frequent technology-related challenge was interpreting the AI output results (8.6%), causing concern for explaining the results of AI. Participants noted that retailers find it challenging to interpret and understand the output result of AI systems. AI and machine learning are complicated to analyse, being a bit of a black box (Participant 8) and "*no one really knows, because it is just too complicated to understand*" (Participant 15)". Participant 17 trains AI models and states the importance of skilled resources to "*know where to look*" and understand the data the models are using. For AI to be implemented successfully, retailers require business resources to access and confirm the output results of AI models.

AI applications can be unstable without the proper hardware and infrastructure to support them. Therefore, when considering the technical challenges that retailers face when implementing AI, first, retailers should access the capability of their internal system for AI to connect, integrate and simulate the results. Consideration of cloud environments could assist to scale processing power and connecting to different data sets from different parts of the business. Second, data is essential for retailers implementing AI applications and should be assessed for its quality and accessibility before commencing AI projects.

6.6.4 Tasks

When retailers implement AI, it causes challenges in the task variable (6.27%). Tasks are associated with all the activities performed inside the organisation. The findings indicate the task challenges are 1) not understanding the best use case for AI (42.1%), 2) automating current tasks (26.3%), and 3) inconsistent processes (21.1%).

6.6.4.1 Identifying the best use case for AI

The most frequent task-related challenge was retailers not understanding the best use case for AI (42.1%), causing concern for integrating and scaling AI into current work processes.

Participants noted not understanding the best use of AI to be a challenge: "*where to use, do you want to know your customers, do you want to know about products or [do] you want to know your audit information?"* (Participant 6). Also, it is crucial for retailers to "*at least know what specifically you want to do with the technology is important"* (Participant 10). Finally, for retailers wanting to start with AI, "*it is always better to go for a specific use case, especially when you are starting*" (Participant 3).

6.6.4.2 Which tasks to automate with AI

The second most frequent task-related challenge was retailers finding it difficult to choose which tasks to automate with AI (26.3%). Participants noted retailers should automate certain people tasks, such as data analytics with AI, as "*it is physically impossible for human beings to process all [of the information]*" (Participant 6). Automating specific tasks in the retail value chain with AI can provide retailers with efficiency across their organisations. Nevertheless, participants noted that some retailers struggle to choose where to apply AI and would instead do nothing other than disrupt something currently working, even though it is highly ineffective.

6.6.4.3 Inconsistent processes

The third most frequent task-related challenge related to inconsistent processes (21.1%) in retail, causing concern for integrating AI into working. Participant 10 noted that retailers "do not have proper processes in place", causing implementation challenges and delays. In addition, participants noted that integrating AI technologies into existing processes is challenging as retailers try to fit AI into the current ways of doing work instead of adapting to work with AI.

When considering the *challenges of retailers' tasks* while integrating AI into their business, retailers should identify the use case for possible automation. In addition, when automating tasks and integrating AI into retail work tasks, consideration should be given to the process to ensure it functions optimally.

In summary, AI challenges related to people and structure were the most prominent when implementing and scaling AI into the retail organisation, followed by technology and tasks. Nevertheless, the challenges show that all the variables, *people, structure, technology*, and *tasks* are interconnected and interdependent on each other.

6.7 DISCUSSION

This article aimed to provide a comprehensive view of retailers' experience using the Leavitt Diamond Model while implementing AI. Therefore, we aimed to understand the possible *structure*, *technology*, *task* and *people* challenges of implementing AI in the retail value chain. The AI challenges related to *people* and *structure* were the most prominent challenges when implementing and scaling AI into the retail organisation. Nevertheless, successfully integrating AI into retail is complex, and success depends on the retailer's ability to balance the interplay between all the variables.

6.7.1 People: Retail employees and future

When considering the *people* challenges, most participants mentioned the people's knowledge about AI, the shortage of relevant skilled resources, current employees' capability to use AI, trust in the AI system and lack of change management as the significant challenges for retailers implementing AI. Our findings differ from other challenging articles where authors Dogru and Keskin (2020), Dwivedi et al. (2021) and Manyika et al. (2017) argue that job displacement could be the most prominent people challenge for implementing AI. While we agree with the authors regarding job displacement, only some participants mentioned it as a challenge. Our findings on skills shortage align with studies from authors Acharya et al. (2018) and Araujo et al. (2020), discussing that AI will require new skills to create a shortage of qualified, skilled AI experts. Therefore, retailers should not only rely on recruiting already trained professionals with adequate skills, as the reality is that jobs would need to adapt to work with AI (Daugherty et al., 2020). Consequently, retailers would require people with the ability, capability, and knowledge to work with AI, and upskilling or reskilling current employees with relevant skills should become a focus for retailers. Nevertheless, a challenge would be determining the skills gap amongst employees required to work with AI.

6.7.2 Structure: Adapting the organisational setting

Second, participants also commented on AI's challenges on the *structures* within a retailer. The participants mentioned the structure-related challenges, articulating the cost vs benefit of investing in AI, the problem AI can solve, conflicting priorities, and integrating AI into the current way of working. Our cost vs benefit challenge finding aligns with Lee and Shin (2020) study discussing this challenge in their article. In contrast, Dwivedi et al. (2021) noted identifying the right questions for exploiting AI and the lack of internal readiness for adopting AI as a challenge. Thus, retail employees do not understand or work with the technology (Makarius et al., 2020). As AI integrates into retail, for retailers to be successful, they need to evolve existing roles and create new roles to ensure the required coordination of tasks with AI (Simon et al., 2020). Similarly, for retailers to successfully integrate AI into business, they are required to adapt their organisational setting to where AI and people are integrated to complement each other (Sanders & Wood, 2020). Equally, enabling AI and people to work together can render retailers long-term benefits.

6.7.3 Technology: Foundations in place

Third, participants commented on the challenges that AI causes on the *technology* within a retailer, stating outdated legacy systems, lack of correct data, inadequate technical infrastructure, and ability to explain the AI output as the retail technology challenges. Our findings align with the literature reviewed. Nevertheless, none of the studies mentioned outdated legacy systems as a challenge, which seems to be specific to retail. Thus, retailers require adequate technical foundations and quality data for AI applications to run optimally. Vidgen et al. (2017) indicated that data quality issues could be caused by various factors, including old legacy systems. However, updating all the old legacy systems can cost millions, whereas participants noted that an option for retailers would consider cloud computing. Similarly, investigating cloud strategies could help retailers scale their processing capacity without heavily investing in updating outdated technology.

6.7.4 Tasks: Integrating AI into processes

Last, participants commented on the challenges that AI causes on the *tasks* within a retailer, mentioning not understanding the best use case for AI, which tasks to automate with AI and inconsistent processes as the retail task challenges. Our challenge for selecting the best use case aligns with studies by Dwivedi et al. (2021) and Feuerriegel et al. (2020). Thus, identifying the possible use case for AI automation can be challenging. Automating specific tasks with AI can assist retailers with performing tasks more efficiently and effectively. Begley et al. (2020) noted that approximately 30 to 40 per cent of activities in retail could be automated with existing AI technologies. Hence, despite the benefits of AI, many retailers are only experimenting or applying AI to single business processes, missing out on the full benefit of integrating the technology (Fountaine et al., 2019; Ganapathy et al., 2020). Not only are AI technologies automating nonvalue added activities through the retail value chain, but it is also changing how retailers operate (Oosthuizen et al., 2020).

While this study by no means presents all the challenges retailers could experience while integrating AI, this study does provide a comprehensive view, using the Leavitt Diamond Model, of the structure, technology, tasks, and people challenges retailers experience while implementing AI. Thus, implementing AI requires retailers to consider all variables to become AI-enabled retailers.

6.8 MANAGERIAL IMPLICATIONS AND RECOMMENDATIONS

This article shows that challenges are caused across all variables, structure, technology, people, and tasks when AI is implemented into organisational retail. There is a complex interplay between all the variables when integrating AI in retail. For retailers to be successful with integrating AI, the focus should be across all the variables in their entirety. When retailers only focus on one variable, i.e., technology, the change creates a knock-on effect, causing structure, people, and tasks challenges.

AI systems are changing the way retailers operate and changing how retailers operate. Therefore, for retailers to successfully implement AI into their business, consideration and focus should be given to its impact on all the variables (people, structure, technology, and tasks). Figure 6.3 shows an updated diamond model with considerations to minimise the impact of integrating AI into the retail business.

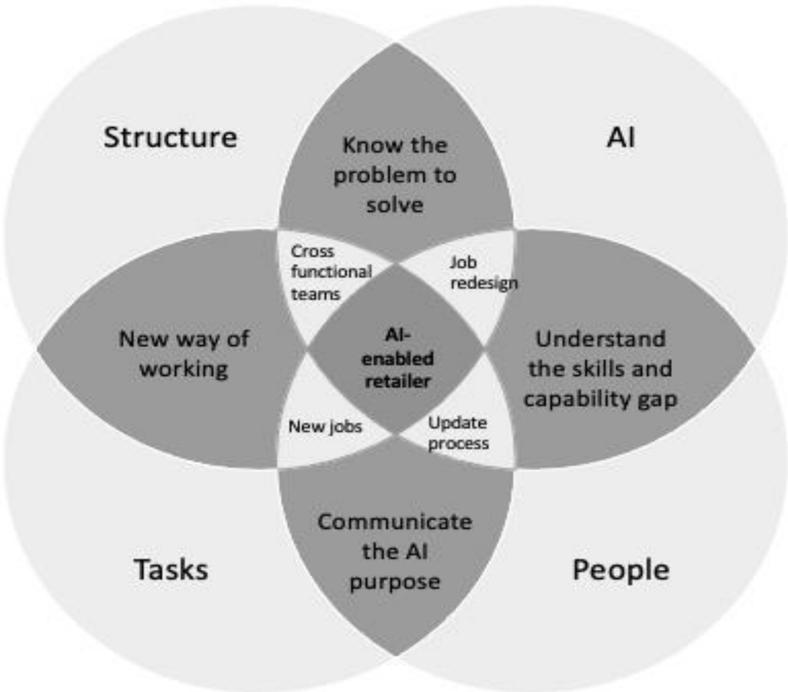


Figure 6.3: Diamond model with consideration to minimise the impact of AI

Companies that successfully integrate AI into workflows, processes and tasks create a more effective human and machine interaction (Deloitte, 2017). Nevertheless, AI projects are at risk of failure without considering all the variables across the retail organisation. Many organisations invested millions in AI systems, data infrastructure, time, and resources, without considering the impact the technology has on the rest of the organisation. For any AI project to succeed in retail, business models need to be adapted where humans and machines complement each other across the value chain. Figure 6.3 shows the considerations to minimise the impact of integrating AI into the retail business. The considerations are discussed in more detail next.

6.8.1 Know the problem to solve with AI

Retailers need to define the AI problem to implement AI successfully before starting an AI project. Similarly, creating an understanding of the problem AI can solve could assist retailers in articulating the value of AI and help drive investment into the technology. Ammanath et al. noted that organisations need to ensure the problem they are trying to solve requires AI, and businesses should not blindly use the technology due to over-eagerness (Ammanath et al., 2020). However, some retail leaders push for a new solution without enough emphasis on solving problems in the retail value chain. Therefore, advancing AI through the retail organisation without a clearly defined problem creates silos and can cause project delays or even failure of integrating AI into the organisation. For this reason, retailers need to establish what problem they are going to solve with AI. AI can drive multiple business outcomes from enhancing customer experience, enabling revenue, saving costs, and enhancing decision making (Oosthuizen et al., 2021).

6.8.2 Understand the skills and capability gap

To reduce the barriers between AI and people, retailers must understand the skills and capability gap. Retailers are human organisations that include dynamic human systems with specific structures, networks of tasks, and information systems, which are managed by people (Leavitt & Bahrami, 1989). The influx of AI systems into retail businesses puts pressure on retailers to find and train a workforce capable of working with automated technologies. Equally, increased automation will remove low skilled ineffective tasks and possibly displace low skilled workers without the adequate skills to work with automated platforms (Kaplan, 2020). It is difficult to estimate the impact AI could have on jobs in retail, with some estimating that up to 50% of tasks can be automated with existing AI (Balchandani et al., 2020; Begley et al., 2020).

Nevertheless, we see changes to the way of working to be more likely. Thus, AI is shifting the nature of jobs in retail, with new skills to include technical proficiency and business skills. For this reason, retailers should prepare for the future AI organisation and access the current workforce to determine the skills and capability gap.

6.8.3 Job design and new jobs

To respond to the shifting nature of jobs in retail, the change in skills will create a need to redesign jobs and/or create new ones to work with AI. A book by Daugherty and Wilson (2018) found the emergence of entirely different roles as AI integrated into the business. Therefore, new jobs are needed to bridge the gap between AI, people, tasks and structure. Similarly, retailers will require new jobs with multiple responsibilities to work with AI, roles to explain the AI output to retail leaders, roles to apply the technology to business problems, and roles to analyse/adjust the systems as needed.

6.8.4 Updated processes

Undertaking any AI project requires retailers to be aware of underestimating the potential costs of AI and the impact on existing processes (Canhoto & Clear, 2019). AI applications can be unstable without the proper hardware, infrastructure, and resources to support them. Thus, implementing AI requires retailers to review inconsistencies in existing processes and consolidate business processes to integrate AI successfully. Alternatively, retailers need to plan for the change by adapting current work processes and not underestimating the impact of inconsistent processes on AI implementations.

6.8.5 Communicate the AI purpose

AI projects are at risk of failure without support from people in the retail organisation. For retailers to successfully integrate AI, retailers need to communicate AI's purpose to employees and how it will help them with their jobs (Satell, 2018). When AI is purely focused from a technology perspective, some employees might not find AI helpful, leading to no actual adoption. For this reason, communicating the benefits of working with AI could lead to less resistance and trust issues amongst users, helping employees become more excited about working with AI.

6.8.6 Ways of working

To enable a new way of working with AI, retailers should adapt their organisational structures to bring the best out of people and AI. While the scale of becoming an AI-enabled retailer can seem overwhelming, introducing AI to the retail employees (both customer-facing and back-office facing) can help retailers shift into a new way of working and automate many tasks (Deloitte, 2021). In retail, employees spend at least 40 per cent of their time on non-value adding, leading to inefficient workflows (Begley et al., 2020). For this reason, retailers should focus on re-engineering structures to accommodate the handoff between AI and employees. In addition, business models need to be adapted in retail where humans and machines supplement each other across the value chain to be successful in retail.

In summary, for retailers to become AI-enabled retailers, integrating AI requires more than only getting the technology to work. It requires integrating new capabilities, a different way of working, process redesign due to automated tasks and a change in employee skill sets. The purpose of this article was to use the Leavitt Diamond Model to investigate the organisational challenges retailers experience when integrating AI into their business.

6.9 LIMITATIONS AND FUTURE RESEARCH

Whilst this article has highlighted the challenges retailers experience when integrating AI into their organisation, it is prudent to point out that the study has limitations. First, this study does not represent all the challenges retailers could experience while integrating AI into retail, and one must be cautious when drawing generalisations across retail as a whole. Similarly, the research design only indicates the challenge's retailer experience at a point in time, and it is likely to change the more retailers implement AI.

The COVID 19 pandemic exposed the shortage of digital skills in retail, leading to some retailers investing in reskilling their current workers. For example, an apparel retailer, Levi's, invests in reskilling current employees by training data scientists' skills (Kapner, 2021). Skilled resources play a fundamental role in the success of AI applications in a retail organisation. What is evident in this study is that there is a skill and capability gap in retail, and it would be helpful to establish the skills required to work the AI in retail. Future research can focus on understanding the skills retailer employees require to work with AI automation. This will be useful to enable a skills gap analysis and provision training to narrow the skills gap. Hopefully, this study can be used as a foundation for future research into AI in retail.

6.10 CONCLUSION: ARTICLE FOUR

There are many challenges retailers experience when integrating AI. The challenges related to *people* and *structure* were the most prominent challenges when implementing and scaling AI into the retail organisation. The article argues that for retailers to integrate AI into business successfully, retailers must adapt their organisational setting to where AI and people are integrated to complement each other. However, when retailers only focus on one variable, i.e., technology, the change creates a knock-on effect, causing structure, people, and tasks challenges.

Article four found a complex interplay between all the Leavitt Diamond Model variables when integrating AI in retail. This article showed that challenges are caused across all variables, structure, technology, people, and tasks when AI is implemented into organisational retail. The article's references are available in Appendix M. The following chapter covers the conclusions and recommendations for this study.

Chapter 7: CONCLUSIONS AND RECOMMENDATIONS

7.1 INTRODUCTION

Traditional retail business models face disruption from retailers that offer more innovative business models (Jin & Shin, 2020). New technologies, like AI, robotics, big data and IoTs, provides retailers with an opportunity to gain a competitive advantage(Acharya et al., 2018, p. 92; Black & van Esch, 2019, p. 10; Vidgen et al., 2017, p. 634). In particular, AI has been touted as the technology that will significantly impact retailers (Kietzmann et al., 2018, p. 265; Shankar, 2018, p. 6). First, retailers interact directly with customers throughout the entire customer journey, leading to *increased data* on the consumer and creating complexities for retailers (Grewal et al., 2018; Lee, 2017, p. 593). Understanding the customer touchpoints increases complexity for retailers (Kietzmann et al., 2018, p. 263). AI can provide retailers with insights to reduce shortcomings in data analysis by recognising patterns and providing insights into customer and sales data (Acharya et al., 2018, p. 92; Ameen et al., 2021, p. 1; Gupta, 2018, p. 170). When AI is used in retail, it can provide retailers with real-time data and personalised customer recommendations (Guha et al., 2021, p. 29). For example, a grocery retailer, Kroger, has an in-house analytics department that combines AI and advanced analytics to personalise customer communications (Weber & Schütte, 2019, p. 273).

Second, omnichannel retailing has *elevated the service expectations of the average customer* (Oh & Polidan, 2018, p. 31), and managing customer interaction across all the retail channels can be complex. AI helps retailers by providing an improved customer experience by offering intelligent applications across the customer journey for customers to interact with retailers (Chopra, 2019; Pillai et al., 2020; Rese et al., 2020; Roy et al., 2017; Y. Xu et al., 2020). For example, Amazon go stores uses AI to automate the in-store check-out process (Guha et al., 2021, p. 39, Shankar, 2018, p. 16).

Third, in the retail value chain, several stakeholders are involved through each value chain stage, adding complexity and manual activities to the value chain. Overly *complex retail value chains generate inefficiencies in operations*. AI can streamline operations by automating manual tasks and reducing costs (Gupta, 2018, p. 21; Manyika & Bughin, 2018; Verhoef et al., 2021, p. 891). For example, Waitrose, a grocery retailer, uses AI to automatically process, capture and place orders for their items (Blueprism, 2019).

Fourth, AI creates opportunities for manufacturers, wholesalers and third parties to *engage with customers directly*, shortening the value chain (Reinartz et al., 2019) and creating new competition for traditional retailers. For example, Under Armour, a sports apparel and footwear wholesaler, connects with customers through their AI-enabled apps and uses the data to provide new products and services (Leighton, 2018).

Several authors argue that retailers need to adopt AI to be more competitive and stay relevant with customers (Adapa et al., 2020; Alexander & Kent, 2021; Ameen et al., 2021; Balaji & Roy, 2017; Pillai et al., 2020; Weber & Schütte, 2019), yet many retailers are slow to invest into the technology. Current research into AI in retail literature, first, focuses on the opportunities retailers could experience with AI, yet the research is predominantly conceptual (Grewal et al., 2017, 2020; B. Guo et al., 2020; Kaur et al., 2020; Shankar, 2018; Wadhawan & Seth, 2016). Second, the review of the literature discovered that research into AI in retail had been predominantly focused on customer-facing value chain stages (i.e., store operations and sales, fulfilment, customer use and support) (Ameen et al., 2021; Araujo, 2019; Balaji & Roy, 2017; F. L. Chen & Ou, 2011; Jain & Gandhi, 2021; Pillai et al., 2020; Pizzi et al., 2021; Rese et al., 2020; Tupikovskaja-Omovie & Tyler, 2020; van Esch et al., 2021), and no previous research on the knowledge of the author, about AI's application across the entire value chain, is yet to be clarified. Therefore, this study aimed to answer the following research question:

How is AI transforming the retail value chain?

Four articles were used to investigate the primary research question. This chapter concludes the findings of each article and the synthesized contribution of all four articles. The first section of this chapter discusses the overall conclusion of each article. Thereafter, the managerial implications, the study's contribution, possible limitations, recommendations, and future research, followed by the conclusion.

7.2 RECONCILIATION OF RESEARCH QUESTIONS

Advances in technology are changing how retailers operate, creating complexities and new business opportunities. However, all the technological changes impact businesses' structure and operations, transforming internal business processes, changing how employees interact and changing how value is created throughout the value chain. The primary research question for this study was:

How is AI transforming the retail value chain?

This research question was the primary question of this study and guided the development of the subsequent research questions for the articles. Thus, this study broadens our understanding of how new technologies impact value chains in general and retail value chains in particular.

- Research question one: What role does AI play in the retail value chain?

- Research question two: What are retailers using AI technologies for in the retail value chain?
- Research question three: What business outcomes can AI drive in the retail value chain?
- Research question four: What are the challenges retailers experience when integrating AI into their value chain?

Four articles were developed to investigate how AI is transforming the retail value chain. Each article was discussed individually. However, it links back to the Leavitt Diamond Model variables, i.e., structure, people, technology and tasks. First, article one investigated AI in the retail value chain, linking to structure variables in the Leavitt Diamond Model. Second, article two investigates the tasks variable in the Leavitt Diamond Model by examining how AI technologies are used in the value chain. Third, article three investigated the outcomes obtained with AI by focusing on the technology variable in the Leavitt Diamond Model. Last, article four investigated the challenges for implementing AI across all Leavitt Diamond Model variables. The following section concludes the research questions for each article, followed by the conclusion of the overall RQ.

7.2.1 Reconciliation of research question one

Article one investigated research question one:

What role does AI play in the retail value chain?

Christensen et al. (2016)'s jobs-to-be-done approach in innovation was used to understand how AI can be successfully applied to the retail value chain to complete specific "jobs". The approach is based on the idea that companies should focus on the essential goals of a product or service to stimulate the effective development and implementation of innovation. Christensen et al. (2016) argue that people 'hire' products and services to get jobs done, and companies can innovate by doing those jobs better. In addition, each job can be broken down into various steps or stages of execution, with validating questions to assess the best job fit at each stage (Bettencourt and Ulwick, 2008).

First, it was argued that the jobs-to-be-done approach (see Chapter 3, in particular, Section 3.4.3 and 3.5) could be successfully applied to AI. Increased insights about the jobs-to-be-done for AI technologies could increase the value the technology delivers to a retailer. Second, using Bettencourt and Ulwick's (2008) customer-centric validation process, the jobs AI performs were clustered into four dimensions in the retail value chain, namely:

i. *Knowledge and insight management AI technologies* refer to the ability to provide insights by managing, sharing, using, creating, and processing information.

ii. *Inventory management AI technologies* refer to those that assist in the process of balancing demand to supply over large assortments to meet customer needs and financial objectives.

iii. *Operations optimisation AI technologies* help retailers operate effectively and efficiently by minimising cost and maximising operational capabilities.

iv. C*ustomer engagement AI technologies* enable retailers to build relationships with their customers.

Following the job mapping approach, it was established that the four AI jobs could fulfil most of the roles in the traditional retail value chain. AI can be extended to multiple functions and perform different roles throughout the value chain. Various AI applications could undertake multiple tasks across the retail value chain, creating a customer-centric process (Bettencourt and Ulwick, 2008) better suited to business amidst new technologies (McChrystal et al., 2015).

Finally, the article suggests that the retail value chain needs to be updated within the improved AI-enabled retail value chain framework (Figure 7.1). The AI-retail value chain framework is iterative and agile, enabling real-time data flows, in contrast to the traditional silo-mentality and linear view of the traditional value chain. The application of current AI technologies to the retail value chain was reviewed, and four dimensions of AI applications were conceptualised.

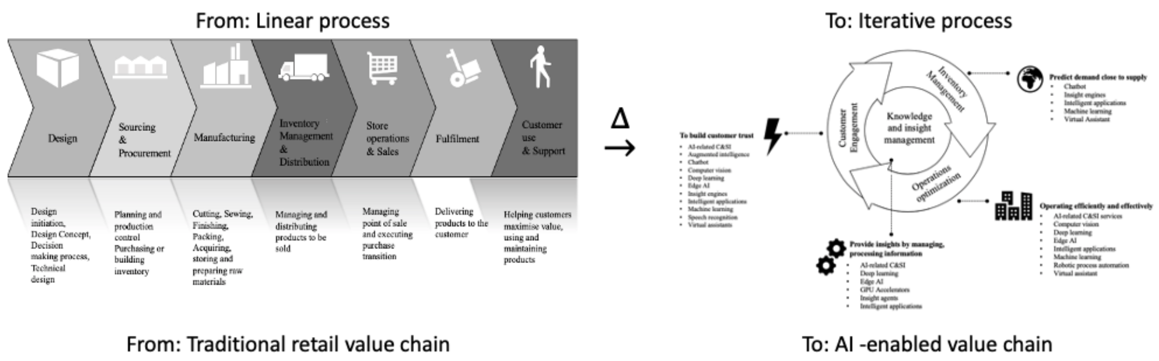


Figure 7.1: Value chain change from a linear process to an iterative process

Regarding question one, AI can best be employed in the retail value chain by serving one of the following purposes: knowledge and insight management, inventory management, operations optimisation, and customer engagement. These four categories of AI technologies in the value chain enabled us to propose a revised AI-enabled retail value chain (see Figure 7.1).

7.2.2 Reconciliation of research question two

Article two investigated research question two:

What are retailers using AI technologies for in the retail value chain?

Guided by the Leavitt Diamond Model, focusing on the *dimension of the task* of the model (Leavitt & Bahrami, 1989), the tasks AI performs were classified across the retail value chain stages (see Chapter 4, in particular, Section 4.6). First, the various AI technologies used to automate tasks across the retail value chain were presented. This followed a detailed discussion of how AI can be used to manage, operate and complete specific tasks in the retail value chain.

It was established that AI could be used to automate multiple activities the across retail value chain. For instance, AI could aid customer use and support by building relationships with customers, demonstrating a product, and detecting counterfeit products. The technology could also enhance the shopping experience by tailoring product recommendations to each customer preference and automating the scheduling of customer orders.

7.2.3 Reconciliation of research question three

Article three was used to investigate research question three:

What business outcomes can AI drive in the retail value chain?

First, this article illustrated how retailers can use AI to attain their goals by using service-dominant logic. Second, a framework of the four outcomes of applying AI in the retail value chain was presented (see Chapter 5, in particular, Figure 5.2), namely, (i) enhancing the customer experience, (ii) improving decision-making across the value chain, (iii) cost-saving and efficiency improvements, and (iv) enabling revenue. The four identified outcomes are interactive and reinforce one another and are defined as:

i. The application of AI for customer experience can be defined as applying AI technologies to enhance all customer interaction throughout the shopping journey.
ii. AI technologies for enhanced decision-making can be defined as applying AI to discover trends and visualize data for human consumption, thus improving decision cycle time.
iii. AI technologies geared towards generating cost reductions and efficiencies are defined as the application of AI to improve the utilization of resources, processes, and working capital, thus reducing the cost of doing business.
iv. AI for enabling revenue can be defined as AI with the ability to enable revenue by interpreting and targeting the presentation of products and services to customers.

Although the outcomes are not mutually exclusive, for example, cost-saving and efficiency practices can support revenue generation, AI technologies should be directed at one of these outcomes, and implementation performance should be measured accordingly.

Second, it was argued that the outcome obtained by AI technology is significantly influenced by where the technology is applied in the value chain. For instance, two retailers investing in the same AI technology in different value chain stages may achieve different outcomes. Therefore, retailers need to be clear on what outcome they aim to achieve through their AI investment and implement it in the appropriate value chain stage.

The investment in AI technology has primarily been made from a product-dominant, input-output perspective. For this reason, retailers should instead approach AI investments from a more strategic service-centric perspective and understand the outcomes that can be achieved through the use of AI in the retail value chain. This article developed a framework of the four outcomes retailers can achieve by investing in AI and show wherein the value chain AI investments can best deliver.

7.2.4 Reconciliation of research question four

The final article of the study builds on the learnings from the previous articles. Despite the promise of AI, most AI investments are failing to deliver on their promised returns (Fountaine et al., 2019). To understand the reasons behind retailers struggling to integrate AI into their business, research question four was developed:

What are the challenges retailers experience when integrating AI in their value chains?

The article used two stages to understand the challenges retailers experience when integrating AI into the retail value chain. First, semi-structured interviews were conducted to understand the challenges retailers experience when implementing AI. The interviews were conducted with 20 experts developing, working, implementing, and using AI in retail.

Second, the Leavitt Diamond Model was used to understand what causes AI implementation challenges for retailers. The Leavitt Diamond Model considers the technology for understanding organisational challenges and the people, tasks, and structure necessary for its successful integration of AI. Leavitt (1965) suggested that everything in an organisation is connected, and no change can occur in isolation. Therefore, using the Leavitt Diamond Model, this article illustrated the *structure*, *technology*, *task* and *human-related* challenges of integrating AI in the retail value chain.

The findings ascertaining the challenges retailers experience when integrating AI are discussed in-depth in Chapter 6, in particular 6.6. However, it can be summarised as follows. The challenges related to *people* and *structure* were the most prominent challenges when implementing and scaling AI into the retail organisation. It was established that the *people* challenges relating to knowledge about AI, shortage of relevant skilled resources and current employees capabilities to work with the technology were the most prominent. The findings differ from other research discussing AI challenges. Authors Dogru and Keskin (2020), Dwivedi et al. (2021) and Manyika et al., 2017 argued that job displacement could be the biggest challenge for implementing AI.

Consequently, arguments were presented that retailers would require people with the ability, capability, and knowledge to work with AI, and upskilling or reskilling current employees with relevant skills should become a focus for retailers. The challenges relating to the *structures* within a retailer were related to articulating the cost vs benefit of investing in AI and understanding the problem AI can solve. The structure findings aligned with Lee and Shin (2020) and Dwivedi et al. (2021) studies. It was argued that for retailers to integrate AI into business successfully, retailers must adapt their organisational setting to where AI and people are integrated to complement each other. However, when retailers only focus on one variable, i.e., technology, the change creates a knock-on effect, causing structure, people, and tasks challenges.

Article four highlighted a complex interplay between all the variables when integrating AI in retail. This article showed that challenges are caused across all variables, structure, technology, people, and tasks when AI is implemented into organisational retail. For retailers to successfully implement AI into their business, consideration and focus should be given to its impact on all the variables (people, structure, technology, and tasks). AI systems are changing the way retailers operate and changing how retailers operate. In response to research question four, an updated diamond model with considerations to minimise the impact of integrating AI into the retail business was created (see figure 6.1).

7.2.5 Reconciliation of the overall research question

Considering the findings from each of the research questions above, an answer can be proved to the primary research question of the study:

How is AI transforming the retail value chain?

Table 7.1 provides a synthesis of how AI is transforming the retail value chain using the Leavitt Diamond Model variables as a theoretical lens to structure the research findings.

Table 7.1: AI transforming the retail value chain

	How is AI transforming the retail value chain?			
Leavitt Diamond Model variable	**Structure**	**Technology**	**People**	**Tasks**
Article one	By changing the shape of the retail value chain from linear to circular (see section 3.5)		By fulfilling jobs in the retail value chain (see section 3.4.3)	
Article two			By shifting the tasks from people to machines (see Section 4.6)	By automating tasks in the retail value chain stages (see Section 4.6)
Article three	By attaining retailers goals through obtaining outcomes (see Section 5.6.2)	By applying the same AI technology in different stages of the value chain may achieve different outcomes (see Section 5.6.3)		
Article four	By changing the way of working, requiring retailers to adapt their organisational setting (see Section 6.6.2.4 and 6.7.2)	By requiring adequate technical infrastructure and quality data to run AI applications (see Section 6.6.3.3 and 6.7.3)	By demanding people with the ability, capability, and knowledge to work with AI (see Section 6.6.1.1 and 6.7.1)	By changing retailers' business processes by automating tasks in the retail value chain (see Section 6.6.4 and 6.7.4)

AI changes how the retailer operates across the structure, technology, people, and tasks. First, AI is transforming the structure variable by changing the shape of the retail value chain from linear to circular to accommodate the iterative nature of AI. AI is changing how retailers attain goals in the retail value chain through achieving specific outcomes. It transforms retailers' organisational settings by changing the way of working.

Second, AI transforms the technology variable by changing the technical infrastructure needed to run, process, and store the applications. The application of different types of AI to attain specific outputs or goals in the value chain. For instance, a Chabot can be used across different value chain stages to answer customer queries or assist employees. AI transforms the retail value chain through achieving different outcomes, depending on the value chain stage the technology was applied into.

Third, AI transforms the people variable by demanding people with the ability, capability and knowledge to work with AI. On the other hand, AI shifts tasks from people to machines by fulfilling four key roles in the value chain: knowledge and insight management, inventory management, operations optimisation, and customer engagement.

Finally, AI can automate multiple tasks in the retail value chain stages leading to the need to update retailers' business processes in the retail value chain. These conclusions have multiple managerial implications, discussed in the following section.

7.3 MANAGERIAL IMPLICATIONS

This section summarises the managerial implications resulting from the articles and the overall managerial implications when looking at the research question.

7.3.1 Managerial implications: Article one

For retailer leaders to reap the long-term benefits of AI technologies, the focus should be given to scaling AI technologies across the entire value chain. Retail managers should move away from their narrowed approach to AI technology investments, i.e., customer-facing technologies only, and consider how AI provides an increased and sustained competitive advantage through the value chain. Furthermore, as many global industries gear up for the widespread adoption of AI technologies, demand and competition will grow for scarce skilled employees who can implement, manage and work alongside the new technology (Butler-Adam, 2018; van Esch & Black, 2019). Therefore, it will be crucial for organisations to have a skilled workforce to support the implementation of AI, and there will be an even higher demand for skilled professionals (Van Esch and Black, 2019). An AI-enabled retail value chain relies heavily on competent employees who supply high-quality data at each touchpoint in the value chain.

7.3.2 Managerial implications: Article two

AI has an increasing impact on the value chain workforce by eliminating specific tasks, redefining roles, and creating new jobs (Marshall & Lambert, 2018), generating employees' need to work alongside AI. Integrating AI into the current retail business processes could be challenging without the workforce with the ability to implement and work alongside the technology. The future skills retailers require would differ from the people skills required today. For retailer leaders to prepare, retailers must access their current employee's skill sets throughout the value chain to understand the capabilities required to work alongside the technology.

7.3.3 Managerial implications: Article three

Retailers should be clear about where they want to apply AI in the retail value chain. Ideally, retailers have an integrated and circular retail value chain, as proposed in article one. However, most value chains are linear and siloed, plagued by legacy systems and incomplete data. This article shows that some outcomes are more likely when AI is applied in particular value chain stages. Therefore, once retailers have decided which outcome they want to attain through the application of AI, both the type of AI and the value chain stage in which they want to apply the technology, their options are narrowed down significantly, and managerial decision making and creating a business case for an AI investment becomes easier. However, the return on investment of any technology project can only be realized if that investment is being appropriately measured and monitored. Therefore, retailer leaders could use the four AI outcomes as a guideline for measuring the return on the AI investment.

7.3.4 Managerial implications: Article four

AI systems change the way retailers operate and how retailers operate, creating many complexities for retail leaders. For retailers to successfully implement AI into their business, consideration and focus should be given to its impact on all the variables (people, structure, technology, and tasks). To assist retail leaders in minimising the impact of integrating AI into the retail business, The diamond model with consideration to minimise the impact of AI can be used as a guide for considerations needed to successfully integrate AI into the retail business (see Section 6.8, in particular, figure 6.3).

AI projects are at risk of failure without considering all the variables across the retail organisation. Many organisations have invested millions into AI systems, data infrastructure, time, and resources, without considering the impact the technology has on the rest of the organisation. For any AI project to succeed in retail, business models need to be adapted where humans and machines complement each other across the value chain. For retailers to become AI-enabled retailers, integrating AI requires more than only getting the technology to work. It requires integrating new capabilities, a different way of working, process redesign due to automated tasks and a change in employee skill sets.

7.3.5 Managerial implications: Overall study

This study shows that AI is transforming retailers in many ways. AI transforms retailers by completing and automating multiple tasks in the retail value chain. Also, AI can create multiple benefits for retailers by the outcomes obtained from implementing AI in the retail value chain. However, transforming with AI requires a change in the way of working, and retailers cannot transform with AI by only implementing the technology to specific business processes. When the technology is only viewed from a technology perspective, it creates challenges within the retailer's business environment. For retailers to transform with AI, this study addressed the following eight managerial implications to ensure successful integration into the business.

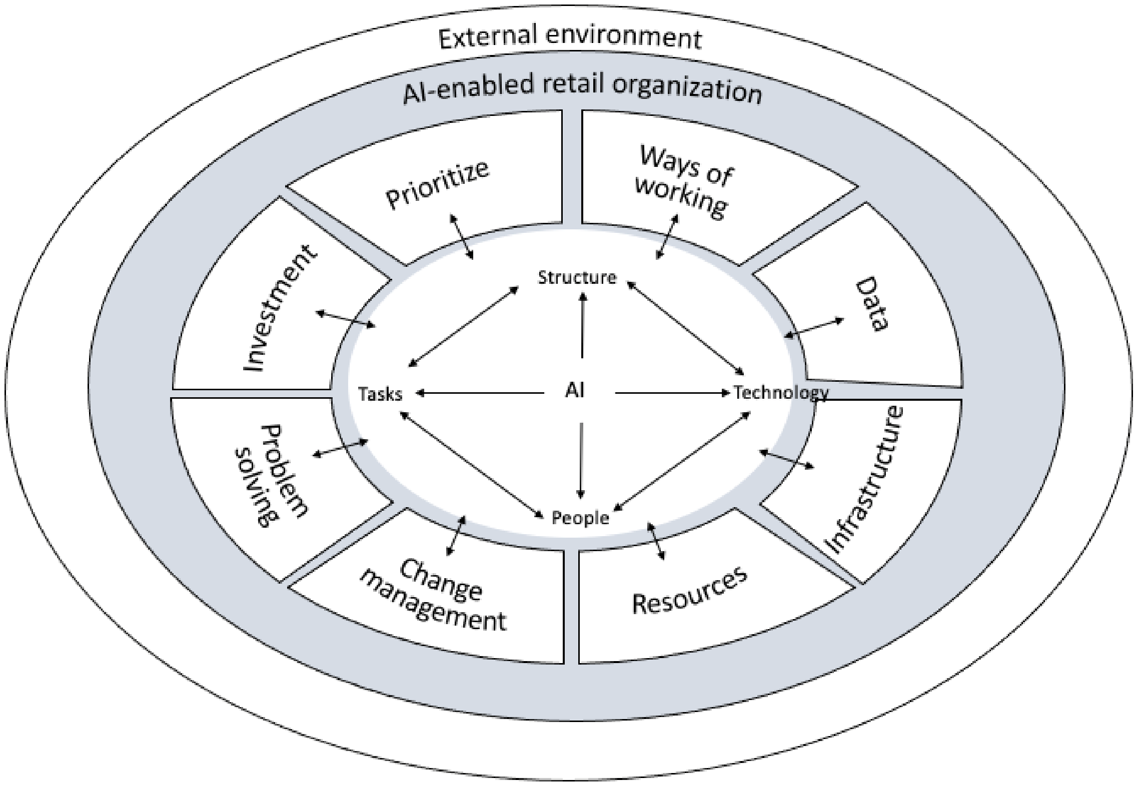


Figure 7.2: The eight imperatives for getting the most out of AI in the retail value chain

In Figure 7.2, the external environment refers to all external factors outside the retail organisation's control. These include new competitors, government legislations and policy changes, the pace of technological change, the COVID pandemic, and economic factors. For instance, the COVID pandemic changed retailing overnight, forcing stores to close. Retailers needed to adapt to a new way of interacting with their customers while keeping their employees safe.

The internal retail organisation are all the forces that the organisation can control, manage, and monitor. Organisations are complex entities with a group of people that share one or more goals (Boella & van der Torre, 2006). It encompasses the retailers' structure, tasks, people, and technology variables. When a change occurs in any of the variables, i.e., technology, the change in the variable creates a knock-on effect onto the others. Therefore, it is essential to ensure that all variables are focused on when any change occurs in the organisation. Hence, the eight imperatives were created to help retail leaders ensure the correct building blocks are in place for the successful integration of AI within the retail organisation. Ensuring a holistic view across people, structure, tasks, and technology could create long-term benefits with AI. The following section discusses the eight imperatives in more detail.

7.3.5.1 Solving the business problems for AI

AI encompasses many different technologies, responsible for performing different activities within the retail value chain leading to confusion amongst retailers about the purpose of the technology. Therefore, it is crucial for any AI project to start with a clearly defined problem AI could solve. For instance, a retailer could have challenges forecasting the correct demand quantities per store. Therefore, a defined problem statement will assist with applying to correct AI to help solve this business problem. Furthermore, organisations need to ensure the problem they are trying to solve requires AI, and the business should not blindly use the technology due to over-eagerness (Ammanath et al., 2020). "Who cares if you can solve a problem with 99 per cent accuracy if no one needs that problem solved?" (Participant 15). In the same way, not defining a problem to solve causes multiple challenges, with retailers underestimating what is needed to implement, integrate and scale AI. Nevertheless, some retail leaders push for a new solution without enough emphasis on solving business problems in the retail value chain.

To understand if an AI even applies to solve a specific business problem, a problem should have these specific characteristics (Day, 2021):

- There are reliable, accurate and available data for the specific problem.
- The problem is caused by business inefficiencies and not technology platforms.
- The problem should be core to your business.
- The problem should be confined the certain boundaries, for instance.
- The problem can be solved at scale.

It is also important to note that AI is not a solution to all business problems, and managers need to be clear on defining the right questions for AI to answer.

7.3.5.2 Data for AI

The primary function of AI is interpreting the data and learning from it. For AI to perform optimally, the systems require large volumes of various datasets to process. To do so, AI systems should be able to access the data. However, this study found that retailers struggle to provide data accessibility and good data quality for AI. Retailer leaders need to recognise the complexities in retrieving, accessing and processing data needed for AI solutions. When starting an AI project, data accessibility should be a management issue to solve and not a purely IT issue (Vial et al., 2021). Data quality issues are a significant challenge for the accurate performance of AI systems. Poor data quality can cause bias in the results of AI systems or even ethical issues if not managed correctly. Also, retailer leaders need to be aware of any privacy challenges associated with collecting data that could potentially affect the personal privacy of the AI systems.

Retailers or businesses must establish data quality control processes and governance practices (Lee & Shin, 2020). Similarly, retailer leaders need to plan for proper data management throughout the entire development lifecycle of AI and not only when projects are in the pilot phases. The data management plan should focus on assessing the data for the AI systems to use, data quality management, and privacy management processes. Focusing on data management can help mitigate the challenges caused by AI systems.

7.3.5.3 Infrastructure requirements for AI

For AI systems to process data and learn from it, AI needs to process it through various learning processes. Managers believing AI is a simple "plug and play solution" will significantly underestimate the actual requirements, which is not the case. Instead, AI requires stable, scalable technical infrastructure environments to consolidate, process, and simulate data. However, retailers are still touted with legacy systems and outdated infrastructure, making it challenging to manage AI system processes. As a result, AI applications can be unstable without the proper hardware, infrastructure, and resources to support them. The foundational hardware needed to implement AI applications can be capital intensive, and retailers should explore the use of cloud computing to run the AI applications. Cloud environments can help retailers scale processing capacity as needed, help connect various data sets from siloed systems into one platform and reduce the upfront investment required.

7.3.5.4 Capital requirements and benefits

Retailers should be aware of underestimating the potential costs of AI (Canhoto & Clear, 2019, p. 5). Reliable estimates for AI requires expertise, understanding context and understanding the business problem. AI requires substantial financial investments (Dwivedi et al., 2021, p. 5) into infrastructure, change in business processes, hiring skilled resources to build and maintain the systems and changing working practices. Also, the payback period of AI systems can take years, making it challenging for retailers to articulate the value of AI to finance teams or other decision-makers, causing AI not to get the investment priority it is needed. Retail leaders need to select the best initiative or business problem to spend their capital investments on, and AI projects must be added to the long-term company strategic roadmaps.

7.3.5.5 Strategic prioritisation and ownership

AI is earmarked to transform retailers, and strategic focus should be given to AI implementation and integrating AI into business. However, this study found that AI competes with other retail investments priorities, such as an investment into a new store. As a result, some retailers wanting to invest in AI started applying AI as proof of concept. However, once-off initiatives lack the entire organisation's focus, leading to AI failures. Therefore, strategic prioritisation is needed to benefit from investment into AI.

Ideally, business-wide prioritisation should come from the CEO (Yao et al., 2019, p. 58). However, in a traditional business such as retail that is conservative towards technology investments, that is unlikely to be the case. Therefore, finding the correct stakeholders to champion a high-risk project like AI is required. The stakeholders need to understand the technology, understand the challenges related to data, and integrate into the business while being willing to learn. The stakeholders can push for strategic prioritisation, take ownership of AI within the business, and ensure future investments in technology, processes, and people.

7.3.5.6 People in retail

This study found that people are one of the most significant challenges retailers experience when implementing AI into the value chain. While AI technologies are helping retailers to provide a personalised offering for customers, automating tasks and processing large volumes of data, the influx of the new AI technologies is putting increased pressure on retailers to find and train a workforce with the skills necessary to manage and work with the technology (Oosthuizen et al., 2020; Pantano, 2020, p. 183–185). To implement AI successfully, retailers require employees with implementation skills, knowledge about the algorithms and AI, platform knowledge and business knowledge. Nevertheless, the skills shortage is a challenge for retailers, and retailers should not only rely on recruiting already trained professionals with adequate skills, as the reality is that jobs would need to adapt to work with AI (Daugherty et al., 2020).

Skilled resources play a fundamental role in successfully integrating AI into a business. Retailers should focus on recruiting employees with the ability, capability, and knowledge to work with AI or upskill current employees to work with the technology. Retailer leaders must understand their organisation's skills and capability gap to reduce the barriers between AI and people. AI is changing how tasks are performed in the value chain by automating them. The automation could remove low skilled ineffective tasks and possibly displace low skilled workers lacking the adequate skills to work with automated platforms. Retailer leaders need to be aware of AI's potential impact on employees in low skilled areas. Thus, AI is shifting the nature of jobs in retail, with new skills to include technical proficiency and business skills. Ideally, retailers should start training low-skilled employees with different skills to benefit from working with automated activities in the future. For this reason, retailers should prepare for the future AI organisation and access the current workforce to determine the skills and capability gap.

7.3.5.7 Change management for AI

With AI's potential to automate multiple tasks in the value chain, it creates uneasiness and resistance amongst employees who think they could lose their jobs due to the technology. This study found a lack of recognition for change management required for integrating AI in retail. Nevertheless, implementing any new technology project, not only AI, should focus on the change management process of integrating the technology into the business. Employees resisting and not using the technology will significantly impact the benefits associated with AI. Therefore, retailers need to have adequate change management practices in place and communicate the purpose of the technology early in the project stages. Communication should include knowledge about AI's purpose in the organisation, the benefits of working with AI, i.e., automation manual tasks, and the overall organisation expectation and accountability of working with the technology.

7.3.5.8 New way of working

This study found that retailers struggle to integrate AI into the current way of working. Partly due to the retail industry being traditional in nature, i.e., buying and selling products. For the successful integration of AI into retail, retailer leaders need to understand that AI involves a change in the way of working by updating processes, workflows, organisational structures and requires job redesigns. When AI applications are siloed across different areas, retailers miss out on integrating AI into the end-to-end value chain process. AI must be adopted and integrated into the way of working before the system can improve productivity in the retail value chain. Therefore, retailers should adapt their organisational structures to bring the best out of people and AI to enable a new way of working with AI.

In summary, there are many managerial implications for retailers to consider when undertaking any AI transformations. When retail and business leaders ensure the eight AI imperatives are in place, they can successfully integrate AI into the business. The recommendations are discussed in the following section.

7.3.6 Recommendations

The study provides multiple recommendations for academia, retail and business and consultants. The recommendations are discussed in more detail.

7.3.6.1 Recommendations for academia

This study found that research into AI in retail is still limited, with current research predominantly conceptual and mainly focusing on the customer-facing value chain stages. Therefore, this study provided four theoretical contributions, namely 1) the shape of the retail value chain needs to be updated 2) the Leavitt Diamond Model was applied in the context of AI in the retail value chain, 3) a new updated Leavitt Diamond Model, i.e., the AI integration pentagon model (see Section 7.5.2) was proposed and 4) the application of jobs theory was applied to AI in retail.

With AI’s growing influence on the retail value chain and business alike, it is recommended for academia to extend the updated AI-enabled value chain research. The research can accelerate the movement of data and tasks in the retail value chain and how retailers' structure should accommodate the new shape of the retail value chain. Second, it is recommended that updated Leavitt Diamond Model (i.e., AI integration pentagon model) linkages be tested empirically. Finally, the application of jobs theory can further be studied at a lower process level to articulate the detailed tasks AI can fulfil.

7.3.6.2 Recommendations for practitioners

Although many consulting practitioners articulate the importance of AI in retail, few frameworks, guidelines, or mechanisms support retailers in adopting AI to deliver the greatest return on investment by transforming with the technology.

Undertaking any AI project can be a daunting task for any retailer or business. It is recommended for practitioners that when undertaking any AI project, it is essential to clearly articulate what the AI technology needs to be used for, i.e., defining the business problem to solve. AI should be the solution to the problem, and the problem needs to be realistic. To identify possible use cases for business problems, retailers can review the AI-enabled value chain framework or the tasks AI can perform in the retail value chain (see Section 3.4 and 4.5). To assist practitioners in articulating the benefits for AI investments, the outcomes framework (see Section 5.4.2) can assist with a guideline of the possible outcome based on where the AI is applied in the value chain.

There is a complex interplay between all the variables (people, structure, tasks and technology). To mitigate the challenges for integrating AI into the retail business, retailers refer to the AI integration consideration framework (see Section 6.6) that identifies considerations retail leaders can use to minimise the impact of integrating AI into the retail business. In addition, undertaking any AI project is complex, and retailers recommend that practitioners refer to the eight imperatives for implementing an AI framework (see Section 7.5.5) to integrate the technology successfully.

7.3.6.3 Recommendations for consultants and AI experts working with retailers

Retailers look to consultants and AI experts for advice on selecting AI systems, and the following recommendations are proposed for consultants. First, this study found a challenge with knowledge in understanding AI and its purpose across the retail value chain. This causes challenges and misconceptions about what technology can and cannot do. As consultants and AI experts, it is essential to educate retailers regarding the complexity of AI and what an AI retail future could resemble. Second, it is crucial to guide retailers to the best possible solutions as experts. Assisting retail leaders with suggesting which AI systems could solve their business problems could help retailers achieve their benefits (see Section 3.4 and 4.5 for application examples, and Section 5.4.2 for outcomes).

Second, a retail organisation has a complex interplay between people, structure, technology, and tasks. Therefore, when selling AI as a solution to retailers, it is essential to emphasise to retail leaders that AI outcomes are dependent on people, structure, technology and tasks all working together. To ensure successful integration for AI into the retail business, the eight imperatives for implementing an AI framework (see Section 7.5.5) could be used as a guideline for transformation with AI.

Last, retailing is traditional, with multiple retailers still using legacy systems for their operations. A challenge for retailers is the cost associated with investing in the infrastructure needed for AI systems to run optimally. Suggest cloud environments for processing, scaling and automating AI in the value chain and recommend ways to upgrade legacy systems to get the most out of AI. The contribution of the study is discussed next.

7.4 CONTRIBUTION OF THE STUDY

Bacharach (1989, p. 496) stated that theoretical statements should be organised and clearly communicated and highlighted the importance of building theory by answering questions concerning how, when and why, instead of only dealing with what was observed. He argued that theories need to be useful and explain and predict the observed phenomena (Bacharach, 1989, p. 501). Scholars have different views regarding theory. However, they agree that theory is based on finding or explaining any phenomena (Zhou et al., 2017, p. 262)

Berthon (2002, p. 421) noted that research is “essentially a problem-solving or phenomenon-exploring exercise”, and knowledge generation is the process by which the phenomenon is solved or explored. For a theory to be complete, Whetten (1989, pp. 490–492) stated that the contribution of a study should contain four essential elements, namely, what, how, why and who, where, when. First, theory should be described and explained following “what” and “how” through constructs or concepts that can be conceptually linked (Whetten, 1989, pp. 490–491). Second, the “why” should explain the theory, including narration derived from pre-existing theory or logical arguments. This is a crucial step in explaining the theory and the importance of why certain phenomena exist (Whetten, 1989, p. 491). Third, to gain new knowledge, assessing the "why" and "how" of the phenomena assists with critiquing elements of the data to gain new insights (Cloutier & Langley, 2020; Whetten, 1989). Fourth, Whetten (1989, p. 492) stated that theorists should acknowledge the possible limitations in the theory's applicability. The possible limitation of this study is discussed in Section 7.10. Table 7.2 summarises the four elements and focuses on this study.

Table 7.2: Whetten's four elements and this study's focus on the elements

Whetten (1989) four elements	**Whetten's description**	**This study's four elements**
What	Describes the constructs that should be considered as part of the phenomena of interest	Constructs = AI + retail value chain Advances in AI are changing the way retailers operate, creating complexities and new business opportunities throughout the value chain.
How	Describes how the constructs are related to each other	AI impacts businesses' structure and operations, transforming internal business processes, changing how employees interact, and creating value throughout the retail value chain. However, when only focusing on the technology aspect of AI creates challenges.
Why	An explanation of the theory to justify the constructs selected and their relationships	AI will not render long term benefits by only focusing on the technology side of AI. There is a complex interplay between all Leavitt Diamond Model variables when implementing AI into retail. For AI to be successfully integrated into the retail value chain, the focus should be given to people, structure, tasks and technology within the retailers
Who, where, when	The possible limitations of the theoretical contribution	This study's focus is on retail; however, the contribution applies to organisations undertaking any AI project

Adapted from source(Whetten, 1989, pp. 490–493)

Theoretical contribution generates knowledge and the expertise it produces to theory (Berthon et al., 2002; Zhou et al., 2017). The theoretical contribution is divided into two dimensions, originality and utility (Corley & Gioia, 2011, pp. 16–18). It initially provides a basis to discuss the nuances gained through either incremental or revelatory insight. In contrast, the utility should improve "current research practice" and improve current managerial or organisational practices, providing insights into academic and professional realms (Corley & Gioia, 2011, pp. 16–18). Figure 7.4 shows this study's theoretical contribution applicability to Corley and Gioia's model quadrants.

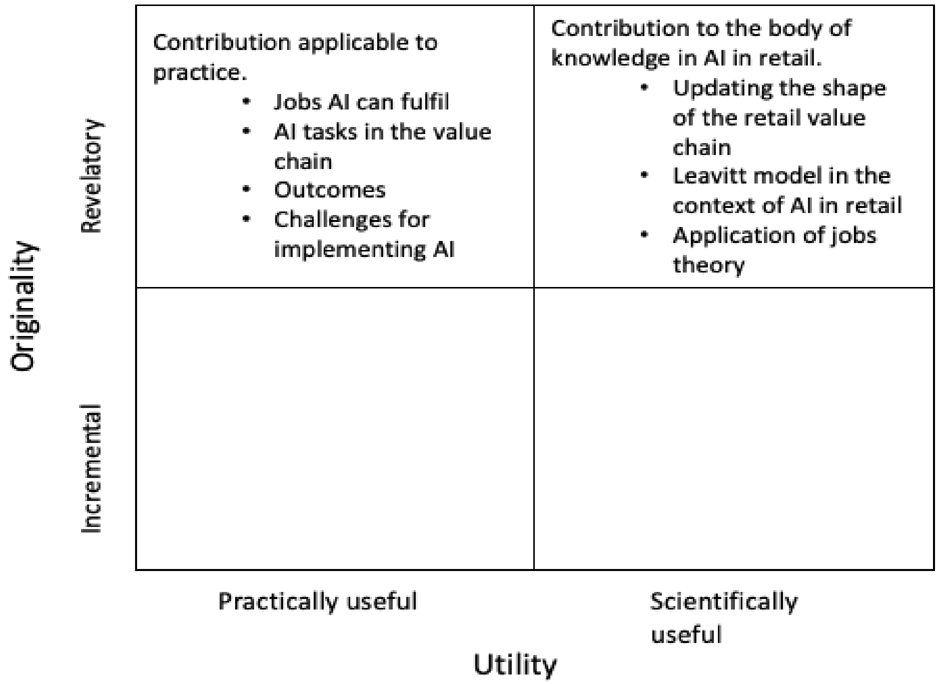


Figure 7.3: This study's theoretical contribution based on Corley and Gioia (2011)

Corley and Gioia (2011, p. 20) argue that research into management and organisational theory has neglected the practical usefulness, with more focus placed on the scientific usefulness of the theory. This is understandable as "practical utility considers specific problems tapping general principles, whereas good theory emphasises generalities"(Corley & Gioia, 2011, p. 20). The following section discusses the theoretical contribution of this study.

7.4.1 Contribution of the study

This section describes the overall theoretical contribution of the study and the contribution to practice.

7.4.1.1 Theoretical contribution of the study

The results of this study contribute to the body of knowledge in several ways. First, this study departs from previous studies on AI in retail literature, which are predominantly conceptual (Grewal et al., 2017, 2020; Hagberg et al., 2016; Jain & Gandhi, 2021; Shankar, 2018). Second, despite AI's increasing popularity, empirical inquiry into AI in the retail value chain remains limited. Therefore, the study addresses this gap in the literature by examining how AI is transforming the retail value chain.

Second, current literature addressing AI in retail mainly focuses on the AI application in customer-facing value chain stages (i.e., store operations and sales, fulfilment, customer use and support) (Ameen et al., 2021; Araujo, 2019; Balaji & Roy, 2017; F. L. Chen & Ou, 2011; Jain & Gandhi, 2021; Pillai et al., 2020; Pizzi et al., 2021; Rese et al., 2020; Tupikovskaja-Omovie & Tyler, 2020; van Esch et al., 2021), and not about AI's application across the entire value chain. Thus, while AI in the retail body of knowledge has increased in recent years, the literature remains limited.

Extant research focused on providing theoretical contributions in exploring the relationships between AI and digital marketing (Kietzmann et al., 2018; Mogaji et al., 2020), advancing knowledge on AI-enabled customer experiences and service (Ameen et al., 2021; Balaji & Roy, 2017; Pillai et al., 2020), researching customer adoption of AI-enabled technologies (J.-S. Chen et al., 2021; Jain & Gandhi, 2021; Pitardi & Marriott, 2021; Pizzi et al., 2021; Rese et al., 2020) and consumer patronage towards AI-enabled checkouts (Esch et al., 2021)). Therefore, no studies illustrated the implementation of AI across the retail value chain to the author's knowledge. Therefore, this study broadens the understanding of how AI is transforming the retail value chain.

This study contributes to theory in three ways, 1) by suggesting the shape of the value chain should change, 2) examining all variables in the Leavitt Diamond Model in the context of AI in the retail value chain, and 3) applying the application of jobs theory to AI in retail.

7.4.1.1.1 Updating the shape of the retail value chain

Research asserts that the traditional retail value chain is experiencing a metamorphosis, yet literature offering managerial guidance on how to respond to these changes is limited (Araujo, 2019; van Esch et al., 2019). With added pressure to remain competitive, many retailers have started to embrace various digital technologies to engage with their customers (Grewal et al., 2017). Many are utilising AI applications to establish this connection (Morgan, 2019). Authors argue that the retail value chain needs revisiting because of new technologies (Hagel et al., 2016; Reinartz et al., 2019), yet limited empirical research have suggested precisely how the retail value chain should change. This study's first theoretical contribution suggests that the retail value chain's shape should change from linear to circular to accommodate the iterative nature of AI. AI has a significant impact on the shape of the retail value chain. For AI to learn from past experiences, the technology requires data, and the effective translation of data into knowledge is crucial for AI's success. The current linear approach to the retail value chain is not conducive to advanced knowledge and insight management AI offers. Hence underpinning the updated AI-enabled retail value chain (see Section 3.4) is knowledge and insight management. The AI-enabled value chain can be deployed to serve one of the following purposes: knowledge and insight management, inventory management, operations optimisation, and customer engagement. The AI-enabled retail value chain principles can be applied to other industries such as consumer, banking, and manufacturing.

7.4.1.1.2 Application of the Leavitt Diamond Model

The Leavitt Diamond Model is an important model to examine the impacts of organisational change by considering the interrelated social (i.e., human and structure) and technical (i.e., tasks and technology) variables (Hartmann & Lussier, 2020; Leavitt, 1965). Scholars have used Leavitt's model to examine a variety of organisational change topics applying it in numerous contexts, including the COVID pandemic shock on B2B organisations (Hartmann & Lussier, 2020) to information systems in the organisational environment (Lyytinen & Newman, 2008), management challenges associated with analytics (Vidgen et al., 2017); marketing and supply chain management (Jüttner et al., 2007), and the use of information technology and the effectiveness of human resource function (Haines & Lafleur, 2008).

This study used the Leavitt Diamond Model variables (i.e. structure, technology, tasks and people) to examine how AI transforms the retail value chain. All articles investigated each component of the Leavitt Diamond Model. This process offered an expansive view to examine the variables of the Diamond model individually to access AI in the retail value chain. Significant studies in AI in retail literature only focus on technology variable of the Leavitt Diamond Model (Balaji & Roy, 2017; Bottani et al., 2019; Grewal et al., 2017, 2020; Guo et al., 2011; Jin & Shin, 2020; Lee, 2017; Wadhawan & Seth, 2016), which is a limitation in research. All variables, especially people, should be considered when integrating AI or any digital projects into retail. Therefore, the second theoretical contribution for this study was using all variables in the Leavitt Diamond Model in the context of AI in the retail value chain.

There is a complex interplay between all variables in the Leavitt Diamond Model when implementing AI into retail. When retailers only focus on one variable, i.e., technology, it creates challenges. To accommodate AI in the organisation, the linkages in the Leavitt Diamond Model should change. AI offers more than only being a technology. Technology is associated with the hardware, software, and processing power, whereas the power of AI is how it uses the technology to accomplish a goal by processing the algorithms. AI aims to generate an output or action depending on its goal. For instance, a digital camera could always take pictures, yet combined with AI computer vision, a camera can now recognise a person's face, unlock the phones and apps, and approve payments.

AI represents opportunities to improve customer service (Lee & Shin, 2020), improve productivity in operations (Dogru & Keskin, 2020), increase efficiency (Manyika & Bughin, 2018), interact with customers (Adapa et al., 2020; Ameen et al., 2021), reduces costs (Wadhawan & Seth, 2016) and creates new business opportunities. Therefore, by separating the focus of AI to its own variable, the thinking is shifted from technology only to instead focus on solving business problems and the transformative opportunities AI can provide organisations. Figure 7.4 shows an updated model where AI links to all variables, structure, technology, people and tasks.

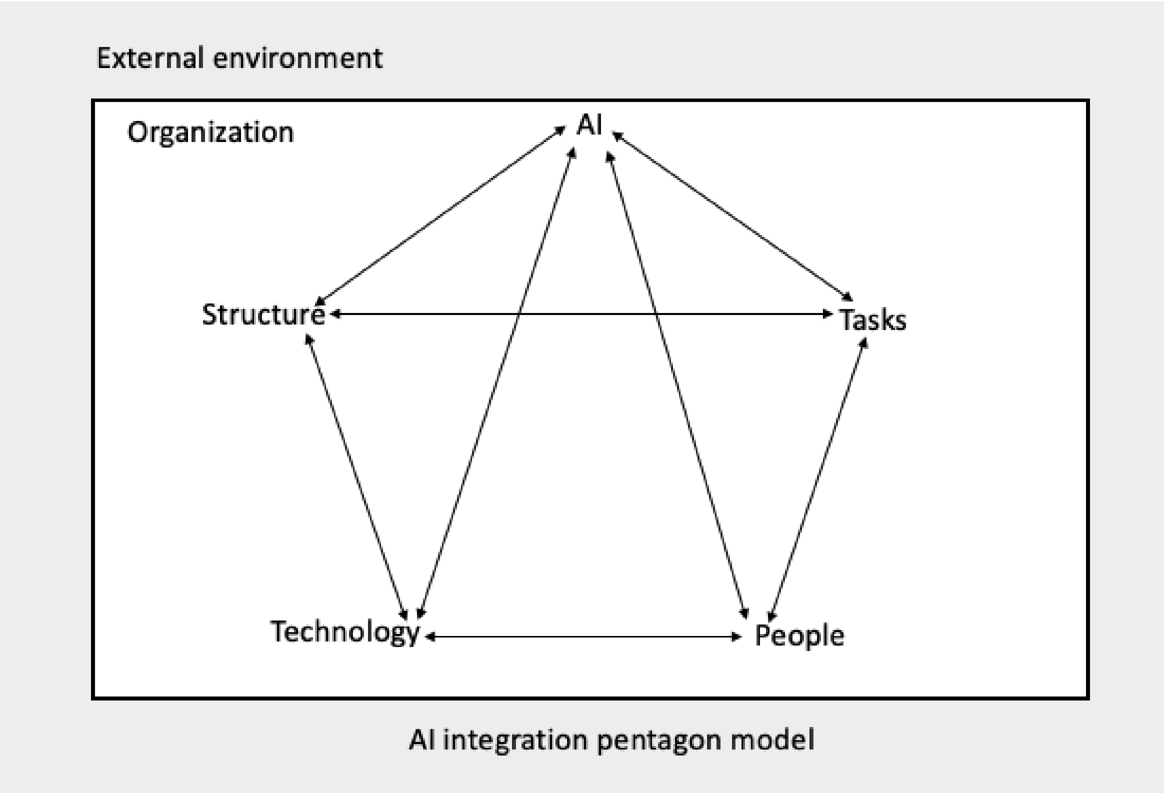


Figure 7.4: Updated variable linkages to accommodate AI the pentagon model

Therefore, the theoretical contribution is an evolved Leavitt Diamond Model accommodating AI as a new variable, not combining AI as part of the technology variable. No other studies have proposed updating the Leavitt Diamond Model to include AI as a new variable to the author's knowledge.

__7.4.1.1.3__ Application of jobs theory – outcomes-based innovation

The application of jobs theory proposes a group of principles that explain how to make marketing more effective and innovation more predictable by focusing on the customer's jobs to be done. Christensen et al. (2016) argue that people 'hire' products and services to get jobs done, and companies can innovate by doing those jobs better. Each job can be broken down into various steps or stages of execution, with validating questions to assess the best job fit at each stage (Bettencourt and Ulwick, 2008). In article one, the job-to-be-done approach was used as a lens to conceptually cluster the jobs AI technologies can perform in the retail value chain. The article conceptually proposed four AI technology dimensions that can fulfil most of the roles in the "traditional" retail value chain.

Ulwick (2016, p. 58) argues that using the jobs-to-be-done theory to define a job is essential. However, he emphasises that uncovering the desired outcome is the key to successfully innovating. Outcomes-based measures have become increasingly important (Burkett, 2013) and stem from service-dominant logic (Vargo and Lusch, 2004) and digital servitisation (Kowalkowski et al., 2017) research. In article three, an outcomes-based approach was used to present a framework of four outcomes for applying AI in the retail value chain and tested the association between the AI outcome and the value chain stage.

Therefore, articles one and three broaden our understanding of applying jobs theory and outcomes-based innovation in the context of AI in the retail value chain. The following section discusses the contribution to practice.

7.4.2 Contribution to practice

Authors have presented a variety of AI applications that can be used in customer-facing value chains (Ameen et al., 2021; Araujo et al., 2020; Balaji & Roy, 2017; Chen & Ou, 2011; Esch et al., 2021; Jain & Gandhi, 2021; Pillai et al., 2020; Pizzi et al., 2021; Rese et al., 2020; Tupikovskaja-Omovie & Tyler, 2020), for instance, enhancing the customer shopping experience. However, the entire value chain is yet to be presented. Moreover, research into AI is predominantly focused on the technology itself (Anica-Popa et al., 2021; Grewal et al., 2017; B. Guo et al., 2020; Haenlein & Kaplan, 2019; Hagel et al., 2016; Kaur et al., 2020) and not on what tasks the technology can perform.

Current studies investigate particular AI types to improve areas in the retail value chain (Balaji & Roy, 2017; Chan et al., 2020; Chen et al., 2021; de Bellis & Johar, 2020; Pillai et al., 2020; Rodgers et al., 2021). However, the literature mainly focuses on the technology instead of what the technology can do for retailers. Furthermore, while most of the studies discuss a specific type of AI or the algorithms associated with AI (Bottani et al., 2019; Cruz-Domínguez & Santos-Mayorga, 2016, Lee, 2017; Priyadarshi et al., 2019), the literature only addresses a small portion of the overall value chain.

Some studies regarding the value and benefits of AI are associated with implementing AI (Cao, 2021; Dogru & Keskin, 2020; Manyika et al., 2017; Shechtman et al., 2018). However, the outcomes of investing in AI in the retail value chain has yet to be articulated in scholarly research. The literature offered various current and emerging challenges for implementing AI into business or society (Adapa et al., 2020; Ammanath et al., 2020; Begley et al., 2018; Dogru & Keskin, 2020; Dwivedi et al., 2021; Kaplan & Haenlein, 2020). However, these often come from managerial recommendations and future research suggestions. In addition, there is limited research into the challenges retailers experience when implementing AI into their organisations.

The retail value chain is experiencing an evolution with AI technologies. Many major retailers such as Walmart, the Home Depot and Target have invested in the technology. However, retailers do not understand how the technology will create value and transform their value chain. AI presents retailers with various options to improve consumer insights, enhance profitability and streamline their business processes, yet many retailers are slow to invest or scale the technology. Retailers know that they need to transform their value chain with AI. This study provides the following contributions to provide retail and business leaders with an understanding of how AI is transforming the value chain:

i. Articulation of how AI can be applied across the value chain, helping understand where AI can solve business problems,
ii. the business case developed for AI by the articulation of the outcomes associated with applying AI, and
iii. an updated diamond model with considerations to minimise the impact of integrating AI into the retail business.

Each of these practical contributions is now discussed in turn.

7.4.2.1 The application of AI

For retail and business leaders to understand how AI transforms the value chain, article 1 proposed an enhanced AI-enabled value chain (see Section 3.4). The AI-enabled value chain provides leaders with an understanding of AI's role in their organisation. AI can best be employed in the retail value chain by serving one of the following purposes: knowledge and insight management, inventory management, operations optimisation, and customer engagement. AI applications over the next decade will remain narrow or applied (Kelly, 2017; Marr, 2017). However, the narrow applications of AI can be extended to multiple functions in the retail value chain. Therefore, the contribution to retail and practice is the AI-enabled framework providing retailers with insight into how to best leverage current AI investments. Retailers should invest in classes of AI technologies (e.g., deep learning capability) and not just specific applications, thereby ensuring that these technologies be used for multiple functions across the value chain. In addition, the AI-enabled value chain framework provides retailers with a list of priorities for investing in AI. i.e., start with knowledge and insight management at the foundation.

AI shifts retailers away from the traditional way of doing business and opens new opportunities within the value chain. AI enables multiple tasks throughout the retail value chain by automating many activities. AI can fully automate certain activities such as harnessing volumes of data, analysing patterns and interpreting findings in a fraction of the time that a human counterpart can complete the task (Y. Chen et al., 2016). Once retailers invest in the classes of AI, the current tasks that AI performs framework can be used as a basis for automating tasks. Therefore, the contribution to retail and practice is formulating the tasks AI fulfils across the retail value chain, helping retail leaders solve business problems with AI.

7.4.2.2 The outcomes associated with AI

A challenge noted amongst retailers is the difficulty articulating the outcomes associated with implementing AI. Article 3 identified four outcomes of applying AI across the retail value chain: AI that enhanced the *customer experience*, *enabled revenue*, led to substantial *cost savings and improvements in efficiency*, or AI that *enhanced decision-making*. This article shows that some outcomes are more likely when AI is applied in particular value chain stages. Therefore, the contribution to retail and practice are once retailers have decided which outcome they want to attain through the application of AI, both the type of AI and the value chain stage in which they want to apply the technology, their options are narrowed down significantly, and managerial decision making and creating a business case for an AI investment becomes easier.

7.4.2.3 Complex interplay between structure, technology, people, and tasks

A vast majority of retailers are experimenting with the possibility of AI (Ganapathy et al., 2020). Despite the promise of AI, most AI investments are failing to deliver on their promised returns (Fountaine et al., 2019). Integrating AI into existing business processes, workflows, and systems is challenging. Article 4 investigates the possible *structure*, *technology*, *task* and human-related challenges of implementing AI in the retail value chain. This article shows the variety of AI-related challenges retailers experience when implementing AI into their businesses, with challenges relating to people and structure the most prominent challenges. However, there is a complex interplay between all the variables (people, structure, tasks and technology) when integrating AI in retail. For retailers to successfully implement AI into their business, consideration and focus should be given to its impact on all the variables (people, structure, technology, and tasks). Therefore, an updated diamond model framework contributes to retail and practice. The framework identifies considerations retail leaders can use to minimise the impact of integrating AI into the retail business.

This study contributes to practice by discussing how AI is transforming the retail value chain through various applications in the value chain. The contribution to the theory and practice leads to several recommendations for academia and practice discussed in more detail in the following section.

Although multiple insights were gained from each article and the study as a whole, the study is not without limitations. The possible limitations of this study are discussed in more detail.

7.5 POSSIBLE LIMITATION OF THE STUDY

The possible limitations of this study revolve around the generalizability of the findings, the methods used, the target population, and the analysis of results. Each is discussed in turn.

7.5.1 Generalisability

This study aimed to understand how AI is transforming the retail value chain. To do so, an exploratory research design was deemed the most appropriate. Exploratory research designs are used to explore research areas that describe words such as "how" or "what" (Creswell, 2014, p. 141) and used to uncover insights into a specific issue or a particular phenomenon such as AI. However, exploratory research designs are typically associated with qualitative research, which is not without its limitations. The most notable limitation is the generalisation of the findings (Eriksson & Kovalainen, 2008, p. 158; Leung, 2015, p. 327) and "claiming that they are relevant to other groups at times and places" (O'Reilly, 2009, p. 82). Generalisation involves "theoretical inference from the data to develop concepts and theory and empirical application of the data to a wider population" (Miller & Brewer, 2003, p. 127). The purpose of this study was not intended to generalise the findings but rather on gaining a firm grasp of the phenomenon of artificial intelligence in the retail value chain by investigating how AI is transforming the retail value chain.

7.5.2 Methods used

This study used several methods to understand better how AI is transforming the retail value chain. The study employed a two-stage design, using two stages of qualitative data collection. Furthermore, while the various methods suited this study well, the design addressed the various research questions and an iterative data analysis. There are still limitations associated with all research methods. The limitations from the methods could originate from the choices the research made, systematic bias intentionally introduced (Ross & Bibler Zaidi, 2019, p. 262), it is labour-intensive and time-consuming process (Cho & Lee, 2014) and data could be misinterpreted by the author (Conboy et al., 2012, p. 115).

7.5.3 Target population and sampling

During stage two of the research, the target population was experts in AI in retail. The experts needed to have AI knowledge in consulting, developing, working with, or implementing AI applications in the retail industry. Therefore, even though the research was well justified in its focus on AI experts in retail, the findings from this study cannot be generalized to the entire retail industry.

Purposive sampling was used to identify relevant participants to investigate the research question regarding AI in retail. Purposive sampling deliberately seeks out participants with a specific characteristic (Morse, 2011). However, participants were selected based on the researchers' judgement about the appropriate characteristics needed for the study, causing potential selection bias in the sample. To mitigate the risk of bias in the sample, it was ensured that there was a representative sample across the AI in retail experts (i.e., AI technology vendors, management consultants, platform technology vendors and retailers). Another potential limitation was the small sample size of 20 participants used. However, article four found saturation was reached at about 16 participants. Thus, while the targeting and sampling suited this study well as the sampling sought participants with appropriate characteristics, there are still limitations associated with all targeting and sampling used in research.

7.5.4 Data collection

Stage one's purpose was to collect data to build theory on AI in retail for articles one to three. To do so, a systematic literature review was conducted. A search of the databases used did not guarantee that all literature available was retrieved for analysis, causing a potential limitation. However, to mitigate this limitation in the data collection process, this study used a well-defined search strategy using the PRISMA method to select, identify and include data for analysis (PRISMA method) (See Section 1.5.2.1 or Section 5.5). During stage two, semi-structured interviews were used as a data collection instrument. The interviews followed an interview protocol in combination with probing. Possible limitations could be the unintended influence of how the participant responded to the questions. While the data collection suited this study well, there are still limitations associated with all data collection methods.

7.5.5 Measurement

A coding strategy followed an iterative process to create a rigorous analysis process for this study to address the various research questions. Qualitative researchers usually are faced with data analysis challenges due to little or no structure in the data (Conboy et al., 2012, p. 115). With a two-stage design approach, the coding becomes quite complex, and the interpretation of results through coding could be a possible limitation. Nevertheless, while iterative coding suited this study well, there are still limitations associated with all measurement procedures to address the various research questions. The data was coded and iteratively grouped through multiple phases to mitigate the limitation. As a result, themes emerged from the review process.

In this study, the analysis was limited to the research questions to understand how AI transforms the retail value chain. No consideration was given to other factors that could transform retail or any criticism towards AI. The following section discusses future research.

7.6 FUTURE RESEARCH

The research field of AI in retail is still young, with most research articles published during the past eight years (see Appendix B). Nevertheless, AI in retail is an essential and much-needed field of study as it enables insights into new upcoming automation of activities within the retail value chain, the simulation of new AI algorithms for technology development and how to enhance the business through the use of AI. Thus, this study presents how AI is transforming the retail value chain. For this reason, future research could replicate this study in other contexts to test the applicability to the Leavitt Diamond Model, the updated shape of the value chain and the application of jobs in other industries.

There are numerous opportunities for future research for AI in the retail field. The most apparent future research directed by this study is understanding AI's impact on retail employees, i.e., the skills and resources required. It will be crucial for organisations to have a skilled workforce to support the implementation of AI, and there will be an even higher demand for skilled professionals (Van Esch & Black, 2019). While companies face external competition in finding skilled employees, low skilled workers could find it challenging to compete with machines and struggle to be employable in the future (Frey & Osborne, 2017). Therefore, future research can focus on the skills and competencies necessary for the organisation to implement the AI-enabled retail value chain. In addition, this research can be helpful to enable a skills gap analysis and provision training to narrow the skills gap in retail.

The study noted that change management practices are needed to enable employees and AI to work together. Future research into the change management practices needed to reduce trust and resistance amongst employees using AI systems. The research should focus on leaders' change management role in AI implementation.

This study provided the theory to explain how AI can be used to solve business problems in retail by using the jobs to be done approach, an analysis of the tasks AI automates, and the outcomes associated with AI. Future studies can test the approaches and outcomes empirically and present retailers with an AI problem-solving framework.

This study provided an overview of the importance of data management for AI applications. Future research could assess how organisations can address these vulnerabilities and avoid the potential biases in data or focus on the ethical considerations needed for successful use of AI. Finally, scaling AI applications across the retail value chain will require the right platforms to be in place, data to be available, and employees to support the initiatives in the long term. Future research should examine the technological and organisational platforms necessary for successfully implementing an AI-enabled value chain. As the technology, most likely to reshape the retail landscape, retailers that embrace AI are poised to enhance every link in their value chain.

The success of AI depends on the people who use the technology in the retail value chain. However, to do this, retailers need to adjust the way of working and internal business processes to enable people and AI to work together. Future research could investigate what an AI and human working business process should be in the retail value chain. The research should focus on business and customer-facing value chain stages, as the stakeholders will be different in each stage. Also, to integrate AI, employees should accept and trust the technology. The current research focused on customer acceptance of AI technology in retail (Chen et al., 2021; Liang et al., 2020), yet few studies have investigated the employee acceptance of AI in the retail value chain. Future research should focus on what is required for employees to build user trust in working with the technology.

A survey by Gartner 2019 estimates that 30 % of businesses are using some form of AI technologies (Hare & Andrews, 2019, p. 3). However, less than half of AI proof of concepts gets integrated and scaled into business (Davis, 2020, p. 3). Similarly, in retail AI adoption rates remain low, even though AI can provide significant value (Dogru & Keskin, 2020, p. 69). For retailers to transform with AI, strategic focus is required for investment prioritisation. Future research could investigate successful AI retailers' strategic priorities and provide a framework for building a successful AI strategy in retail.

The global coronavirus pandemic has changed how retailers interact with their customers, with retailers needing to adapt to keep their employees and customers safe. Retailers have adjusted to different methods of fulfilling customer orders, for example, curb side pickup. Future research can investigate what AI methods retailers can use to limit customer contact while providing the best possible customer service. The pandemic created upstream disruptions in the global supply chains of goods and services, with customers panic buying (Nikolopoulos et al., 2021, p. 99). The disruptions created challenges for retailers' short-term forecasts (daily and weekly), affecting the retail value chain. Forecasting during a pandemic will continue to be a challenge for retailers. Future research could develop an AI pandemic forecasting model that can easily anticipate environment shock in the retail value chain.

Retailers are under increasing pressure to decrease their operations' internal and external environmental impacts (Naidoo & Gasparatos, 2018, p. 125). Sustainable manufacturing and shipping practices should be at the forefront of every retailer’s and brand’s priorities in the coming years (Erez, 2019). With a trend towards a circular economy and sustainability practices in retail, retailers could look towards AI. AI could potentially provide retailers with visibility throughout the entire retail value chain helping build sustainability practices. Future research could focus on how AI can help and guide retailers to understand how sustainable their operations and practices are and how to manage products through a circular economy. Also, future research can focus on how AI can support building a sustainable business model in retail.

7.7 CONCLUSION

AI is transforming how retailers operate. AI shifts retailers to move away from the traditional way of doing business and opens up new opportunities within the value chain. When retailers adopt AI across the retail functions and processes at scale, they can unlock unprecedented value and transform their businesses. AI offers every retailer an opportunity to take advantage of adapting business models in a digitalised world and compete for market share.

AI can only perform specific tasks in the retail value chain. The need for people working alongside the technology will be an essential factor for retailers when automating tasks in the value chain. AI can best be employed in the retail value chain by serving one of the following purposes: knowledge and insight management, inventory management, operations optimisation and customer engagement. Nevertheless, investments in AI should focus on solving a business problem and not merely implementing AI as a technology. Therefore, retailers should approach AI investments from a more strategic service-centric perspective and understand the outcomes that can be achieved in the retail value chain.

When undertaking any AI initiative, the focus should be given to all the organisational variables, people, structure, tasks and technology to ensure success. However, implementing AI from only focusing on the technology creates challenges for retailers wanting to integrate the technology into their business. In addition, implementing AI requires retailers to adapt the way of working across the value chain.

For retailers to transform with AI, this study suggests the following eight imperatives for transforming with AI in the retail value chain, namely:

- It is essential to articulate what the technology needs to be used for clearly—the solution to the business problem, not the solution for the solution sake.

- Ensure that the data lines up with the business problem and do not underestimate the complexity of managing data for AI.
- AI requires scalable technical infrastructure to consolidate, process and simulate data.
- AI implementations are capital intensive, and reliable estimates for AI projects require expertise, understanding context and understanding the business problem.
- Strategic prioritisation and ownership in the organisation are required to integrate AI successfully.
- To implement AI successfully, retailers require employees with implementation skills, knowledge about the algorithms and AI, platform knowledge and business knowledge. In addition, retailers should prepare for the future AI organisation and access the current workforce to determine the skills and capability gap.
- Adequate change management practices need to be in place, and communications of the purpose of the technology should start in the early project stages to avoid resistance from people working with the technology.
- To enable a new way of working with AI, retailers should adapt their organisational structures and job designs to bring the best out of people and AI.

In conclusion, many considerations are required for retailers to transform with AI successfully. AI is changing how retailers operate and can create many benefits. When retail and business leaders focus on the organisation, it can assist with the successful integration of AI into the business.

Reference list

Acharya, A., Singh, S. K., Pereira, V., & Singh, P. (2018). Big data, knowledge co-creation and decision making in fashion industry. *International Journal of Information Management*, 42, 90–101. https://doi.org/10.1016/j.ijinfomgt.2018.06.008

Adapa, S., Fazal-e-Hasan, S. M., Makam, S. B., Azeem, M. M., & Mortimer, G. (2020). Examining the antecedents and consequences of perceived shopping value through smart retail technology. *Journal of Retailing and Consumer Services,* 52, 101901. https://doi.org/10.1016/j.jretconser.2019.101901

Agresti, A. (2002). Categorical data analysis (2nd ed). Wiley-Interscience.

Ahmady, G. A., Mehrpour, M., & Nikooravesh, A. (2016). Organisational Structure. *Procedia - Social and Behavioral Sciences,* 230, 455–462. https://doi.org/10.1016/j.sbspro.2016.09.057

Alexander, B., & Kent, A. (2021). Tracking technology diffusion in-store: A fashion retail perspective. *International Journal of Retail & Distribution Management,* ahead-of-print(ahead-of-print). https://doi.org/10.1108/IJRDM-05-2020-0191

Alibaba. (2021). Alibaba Group. History and Milestones. https://www.alibabagroup.com/en/about/history?year=2010

Ambrogio, K. (2019, November 7). Australia's Favorite Department Store Gets More Agile with Oracle. Oracle News Connect. https://www.oracle.com/corporate/pressrelease/myer-implements-oracle-110719.html

Ameen, N., Tarhini, A., Reppel, A., & Anand, A. (2021). Customer experiences in the age of artificial intelligence. Computers in Human Behavior, 114, 106548. https://doi.org/10.1016/j.chb.2020.106548

Ammanath, B., Jarvis, D., & Hupfer, S. (2020, July 14). Thriving in the era of pervasive AI. Deloitte Insights. https://www2.deloitte.com/us/en/insights/focus/cognitive-technologies/state-of-ai-and-intelligent-automation-in-business-survey.html

Anica-Popa, I., Anica-Popa, L., Rădulescu, C., & Vrîncianu, M. (2021). The Integration of Artificial Intelligence in Retail: Benefits, Challenges and a Dedicated Conceptual Framework. *Amfiteatru Economic,* 23(56), 120. https://doi.org/10.24818/EA/2021/56/120

Araujo, M. (2019). The Intelligent Enterprise for the Retail Industry. 32.

Ardolino, M., Rapaccini, M., Saccani, N., Gaiardelli, P., Crespi, G., & Ruggeri, C. (2018). The role of digital technologies for the service transformation of industrial companies. International *Journal of Production Research,* 56(6), 2116–2132. https://doi.org/10.1080/00207543.2017.1324224

Arthur, R. (2018). Artificial Intelligence Empowers Designers In IBM, Tommy Hilfiger And FIT Collaboration. Forbes. https://www.forbes.com/sites/rachelarthur/2018/01/15/ai-ibm-tommy-hilfiger/

Assarroudi, A., Heshmati Nabavi, F., Armat, M. R., Ebadi, A., & Vaismoradi, M. (2018). Directed qualitative content analysis: The description and elaboration of its underpinning methods and data analysis process. *Journal of Research in Nursing*, 23(1), 42–55. https://doi.org/10.1177/1744987117741667

Bacharach, S. B. (1989). Organisational Theories: Some Criteria For Evaluation. Academy of Management. *The Academy of Management Review,* 14(4), 496.

Baird, N. (2019, February). Snapshot 2019: The State Of AI In Retail. Forbes. https://www.forbes.com/sites/nikkibaird/2019/02/14/snapshot-2019-the-state-of-ai-in-retail/#51351730773b

Balaji, M. S., & Roy, S. K. (2017). Value co-creation with Internet of things technology in the retail industry. *Journal of Marketing Management*, 33(1–2), 7–31. https://doi.org/10.1080/0267257X.2016.1217914

Balchandani, A., Hancock, B., Phillips, S., & Wachinger, T. (2020). How technology is disrupting the UK retail industry | McKinsey (p. 22). Mckinsey Global Institute. https://www.mckinsey.com/industries/retail/our-insights/rebooting-retail-how-technology-will-shape-the-future-of-retail#

Barlow, C. A. (2010). Encyclopedia of Case Study Research (A. Mills, G. Durepos, & E. Wiebe, Eds.). SAGE Publications, Inc. https://doi.org/10.4135/9781412957397

Barredo Arrieta, A., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., Garcia, S., Gil-Lopez, S., Molina, D., Benjamins, R., Chatila, R., & Herrera, F. (2020). Explainable Artificial

Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information Fusion*, 58, 82–115. https://doi.org/10.1016/j.inffus.2019.12.012

Barseghian, A. (2019, October 7). Council Post: How Nike Is Using Analytics To Personalise Their Customer Experience. Forbes. https://www.forbes.com/sites/forbestechcouncil/2019/10/07/how-nike-is-using-analytics-to-personalise-their-customer-experience/

Bednar, P. M., & Welch, C. (2020). Socio-Technical Perspectives on Smart Working: Creating Meaningful and Sustainable Systems. *Information Systems Frontiers,* 22(2), 281–298. https://doi.org/10.1007/s10796-019-09921-1

Begley, S., Fox, R., Lunawat, G., & MacKenzie, I. (2018, August). How analytics and digital will drive next-generation retail merchandising. https://www.mckinsey.com/industries/retail/our-insights/how-analytics-and-digital-will-drive-next-generation-retail-merchandising

Berg, A., Heyn, M., Rölkens, F., & Simon, P. (2018, May). Faster fashion: How to shorten the apparel calendar. Mckinsey and Co, 6.

Berthiaume, D. (2019, June 4). Ultra-Beauty shoppers behold new AR, AI features. Chain Store Age the Business of Retail. https://chainstoreage.com/technology/ulta-beauty-shoppers-behold-new-ar-ai-features

Berthon, P., Pitt, L., Ewing, M., & Carr, C. L. (2002). Potential Research Space in MIS: A Framework for Envisioning and Evaluating Research Replication, Extension, and Generation. *Information Systems Research,* 13(4), 416–427. https://doi.org/10.1287/isre.13.4.416.71

Bettencourt, L. A., & Ulwick, A. W. (2008). The Customer-Centered Innovation Map. *Harvard Business Review,* 9.

Bharadwaj, R. (2019, November 21). Artificial Intelligence in the Textile Industry—Current and Future Applications. Emerj. https://emerj.com/ai-sector-overviews/artificial-intelligence-in-the-textile-industry-current-and-future-applications/

Bieniek, C., & Lobaugh, K. (2015). What got you here won’t get you there: Evolving the merchandising function in today’s battle for share. Deloitte.

Björkdahl, J. (2020). Strategies for Digitalisation in Manufacturing Firms. *California Management Review,* 62(4), 17–36. https://doi.org/10.1177/0008125620920349

Black, J. S., & van Esch, P. (2019). AI-enabled recruiting: What is it and how should a manager use it? Business Horizons, S0007681319301612. https://doi.org/10.1016/j.bushor.2019.12.001

Blair, A. (2018, October 29). New Sam's Club Store Will Be A Mobile-First, AI-Powered Tech Lab. Retail Touch Points. https://retailtouchpoints.com/features/news-briefs/new-sam-s-club-store-will-be-a-mobile-first-ai-powered-tech-lab

Blueprism. (2019). Inside John Lewis – How RPA is transforming retail. https://www.blueprism.com/uploads/resources/case-studies/BluePrism_JohnLewisPartnership.pdf

Boella, G., & van der Torre, L. (2006). Coordination and Organisation. *Electronic Notes in Theoretical Computer Science,* 150(3), 3–20. https://doi.org/10.1016/j.entcs.2006.03.002

Bolton, R. N., Chapman, R. G., & Mills, A. J. (2019). Harnessing Digital Disruption With Marketing Simulations. *Journal of Marketing Education*, 41(1), 15–31. https://doi.org/10.1177/0273475318803417

Boslaugh, S. (2008). Encyclopedia of Epidemiology. SAGE Publications, Inc. https://doi.org/10.4135/9781412953948

Bostrom, R. P., & Heinen, J. S. (1977). MIS Problems and Failures: A Socio-Technical Perspective. *Part I: The Causes. MIS Quarterly,* 1(3), 17. https://doi.org/10.2307/248710

Bottani, E., Centobelli, P., Gallo, M., Kaviani, M. A., Jain, V., & Murino, T. (2019). Modelling wholesale distribution operations: An artificial intelligence framework. *Industrial Management & Data Systems,* 119(4), 698–718. https://doi.org/10.1108/IMDS-04-2018-0164

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology,* 3(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Bryant, A., Bryant, A., Bryant, A., & Casper, M. (2007). The SAGE Handbook of Grounded Theory. In pages 1-28, The SAGE Handbook of Grounded Theory. SAGE Publications Ltd. https://doi.org/10.4135/9781848607941

Brynjolfsson, E., Hu, Y. J., & Rahman, M. S. (2013). Competing in the Age of Omnichannel Retailing. *MIT Sloan Management Review*, 54(4), 10.

Bughin, J., Hazan, E., Ramaswamy, S., Chui, M., Allas, T., Dahlström, P., Henke, N., & Trench, M. (2017). Artificial intelligence the next digital frontier? (p. 80). Mckinsey Global Institute. www.mckinsey.com/mgi

Burkett, H. (2013). Moving from outputs to outcomes in the public health sector: A case study. *Journal of the Grant Professionals Association*, 11(1), 84–95.

Burkett, M. (2013). Future Supply Chain 2028: Four Factors to Watch (p. 27). Gartner.

Burström, T., Parida, V., Lahti, T., & Wincent, J. (2021). AI-enabled business-model innovation and transformation in industrial ecosystems: A framework, model and outline for further research. *Journal of Business Research*, 127, 85–95. https://doi.org/10.1016/j.jbusres.2021.01.016

Butler-Adam, J. (2018). The Fourth Industrial Revolution and education. *South African Journal of Science,* 114(5/6). https://doi.org/10.17159/sajs.2018/a0271

Cai, Y.-J., & Lo, C. K. Y. (2020). Omni-channel management in the new retailing era: A systematic review and future research agenda. *International Journal of Production Economics*, 229, 107729. https://doi.org/10.1016/j.ijpe.2020.107729

Cammett, M. (2006). Development and the Changing Dynamics of Global Production: Global Value Chains and Local Clusters in Apparel Manufacturing. *Competition & Change,* 10(1), 23–48. https://doi.org/10.1179/102452906X91993

Campbell, C., Sands, S., Ferraro, C., Tsao, H.-Y. (Jody), & Mavrommatis, A. (2020). From data to action: How marketers can leverage AI. *Business Horizons,* 63(2), 227–243. https://doi.org/10.1016/j.bushor.2019.12.002

Candelon, F., Reichert, T., Duranton, S., di Carlo, R. C., & Stokol, G. (2020, October 29). Deploying AI to Maximize Revenue. BCG. https://www.bcg.com/en-au/publications/2020/deploying-ai-artificial-intelligence-to-maximize-revenue

Canhoto, A. I., & Clear, F. (2019). Artificial intelligence and machine learning as business tools: A framework for diagnosing value destruction potential. Business Horizons, S0007681319301570. https://doi.org/10.1016/j.bushor.2019.11.003

Cao, L. (2014). Business Model Transformation in Moving to a Cross-Channel Retail Strategy: A Case Study. *International Journal of Electronic Commerce*, 18(4), 69–96. https://doi.org/10.2753/JEC1086-4415180403

Cao, L. (2021). Artificial intelligence in retail: Applications and value creation logics. International *Journal of Retail & Distribution Management, ahead-of-print(ahead-of-print).* https://doi.org/10.1108/IJRDM-09-2020-0350

Capgemini. (2018). Building the Retail Superstar: How unleashing AI across functions offers a multi-billion dollar opportunity. Capgemini Worldwide. https://www.capgemini.com/research/building-the-retail-superstar-how-unleashing-ai-across-functions-offers-a-multi-billion-dollar-opportunity/

Carlsson, C. (2018). Decision analytics—Key to digitalisation. *Information Sciences*, 460–461, 424–438. https://doi.org/10.1016/j.ins.2017.08.087

Chan, C. O., Lau, H. C. W., & Fan, Y. (2020). Implementing IoT-Adaptive Fuzzy Neural Network Model Enabling Service for Supporting Fashion Retail. *Proceedings of the 4th International Conference on Machine Learning and Soft Computing*, 19–24. https://doi.org/10.1145/3380688.3380692

Chao, G., Cheung, J., Haller, K., & Lee, J. (2019). The coming AI revolution in retail and consumer products: Intelligent automation is transforming both industries in unexpected ways (IBM Institute for Business Value, p. 24). National Retail Federation. https://nrf.com/sites/default/files/2019-01/The%20coming%20AI%20revolution.pdf

Chen, F. L., & Ou, T. Y. (2011). Sales forecasting system based on Gray extreme learning machine with Taguchi method in retail industry. *Expert Systems with Applications*, 38(3), 1336–1345. https://doi.org/10.1016/j.eswa.2010.07.014

Chen, J.-S., Le, T.-T.-Y., & Florence, D. (2021). Usability and responsiveness of artificial intelligence chatbot on online customer experience in e-retailing. *International Journal of Retail & Distribution Management, ahead-of-print(ahead-of-print).* https://doi.org/10.1108/IJRDM-08-2020-0312

Chen, Y., Elenee Argentinis, J., & Weber, G. (2016). IBM Watson: How Cognitive Computing Can Be Applied to Big Data Challenges in Life Sciences Research. *Clinical Therapeutics*, 38(4), 688–701. https://doi.org/10.1016/j.clinthera.2015.12.001

Cho, J., & Lee, E.-H. (2014). Reducing Confusion about Grounded Theory and Qualitative Content Analysis: Similarities and Differences. The Qualitative Report. https://doi.org/10.46743/2160-3715/2014.1028

Choi, T.-M., Hui, C.-L., Liu, N., Ng, S.-F., & Yu, Y. (2014). Fast fashion sales forecasting with limited data and time. *Decision Support Systems*, 59, 84–92. https://doi.org/10.1016/j.dss.2013.10.008

Chopra, K. (2019). Indian shopper motivation to use artificial intelligence: Generating Vroom's expectancy theory of motivation using grounded theory approach. *International Journal of Retail & Distribution Management,* 47(3), 331–347. https://doi.org/10.1108/IJRDM-11-2018-0251

Christensen, C., Hall, T., Dillon, K., & Duncan, D. S. (2016). Competing against luck. The Story of Innovation and Customer Choice. First Edition. New York, NY: HarperBusiness an Imprint of HarperCollins Publishers.

Christensen, C. M., & Raynor, M. E. (2013). The Innovator's Solution: Creating and Sustaining Successful Growth. Harvard Business Review Press. https://store.hbr.org/product/the-innovator-s-solution-creating-and-sustaining-successful-growth/16444

Chui, M., Manyika, J., & Miremadi, M. (2018, January 11). What AI can and can't do (yet) for your business. McKinsey. https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/what-ai-can-and-cant-do-yet-for-your-business

Chuprina, R. (2019, December 20). Artificial Intelligence for Retail in 2020: 12 Real-World Use Cases. https://spd.group/artificial-intelligence/ai-for-retail/

Cloutier, C., & Langley, A. (2020). What Makes a Process Theoretical Contribution? Organisation Theory, 1(1), 263178772090247. https://doi.org/10.1177/2631787720902473

Conboy, K., Fitzgerald, G., & Mathiassen, L. (2012). Qualitative methods research in information systems: Motivations, themes, and contributions. European Journal of Information Systems, 21(2), 113–118. https://doi.org/10.1057/ejis.2011.57

Corley, K. G., & Gioia, D. A. (2011). Building Theory About Theory Building: What Constitutes a Theoretical Contribution? *Academy of Management Review,* 36(1), 12–32. https://doi.org/10.5465/amr.2009.0486

Cosgrove, E. (2020, January 14). H&M's AI operation helps make its supply chain more sustainable. Supply Chain Dive. https://www.supplychaindive.com/news/HM-AI-supply-chain-sustainable/570400/

Creswell, J. W. (2012). Mixed Methods Research. In The SAGE Encyclopedia of Qualitative Research Methods. SAGE Publications, Inc. https://doi.org/10.4135/9781412963909

Creswell, J. W. (2014). Research Design: Qualitative, Quantititive and Mixed methods approaches. SAGE Publications, Inc.

Cruz-Domínguez, O., & Santos-Mayorga, R. (2016). Artificial intelligence applied to assigned merchandise location in retail sales systems. The South African Journal of Industrial Engineering, 27(1). https://doi.org/10.7166/27-1-1192

DalleMule, L., & Davenport, T. H. (2017, May 1). What's Your Data Strategy? Harvard Business Review, May-June 2017. https://hbr.org/2017/05/whats-your-data-strategy

Daugherty, P., Ghosh, B., & Wilson, J. (2020). Your legacy or your legend? A CEO's guide to getting the most out of new technologies (Future Systems, p. 34) [Research Report]. Accenture. https://www.accenture.com/_acnmedia/Thought-Leadership-Assets/PDF-2/Accenture-Legacy-or-Legend-PDF-Report.pdf#zoom=50

Daugherty, P. R., & Wilson, J. H. (2018). Human + Machine: Reimagining Work in the Age of AI (Kindle). Harvard Business Review Press.

Davenport, T. H., & Ronanki, R. (2018). Artificial Intelligence for the Real World. 10.

Davies, P. (2011). Exploratory Research. In The SAGE Dictionary of Social Research Methods. SAGE Publications, Ltd. https://doi.org/10.4135/9780857020116

Davis, F. (1985). A technology acceptance model for empirically testing new end-user information systems: Theory and results [Sloan School of Management, MIT]. https://scholar.google.com/citations?view_op=view_citation&hl=en&user=rKH2D8MAAAAJ&citation_for_view=rKH2D8MAAAAJ:pqnbT2bcN3wC

Davis, M. (2020). Accelerating AI Deployments—Paths of Least Resistance (No. G00722711; Artificial Intelligence, p. 17). file:///Users/kimo/Downloads/Accelerating_AI_Depl_722711_ndx.pdf

Davis, M. C., Challenger, R., Jayewardene, D. N. W., & Clegg, C. W. (2014). Advancing socio-technical systems thinking: A call for bravery. *Applied Ergonomics*, 45(2), 171–180. https://doi.org/10.1016/j.apergo.2013.02.009

Day, G. (2021). Pinpointing the Problems: Which Ones Are Right for AI? MIT Sloan Management Review, Part 1 in a series on the journey to AI success, 8.

Day, G. S., & Schoemaker, P. J. H. (2019). See Sooner, Act Faster: How Vigilant Leaders Thrive in an Era of Digital Turbulence. MIT Press.

de Bellis, E., & Johar, G. V. (2020). Autonomous Shopping Systems: Identifying and Overcoming Barriers to Consumer Adoption. *Journal of Retailing*, 96(1), 74–87. https://doi.org/10.1016/j.jretai.2019.12.004

De Bruyn, A., Viswanathan, V., Beh, Y. S., Brock, J. K.-U., & von Wangenheim, F. (2020). Artificial Intelligence and Marketing: Pitfalls and Opportunities. *Journal of Interactive Marketing*, 51, 91–105. https://doi.org/10.1016/j.intmar.2020.04.007

de Leon, S. P. (2019, August 27). How thredUP is Driving the Circular Fashion Movement with AI. Forbes. https://www.forbes.com/sites/cognitiveworld/2019/08/27/how-thredup-circular-fashion-ai/#615d567f79a0

DeCuir-Gunby, J. T., & Schutz, P. A. (2017). Developing a Mixed Methods Proposal: A Practical Guide for Beginning Researchers. SAGE Publications, Inc. https://doi.org/10.4135/9781483399980

Deloitte. (2017). Bullish on the business value of cognitive. https://www2.deloitte.com/content/dam/Deloitte/us/Documents/deloitte-analytics/us-da-2017-deloitte-state-of-cognitive-survey.pdf

Deloitte. (2021). The age of with: Leveraging AI to connect the retail enterprise of the future. Deloitte. https://www2.deloitte.com/ca/en/pages/consumer-industrial-products/articles/age-of-with-ai.html

Djafri, L., Amar Bensaber, D., & Adjoudj, R. (2018). Big Data analytics for prediction: Parallel processing of the big learning base with the possibility of improving the final result of the prediction. *Information Discovery and Delivery*, 46(3), 147–160. https://doi.org/10.1108/IDD-02-2018-0002

Dogru, A. K., & Keskin, B. B. (2020). AI in operations management: Applications, challenges and opportunities. *Journal of Data, Information and Management*, 2(2), 67–74. https://doi.org/10.1007/s42488-020-00023-1

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data – evolution, challenges and research agenda. *International Journal of Information Management,* 48, 63–71. https://doi.org/10.1016/j.ijinfomgt.2019.01.021

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., … Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, 57, 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Edwards, J. (2019, August 16). Predictive analytics: Transforming data into future insights. CIO. https://www.cio.com/article/3273114/what-is-predictive-analytics-transforming-data-into-future-insights.html

Elliot, B., & Andrews, W. (2017). A Framework for Applying AI in the Enterprise. Gartner.

Emont, J. (2018, February 16). The Robots Are Coming for Garment Workers. That's Good for the U.S., Bad for Poor Countries. *The Wall Street Journal*. https://www.wsj.com/articles/the-robots-are-coming-for-garment-workers-thats-good-for-the-u-s-bad-for-poor-countries-1518797631

Erez, R. (2019, October 1). Sustainability In Retail: Good For Business, Great For Humanity. Forbes. https://www.forbes.com/sites/royerez/2019/10/01/sustainability-in-retail-good-for-business-great-for-humanity/

Eriksson, P., & Kovalainen, A. (2008). Qualitative Methods in Business Research. SAGE Publications Ltd. https://doi.org/10.4135/9780857028044

Fairhurst, A. E., & Fiorito, S. S. (1990). Retail buyers' decision-making process: An investigation of contributing variables. *The International Review of Retail, Distribution and Consumer Research*, 1(1), 87–100. https://doi.org/10.1080/09593969000000007

Fan, X., Chai, Z., Deng, N., & Dong, X. (2020). Adoption of augmented reality in online retailing and consumers' product attitude: A cognitive perspective. *Journal of Retailing and Consumer Services,* 53, 101986. https://doi.org/10.1016/j.jretconser.2019.101986

Feuerriegel, S., Dolata, M., & Schwabe, G. (2020). Fair AI: Challenges and Opportunities. Business & Information Systems Engineering, 62(4), 379–384. https://doi.org/10.1007/s12599-020-00650-3

Fiorito, S. S., Gable, M., & Conseur, A. (2010). Technology: Advancing retail buyer performance in the twenty-first century. *International Journal of Retail & Distribution Management,* 38(11/12), 879–893. https://doi.org/10.1108/09590551011085966

Firmin, M. W. (2012). Unstructured Interview. In The SAGE Encyclopedia of Qualitative Research Methods. SAGE Publications, Inc. https://doi.org/10.4135/9781412963909

Fountaine, T., McCarthy, B., & Saleh, T. (2019). Building the AI-Powered Organisation. 13.

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, 114, 254–280. https://doi.org/10.1016/j.techfore.2016.08.019

G. Sternbeck, M., & Kuhn, H. (2014). Grocery retail operations and automotive logistics: A functional cross-industry comparison. *Benchmarking: An International Journal*, 21(5), 814–834. https://doi.org/10.1108/BIJ-07-2012-0048

Ganapathy, V., Green, M., & Schottmiller, P. (2020, January 7). AI in Retail Transformation | Accenture. https://www.accenture.com/au-en/insights/retail/artificial-intelligence-retail-value

Gauri, D. K., Jindal, R. P., Ratchford, B., Fox, E., Bhatnagar, A., Pandey, A., Navallo, J. R., Fogarty, J., Carr, S., & Howerton, E. (2021). Evolution of retail formats: Past, present, and future. *Journal of Retailing*, 97(1), 42–61. https://doi.org/10.1016/j.jretai.2020.11.002

Gerbert, P., Hecker, M., Steinhäuser, S., & Ruwolt, P. (2017). Putting Artificial Intelligence to work. The Boston Consulting Group. https://www.bcg.com/en-au/publications/2017/technology-digital-strategy-putting-artificial-intelligence-work.aspx

Gonzalez-Jimenez, H. (2018). Taking the fiction out of science fiction: (Self-aware) robots and what they mean for society, retailers and marketers. *Futures,* 98, 49–56. https://doi.org/10.1016/j.futures.2018.01.004

Goworek, H. (2014). An investigation into retail buying roles and responsibilities for own-label clothing: A multiple case-study. *The Journal of The Textile Institute*, 105(7), 760–769. https://doi.org/10.1080/00405000.2013.848046

Grewal, D., Motyka, S., & Levy, M. (2018). The Evolution and Future of Retailing and Retailing Education. *Journal of Marketing Education,* 40(1), 85–93. https://doi.org/10.1177/0273475318755838

Grewal, D., Noble, S. M., Roggeveen, A. L., & Nordfalt, J. (2020). The future of in-store technology. *Journal of the Academy of Marketing Science*, 48(1), 96–113. https://doi.org/10.1007/s11747-019-00697-z

Grewal, D., Roggeveen, A. L., & Nordfält, J. (2017). The Future of Retailing. *Journal of Retailing*, 93(1), 1–6. https://doi.org/10.1016/j.jretai.2016.12.008

Grill-Goodman, J. (2019, June 21). How Walmart Uses Computer Vision. RIS News. https://risnews.com/how-walmart-uses-computer-vision

Guha, A., Grewal, D., Kopalle, P. K., Haenlein, M., Schneider, M. J., Jung, H., Moustafa, R., Hegde, D. R., & Hawkins, G. (2021). How artificial intelligence will affect the future of retailing. *Journal of Retailing,* 97(1), 28–41. https://doi.org/10.1016/j.jretai.2021.01.005

Guo, Z., Wong, W., Leung, S., & Li, M. (2011). Applications of artificial intelligence in the apparel industry: A review. *Textile Research Journal*, 81(18), 1871–1892. https://doi.org/10.1177/0040517511411968

Gupta, S. (2018). Driving digital strategy: A guide to reimagining your business. *Harvard Business Review Press*.

Gupta, S., Kar, A. K., Baabdullah, A., & Al-Khowaiter, W. A. A. (2018). Big data with cognitive computing: A review for the future. *International Journal of Information Management*, 42, 78–89. https://doi.org/10.1016/j.ijinfomgt.2018.06.005

Haenlein, M., & Kaplan, A. (2019). A Brief History of Artificial Intelligence: On the Past, Present, and Future of Artificial Intelligence. *California Management Review*, 61(4), 5–14. https://doi.org/10.1177/0008125619864925

Haenlein, M., Kaplan, A., Tan, C.-W., & Zhang, P. (2019). Artificial intelligence (AI) and management analytics. *Journal of Management Analytics*, 6(4), 341–343. https://doi.org/10.1080/23270012.2019.1699876

Hagberg, J., Sundstrom, M., & Egels-Zandén, N. (2016). The digitalisation of retailing: An exploratory framework. *International Journal of Retail & Distribution Management*, 44(7), 694–712. https://doi.org/10.1108/IJRDM-09-2015-0140

Hagel, J., Seely Brown, J., Wooll, M., & de Maar, A. (2016, January 11). Shorten the value chain: Transforming the stages of value delivery. https://www2.deloitte.com/insights/us/en/focus/disruptive-strategy-patterns-case-studies/disruptive-strategy-value-chain-models.html

Haines, V. Y., & Lafleur, G. (2008). Information technology usage and human resource roles and effectiveness. *Human Resource Management, 47(3*), 525–540. https://doi.org/10.1002/hrm.20230

Hardaker, A. (2017, September 18). LovetheSales.com AI 10,000 times faster than a human [BusinessCloud]. https://www.businesscloud.co.uk/news/lovethesalescom-ai-10000-times-faster-than-a-human/

Hare, J., & Andrews, W. (2019). Survey Analysis: AI and ML Development Strategies, Motivators and Adoption Challenges. 16.

Hartmann, N. N., & Lussier, B. (2020). Managing the sales force through the unexpected exogenous COVID-19 crisis. *Industrial Marketing Management*, 88, 101–111. https://doi.org/10.1016/j.indmarman.2020.05.005

Hayes, A. (2019, September 2). Big-Box Retailers: What You Should Know. Investopedia. https://www.investopedia.com/terms/b/big_box_retailer.asp

Heater, B. (2019, April 11). The startup behind Walmart's shelf-scanning robots. Tech Crunch. https://techcrunch.com/2019/04/10/the-startup-behind-walmarts-shelf-scanning-robots/?guccounter=1

Himmelreich, A. (2020, April 2). Using artificial intelligence to advance retail and consumer products to truly personalised service. Capgemini. https://www.capgemini.com/wp-content/uploads/2020/04/AI-to-Future-POV.pdf

History.com. (2020, March 30). World Wide Web (WWW) launches in the public domain. HISTORY. https://www.history.com/this-day-in-history/world-wide-web-launches-in-public-domain

Hoffman, F. P., & Freyn, S. L. (2019). The future of competitive intelligence in an AI-enabled world. *International Journal of Value Chain Management*, 10(4), 275–289.

Hollebeek, L. D., Sprott, D. E., & Brady, M. K. (2021). Rise of the Machines? Customer Engagement in Automated Service Interactions. *Journal of Service Research*, 24(1), 3–8. https://doi.org/10.1177/1094670520975110

Holweg, M., & Helo, P. (2014). Defining value chain architectures: Linking strategic value creation to operational supply chain design. *International Journal of Production Economics*, 147, 230–238. https://doi.org/10.1016/j.ijpe.2013.06.015

Home Depot. (2018, August 20). 5 TECHNOLOGIES CHANGING HOW WE SHOP. https://corporate.homedepot.com/newsroom/5-technologies-changing-how-we-shop

Hsieh, H.-F., & Shannon, S. E. (2005). Three Approaches to Qualitative Content Analysis. *Qualitative Health Research*, 15(9), 1277–1288. https://doi.org/10.1177/1049732305276687

Hübner, A., Amorim, P., Kuhn, H., Minner, S., & Van Woensel, T. (2018). *Retail operations. OR Spectrum*, 40(4), 831–835. https://doi.org/10.1007/s00291-018-0535-1

Hwang, S. (2019). A network clock model for time awareness in the Internet of things and artificial intelligence applications. *The Journal of Supercomputing*, 75(8), 4309–4328. https://doi.org/10.1007/s11227-019-02774-0

Ikea. (2020). Say hej to IKEA Place. Ikea. https://www.ikea.com/au/en/customer-service/mobile-apps/say-hej-to-ikea-place-pub1f8af050

Jain, S., & Gandhi, A. V. (2021). Impact of artificial intelligence on impulse buying behaviour of Indian shoppers in fashion retail outlets. *International Journal of Innovation Science*, 13(2), 193–204. https://doi.org/10.1108/IJIS-10-2020-0181

Jin, B. E., & Shin, D. C. (2020). Changing the game to compete: Innovations in the fashion retail industry from the disruptive business model. *Business Horizons*, 63(3), 301–311. https://doi.org/10.1016/j.bushor.2020.01.004

Jindal, P., Zhu, T., Chintagunta, P., & Dhar, S. (2020). Marketing-Mix Response Across Retail Formats: The Role of Shopping Trip Types. *Journal of Marketing*, 84(2), 114–132. https://doi.org/10.1177/0022242919896337

Johnston, R. (2017, September 26). IKEA's New Augmented Reality App Means You're Never Not At IKEA. Gizmodo. https://www.gizmodo.com.au/2017/09/ikeas-new-augmented-reality-app-means-youre-never-not-at-ikea/

Juniper Research. (2019, April 10). AI Spending by Retailers to Reach $12 Billion by 2023, Driven by the Promise of Improved Margins. https://www.juniperresearch.com/press/press-releases/ai-spending-by-retailers-reach-12-billion-2023

Jüttner, U., Christopher, M., & Baker, S. (2007). Demand chain management-integrating marketing and supply chain management. Industrial Marketing Management, 36(3), 377–392. https://doi.org/10.1016/j.indmarman.2005.10.003

Kaplan, A. (2020). Retailing and the Ethical Challenges and Dilemmas Behind Artificial Intelligence. In Retail Futures: The Good, the Bad and the Ugly of the Digital Transformation (Kindle Edition). Retailing and the Ethical Challenges and Dilemmas Behind Artificial Intelligence Retail Futures . Emerald Publishing Limited.

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. Business Horizons, 62(1), 15–25. https://doi.org/10.1016/j.bushor.2018.08.004

Kaplan, A., & Haenlein, M. (2020). Rulers of the world, unite! The challenges and opportunities of artificial intelligence. Business Horizons, 63(1), 37–50. https://doi.org/10.1016/j.bushor.2019.09.003

Kaplan, J. (1984). The Industrialization of Artificial Intelligence: From By-Line to Bottom Line. *The AI Magazine*, 5(2), 7.

Kapner, S. (2021, May 16). Not Qualified for a Job? These Companies Will 'Reskill' You. *Wall Street Journal*. https://www.wsj.com/articles/retailers-try-to-solve-labor-imbalances-by-reskilling-staff-11621157407

Kaur, J., Arora, V., & Bali, S. (2020). Influence of technological advances and change in marketing strategies using analytics in retail industry. *International Journal of System Assurance Engineering and Management,* 11(5), 953–961. https://doi.org/10.1007/s13198-020-01023-5

Kelly, K. (2017). The Inevitable: Understanding the 12 Technological Forces That Will Shape Our Future. Penguin Books.

Kerzel, U. (2021). Enterprise AI Canvas Integrating Artificial Intelligence into Business. *Applied Artificial Intelligence*, 35(1), 1–12. https://doi.org/10.1080/08839514.2020.1826146

Kietzmann, J., Hermkens, K., McCarthy, I. P., & Silvestre, B. S. (2011). Social media? Get serious! Understanding the functional building blocks of social media. *Business Horizons*, 54(3), 241–251. https://doi.org/10.1016/j.bushor.2011.01.005

Kietzmann, J., Paschen, J., & Treen, E. (2018). Artificial Intelligence in Advertising: How Marketers Can Leverage Artificial Intelligence Along the Consumer Journey. *Journal of Advertising Research,* 58(3), 263–267. https://doi.org/10.2501/JAR-2018-035

Lai, K.-H., Cheng, T. C. E., & Tang, A. K. Y. (2010). Green Retailing: Factors for Success. California *Management Review*, 52(2), 6–31. https://doi.org/10.1525/cmr.2010.52.2.6

Lake, K. (2018, May). Stitch Fix's CEO on Selling Personal Style to the Mass Market. *Harvard Business Review.* https://hbr.org/2018/05/stitch-fixs-ceo-on-selling-personal-style-to-the-mass-market

Leavitt, H. J. (1965). Applied organisational change in industry: Structural, technological and humanistic approaches. In The handbook of organisations (RLE: Organisations) (Vol. 20). Carnegie Institute of Technology, Graduate School of Industrial Administration.

Leavitt, H. J., & Bahrami, H. (1989). Managerial Psychology: Managing Behavior in Organisations (1st edition). University of Chicago Press.

Lee, C. K. H. (2017). A GA-based optimisation model for big data analytics supporting anticipatory shipping in Retail 4.0. *International Journal of Production Research*, 55(2), 593–605. https://doi.org/10.1080/00207543.2016.1221162

Lee, H., Mendelson, H., Rammoham, S., & Blake, L. (2018). Value Chain Innovation: The Promise of AI (Value Chain Innovation Initiative). *Stanford Business.*

Lee, I., & Shin, Y. J. (2020). Machine learning for enterprises: Applications, algorithm selection, and challenges. *Business Horizons,* 63(2), 157–170. https://doi.org/10.1016/j.bushor.2019.10.005

Leighton, M. (2018, September 6). Under Armour's new 'smart shoes' give runners real-time and post-workout data on their fitness performance. Business Insider. https://www.businessinsider.com/under-armour-hovr-review-smart-shoes-2018-3?r=AU&IR=T

Leung, L. (2015). Validity, reliability, and generalizability in qualitative research. *Journal of Family Medicine and Primary Care*, 4(3), 324–327. https://doi.org/10.4103/2249-4863.161306

Lewins, A., & Silver, C. (2011). Using Software in Qualitative Research. SAGE Publications, Ltd. https://doi.org/10.4135/9780857025012

Lewis-Beck, M., Bryman, A., & Futing Liao, T. (2004). Systematic Review. In The SAGE Encyclopedia of Social Science Research Methods. Sage Publications, Inc. https://doi.org/10.4135/9781412950589.n998

Lewis-Beck, M. S., Bryman, A., & Futing Liao, T. (2004). The SAGE encyclopedia of social science research methods. Sage Publications, Inc.

Li & Fung. (2019, December 13). Li & Fung and First Insight Announce Global Strategic Partnership to Integrate Voice of the Customer Analytics into Li & Fung's Digital Supply Chain Solutions. https://www.lifung.com/press-release/li-fung-first-insight-announce-global-strategic-partnership-integrate-voice-customer-analytics-li-fungs-digital-supply-chain-solutions/

Li, B., Hou, B., Yu, W., Lu, X., & Yang, C. (2017). Applications of artificial intelligence in intelligent manufacturing: A review. Frontiers of Information Technology & Electronic Engineering, 18(1), 86–96. https://doi.org/10.1631/FITEE.1601885

Liang, Y., Lee, S.-H., & Workman, J. E. (2020). Implementation of Artificial Intelligence in Fashion: Are Consumers Ready? *Clothing and Textiles Research Journal*, 38(1), 3–18. https://doi.org/10.1177/0887302X19873437

LinkedIn. (2020). About LinkedIn. About LinkedIn. https://about.linkedin.com/

Loske, D., & Klumpp, M. (2021). Intelligent and efficient? An empirical analysis of human–AI collaboration for truck drivers in retail logistics. The International Journal of Logistics Management, ahead-of-print(ahead-of-print). https://doi.org/10.1108/IJLM-03-2020-0149

Loughran, M. (2018). The promise of AI for industrial automation. *The Chemical Engineer*, 44–46.

Lowe's. (n.d.). A Helping Hand. Lowe's Innovation Lab. http://www.lowesinnovationlabs.com/lowebot/

Lyytinen, K., & Newman, M. (2008). Explaining information systems change: A punctuated socio-technical change model. *European Journal of Information Systems*, 17(6), 589–613. https://doi.org/10.1057/ejis.2008.50

Mahroof, K. (2019). A human-centric perspective exploring the readiness towards smart warehousing: The case of a large retail distribution warehouse. *International Journal of Information Management*, 45, 176–190. https://doi.org/10.1016/j.ijinfomgt.2018.11.008

Makarius, E. E., Mukherjee, D., Fox, J. D., & Fox, A. K. (2020). Rising with the machines: A sociotechnical framework for bringing artificial intelligence into the organisation. *Journal of Business Research*, 120, 262–273. https://doi.org/10.1016/j.jbusres.2020.07.045

Manyika, J., & Bughin, J. (2018a, October). The promise and challenge of the age of artificial intelligence. McKinsey Global Institute. https://www.mckinsey.com/featured-insights/artificial-intelligence/the-promise-and-challenge-of-the-age-of-artificial-intelligence

Manyika, J., & Bughin, J. (2018b, October). The promise and challenge of the age of artificial intelligence. McKinsey Global Institute. https://www.mckinsey.com/featured-insights/artificial-intelligence/the-promise-and-challenge-of-the-age-of-artificial-intelligence

Manyika, J., Chui, M., Miremadi, M., Bughin, J., George, K., Willmott, P., & Dewhurst, M. (2017). Harnessing automation for a future that works. Mckinsey Global Institute. https://www.mckinsey.com/featured-insights/digital-disruption/harnessing-automation-for-a-future-that-works

Marr, B. (2017, August 29). How Walmart Is Using Machine Learning AI, IoT And Big Data To Boost Retail Performance. Forbes. https://www.forbes.com/sites/bernardmarr/2017/08/29/how-walmart-is-using-machine-learning-ai-iot-and-big-data-to-boost-retail-performance/#35637d5e6cb1

Marr, B. (2018, August 10). How Fashion Retailer H&M Is Betting On Artificial Intelligence And Big Data To Regain Profitability. Forbes. https://www.forbes.com/sites/bernardmarr/2018/08/10/how-fashion-retailer-hm-is-betting-on-artificial-intelligence-and-big-data-to-regain-profitability/#1e4e9ef75b00

Marr, B. (2019). Artificial intelligence in practice: How 50 successful companies used artificial intelligence to solve problems (First Edition). Wiley.

Marshall, T. E., & Lambert, S. L. (2018). Cloud-Based Intelligent Accounting Applications: Accounting Task Automation Using IBM Watson Cognitive Computing. *Journal of Emerging Technologies in Accounting,* 15(1), 199–215. https://doi.org/10.2308/jeta-52095

Masri, F., Wood-Harper, T., & Kawalek, P. (2017). Systems Thinking: Analysis of Electronic Patient Records Implementation and Knowledge Transfer Practice. BP Trust in the UK, NHS. *International Journal Of Management and Applied Research*, 4(2), 105–121. https://doi.org/10.18646/2056.42.17-009

MAXQDA. (2020). What is MAXQDA. Maxqda.Com. https://www.maxqda.com/what-is-maxqda

McChrystal, G. S., Collins, T., Silverman, D., & Fussell, C. (2015). Team of teams: New rules of engagement for a complex world. Penguin.

McCormick, J. (2020, August 7). AI Project Failure Rates Near 50%, But It Doesn't Have to Be That Way, Say Experts. Wall Street Journal. https://www.wsj.com/articles/ai-project-failure-rates-near-50-but-it-doesnt-have-to-be-that-way-say-experts-11596810601

McKinsey. (2008). Enduring Ideas: The 7-S Framework | McKinsey. https://www.mckinsey.com/business-functions/strategy-and-corporate-finance/our-insights/enduring-ideas-the-7-s-framework

McKinsey. (2020, October). How COVID-19 has pushed companies over the technology tipping point—And transformed business forever. McKinsey. https://www.mckinsey.com/business-functions/strategy-and-corporate-finance/our-insights/how-covid-19-has-pushed-companies-over-the-technology-tipping-point-and-transformed-business-forever

Medeiros, J. (2018, May 1). Here's How North Face Boosted Conversions Using AI. Modev. https://www.modev.com/blog/heres-how-north-face-boosted-conversions-using-ai

Meticulous Research. (2020, July). Artificial Intelligence in Retail Market—Global Opportunity Analysis and Industry Forecast (2020-2027). Meticulous Research. https://www.meticulousresearch.com/product/artificial-intelligence-in-retail-market-4979/

Michael, P. (1985). Competitive advantage: Creating and sustaining superior performance. NY Free Press.

Miller, R., & Brewer, J. (2003). The A-Z of Social Research. SAGE Publications, Ltd. https://doi.org/10.4135/9780857020024

Mills, A., Durepos, G., & Wiebe, E. (2010). Encyclopedia of Case Study Research. https://doi.org/10.4135/9781412957397

Milnes, H. (2016, April 13). How Color IQ, Sephora's shade-matching skin care tool, boosts brand loyalty. https://digiday.com/marketing/color-iq-sephoras-shade-matching-skin-care-tool-boosts-brand-loyalty/

Mogaji, E., Soetan, T. O., & Kieu, T. A. (2020). The implications of artificial intelligence on the digital marketing of financial services to vulnerable customers. *Australasian Marketing Journal (AMJ), S1441358220300380.* https://doi.org/10.1016/j.ausmj.2020.05.003

Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., & Group, T. P. (2009). Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement. PLOS Medicine, 6(7), e1000097. https://doi.org/10.1371/journal.pmed.1000097

Morgan, B. (2019, March 4). The 20 Best Examples Of Using Artificial Intelligence For Retail Experiences. https://www.forbes.com/sites/blakemorgan/2019/03/04/the-20-best-examples-of-using-artificial-intelligence-for-retail-experiences/#44d8add44664

Morse, J. M. (2011). Purposive Sampling. In The SAGE Encyclopedia of Social Science Research Methods (p. 885). Sage Publications, Inc. https://doi.org/10.4135/9781412950589

Muhuri, P. K., Shukla, A. K., & Abraham, A. (2019). Industry 4.0: A bibliometric analysis and detailed overview. *Engineering Applications of Artificial Intelligence*, 78, 218–235. https://doi.org/10.1016/j.engappai.2018.11.007

Müller, V. C., & Bostrom, N. (2016). Future Progress in Artificial Intelligence: A Survey of Expert Opinion. In V. C. Müller (Ed.), Fundamental Issues of Artificial Intelligence (pp. 555–572). Springer International Publishing. https://doi.org/10.1007/978-3-319-26485-1_33

Nadkarni, S., & Prügl, R. (2020). Digital transformation: A review, synthesis and opportunities for future research. Management Review Quarterly. https://doi.org/10.1007/s11301-020-00185-7

Naidoo, M., & Gasparatos, A. (2018). Corporate environmental sustainability in the retail sector: Drivers, strategies and performance measurement. *Journal of Cleaner Production*, 203, 125–142. https://doi.org/10.1016/j.jclepro.2018.08.253

Neuendorf, K. A. (2017). The Content Analysis Guidebook. SAGE Publications, Inc. https://doi.org/10.4135/9781071802878

Nike. (2020). Product Advice From Nike Experts. https://www.nike.com/membership/experts-on-demand

Nikolopoulos, K., Punia, S., Schäfers, A., Tsinopoulos, C., & Vasilakis, C. (2021). Forecasting and planning during a pandemic: COVID-19 growth rates, supply chain disruptions, and governmental decisions. *European Journal of Operational Research*, 290(1), 99–115. https://doi.org/10.1016/j.ejor.2020.08.001

Oh, H., & Polidan, M. (2018). Retail Consulting Class: Experiential Learning Platform to Develop Future Retail Talents. *Journal of Marketing Education*, 40(1), 31–46. https://doi.org/10.1177/0273475317743015

Olanrewaju, T., & Willmott, P. (2013). Finding your digital sweet spot. McKinsey and Co., November, Available at: https://www. Mckinsey. Com/Insights/Business_ Technology/Finding_your_digital_sweet_spot

Oosthuizen, K., Botha, E., Robertson, J., & Montecchi, M. (2020). Artificial intelligence in retail: The AI-enabled value chain. *Australasian Marketing Journal (AMJ),* S144135822030077X. https://doi.org/10.1016/j.ausmj.2020.07.007

O'Reilly, K. (2009). Key Concepts in Ethnography. SAGE Publications Ltd. https://doi.org/10.4135/9781446268308

Paghaleh, M. J., Shafiezadeh, E., & Mohammadi, M. (2011). Information Technology and its Deficiencies in Sharing Organisational Knowledge. 2(8), 8.

Pantano, E., & Pizzi, G. (2020). Forecasting artificial intelligence on online customer assistance: Evidence from chatbot patents analysis. *Journal of Retailing and Consumer Services, 55, 102096*. https://doi.org/10.1016/j.jretconser.2020.102096

Parida, V., Sjödin, D. R., Lenka, S., & Wincent, J. (2015). Developing Global Service Innovation Capabilities: How Global Manufacturers Address the Challenges of Market Heterogeneity. Research-Technology Management. https://doi.org/10.5437/08956308X5805360

Paschen, J., Kietzmann, J., & Kietzmann, T. C. (2019). Artificial intelligence (AI) and its implications for market knowledge in B2B marketing. *Journal of Business & Industrial Marketing*, 34(7), 1410–1419. https://doi.org/10.1108/JBIM-10-2018-0295

Paschen, J., Wilson, M., & Ferreira, J. J. (2020). Collaborative intelligence: How human and artificial intelligence create value along the B2B sales funnel. *Business Horizons, 63(3), 403–414*. https://doi.org/10.1016/j.bushor.2020.01.003

Paschen, U., Pitt, C., & Kietzmann, J. (2019). Artificial intelligence: Building blocks and an innovation typology. *Business Horizons,* 63(2), 147–155. https://doi.org/10.1016/j.bushor.2019.10.004

Patton, M. Q. (1990). Qualitative Evaluation and Research Methods. SAGE Publications.

Peters, T. J., & Waterman, R. H. (2012). In Search of Excellence: Lessons from America's Best-Run Companies. Harper Collins.

Petropoulos, F., Kourentzes, N., Nikolopoulos, K., & Siemsen, E. (2018). Judgmental selection of forecasting models. *Journal of Operations Management*, 60, 34–46. https://doi.org/10.1016/j.jom.2018.05.005

Philips. (2020). Philips OneBlade: Trim, Edge, Shave. Philips. https://www.philips.co.za/c-m-pe/oneblade-trim-edge-and-shave

Pillai, R., Sivathanu, B., & Dwivedi, Y. K. (2020). Shopping intention at AI-powered automated retail stores (AIPARS). *Journal of Retailing and Consumer Services*, 57, 102207. https://doi.org/10.1016/j.jretconser.2020.102207

Pinterest. (2017). Pinterest Style finder and West Elm. Pinterest. https://pinterest-style-finder.westelm.com

Pitardi, V., & Marriott, H. R. (2021). Alexa, she's not human but… Unveiling the drivers of consumers' trust in voice-based artificial intelligence. *Psychology & Marketing*, 38(4), 626–642. https://doi.org/10.1002/mar.21457

Pizzi, G., Scarpi, D., & Pantano, E. (2021). Artificial intelligence and the new forms of interaction: Who has the control when interacting with a chatbot? *Journal of Business Research*, 129, 878–890. https://doi.org/10.1016/j.jbusres.2020.11.006

Poole, D. L., & Mackworth, A. K. (2017). Artificial intelligence: Foundations of computational agents (2nd edition). Cambridge University Press.

Porter, M. E. (1998). Competitive Advantage: Creating and Sustaining Superior Performance. SIMON & SCHUSTER.

Preece, A. (2018). Asking 'Why' in AI: Explainability of intelligent systems - perspectives and challenges. *Intelligent Systems in Accounting, Finance and Management*, 25(2), 63–72. https://doi.org/10.1002/isaf.1422

Press, G. (2019, July 19). This Week In AI Stats: Up To 50% Failure Rate In 25% Of Enterprises Deploying AI. Forbes. https://www.forbes.com/sites/gilpress/2019/07/19/this-week-in-ai-stats-up-to-50-failure-rate-in-25-of-enterprises-deploying-ai/

Priyadarshi, R., Panigrahi, A., Routroy, S., & Garg, G. K. (2019). Demand forecasting at retail stage for selected vegetables: A performance analysis. *Journal of Modelling in Management*, 14(4), 1042–1063. https://doi.org/10.1108/JM2-11-2018-0192

Purcărea, T., Ioan-Franc, V., Ionescu, Ş.-A., & Purcărea, I. M. (2021). The profound nature of the connection between the impact of using artificial intelligence in retail in retail on buying and the consumers perceptions of artificial intelligence on the parth to the next normal. *Amfiteatru Economic,* 23(56), 25.

Ransbotham, s, Kiron, D., Gerbert, P., & Reeves, M. (2017). Reshaping business with artificial intelligence- Closing the gap between ambition and action. (Research Project No. 59181). *MIT Sloan Management review*. https://sloanreview.mit.edu/projects/reshaping-business-with-artificial-intelligence/

Reddy, T. (2017, October 17). How chatbots can help reduce customer service costs by 30%. https://www.ibm.com/blogs/watson/2017/10/how-chatbots-reduce-customer-service-costs-by-30-per cent/

Reinartz, W., Wiegand, N., & Imschloss, M. (2019). The impact of digital transformation on the retailing value chain. *International Journal of Research in Marketing*, 36(3), 350–366. https://doi.org/10.1016/j.ijresmar.2018.12.002

Rese, A., Ganster, L., & Baier, D. (2020). Chatbots in retailers' customer communication: How to measure their acceptance? *Journal of Retailing and Consumer Services*, 56, 102176. https://doi.org/10.1016/j.jretconser.2020.102176

Riegger, A.-S., Klein, J. F., Merfeld, K., & Henkel, S. (2021). Technology-enabled personalisation in retail stores: Understanding drivers and barriers. *Journal of Business Research*, 123, 140–155. https://doi.org/10.1016/j.jbusres.2020.09.039

Rieple, A., & Singh, R. (2010). A value chain analysis of the organic cotton industry: The case of UK retailers and Indian suppliers. *Ecological Economics*, 69(11), 2292–2302. https://doi.org/10.1016/j.ecolecon.2010.06.025

Rimol, M. (2020, August 24). 6 Trends on the Gartner Hype Cycle for the Digital Workplace, 2020. https://www.gartner.com/smarterwithgartner/6-trends-on-the-gartner-hype-cycle-for-the-digital-workplace-2020/

RIS. (2020, June 5). Simons Optimizes Inventory With AI & Predictive Analytics. RIS News. https://risnews.com/simons-optimizes-inventory-ai-predictive-analytics

Robinson, E. (2018, January 15). Morrisons implements Blue Yonder's AI stock replenishment technology. The Record. https://www.technologyrecord.com/Article/morrisons-implements-blue-yonders-ai-stock-replenishment-technology-62728

Romero, I., & Martínez-Román, J. A. (2015). Determinants of technology adoption in the retail trade industry—The case of SME's in spain. *Amfiteatru Economic*, 17(39), 16.

Ross, P. T., & Bibler Zaidi, N. L. (2019). Limited by our limitations. *Perspectives on Medical Education*, 8(4), 261–264. https://doi.org/10.1007/s40037-019-00530-x

Roulston, K. J. (2012). Probes and Probing. In The SAGE Encyclopedia of Qualitative Research Methods. *SAGE Publications, Inc*. https://doi.org/10.4135/9781412963909

Roy, S. (2019, April 23). How Burberry is leveraging technology to lead in the digital age. Techwire Asia. https://techwireasia.com/2019/04/how-burberry-is-leveraging-technology-to-lead-in-the-digital-age/

Roy, S. K., Balaji, M. S., Sadeque, S., Nguyen, B., & Melewar, T. C. (2017). Constituents and consequences of smart customer experience in retailing. *Technological Forecasting and Social Change*, 124, 257–270. https://doi.org/10.1016/j.techfore.2016.09.022

Salento, A. (2018). Digitalisation and the regulation of work: Theoretical issues and normative challenges. *AI & SOCIETY*, 33(3), 369–378. https://doi.org/10.1007/s00146-017-0738-z

Sanders, N. R., Boone, T., Ganeshan, R., & Wood, J. D. (2019). Sustainable Supply Chains in the Age of AI and Digitization: Research Challenges and Opportunities. *Journal of Business Logistics*, 40(3), 229–240. https://doi.org/10.1111/jbl.12224

Sanders, N. R., & Wood, J. D. (2020, August 24). The Secret to AI Is People. Harvard Business Review. https://hbr.org/2020/08/the-secret-to-ai-is-people

Sankaran, G., Knahl, M., Siestrup, G., & Vasileiou, I. (2019). Value of Smart Data for Supply Chain Decisions in a Data Rich, Uncertain World. CERC. https://www.semanticscholar.org/article/Value-of-Smart-Data-for-Supply-Chain-Decisions-in-a-Sankaran-Knahl/93fb75c8d51f55a71896a1a1fb64acbab6007a0c

Satell, G. (2018). How to Make an AI Project More Likely to Succeed. 5.

Schaeffer, E., Cabanes, J., & Gupta, A. (2018). Manufacturing the future. Accenture. https://www.accenture.com/_acnmedia/PDF-74/Accenture-Pov-Manufacturing-Digital-Final.pdf

Schmelzer, R. (2020, May 2). Is Augmented Intelligence The Best Perspective On AI? Forbes. https://www.forbes.com/sites/cognitiveworld/2020/05/02/is-augmented-intelligence-the-best-perspective-on-ai/

Schmitt, B. (2020). Speciesism: An obstacle to AI and robot adoption. Marketing Letters, 31(1), 3–6. https://doi.org/10.1007/s11002-019-09499-3

Schwab, K. (2016, January 14). The Fourth Industrial Revolution: What it means, how to respond. World Economic Forum. www.weforum.org/agenda/2016/01/the-fourth-industrial-revolution-what-it-means-and-how-to-respond/

Seidel, S., Recker, J., Queensland University of Technology, vom Brocke, J., & University of Liechtenstein. (2013). Sensemaking and Sustainable Practicing: Functional Affordances of Information Systems in Green Transformations. *MIS Quarterly*, 37(4), 1275–1299. https://doi.org/10.25300/MISQ/2013/37.4.13

Shankar, V. (2018). How Artificial Intelligence (AI) is Reshaping Retailing. *Journal of Retailing*, 94(4), vi–xi. https://doi.org/10.1016/S0022-4359(18)30076-9

Shechtman, R., Spitz, C., Wimbish, R., & Thyagaraj, S. (2018). Merchandising of the future [Accenture].

Shi, M., & Yan, X. (2017). Heterogeneous consumers, search and retail formats. *Frontiers of Business Research in China,* 11(1), 18. https://doi.org/10.1186/s11782-017-0017-3

Shin, D. (2021). The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI. International Journal of Human-Computer Studies, 146, 102551. https://doi.org/10.1016/j.ijhcs.2020.102551

Shrivastava, S. (2017). Digital Disruption is Redefining the Customer Experience: The Digital Transformation Approach of the Communications Service Providers. 10(1), 13.

Sicular, S., Hare, J., & Brant, K. (2019). Hype Cycle for Artificial Intelligence, 2019 (No. G00369840; p. 79). Gartner. https://www.gartner.com/smarterwithgartner/top-trends-on-the-gartner-hype-cycle-for-artificial-intelligence-2019/

Silva, E. S., Hassani, H., & Madsen, D. Ø. (2019). Big Data in fashion: Transforming the retail sector. *Journal of Business Strategy, ahead-of-print(ahead-of-print)*. https://doi.org/10.1108/JBS-04-2019-0062

Simon, P., Tufft, C., & Zampella, P. (2020, August 28). Closing the skills gap in retail with people analytics [McKinsey & Company]. Reinventing Retail with People Analytics.

https://www.mckinsey.com/industries/retail/our-insights/closing-the-skills-gap-in-retail-with-people-analytics?cid=app

Simonite, T. (2017, January 18). AI Software Learns to Make AI Software. MIT Technology Review. https://www.technologyreview.com/2017/01/18/154516/ai-software-learns-to-make-ai-software/

Simpson, J., Ohri, L., & Lobaugh, K. (2017). The new digital divide: The future of digital influence in retail. Deloitte. https://www2.deloitte.com/us/en/pages/consumer-business/topics/retail-wholesale-distribution.html

Sivarajah, U., Kamal, M. M., Irani, Z., & Weerakkody, V. (2017). Critical analysis of Big Data challenges and analytical methods. *Journal of Business Research*, 70, 263–286. https://doi.org/10.1016/j.jbusres.2016.08.001

Sklyar, A., Kowalkowski, C., Tronvoll, B., & Sörhammar, D. (2019). Organizing for digital servitisation: A service ecosystem perspective. *Journal of Business Research*, 104, 450–460. https://doi.org/10.1016/j.jbusres.2019.02.012

Smith, C., Norton, B., & Ellis, D. (1992). LEAVITT'S DIAMOND AND THE FLATTER LIBRARY: A CASE STUDY IN ORGANISATIONAL CHANGE. *Library Management,* 13(5), 18–22. https://doi.org/10.1108/01435129210020352

Smith, L., Maull, R., & C.L. Ng, I. (2014). Servitisation and operations management: A service dominant-logic approach. *International Journal of Operations & Production Management,* 34(2), 242–269. https://doi.org/10.1108/IJOPM-02-2011-0053

Smith, T. J., & McKenna, C. M. (2013). A Comparison of Logistic Regression Pseudo R2 Indices. 39, 10.

Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines. *Journal of Business Research,* 104, 333–339. https://doi.org/10.1016/j.jbusres.2019.07.039

Sohn, K., Sung, C. E., Koo, G., & Kwon, O. (2020). Artificial intelligence in the fashion industry: Consumer responses to generative adversarial network (GAN) technology. International *Journal of Retail & Distribution Management*, 49(1), 61–80. https://doi.org/10.1108/IJRDM-03-2020-0091

Sowa, K., Przegalinska, A., & Ciechanowski, L. (2021). Cobots in knowledge work. *Journal of Business Research*, 125, 135–142. https://doi.org/10.1016/j.jbusres.2020.11.038

Spicer, R. (2020, March 2). Growing Fashion Retailer Taps Oracle Retail Solutions to Increase Focus on Customers [Oracle retail blog]. Best Practices and Trends. https://blogs.oracle.com/retail/growing-fashion-retailer-taps-oracle-retail-solutions-to-increase-focus-on-customers-v2

Stanciu, V., & Rîndașu, S.-M. (2021). Artificial Intelligence in Retail: Benefits and Risks Associated With Mobile Shopping Applications. *Amfiteatru Economic*, 23(56), 46. https://doi.org/10.24818/EA/2021/56/46

Standish, J., & Ganapathy, V. (2020, January 14). AI in Retail: Time to Stop Experimenting and Start Delivering Value at Scale. WWD.Com. https://wwd.com/business-news/technology/accenture-ai-retail-think-tank-1203422562/

Statista. (2020, July). Global retail sales 2022. Statista. https://www.statista.com/statistics/443522/global-retail-sales/

Suriyantphupha, P., & Bourlakis, M. (2019*). Information Technology in a Traditional Retail Supply Chain: A Structured Literature Review*. Projectics / Proyéctica / Projectique, n°22(1), 89. https://doi.org/10.3917/proj.022.0089

Tarafdar, M., Beath, C. M., & Ross, J. W. (2019). Using AI to Enhance Business Operations. *MIT Sloan Management Review,* 60(4), 10.

Target. (2017, September 25). Finding the Perfect Product Is As Easy As Taking a Pic, Thanks to This New Target + Pinterest Collab. Target. https://corporate.target.com/article/2017/09/pinterest-lens

Thyer, B. A. (2010). The Handbook of Social Work Research Methods. SAGE Publications, Inc. https://doi.org/10.4135/9781544364902

Trotter, C. (2018, April 12). 50 Best AI Retail Applications. https://www.insider-trends.com/50-best-ai-retail-applications/#ixzz5DQ4CdcsH

Tupikovskaja-Omovie, Z., & Tyler, D. (2020). Clustering consumers' shopping journeys: Eye tracking fashion m-retail. Journal of Fashion Marketing and Management: *An International Journal, ahead-of-print(ahead-of-print*). https://doi.org/10.1108/JFMM-09-2019-0195

Ulwick, A. W. (2016). Jobs to be Done: Theory to Practice (1st edition). IDEA BITE PRESS.

Valenduc, G., & Vendramin, P. (2017). Digitalisation, between disruption and evolution. Transfer: *European Review of Labour and Research*, 23(2), 121–134. https://doi.org/10.1177/1024258917701379

van Eck, N. J., & Waltman, L. (2014). Visualizing Bibliometric Networks. In Y. Ding, R. Rousseau, & D. Wolfram (Eds.), Measuring Scholarly Impact (pp. 285–320). Springer International Publishing. https://doi.org/10.1007/978-3-319-10377-8_13

van Eck, N. J., & Waltman, L. (2021). VOSviewer Manual. 54.

van Esch, P., Arli, D., Gheshlaghi, M. H., Andonopoulos, V., von der Heidt, T., & Northey, G. (2019). Anthropomorphism and augmented reality in the retail environment. *Journal of Retailing and Consumer Services,* 49, 35–42. https://doi.org/10.1016/j.jretconser.2019.03.002

van Esch, P., & Black, J. S. (2019). Factors that influence new generation candidates to engage with and complete digital, AI-enabled recruiting. *Business Horizons*, 62(6), 729–739. https://doi.org/10.1016/j.bushor.2019.07.004

van Esch, P., Cui, Y. (Gina), & Jain, S. P. (2021). Self-efficacy and callousness in consumer judgments of AI-enabled checkouts. *Psychology & Marketing*, 38(7), 1081–1100. https://doi.org/10.1002/mar.21494

Vargo. (2020, January 7). Vargo designs solutions for GAP Inc facilities in Arizona and the UK. Vargo Solutions. https://vargosolutions.com/vargo-designs-solutions-for-gap-inc-facilities-in-arizona-and-the-uk/

Vargo, S. L., & Akaka, M. A. (2009). Service-Dominant Logic as a Foundation for Service Science: Clarifications. *Service Science*, 1(1), 32–41. https://doi.org/10.1287/serv.1.1.32

Vargo, S. L., & Lusch, R. F. (2004). Evolving to a New Dominant Logic for Marketing. *Journal of Marketing,* 68(1), 1–17. https://doi.org/10.1509/jmkg.68.1.1.24036

Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Qi Dong, J., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research*, 122, 889–901. https://doi.org/10.1016/j.jbusres.2019.09.022

Vial, G., Jiang, J., Giannelia, T., & Cameron, A.-F. (2021). The Data Problem Stalling AI. 9.

Vidgen, R., Shaw, S., & Grant, D. B. (2017). Management challenges in creating value from business analytics. *European Journal of Operational Research,* 261(2), 626–639. https://doi.org/10.1016/j.ejor.2017.02.023

Vincent, J. (2018, May 8). Welcome to the automated warehouse of the future. The Verge. https://www.theverge.com/2018/5/8/17331250/automated-warehouses-jobs-ocado-andover-amazon

Wadhawan, N., & Seth, D. A. (2016). Technology Revolutionizing Retail Practices in Digital Era. Conscientious and Unimpeachable Technologies 2016, 60–62.

Walmart. (2021). Our History. Corporate - US. https://corporate.walmart.com/our-story/our-history

Weber, F. D., & Schütte, R. (2019). State-of-the-art and adoption of artificial intelligence in retailing. *Digital Policy, Regulation and Governance*, 21(3), 264–279. https://doi.org/10.1108/DPRG-09-2018-0050

Weightman, G. (2015, September 23). The History of the Bar Code. Smithsonian Magazine. https://www.smithsonianmag.com/innovation/history-bar-code-180956704/

Westerman, G., Bonnet, D., & McAfee, A. (2014). Leading Digital: Turning Technology into Business Transformation. Harvard Business Review Press.

Whetten, D. A. (1989). What Constitutes a Theoretical Contribution*? The Academy of Management Review,* 14(4), 490–495. https://doi.org/10.2307/258554

Wierenga, B. (2010). Marketing and Artificial Intelligence: Great Opportunities, Reluctant Partners. In J. Casillas & F. J. Martínez-López (Eds.), Marketing Intelligent Systems Using Soft Computing: Managerial and Research Applications (Vol. 258). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-15606-9

Wigand, D. (2017). Building on Leavitt’s Diamond Model of Organisations: The Organisational Interaction Diamond Model and the Impact of Information Technology on Structure, People, and Tasks. 10.

Wirth, N. (2018). Hello marketing, what can artificial intelligence help you with? International *Journal of Market Research,* 60(5), 435–438. https://doi.org/10.1177/1470785318776841

World Economic Forum. (2018). The Future of Jobs Report 2018. https://www.weforum.org/reports/the-future-of-jobs-report-2018

Wozniak, M., & Polap, D. (2020). Intelligent Home Systems for Ubiquitous User Support by Using Neural Networks and Rule-Based Approach. *IEEE Transactions on Industrial Informatics*, 16(4), 2651–2658. https://doi.org/10.1109/TII.2019.2951089

Wrigley, N., & Lowe, M. (2010). The Globalization of Trade in Retail Services (OECD Trade Policy Linkages and Services Division, p. 40). OECD. https://www.researchgate.net/publication/228710305_The_Globalization_of_Trade_in_Retail_Services

Xu, L. D., Xu, E. L., & Li, L. (2018). Industry 4.0: State of the art and future trends. International *Journal of Production Research*, 56(8), 2941–2962. https://doi.org/10.1080/00207543.2018.1444806

Xu, Y., Shieh, C.-H., van Esch, P., & Ling, I.-L. (2020). AI Customer Service: Task Complexity, Problem-Solving Ability, and Usage Intention. *Australasian Marketing Journal*, 28(4), 189–199. https://doi.org/10.1016/j.ausmj.2020.03.005

Yao, M., Jia, M., & Zhou, A. (2019). Applied artificial intelligence: A handbook for business leaders.

Yrjölä, M., Saarijärvi, H., & Nummela, H. (2018). The value propositions of multi-, cross-, and omni-channel retailing. *International Journal of Retail & Distribution Management*, 46(11/12), 1133–1152. https://doi.org/10.1108/IJRDM-08-2017-0167

Zentes, J., Morschett, D., & Schramm-Klein, H. (2012). Retail Formats – General Merchandise. In J. Zentes, D. Morschett, & H. Schramm-Klein (Eds.), Strategic Retail Management: Text and International Cases (pp. 49–69). Gabler Verlag. https://doi.org/10.1007/978-3-8349-6740-4_4

Zeta. (2020, February 20). The RealReal Boosts ROAS by 57% by partnering with Zeta. Zeta Global. https://zetaglobal.com/case-studies/case-study-the-realreal-boosts-roas/

Zhang, D., Pee, L. G., & Cui, L. (2021). Artificial intelligence in E-commerce fulfillment: A case study of resource orchestration at Alibaba's Smart Warehouse. *International Journal of Information Management,* 57, 102304. https://doi.org/10.1016/j.ijinfomgt.2020.102304

Zhou, J., Shafique, M. N., Adeel, A., Nawaz, S., & Kumar, P. (2017). What is Theoretical Contribution? A Narrative Review. *Sarhad Journal of Management Sciences,* 3(2), 261–271. https://doi.org/10.31529/sjms.2017.3.2.6

Zikmund, W. G. (2010). Business research methods. South-Western Cengage Learning.

Zolkiewski, J., Story, V., Burton, J., Chan, P., Gomes, A., Hunter-Jones, P., O'Malley, L., Peters, L. D., Raddats, C., & Robinson, W. (2017). Strategic B2B customer experience management: The importance of outcomes-based measures. *Journal of Services Marketing*, 31(2), 172–184. https://doi.org/10.1108/JSM-10-2016-0350

APPENDICES

Appendix A: Current studies in AI in retail

No	Title	Authors	Total Citations as of 29 June 21	Theoretical focus	Research Focus	Link to the retail value chain stage	Facing	Link to Leavitt Diamond Model	AI technology mentioned
1	The future of employment: How susceptible are jobs to computerisation?	(Frey & Osborne, 2017)	8403	Occupational choice, Skill demand; Technological change	Changing occupations with computerisation and AI technologies	No link	No link	Technology, People	Computerisation in general
2	The Future of Retailing	(Grewal et al., 2017)	961	Retail; Future technologies	The article focuses on the future of retail by highlighting five key areas, Technology, Visual display, Consumption and engagement, big data collection and analytics	Customer use and support	Customer-facing	Technology	AI in general
3	Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence	(Kaplan & Haenlein, 2019)	738	Internet of things; Big data; AI	Discussion on AI application	No link	No link	Technology	AI in general
4	The digitalisation of retailing: an exploratory framework	(Hagberg et al., 2016)	478	Retail; Digitalisation	This article addresses a significant and ongoing transformation in retailing and develops a framework	Store operations and sales	Customer-facing	Technology; Tasks	Technology in general
5	A Brief History of Artificial Intelligence: On the Past, Present, and Future of Artificial Intelligence	(Haenlein & Kaplan, 2019)	296	AI; Big data; Strategy	Review of AI history	No link	No link	Technology	AI in general
6	Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy	(Dwivedi et al., 2021),	285	AI, Research agenda	This article focuses on emerging AI challenges and opportunities across a variety of sectors, including retail	Store operations and sales; Customer support and end-use	Customer-facing	Structure, Technology, People and Tasks	AI in general

7	Value co-creation with Internet of things technology in the retail industry	(Balaji & Roy, 2017)	215	Marketing; retail management	Customers experience shopping with IoT technology	Customer use and support	Customer-facing	Technology	IoT, AI
8	Artificial Intelligence in Advertising How Marketers Can Leverage Artificial Intelligence Along the Consumer Journey	(Kietzmann et al., 2018)	111	AI; Marketing	AI application along the customer journey	Customer use and support	Customer-facing	Technology; Tasks	Multiple AI types
9	How Artificial Intelligence (AI) Is Reshaping Retailing	(Shankar, 2018)	103	AI; Retail	Resents a framework for understanding AI. This article also outlines how AI can be applied in retail.	Link to all stages	Link to all stages	Structure, Technology	AI in general
10	The future of in-store technology	(Grewal et al., 2020)	100	Retail; Future technologies	a conceptual framework for understanding new and futuristic in-store technology infusions	Store operations and sales	Customer-facing	Technology	None
11	The Evolution and Future of Retailing and Retailing Education	(Grewal et al., 2018)	95	Retail, Future Education	The article outlines retail innovations and how retail has evolved. Calls out new retail technologies that should be included in retail education, AI, Service robots, IoT, Blockchain,	No link	No link	Technology	AI in general
12	Applications of artificial intelligence in the apparel industry: a review	(Guo et al., 2011)	84	AI, Apparel industry	Review of AI literature in apparel	Design; Sourcing/Procurement; Manufacturing and assembly	Business-facing	Technology	Various AI types
13	Rulers of the world, unite! The challenges and opportunities of artificial intelligence	(Kaplan & Haenlein, 2020)	76	AI; Business	Analysis of AI using PESTEL	No link	No link	Economical	AI in general
14	A human-centric perspective exploring the readiness towards smart warehousing: The case of a large retail distribution warehouse	Mahroof, 2019)	68	Artificial Intelligence, Logistics; Technical readiness	The research explores the barriers and opportunities of AI within a major retailer's warehouse.	Inventory Management and Distribution	Business-facing	People; Technology; Tasks	AI in general
15	Artificial intelligence (AI) and its implications for market knowledge in B2B marketing	(Paschen et al., 2019)	67	Marketing; AI	describes the foundational building blocks of any artificial intelligence system and their interrelationships	No link	No link	Technology	AI in general

16	A GA-based optimisation model for big data analytics supporting anticipatory shipping in Retail 4.0	(Lee, 2017)	57	Retail, Big data	Optimisation model using Big data to support anticipatory shipping	Fulfilment	Custome r-facing	Technology	genetic algorithm (GA)-based optimisation mode
17	Artificial intelligence: Building blocks and an innovation typology	(Paschen et al., 2019)	51	AI, Information systems	AI building blocks	No link	No link	Technology	Multiple AI types
18	Autonomous Shopping Systems: Identifying and Overcoming Barriers to Consumer Adoption	de Bellis & Venkataramani Johar, 2020)	46	Artificial Intelligence; Consumers; Retail	Examining the barriers to adoption of autonomous systems	Store operations and sales; Customer support and end-use	Custome r-facing	People; Technology; Tasks	Virtual assistants
19	State-of-the-art and adoption of artificial intelligence in retailing	(Weber & Schütte, 2019)	32	Artificial Intelligence; Retail	The article shows the application of AI to different value-added core tasks depending on the area you apply it to	Link to all stages	Link to all stages	Tasks	AI in general
20	Indian shopper motivation to use artificial intelligence: Generating Vroom's expectancy theory of motivation using grounded theory approach	(Chopra, 2019)	29	Artificial intelligence; Consumer motivation; Retail	he findings indicate that Vroom's expectancy theory of motivation can be used to explain the motivation of young consumers to use AI tools to aid in taking shopping decisions.	Store operations and sales; Customer support and end-use	Custome r-facing	Technology, People	Chatbot, Augmented reality, Voice assistant
21	Shopping intention at AI-powered automated retail stores (AIPARS)	(Pillai et al., 2020)	24	Technology readiness; Consumers; Retail	The outcome of the study reveals that Innovativeness and Optimism of consumers affect the perceived ease and perceived usefulness.	Store operations and sales; Customer support and end-use	Custome r-facing	Technology, People	RFID, AR systems
22	Changing the game to compete: Innovations in the fashion retail industry from the disruptive business model	(Jin & Shin, 2020)	23	Business innovation disrupting the fashion retail industry	The study analyses how business-model innovations have disrupted the fashion retail industry	Inventory Management and Distribution	Business-facing	Technology	AI in general
23	Taking the fiction out of science fiction: (Self-aware) robots and what they mean for society, retailers and marketers	(Gonzalez-Jimenez, 2018)	22	Artificial Intelligence; Consumer; Retail	The article outlines examples of how human-robot interactions can be shaped with AI	No link	No link	People/Envi ronment	AI; Robots

24	Rising with the machines: A sociotechnical framework for bringing artificial intelligence into the organisation	(Makarius et al., 2020)	21	Artificial Intelligence; Organisational socialisation; Sociotechnical	Organisational socialisation approach to build an understanding of the process of integrating AI into the organisation.	No link	No link	All	AI in general
25	Chatbots in retailers' customer communication: How to measure their acceptance?	(Rese et al., 2020)	20	Artificial Intelligence; Consumers Acceptance	The study measured the customer acceptance of a chatbot at an online retailer	Customer use and support	Custome r-facing	Technology, People	Chatbots
26	Customer experiences in the age of artificial intelligence	(Ameen et al., 2021)	17	Artificial Intelligence; Consumer; Retail	AI-enabled customer experiences	Customer use and support	Custome r-facing	Technology; People	AI in general
27	Modelling wholesale distribution operations: an artificial intelligence framework	(Bottani et al., 2019)	16	Artificial Intelligence; Supply chain management; Wholesale	The study implements ANN's to test if out of stocks can be decreased	Inventory management and distribution	Business-facing	Technology	Artificial neural networks, Multiple neural networks
28	Speciesism: an obstacle to AI and robot adoption	(Schmitt, 2020)	13	AI, Research agenda	Research agenda proposal	Customer use and support	Custome r-facing	Technology	AI in general
29	Artificial intelligence applied to assigned merchandise location in retail sales systems	Cruz-Dominguez, O.; Santos-Mayorga, R.	8	Artificial Intelligence; Warehouse; Retail	The study simulated a neural network and generic algorithm to determine merchandise locations	Inventory management and distribution	Business-facing	Technology	Neural networks
30	How artificial intelligence will affect the future of retailing	(Shankar, 2018)	7	Artificial Intelligence; Retail	The article developed a framework to understand how a retailer may adopt AI and offers a future research agenda	Customer use and support	Custome r-facing	Technology; People, tasks	AI, Bots
31	Demand forecasting at retail stage for selected vegetables: a performance analysis	(Priyadarshi et al., 2019)	7	Artificial Intelligence; Retail	Comparison of different AI models to test the performance and accuracy of sales forecasts	Inventory management and distribution	Business-facing	Technology	AI, ANN, Support vector machines
32	Technology Revolutionizing Retail Practices in Digital Era	(Wadhawan & Seth, 2016)	4	Technology changing retail practices	Evolution of retail with digitalisation	No link	No link	Technology	Technology in general
33	Deep Store: Understanding Customer Behaviours in Unmanned Stores	(Guo et al., 2020)	3	Artificial Intelligence; Consumers	The article represents the usage of different technologies needed for a smart store	Store operations and sales; Customer support and end-use	Custome r-facing	Technology	IoT, AI

34	Artificial Intelligence in retail: The AI-enabled value chain	Our article (Oosthuizen et al., 2020)	3	Artificial Intelligence; Retail; Value chain	Presents a retail AI-enabled framework	Link to all stages	Link to all stages	Technology, Tasks	Various AI types
35	Artificial intelligence-driven music biometrics influencing customers' retail buying behaviour	(Rodgers et al., 2021)	3	Artificial Intelligence; Retail; Customer experience	The study shows how AI-influences music influences shopping behaviour in a store	Store operations and sales	Custome r-facing	Technology, People	Deep Learning, Machine Learning
36	Influence of technological advances and change in marketing strategies using analytics in retail industry	(Kaur et al., 2020)	3	Artificial Intelligence; Marketing	The study examines data analytics in retail to capture and retain customers through marketing and merchandising strategies	Store operations and sales; Customer support and end-use	Custome r-facing	Technology	Analytics, AI in general
37	Alexa, she's not human but horizontal ellipsis Unveiling the drivers of consumers' trust in voice-based artificial intelligence	(Pitardi & Marriott, 2021)	2	Artificial Intelligence: Technology adoption	The study shows an integrated approach for examining AI interactions and how to improve customers trust in an online setting	Customer use and support	Custome r-facing	Technology, People	VA
38	Clustering consumers' shopping journeys: eye-tracking fashion m-retail	(Tupikovskaja-Omovie & Tyler, 2020)	2	Customer behaviour; Fashion retailing; Mobile	This article represents a customer segmentation approach for customer shopping journey using mobile eye-tracking technology	Store operations and sales	Custome r-facing	Technology	Eye tracking glasses
39	Artificial intelligence and the new forms of interaction: Who has the control when interacting with a chatbot?	(Pizzi et al., 2021)	2	Artificial Intelligence; Consumer behaviour	The study examines how customers react when AI tools assist their choices	Customer use and support	Custome r-facing	Technology, People	Conversational AI
40	Self-efficacy and callousness in consumer judgments of AI-enabled checkouts	(Esch et al., 2021)	1	Artificial Intelligence; Shopping convenience; Consumers	The study examines data analytics in retail to capture and retain customers through marketing and merchandising strategies	Store operations and sales; Customer support and end-use	Custome r-facing	Technology, People	AI in general
41	Artificial intelligence in retail: applications and value creation logics	(Cao, 2021)	1	Artificial Intelligence; Value creation; Retail	five main strategies for AI-related data management	Link to all stages	Link to all stages	Technology	AI in general
42	Artificial intelligence in the fashion industry: consumer responses to generative adversarial network (GAN) technology	(Sohn et al., 2020)	1	Artificial Intelligence; Consumption; Consumer behaviour	This study evaluates the utility of GANs from consumers' perspective based on the the perceived value of GAN-generated product designs	Customer use and support	Custome r-facing	Technology	generative adversarial network

43	Usability and responsiveness of artificial intelligence chatbot on online customer experience in e-retailing	(Chen et al., 2021)	1	Retail; Chatbot; Customer experience	explores the role of AI chatbots in influencing the online customer experience and customer satisfaction in e-retailing.	Customer use and support	Custome r-facing	Technology, People	Chatbots
44	Artificial intelligence in retail: Benefits and risks associated with mobile shopping applications A	(Stanciu & Rîndașu, 2021)	0	Artificial Intelligence; Retail; Mobile	practical implications of using artificial intelligence (AI) based solutions in the case of retail mobile applications,	Customer use and support	Custome r-facing	Technology	AI, ML
45	Impact of artificial intelligence on impulse buying behaviour of Indian shoppers in fashion retail outlets	(Jain & Gandhi, 2021)	0	Artificial Intelligence; Fashion Retail	The impact of modern technologies which the retailers use to enhance sales and consumer engagement was studied.	Customer use and support	Custome r-facing	Technology, People	AI in general
46	Intelligent and efficient? An empirical analysis of human-AI collaboration for truck drivers in retail logistics	(Loske & Klumpp, 2021)	0	Information technology; Retail logistics	This study represents one of the first quantitative efficiency analyses of the impact of digitalisation on transport performance (i.e. truck driver efficiency). Furthermore, we build an econometric model combining behavioural aspects with actual technology usage in a real application scenario.	Inventory Management and Distribution	Business-facing	Technology, People	AI in general
47	The integration of artificial intelligence in retail: Benefits, challenges and a dedicated conceptual framework	(Anica-Popa et al., 2021)	0	Artificial Intelligence; Retail; Customer experience	AI benefits and associated risks for implementing AI in retail	Store operations and sales; Customer support and end-use	Custome r-facing	Technology	AI in general
48	The profound nature of the linkage between the impact of the used of artificial intelligence in retail on buying and consumer perceptions of artificial intelligence on the path to the next normal	(Purcărea et al., 2021)	0	Artificial Intelligence; Retail; Customer experience	The linkage between AI and consumers perception in a supermarket	Store operations and sales; Customer support and end-use	Custome r-facing	Technology	AI, VA's
49	Impact of artificial intelligence on impulse buying behaviour of Indian shoppers in fashion retail outlets	(Jain & Gandhi, 2021)	0	Impact of modern technologies such as artificial intelligence on impulse buying behaviour	Impact of modern technologies such as artificial intelligence on impulse buying behaviour	Customer use and support	Custome r-facing	Technology, People	Chatbot, virtual assistant, self-checkout, smart mirrors

Appendix B: Bibliometric mapping

To gain an understanding of the literature available, a bibliometric mapping was completed. Van Eck et al., 2010 defines bibliometric mapping as a “powerful tool for studying the structure and the dynamics of scientific fields”. Bibliometric analysis helps researchers analyse current trends in literature and motivates future research work (Muhuri et al., 2019, p. 0). The bibliometric maps were created to understand better literature available for the research constructs, namely, artificial intelligence or AI; Retail; and Value chain and help understand the gap in the literature.

To create the bibliometric maps, the web of science was used as a platform to create bibliographic database files. Web of Science provides comprehensive citation data for many academic disciplines. To create the database needed for bibliometric maps, an advance search was conducted on the web of science core collection database using keywords search term ALL=(“Artificial intelligence” OR “AI”) AND ALL=(“Retail”). The search rendered 926 publication results. Figure B.1 show the returned search results with citations.

	2017	2018	2019	2020	2021	Total	Average Citations per Year
Use the checkboxes to remove individual items from this Citation Report or restrict to items published between 1970 and 2021 Go	423	532	768	1350	991	6700	152.27
1. **Modeling supply chain dynamics: A multiagent approach** By: Swaminathan, JM; Smith, SF; Sadeh, NM DECISION SCIENCES Volume: 29 Issue: 3 Pages: 607-632 Published: SUM 1998	20	18	18	14	6	459	19.13
2. **CORPORATE DISTRESS DIAGNOSIS - COMPARISONS USING LINEAR DISCRIMINANT-ANALYSIS AND NEURAL NETWORKS (THE ITALIAN EXPERIENCE)** By: ALTMAN, EI; MARCO, G; VARETTO, F JOURNAL OF BANKING & FINANCE Volume: 18 Issue: 3 Pages: 505-529 Published: MAY 1994	21	20	21	30	9	386	13.79
3. **Multiple Antimicrobial Resistance in Plague: An Emerging Public Health Risk** By: Welch, Timothy J.; Fricke, W. Florian; McDermott, Patrick F.; et al. PLOS ONE Volume: 2 Issue: 3 Article Number: e309 Published: MAR 21 2007	16	13	13	13	6	279	18.60
4. **The Future of Retailing** By: Grewal, Dhruv; Roggeveen, Anne L.; Nordfalt, Jens JOURNAL OF RETAILING Volume: 93 Issue: 1 Special Issue: SI Pages: 1-6 Published: MAR 2017	3	27	83	101	59	273	54.60
5. **Plasmid replicon typing of commensal and pathogenic Escherichia coli isolates** By: Johnson, Timothy J.; Wannemuehler, Yvonne M.; Johnson, Sara J.; et al. APPLIED AND ENVIRONMENTAL MICROBIOLOGY Volume: 73 Issue: 6 Pages: 1976-1983 Published: MAR 2007	13	16	24	17	9	227	15.13
6. **Genetic algorithm-based heuristic for feature selection in credit risk assessment** By: Oreski, Stjepan; Oreski, Goran EXPERT SYSTEMS WITH APPLICATIONS Volume: 41 Issue: 4 Pages: 2052-2064 Part: 2 Published: MAR 2014	23	30	30	41	12	183	22.88

Figure B.1. Returned search results AI in retail

The research field of AI in retail is still young. The majority of articles were published in the past eight years from 2013, with a spike in AI and retail publications in 2020. Figure B.2 show the total publications dashboard.

Figure B.2. Total publication AI in retail

When looking at the subject publications, many (702) publications are in computer science, with 81 publications in business, 56 in management, and 55 in operations research. Figure B.3 show the number of articles by publication.

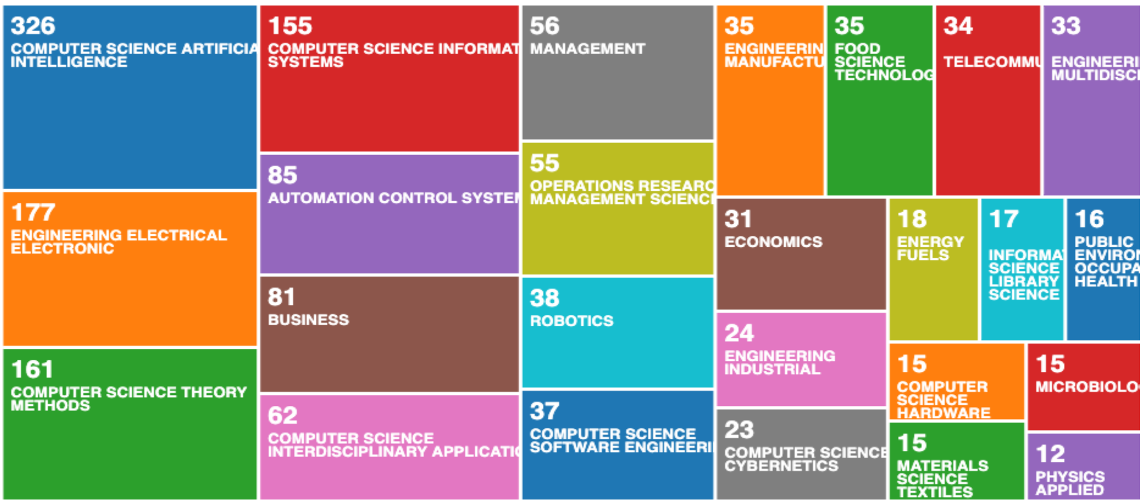


Figure B.3. Number of articles by publication

Once the data records terms were finalized, the full data record was downloaded into a plain text, tab-delimited file. To create the bibliometric map, the software tool VOSviewer was used. VOSviewer is a software tool for constructing and visualizing bibliometric networks. VOSviewer displays only the distance between two nodes indicating the relatedness of the nodes, and is suitable for visualizing large networks (van Eck & Waltman, 2010).

The first map is an analysis of the text data in the publications. Figure B.4 shows the relatedness of the nodes. Artificial intelligence and retail are on opposite ends of the map.

The first map is an analysis of the text data in the publications. Figure B.4 shows the keyword occurrences that indicate the number of documents in which the keyword occurs. The occurrence attribute indicates the number of documents in which a term occurs at least once (van Eck & Waltman, 2021). Artificial intelligence and retail are on opposite ends of the map.

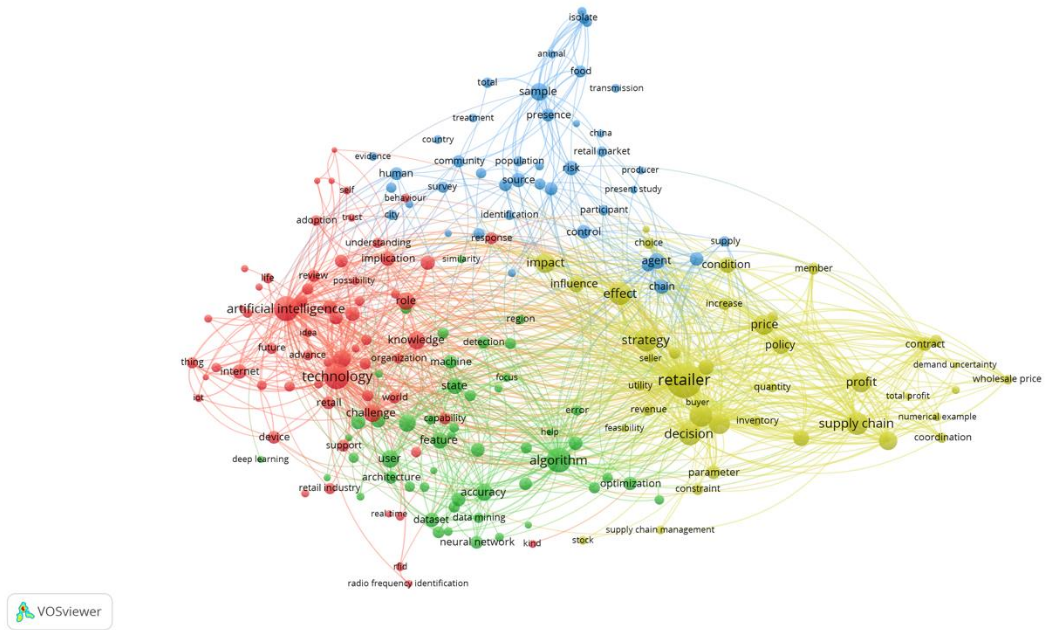


Figure B.4. AI in retail keyword cooccurrence relatedness of nodes

The following map is a keyword search by authors. Figure B.5 shows the bibliometric map of the authors keywords found during the identification process for all returned results for AI in retail literature. The keywords in the bibliometric map were extracted from author-supplied keyword lists of a publication (van Eck & Waltman, 2014, p. 4).

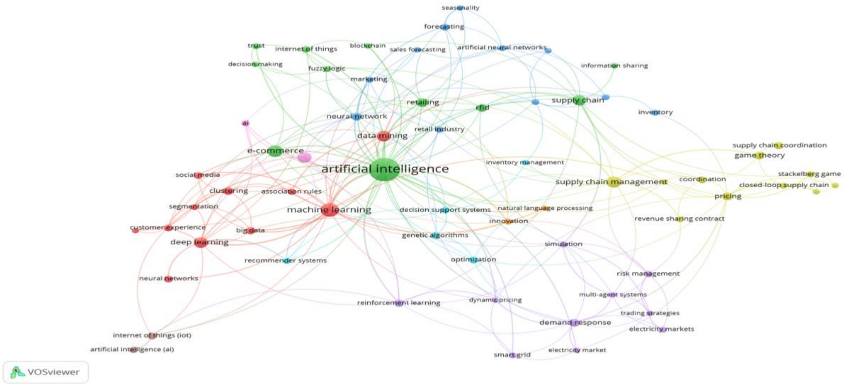


Figure B.5. AI in retail literature author keywords

The final map shows the number of authors in the AI in the retail field. Figure B.6 show the authors with two or more citation.

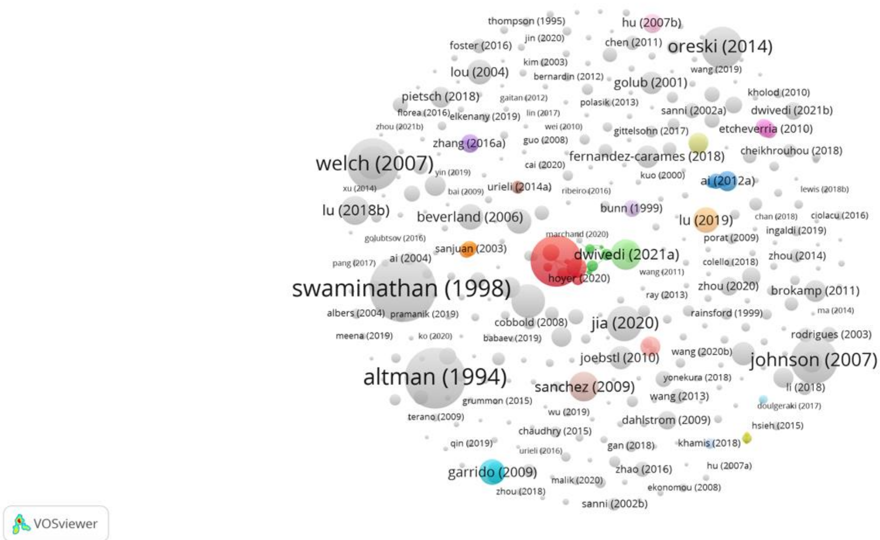


Figure B.6. Authors in the AI in retail literature field of study

Appendix C: Published article in Australasian Marketing Journal

ARTICLE IN PRESS

JID: AMJ [m5G;August 24, 2020;8:27]

Australasian Marketing Journal xxx (xxxx) xxx

Contents lists available at ScienceDirect

Australasian Marketing Journal

journal homepage: www.elsevier.com/locate/ausmj

Artificial intelligence in retail: The AI-enabled value chain

Kim Oosthuizen[a], Elsamari Botha[b,*], Jeandri Robertson[c], Matteo Montecchi[d]

[a] University of Stellenbosch Business School, Cape Town, South Africa
[b] Department of Management, Marketing and Entrepreneurship, University of Canterbury; and University of Stellenbosch Business School, Cape Town, South Africa
[c] School of Management Studies, Marketing Section, University of Cape Town, Cape Town, South Africa
[d] King's Business School, King's College London, London, United Kingdom

ARTICLE INFO

Article history:
Received 7 February 2020
Revised 24 July 2020
Accepted 28 July 2020
Available online xxx

1. Introduction

Traditional retailers' business models are facing disruption by new entrants who can deliver greater value to customers more efficiently. In recent years, authors have argued that the traditional value chain drives inefficiencies (Begley et al., 2018) and that the value chain is shortening as manufacturers, third parties and customers are increasingly engaging with customers directly (Reinartz et al., 2019). These inefficiencies combined with the inability to adapt to a changing competitive landscape leaves traditional retailers vulnerable to disruption from market entrants. To remain competitive and survive in an ever-changing and diversified customer market, retailers need to become leaner (Campbell et al., 2020), more agile (Goworek, 2014), and innovate their value chain by adopting new technologies (Lee et al., 2018). Of the new technologies that are impacting the retail industry, AI has been earmarked as the most transformative (Kietzmann et al., 2018; Lee et al., 2018; Silva et al., 2019). Yet while there is great excitement about artificial intelligence (AI), it has yet to fully deliver on its promise (Ransbotham et al., 2017) and academics and practitioners are in the early stages of understanding the application of AI (Van Esch et al., 2020). This article introduces a conceptual framework to understand the role that AI can play in the retail value chain by proposing an AI-enabled retail value chain.

As a starting point, we provide a brief overview of the traditional retail value chain and the activities, stakeholders, and technology involved at each stage. The disruption of the retail industry is then explained, followed by a particular focus on the role that AI has played in disrupting this industry. We then map various AI technologies based on Gartner's (Sicular et al., 2019), to each stage in the value chain and show that some AI technology investments can serve multiple purposes in the value chain. Then, we use Christensen's jobs-to-be-done approach (Christensen, 2003; Christensen et al., 2016a; Christensen et al., 2016b) to better understand the value of AI in the retail industry. The main aim of this article, therefore, is to better understand what an AI-enabled retail value chain would look like.

This article provides two important contributions to the emerging literature on AI and its implementation in marketing and retailing. First, we show how AI technologies can be used across various retail value chain activities. While several authors have addressed the relevance of AI to business in general (Kietzmann et al., 2018; Paschen et al., 2019a; Poole and Mackworth, 2010; Ransbotham et al., 2017; Van Esch et al., 2019), the strategic role and implementation of AI in retailing organizations has been subject to limited critical scrutiny (Van Esch, 2019). By mapping specific AI technologies against the retail value chain, we provide retail managers with some guidance regarding which AI technology investments to prioritize, or how current AI investments can be leveraged.

Second, while authors argue that the retail value chain needs revisiting because of new technologies (Hagel et al., 2016; Reinartz et al., 2019), no academic studies, to the knowledge of the authors, have suggested exactly how the retail value chain should change. Guided by the jobs-to-be-done approach to innovation (Christensen et al., 2016a; Christensen et al., 2016b) we identify four key roles for AI solutions in the retail value chain: knowledge and insight management, inventory management, operations optimization, and customer engagement. This approach

* Corresponding author.
E-mail addresses: kim.botes03@gmail.com (K. Oosthuizen), elsamari.botha@canterbury.ac.nz (E. Botha), jeandri.roberston@uct.ac.za (J. Robertson), matteo.montecchi@kcl.ac.uk (M. Montecchi).

https://doi.org/10.1016/j.ausmj.2020.07.007

Please cite this article as: K. Oosthuizen, E. Botha and J. Robertson et al., Artificial intelligence in retail: The AI-enabled value chain, Australasian Marketing Journal, https://doi.org/10.1016/j.ausmj.2020.07.007

is customer-centric (Bettencourt and Ulwick, 2008), not Tayloristic and process-driven and, therefore, better suited to the complex nature of business amidst new technologies (McChrystal et al., 2015). Contrary to the more traditional silo-mentality and linear view of the value chain, we argue that AI solutions can perform multiple roles simultaneously, thus establishing interconnectivity between the different value chain activities. First, however, the digital disruption of the traditional retail value chain is discussed.

2. Digital disruption of the traditional retail value chain

In his seminal work, Michael Porter (1985) used the term value chain to describe a set of activities performed to design, produce, market, deliver, and support products within businesses (Hagel et al., 2016). Often referred to as the supply chain (Levy and Weitz, 2009), the value chain is a set of processes that deliver value across primary activities (for example, inbound logistics, operations, outbound logistics, marketing and sales, and service), and secondary activities (including firm infrastructure, human resource management, technology development and procurement). The activities in the traditional value chain move in a sequence of linear steps, which facilitates the process from product design, to the point of consumption (Reinartz et al., 2019). In retailing, the value chain encompasses all the stakeholders and processes needed for retailers to deliver an end product or service to a customer (Levy and Weitz, 2009). From the supplier, to the manufacturer, to the retailer - each stakeholder in the value chain contributes toward adding value to the customer. Table 1 details the stages involved in the traditional retail value chain, including the objectives and typical activities in each stage (Hagel et al., 2016; Rieple and Singh, 2010). The stakeholders and technologies typically involved in each stage have been included.

New digital technologies have, however, disrupted the traditional retail business model by changing marketplaces from brick and mortar only to omnichannel, which significantly alter the customer purchase journey (Bolton et al., 2019; Carlsson, 2018; Van Esch et al., 2019a and b). Customers are more connected than ever (Kietzmann et al., 2011), and the transformation from store to omnichannel retailing has elevated their service expectations (Oh and Polidan, 2018). As the rate with which these new technologies enter the market increases (Brynjolfsson and McAfee, 2016; Gupta, 2018), the accelerated rate of change blurs the market boundaries and holds unpredictable consequences for retailers (Day and Schoemaker, 2019). For instance, innovative and fast-growing digital entrants like Alibaba and Amazon, have already adversely affected traditional retailers like Toys 'R'Us and Radioshack, by using their digital resources to not only disrupt the retail industry but also seemingly unrelated industries, like banking and global shipping (Verhoef et al., 2019).

As new digital technologies continue to transform the retail industry (Hagberg et al., 2016; Romero and Martínez-Román, 2015; Van Esch et al., 2019), the retail value chain needs to evolve with it (Fiorito et al., 2010). However, majority retailers still employ the traditional value chain, or variations thereof (like the introduction of multiple channels to serve customer needs), which holds the following four risks. First, while each stage of the retail value chain adds value, it also adds complexity by increasing the number of stakeholders and their accompanying support structures involved. Complicated value chains inhibit retailers to understand and swiftly respond to customer preferences (Hagel et al. 2016). Second, various stakeholders are likely to use their own platforms and software, making it difficult to integrate systems and manage data. Legacy systems often inhibit organizations' agility to respond to changing customer needs and use the data for competitive advantage (Westerman et al., 2014). The ability to manage mass amounts and different sources of data are critical to a company's success (DalleMule and Davenport, 2017; Sankaran et al., 2019), and data-driven decisions are becoming increasingly important in supply chains (Sankaran et al., 2019). Third, the more complex and long the value chain is, the more expensive products and services become, and the longer it takes to reach customers. Finally, overly complex value chains leave organizations vulnerable to digital disruption from smaller, more agile firms that leverage new technologies to reduce costs and scale up quickly (Gupta, 2018; Verhoef et al., 2019).

According to Ransbotham et al. (2017) expectations for the commercial application of AI in business, particularly in retailing, are sky-high. While there are, however, existing analytical tools for managers to gauge AI's influence on the retail and other industries (U Paschen et al., 2019a), how to create and leverage AI's value for commercial advantage in the value chain still seems complex to most. To assist in this delineation, the following section explicates what exactly AI is and how it is currently applied in retailing.

3. Artificial intelligence in the retail value chain

3.1. Artificial intelligence

Most extant conceptualizations of AI make reference to computer systems with human-like intelligence (Wierenga, 2010), which encompasses these systems' abilities "to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Kaplan and Haenlein, 2019: 17). In their definition, the Oxford Dictionary includes tasks such as visual perception, speech recognition, decision-making, and the translation between languages, with the Merriam-Webster Dictionary emphasizing that AI imitates intelligent human behavior. Poole and Mackworth (2010: 3) offer a slightly nuanced explanation by framing AI as "computational agents that act intelligently". This definition describes AI as agents capable of perceiving an environment in order to take action, with the goal being to maximize the likelihood of achieving success (Paschen et al., 2019a). From a systems perspective, the definition also implies a rational view of AI, where an AI system would, given what it knows, act to achieve the best possible outcome (Paschen et al., 2019a).

For the purposes of this paper, we adopt the definition by Poole and Mackworth (2010), as it highlights two conceptual delineations. First, it highlights the different evolutionary stages of AI (Haenlein and Kaplan, 2019). What might have been considered intelligent behavior displayed by a machine five years ago, is now hardly noteworthy. Three stages of AI are differentiated: artificial *narrow* intelligence (applied, below human-level AI, e.g., Siri voice recognition), artificial *generalized* intelligence (strong, human-level AI, e.g., Siri developing the ability to autonomously perform tasks like driving a car), and artificial *superintelligence* (conscious/self-aware, above human-level AI, e.g., Siri developing superhuman capabilities to instantaneously solve complex problems). Most of the commercial AI technologies available today are classified as "narrow" and almost all of the AI technology to be integrated into business in the next ten years will be "narrow" or "applied" (Kelly, 2017; Marr, 2017). For example the use of AI to create ads (Bakpayev et al., 2020). This applies to retailing as well.

The second defining characteristic highlighted in the Poole and Mackworth (2010) definition is the notion that AI represents knowledge, expertise, and intuition to solve problems. AI requires tailored knowledge to be built into a "carefully constructed system" (Kaplan, 1984: 52), where the storage of past knowledge should reflect experiences that would inform subsequent intelligent behavior (Paschen et al., 2019a). In AI systems, these knowledge representations could include inputs (structured and unstructured data); processes (machine learning); or self-generated AI-

Please cite this article as: K. Oosthuizen, E. Botha and J. Robertson et al., Artificial intelligence in retail: The AI-enabled value chain, Australasian Marketing Journal, https://doi.org/10.1016/j.ausmj.2020.07.007

Table 1
Traditional Retail Value Chain

Retail Value Chain Stages	Activities	Stakeholders	Key Driver	Decision	Outcome	Technology Application Examples
Design	Design initiation, Design concept; Decision making process; Technical design	Retail; Manufacturer; Suppliers; Customers	Product trends; Customer needs; Bring new product to market quicker; Market research; Product quality	Which products to design; Product specification; Materials	Pattern Design and specifications; Productions planning and control; Garment evaluation	CAD system; Fabric quality checking; Online product searches
Sourcing/Procurement	Planning and production control; Purchasing or building inventory	Retailer; Manufacturer; Suppliers	Tailoring assortment for customer needs; Understanding customer segments; Product selection; Price negotiation; Liaising with suppliers	Which products will fulfil customer needs? When is the product needed in store? Buy quantity; Align to budget; Which supplier or manufacturer?	Sales budget planning; Merchandise strategy; Merchandise financial planning; Assortment planning; Supplier/Manufacturer selection; Order placement	Assortment planning; Merchandise financial planning; Size profile optimization; Excel
Manufacturing and assembly	Cutting, Sewing, Finishing, Packing, Acquiring, Storing and preparing raw materials	Manufacturer; Supplier; Shipping	Accurate forecasting; One-time ordering; Product flow visibility; Product quality	Cutting; Sewing; Finishing and distribution; Productions scheduling; Factory management; Quality checking	Cutting quantity; Job scheduling; Assembly line; Fabric laying; Cutting; Overall handling; Workforce planning	ERP systems; Assembly; Work force scheduling; Materials management
Inventory management and distribution	Managing and distributing products to be sold	Retail; Suppliers; Logistics; Distribution	End-to-End inventory visibility; Consistent and accurate sales and inventory forecasting; Monitoring product deliveries	Monitoring deliveries; Monitoring inventory; Scheduling DC to store deliveries	Movement of products from manufacturer to DC or store sales forecasting; Allocation to stores; Forecasting; Determining replenishment information; Controlling inventory levels; Workforce planning	Product information management; Order processing; Demand planning; Product allocation
Store operations and Sales	Managing point of sale and executing purchase transition	Retail; Suppliers; Logistics; Customer; Competitors	Performance management; Price and markdown optimisation; Monitoring stock levels	Maximising sales; Minimising markdowns; Managing product life cycle; Price point management; Customer service	Promotions and markdown planning; Reordering; Key products; Reverse logistics; Repairs, returns and maintenance support; Traffic management	Pricing management; Promotional planning; Product lifecycle management; POS system
Fulfilment	Delivering products to the customer	Retail; Suppliers; Manufacturer	Matching demand to product supply	Managing out of stocks; Maximising sales; Managing inventory; Reorder negotiation	Product replenishment; Logistics management; Movement of products to stores; Forecast accuracy; Inventory placement optimisation for omni fulfilment; Workforce planning	Demand prediction, inventory management; Ordering items
Customer use and support	Helping customers maximise value; Using and maintaining products	Retail; Customer; Logistics	Offering customers personalised or customized offerings	Identify high value customers and products; Supporting customer queries	Satisfied customers; Personalised offerings; Product recommendations	Online platform; POS systems; CRM management

SOURCE: Adapted from Cammett, 2006; Hagel et al., 2016; Lee et al., 2018; Michael, 1985; Reinartz et al., 2019; Rieple & Singh, 2010

Table 2
Example applications of Retailers' AI Technology in the Value Chain

Value Chain Stage	Retailer	AI Technology (Gartner Hype Cycle)	Detail of Technology Use
Design	Adidas	Machine learning	Using Machine learning Adidas is using a "speed factory" to help customers design their own personalised shoes and making them in 24 hours and shipping to customers
Sourcing/Procurement	Simons	Insight engines	Simons implemented analytics for improved insight on projected demand and inventory optimization recommendations that get the right product to the right store proactively
Manufacturing	Mohammadi Fashion Sweaters	Intelligent applications	AI enabled sewing machines that knit sweaters
Inventory management and distribution	ThredUp	Deep learning	Scanning close to 100 million unique inbound items via image recognition enabling automated visual tagging of products and assigning a unique item code
Fulfilment	The Home Depot	Edge AI	The Home Depot Inc. is connecting in-store robotics with an intelligent enterprise approach. It is using drones and robotics to create an efficient in-store experience that delights customers and provides faster order fulfillment
Store operations and Sales	Sephora	Augmented Intelligence	The app allows customers to try products virtually via augmented reality. The tool scans a customer's face, figures out where their lips and eyes are then matches colours and suggests products for consumers to buy.
Customer use and support	Ikea	Augmented Intelligence	The augmented reality helps the customer virtually "place" true to scale 3D furniture in their home.

SOURCE: Adapted from Araujo, 2019; de Leon, 2019; Emont, 2018; Galer, 2018; Ikea, n.d.; RIS, 2020; Sephora, 2017

output (robotics) (Paschen et al., 2019a, Paschen et al., 2019b). As AI continuously advances, our understanding of its various applications similarly needs to develop at a breakneck pace. Research into AI and its implications for business has burgeoned with studies looking at AI in recruitment (Black and Van Esch, 2020; Van Esch et al., 2019, 2020; Van Esch & Black, 2019) and marketing (Bakpayev et al., 2020, 2020; Mogaji et al., 2020; Paschen et al., 2020; Xu et al., 2020, 2020) amongst others. Feng *et al.* (2020) provide a summary of all the key AI-related studies in marketing. The following section looks at the application of AI technologies in retail in particular, in order to better understand their role in the retail value chain.

3.2. AI in retail

Although AI technologies have advanced in recent years, AI still remains in its infancy (Bughin et al., 2017). A vast majority of retailers have started testing the possibility of AI, yet many retailers are missing the full benefit of scaling the technology throughout the value chain (Standish and Ganapathy, 2020). Many AI applications, already available or under development, contribute to retailers' confusion and frustration with regards to which AI technologies to invest in. To assess the potential application of AI-enabled solutions across the various retail value chain activities, this section first focuses on providing an overview of where AI is *currently* being applied in retail.

To develop an understanding of the *current* application AI technologies used in retailing, we first reviewed the 2019 Gartner hype cycle for artificial intelligence report (Sicular et al., 2019), focusing on the AI technologies predicted to reach mainstream adoption in the next five years. The report examines trends and innovations in the AI sector and classifies the different AI applications (Sicular et al., 2019). These include speech recognition, graphic processing unit (GPU) accelerators, robotic process automation software, artificial intelligence (AI)-related consulting and system integration (C & SI) services, augmented intelligence, chatbots, machine learning, deep learning, edge AI, intelligent applications, virtual personal assistant (VPA)-enabled wireless speakers, virtual assistants, field-programmable gate array (FPGA) accelerators, computer vision, insight engines, data labelling and annotation services, and automated machine learning (AutoML) (Sicular et al., 2019).

Using the retail value chain presented in Table 1 to better understand the possible role of AI therein, we identified retailers who currently apply AI technologies in their value chain. Table 2 illustrates examples of retailers applying various AI technologies throughout the value chain.

Retailers are already beginning to apply AI applications in parts of the value chain (Bughin et al., 2017). However, both researchers and practitioners are only in the early stages of fully understanding the application of AI (Van Esch et al., 2020). And as is evidenced in Table 2, some AI applications were used for more than one value chain activity. For example, Augmented Intelligence was used for store operations and sales by one retailer, and customer use and support by another. This prompted the authors to take a broader view of where each AI technology can be applied in the retail value chain.

While an understanding of current application of AI in retail can help identify current gaps in its use, it does not provide insight into its most effective use in the retail value chain. To further develop our understanding of the opportunities and address this gap, we next use Clayton Christensen's (2003) jobs-to-be-done approach as a guideline to identify four conceptual dimensions which highlight how AI can best be applied to the retail value chain.

3.3. Reimagining AI in the retail value chain: a jobs-to-be-done approach

Using a customer-centric innovation view to understanding value (Bettencourt and Ulwick, 2008), the jobs-to-be-done approach was developed by Clayton Christensen in his 2003 book, *The Innovator's Solution*, and later expanded upon in *Competing Against Luck* (Christensen et al., 2016a). The theory proposes a group of principles that explain how to make marketing more effective and innovation more predictable by focusing on the customer's jobs to be done. Christensen et al.'s (2016a) approach is based on the idea that, in order to stimulate the effective development and implementation of innovation, companies should focus on the key goals of a product or service. For example, when considering how to best improve a razor blade, companies should be less concerned with improving the product itself (e.g., adding more blades), and more concerned with what "job" the razor blades do (e.g., quick and easy grooming). As an example, Philips recently presented their OneBlade range of razor blades, that not

Please cite this article as: K. Oosthuizen, E. Botha and J. Robertson et al., Artificial intelligence in retail: The AI-enabled value chain, Australasian Marketing Journal, https://doi.org/10.1016/j.ausmj.2020.07.007

only shaves, but also trims and styles any length of hair for multiple looks (Philips, 2020). In essence, Christensen et al. (2016a) argue that people 'hire' products and services to get jobs done, and companies can innovate through doing those jobs better. Each job can be broken down into various steps or stages of execution, with validating questions to assess the best job fit at each stage (Bettencourt and Ulwick, 2008).

We argue that this approach can successfully be applied to not only final products and services, but also to the application of technology like AI in the workplace. Better understanding the jobs-to-be-done by AI technologies will increase the value it delivers to the company. Following the job mapping approach by Bettencourt and Ulwick (2008), the authors iteratively followed a customer-centric validation process, guided by the retail value chain processes as a reference point, to conceptually cluster what jobs AI can perform in the retail value chain. From this perspective four job dimensions emerged, which are discussed in greater depth in the following sections:

(1) *Knowledge and insight management AI technologies* refer to the ability to provide insights by managing, sharing, using, creating and processing information.

(2) *Inventory management AI technologies* refer to those that assist in the process of balancing demand to supply over large assortments to meet customer needs and financial objectives.

(3) *Operations optimization AI technologies* help retailers operate effectively and efficiently by minimising costs and maximising operational capabilities.

(4) *Customer engagement AI technologies* enable retailers to build relationships with their customers.

Table 3 details current AI technologies that fulfil these four 'jobs-to-be-done' dimensions set against the traditional stages of the retail value chain. Each of these four dimensions of AI applications in the retail value chain is now discussed in the following section.

3.3.1. Knowledge and insight management

Knowledge and insight management AI technologies provide insights throughout the value chain by managing, sharing, using, creating and processing information. Data is one of the foundations of AI (Haenlein et al., 2019), and the effective translation of that data into knowledge is key to its success. This dimension includes the process of transforming structured and unstructured data inputs into outputs that contribute to the organization's knowledge base. Paschen et al. (2019a) refer to this as the building block of AI. Current examples include deep learning, intelligent applications, and insight engines amongst others. The importance of transforming data into knowledge has been stressed by various authors (Paschen et al., 2019a; Black and Van Esch, 2020). Although there is more data available than ever before, only a fraction is integrated and analyzed within businesses (Chen et al., 2016). While some companies use data to create a competitive advantage, many businesses fall short of gaining real insights from their data. This can mainly be ascribed to big data requiring powerful technologies, computer processing power, skilled personnel and predictive models to crunch enormous amounts of data (Djafri et al., 2018; Gupta, 2018).

The analysis, processing and interpretation of data is a time-consuming activity in the retail value chain; thus, more sophisticated AI technologies can be utilized to reduce the shortcomings of human efforts (Chen et al., 2016; Gupta, 2018; Sivarajah et al., 2017). Insight engines can anticipate future customer product needs and assist retailers in sourcing optimal assortments for their customers. Gaining knowledge and insights from value chain data should, therefore, be a key motivator to implement AI technologies in the retail value chain. However, for AI to reach its full potential, siloed legacy IT systems should be replaced with robust and scalable technology (Wirth, 2018). Therefore, the current linear approach to the retail value chain is not conducive to the advanced knowledge and insight management available through AI technologies.

3.3.2. Inventory management

Retailers have two main inventory management objectives: first, to buy products to fulfil customers' requirements; and second, to plan the inventory flow to maximise profits (Fairhurst and Fiorito, 1990). As retailers are always trying to match supply to demand, they are continually revising their sales forecasts to anticipate demand throughout the value chain (Goworek, 2014). To achieve the required forecasting capabilities, they need very specific sources of knowledge and insight. AI technologies can assist in the process of balancing demand and supply over large assortments to meet the customers' needs and the company's financial objectives. Current AI applications in this category are those that can drive lower inventory levels, anticipate future demands and create localised assortments leading to reduced working capital for retailers (Chao et al., 2019; Chuprina, 2019; Marr, 2018). These AI solutions include chatbots, insight engines, intelligent application, machine learning and virtual assistants.

AI can furthermore assist retailers in streamlining inventory management by predicting demand, keeping popular items stocked on shelves, and using clustering technologies to anticipate future customer requirements. Machine learning, deep learning and intelligent applications could match supply to demand by using multiple data sources and adjusting demand accordingly (Bughin et al., 2017). Predictive inventory management could drive improvements in forecast accuracy and optimize the inventory throughout the retail value chain, leading to increased profits and cost-saving for the retailer (Petropoulos et al., 2018). The eCommerce retailer, Otto Group, has for example reduced their out-of-stock rate by 80% by using predictive machine learning applications, which also boosted revenue, increased margins and assisted to respond to market shifts (Trotter, 2018).

3.3.3. Operations optimization

AI applications assisting with operations optimization are designed to improve operations efficiently and effectively by minimising cost and maximising operational capabilities (Li et al., 2017). Inefficient operations slow down the movement of products through the value chain, moving the customer further away from a successful purchase (Rieple and Singh, 2010). AI applications for this purpose, include AI-related C&SI services, computer vision, deep learning, Edge AI, intelligent applications, machine learning robotic, process automation and virtual assistants which all shorten the value chain by improving production speed and managing inventory flow to the customer.

Various authors agree that streamlining operational processes creates efficiencies throughout the retail value chain (Bughin et al., 2017; Li et al., 2017; Marr, 2019; Daugherty and Wilson, 2018). For example, JD.com, one of China's largest retailers, has introduced AI to drive efficiencies in their operations (Marr, 2019). The introduction of the AI applications allowed the retailer to deliver 92% of their orders on the same or next day (Trotter, 2018). Nike implemented augmented intelligence to design customised shoes for its customers, and the end-to-end process only takes two weeks from design to customer delivery (Chao et al., 2019). Optimizing operations can offer unexpected benefits by increasing operational efficiency, increasing agility and speed across the retail value chain. These improvements should be the driving force behind implementing AI in retail operations.

Please cite this article as: K. Oosthuizen, E. Botha and J. Robertson et al., Artificial intelligence in retail: The AI-enabled value chain, Australasian Marketing Journal, https://doi.org/10.1016/j.ausmj.2020.07.007

Table 3
AI jobs-to-be-done in the Retail Value Chain

		Current applications of AI in the retail value chain						
Jobs to be done area of application	**Objective**	**Design**	**Sourcing/ Procurement**	**Manufacturing and assembly**	**Inventory management and distribution**	**Store operations and Sales**	**Fulfilment**	**Customer use and support**
Customer engagement	To build customer trust through personalisation	Machine Learning	Deep learning			AI-related C&SI Services; Augmented intelligence; Chatbot; Computer vision; Deep learning; Intelligent applications; Machine learning; Virtual assistant		Augmented intelligence; Chatbot; Computer vision; Deep learning; Edge AI; Insight engines; Machine learning; Speech recognition; Virtual assistant
Inventory Management	Predict demand close to supply by anticipating customer needs and achieving financial objectives		Intelligent applications		Intelligent applications; Machine learning	Chatbot; Virtual assistant	Insight engines; Intelligent applications; Machine learning	
Operations optimization	Operating efficiently and effectively by minimising cost and maximising operational capabilities		Robotic process automation software	AI-related C&SI services; Deep learning; Intelligent applications	Deep learning; Edge AI; Robotic process automation software	AI-related C&SI services; Computer vision; Edge AI; Intelligent applications; Machine learning; Robotic process automation software; Virtual assistant	Edge AI	
Knowledge and insight management	Ability to provide insights by managing, sharing, using, creating and processing information	Deep learning; Insight engines	Deep learning; Insight engines		Insight engines	Deep learning; Edge AI; GPU accelerators; Insight engines		AI-related C&SI services; Insight engines; Intelligent applications

Please cite this article as: K. Oosthuizen, E. Botha and J. Robertson et al., Artificial intelligence in retail: The AI-enabled value chain, Australasian Marketing Journal, https://doi.org/10.1016/j.ausmj.2020.07.007

3.3.4. Customer engagement

The value of using AI in customer-facing activities is well documented and Xu *et al.* (2020) recently provided a definition of AI in the context of customer service as "a technology-enabled system for evaluating real-time service scenarios using data collected from digital and/or physical sources in order to provide personalized recommendations, alternatives, and solutions to customers' enquiries or problems". To create a customer-centric value chain, retailers need to exceed customer expectations to survive in a competitive market. To deliver seamless shopping experiences across all channels, retailers need to build connections with their customers (Araujo, 2019). Therefore, AI technologies for customer engagement in the retail value chain are predominantly focused on the customer journey, enabling customer engagement, enhanced customer service, and sales support functions (Kaplan and Haenlein, 2019). As per Table 3, the majority of retailers currently focus on AI applications that would facilitate customer engagement. Retailers are utilizing AI applications to connect and build relationships with customers by personalizing their product recommendations and purchases, helping them find their way around the store, and answering product-related questions in real time using apps (Morgan, 2019; Standish and Ganapathy, 2020). A common example of such personalization is the use of chatbots to reduce customer service costs and speed up customer response time to queries (Reddy, 2017).

Current AI technologies that assist retailers in engaging with customers across the retail value chain (and not only in the final stages of the value chain) include speech recognition, robotic process automation, AI-related C&SI services, augmented intelligence, chatbots, computer vision deep learning, Edge AI, insight engines, intelligent applications, machine learning, speech recognition and virtual assistants. At retailer Sephora, for example, in-store employees are equipped with handheld devices to scan a customer's face, creating a personalized cosmetic shade to match the customer's complexion. The shade matching creates a unique code enabling the customer to personalize purchases across all channels (Milnes, 2016). The North Face, a retailer of technical outerwear, utilizes augmented intelligence to help consumers find clothing and apparel suited to specific weather conditions (Trotter, 2018). These customer engagement AI applications are building customer loyalty through personalization, moving away from the purely transactional towards a more customer-centric approach.

4. The AI-enabled retail value chain framework

In the previous section, we used the jobs-to-be-done approach (Christensen et al., 2016a; Christensen et al., 2016b) to better understand how AI can be successfully applied to the retail value chain. We conceptually proposed four AI technology dimensions, which fulfil the majority of the roles in the "traditional" retail value chain. The majority of current AI applications are narrow in nature (Marr, 2017) and are being implemented in some offerings and processes (Ransbotham et al., 2017). However, we suggest that various AI applications, such as machine learning, intelligent applications, Edge AI and deep learning, can undertake multiple tasks across the retail value chain. Retail managers would therefore get the greatest return on investment in investing in these AI technologies.

When applied more generally to the retail value chain, the four dimensions identified in section 3.3 can be represented as an improved value chain that stands in contrast to the silo mentality and linear process proposed in many traditional retail value chains (see Figure 1). The process contained within the AI-enabled retail value chain framework is iterative and agile, which enables real-time data flows.

The dimensions in the AI-enabled retail value chain framework are not mutually exclusive. As the backbone of any AI implementation, *knowledge and insight management* provides insights throughout the value chain by managing, sharing, using, creating and processing information. Its objective is to generate knowledge and insights in support of all value chain activities. The appropriate use of AI technologies provides responsive R&D, dynamic price recommendations, and the extensive processing of transactional data. By collecting and analysing data across various data sources, the AI applications can anticipate future product and customer needs.

AI-enabled *customer engagement* retail activities include a myriad of functions geared toward not only optimizing customer interactions, but building customer relationships. For example, these functions include supporting customers to navigate the store, answering questions and creating personalized product recommendations. Retailers investing in customer-facing AI technologies are creating a unique competitive advantage in the market. Technological innovations such as AI help new entrants to seamlessly move through the value chain stages in the design, manufacture, commercialization, distribution and support of products - enabling them to connect with their customers.

In *inventory management*, AI can assist retailers in matching supply and demand by using multiple data sources and adjusting demand accordingly through the implementation of machine learning, deep learning, and other AI intelligent applications. Predictive inventory management could drive improvements in forecasting accuracy and optimizing inventory throughout the retail value chain, which could lead to increased profits and cost-saving for the retailer. Retailers that want to benefit from this category of AI applications need to work towards identifying employees' capability to work alongside intelligent applications (Black and Van Esch, 2020).

Optimizing operational efficiencies by streamlining processes with AI applications, can remove silos throughout the value chain. Major manufacturers and retailers are already using AI-based technologies throughout their distribution centres to streamline their operations (Grewal et al., 2017).

5. Conclusion and managerial implications

Research asserts that the traditional retail value chain is experiencing a metamorphosis, yet, literature offering managerial guidance on how to respond to these changes is limited (Araujo, 2019; Van Esch et al., 2019). With added pressure to remain competitive, many retailers have started to embrace a variety of digital technologies to engage with their customers (Grewal et al., 2017), and many are utilizing AI applications to establish this connection (Morgan, 2019). To bridge this gap, the application of current AI technologies to the retail value chain was reviewed, and four dimensions of AI applications were conceptualized. AI can best be employed in the retail value chain by serving one of the following purposes: knowledge and insight management, inventory management, operations optimization and customer engagement. These four categories of AI technologies in the value chain enabled us to propose a revised AI-enabled retail value chain.

Although extant literature suggests that most AI applications over the next decade will remain narrow or applied (Kelly, 2017; Marr, 2017), we propose that these narrow applications of AI can be extended to multiple functions in the retail value chain. Therefore, retailers should invest in classes of AI technologies (e.g. deep learning capability) and not just specific applications thereby ensuring that these technologies can be used for multiple functions across the value chain. In addition, this framework provides retailers with a list of priorities for investing in AI. In particular, retailers should start with knowledge and insight management at the foundation. Using this framework, single AI applications can be ap-

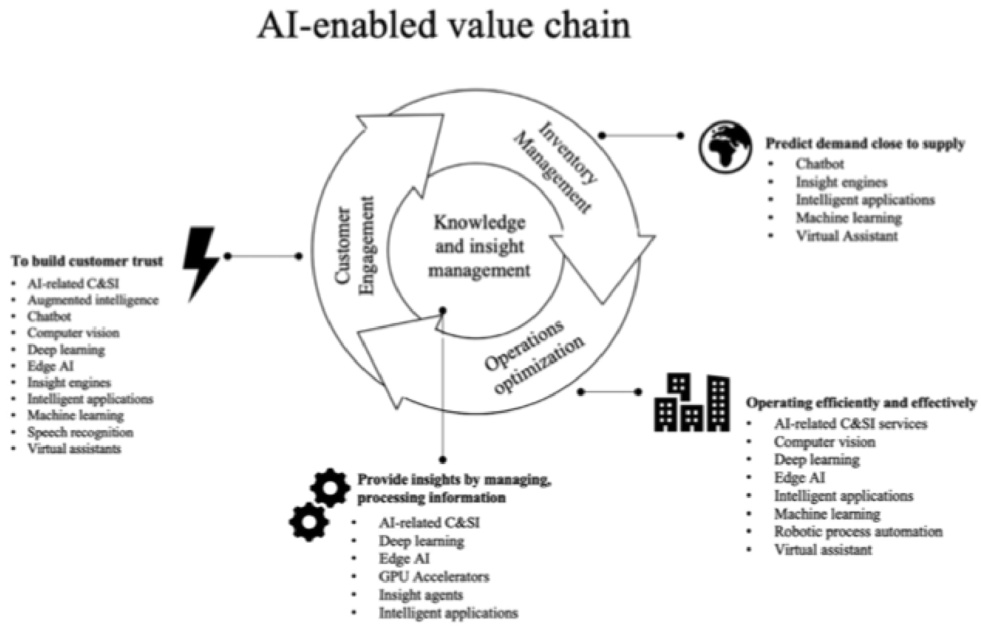


Figure 1. AI-enabled Retail Value Chain

plied to multiple tasks. Therefore, the framework (in combination with the analysis of the AI jobs-to-be-done dimensions presented in Table 3) provides retailers with insight into how to best leverage current AI investments.

Retail managers need to focus on scaling AI technologies across the value chain to reap the full long-term benefits. Broadening their horizons, retailer management should move away from a narrow focus on technology investments for distribution channels and customer-facing technologies only (Olanrewaju and Willmott, 2013). For increased and sustained competitive advantage, the suggested conceptual framework can help retailers transform their value chains in order to compete and thrive in the changing retail landscape.

6. Future research

To further build on the four identified value-adding dimensions that AI solutions can fulfill in the retailers' value chain, future research could explore how these different AI dimensions contribute to organizations' competitive advantage in different product-market contexts. Furthermore, as many global industries gear up for the widespread adoption of AI technologies, demand and competition will grow for scarce skilled employees with the ability to implement, manage and work alongside the new technology (Van Esch et al., 2019; Butler-Adam, 2018). It will be crucial for organizations to have a skilled workforce to support the implementation of AI, and there will be an even higher demand for skilled professionals (Van Esch and Black, 2019). While companies face external competition in finding skilled employees, low skilled workers could find it challenging to compete with machines and struggle to be employable in the future (Frey and Osborne, 2017). Future research can focus on the skills and competencies necessary for the organization that wishes to implement the AI-enabled retail value chain.

An AI-enabled retail value chain is heavily reliant on trained employees who supply high-quality data at each touch point in the value chain. If the data is less than optimal, this may create vulnerabilities and areas of risk, as organizations may unintentionally create biases with accompanying negative outcomes through the data that is being provided for intelligent automation. Future research could assess how organizations can address these vulnerabilities and avoid the potential biases. Finally, scaling AI applications across the retail value chain will require the right platforms to be in place, data to be available and employees to support the initiatives in the long term. Future research should examine the technological and organizational platforms necessary for the successful implementation of an AI-enabled value chain. As the technology, most likely to reshape the retail landscape, retailers that embrace AI are poised to enhance every link in their value chain.

References

Araujo, M., 2019. The Intelligent Enterprise for the Retail Industry.: 32.
Begley, S., Fox, R., Lunawat, G., et al. (2018) How analytics and digital will drive next-generation retail merchandising. Available at: https://www.mckinsey.com/industries/retail/our-insights/how-analytics-and-digital-will-drive-next-generation-retail-merchandising.
Bettencourt, L., Ulwick, A.W., 2008. The Customer-Centered Innovation Map. Harvard Business Review. 1 MayAvailable at https://hbr.org/2008/05/the-customer-centered-innovation-map. accessed 31 January 2020.
Black, J.S., Van Esch, P., 2020. AI-enabled recruiting: What is it and how should a manager use it. Business Horizons 63 (2), 215–226.
Bolton, R.N., Chapman, R.G., Mills, A.J., 2019. Harnessing Digital Disruption With Marketing Simulations. Journal of Marketing Education 41 (1), 15–31. doi:10.1177/0273475318803417.
Brynjolfsson, E., McAfee, A., 2016. The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies, 1 edition W. W. Norton & Company, New York London.

Please cite this article as: K. Oosthuizen, E. Botha and J. Robertson et al., Artificial intelligence in retail: The AI-enabled value chain, Australasian Marketing Journal, https://doi.org/10.1016/j.ausmj.2020.07.007

Appendix D: Declaration of other authors/contributors

In cases where other authors have contributed to the content (e.g. co-authors in peer-reviewed and published articles), the following declaration should be included in the dissertation)

Declaration by the candidate

With regard to [Chapter 3: Article 1 – Artificial Intelligence in retail: The AI-enabled value chain], the nature and scope of my contribution were as follows:

Nature of contribution	Extent of contribution (%)
Conducted the analysis of the data by myself. Identified the key new stages of the AI-enabled value chain. Wrote the first draft of the article. Completed final draft of the article.	80%

The following co-authors have contributed [Chapter 3: Article 1 – Artificial Intelligence in retail: The AI-enabled value chain]:

Name	e-mail address	Nature of contribution	Extent of contribution (%)
Dr. Elsamari Botha	elsamari.botha@canterbury.ac.nz	Critical edit and composition of article	15%
Jeandri Robertson	jeandri.robertson@ltu.se	Critical edit	4%
Dr Matteo Montecchi	matteo.montecchi@kcl.ac.uk	Final edit	1%

Signature of candidate: Declaration with signature in possession of candidate and supervisor. [1]

Date: 3 September 2021

[1] < Please note: To keep the signatures of individual out of the public domain, the declaration – if a declaration such as this must be included with the dissertation – must be included with the dissertation without signatures and the following text must be included in place of the signatures: “Declaration with signature in possession of candidate and supervisor.” The candidate and supervisor must then ensure that the declaration with signatures are kept in a safe place, available for possible future enquiries.>

Declaration by co-authors

The undersigned hereby confirm that

1. the declaration above accurately reflects the nature and extent of the contributions of the candidate and the co-authors to this article,
2. no other authors contributed to this article besides those specified above, and
3. potential conflicts of interest have been revealed to all interested parties and that the necessary arrangements have been made to use the material in this article of this dissertation.

Signature	Institutional affiliation	Date
Declaration with signature in possession of candidate and supervisor	Elsamari Botha, University of Canterbury and University of Stellenbosch Business School	3 September 2021
Declaration with signature in possession of candidate and supervisor	Jeandri Robertson, University of Cape Town	3 September 2021
Declaration with signature in possession of candidate and supervisor	Dr Matteo Montecchi, Kings College London	3 September 2021

Declaration of other authors/contributors

In cases where other authors have contributed to the content (e.g. co-authors in peer-reviewed and published articles), the following declaration should be included in the dissertation)

Declaration by the candidate

With regard to [Chapter 5: Article 3 – Applying service-dominant logic to AI investments in retail: the outcomes of an AI-enabled value chain] the nature and scope of my contribution were as follows:

Nature of contribution	Extent of contribution (%)
Came up with outcomes and recommendations discussed in article. Completely wrote the first draft. Edit modifications by co-authors for the final draft of the article.	70%

The following co-authors have contributed to [Chapter 5: Article 3 – Applying service-dominant logic to AI investments in retail: the outcomes of an AI-enabled value chai]:

Name	e-mail address	Nature of contribution	Extent of contribution (%)
Dr. Elsamari Botha	Elsamari.botha@canterbury.ac.nz	Identifying relevant theory, layout of the article, sense-checking along the way.	25%
Prof. Martin Butler	martin.butler@usb.ac.za	Critical edit.	5%

Signature of candidate: *Declaration with signature in possession of candidate and supervisor*. [2]

Date: 3 September 2021

Declaration by co-authors

The undersigned hereby confirm that

4. the declaration above accurately reflects the nature and extent of the contributions of the candidate and the co-authors this article,
1. no other authors contributed this article besides those specified above, and
2. potential conflicts of interest have been revealed to all interested parties and that the necessary arrangements have been made to use the material in this article of this dissertation.

Signature	Institutional affiliation	Date
Declaration with signature in possession of candidate and supervisor	Elsamari Botha, University of Canterbury	3 September 2021
Declaration with signature in possession of candidate and supervisor	Martin Butler, University of Stellenbosch	3 September 2021

2

Appendix E: Ethical clearance approval letter

USB
University of Stellenbosch Business School

07 August 2020

Dear Kim

Re: Ethical screening: Kim Oosthuizen - Approved (USB-2020-16968)

US ID No	:	18851703
Research programme	:	PhD in Business Management and Administration
Title	:	AI in retail: AI-enabled value chain
Supervisor	:	Prof Martin Butler / Prof Elsamari Botha

The Departmental Ethics Screening Committee of the University of Stellenbosch Business School (USB DESC) reviewed your application for the above-mentioned research. The research as set out in the application has been approved.

You as researcher are obliged to maintain the ethical integrity of your research. As such, you should adhere to the ethical guidelines of Stellenbosch University and remain within the scope of your ethical clearance application and the supporting evidence submitted to the USB DESC. Should any aspect of your research change from the information as presented to the USB DESC, you are under the obligation to report it immediately to your supervisor. Should there be any uncertainty in this regard, consult with the USB DESC.

Please note that this approval may still be subject to ratification by the Stellenbosch University Research Ethics Committee. For more information on this ratification, please contact Clarissa Graham at cgraham@sun.ac.za.

We wish you success with your research and trust that it will make a positive contribution to the quest for knowledge at the USB and Stellenbosch University.

Should any research subject, participating organisation or person affected by this research have any questions about the research, feel free to contact any of the following:

Researcher	:	kim.botes03@gmail.com
Supervisor	:	martin.butler@usb.ac.za / emc@usb.ac.za

Yours sincerely

Digitally signed by Prof Mias de Klerk
DN: cn=Prof Mias de Klerk, o=USB, ou, email=mias.deklerk@usb.ac.za, c=ZA
Date: 2020.08.07 11:45:01 +02'00'

Professor Mias de Klerk
Chair: USB Departmental Ethics Screening Committee

S100 1918-2018 AACSB ACCREDITED EFMD EQUIS ACCREDITED ASSOCIATION AMBA ACCREDITED

University of Stellenbosch Business School
Address: PO Box 610 Bellville 7535 Carl Cronjé Drive Bellville 7530
Tel: +27 (0)21 918 4111 • **Email:** usbcom@usb.ac.za • **Website:** www.usb.ac.za

Appendix F: Interview protocol for stage two data collection

USB
University of Stellenbosch Business School

CONFIDENTIAL: INTERVIEW PROTOCOL

Title of research project	:	Artificial Intelligence in retail: The AI-enabled value chain
Researcher	:	Kim Oosthuizen
Research supervisor	:	Prof Elsamari Botha/Prof Martin Butler
Department	:	University of Stellenbosch Business School
Qualification	:	PhD in Business Management and Administration

The purpose of this study is to explore how AI technologies are changing the retail value chain and to confirm/validate an AI-enabled retail value chain framework.

Section A:

Knowledge and insight management AI technologies refer to the ability to provide insights by managing, sharing, using, creating and processing information. An example is online retailer proven skincare that is using a database of over 20k skincare ingredients, 100k individual products information, 8 million reviews and 4k scientific publications to create products that suits each customers skin (Proven, 2019).

1. Questions sections A:
   1.1. For a company to undertake an AI project, describe what infrastructure the company should have in place?
   1.2. Describe the types of data required for AI?
   1.3. Describe what do you need for AI technologies process AI data and insights?
   1.4. Describe how AI can drive insights for retailers?
   1.5. Describe the types of AI that can drive insights and please give an example of each?
   1.6. What are the benefits of using AI to assist with knowledge and insight management?
   1.7. What are the major obstacles for retailers to implement this?

University of Stellenbosch Business School
Address: PO Box 610 Bellville 7535 Carl Cronjé Drive Bellville 7530
Tel: +27 (0)21 918 4111 · **Email:** usbcom@usb.ac.za · **Website:** www.usb.ac.za

Section B:

Inventory management AI technologies refer to those that assist in the process of balancing demand to supply over large assortments to meet customer needs and financial objectives. For example, the eCommerce retailer, Otto Group, is using predictive machine learning applications to boost revenue, increase margins and respond to market shifts. The application has assisted the retailer in reducing their out-of-stock rate by 80% (Trotter, 2018).

2. Questions section B:
   - 2.1. Which AI technologies are available that can assist with inventory management in retail?
   - 2.2. Describe the process of how AI technologies can assist in inventory management?
   - 2.3. Which inventory management systems could benefit from AI technology?
   - 2.4. What are the benefits of using AI to assist with inventory management?
   - 2.5. What are the major obstacles for retailers to implement AI applications for inventory management?

Section C:

Operations optimization AI technologies help retailers operate effectively and efficiently by minimising cost and maximising operational capabilities. For example, JD.com, one of China's largest retailers, has introduced AI to drive efficiencies in their operations (Marr, 2019). The introduction of the AI applications allowed the retailer to deliver 92% of their orders on the same or next day (Trotter, 2018).

3. Questions section C
   - 3.1. Which AI technologies can be used to assist with operations optimization?
   - 3.2. Describe the process of how AI technologies can assist with operations optimization?
   - 3.3. What are the major obstacles for retailers to implement AI applications for operations optimization?

Section D:

Customer engagement AI technologies enable retailers to build relationships with their customers. The North Face, a retailer of technical outerwear, utilises augmented intelligence to help consumers find clothing and apparel suited to specific weather conditions (Trotter, 2018).

4. Questions section C
   - 4.1. Which AI technologies can be used to assist with customer engagement?
   - 4.2. What are the benefits of using AI to assist with customer engagement?
   - 4.3. What are the major obstacles for retailers to implement AI applications for customer engagement?

Section E:

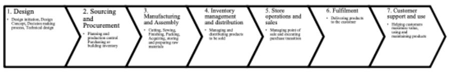
AI in retail value chain framework

5. Questions section E
   - 5.1. Please consider the traditional retail value chain [Appendix A]
     - 5.1.1. Which areas in the Value chain function will benefit the most from AI technology?
     - 5.1.2. How could AI technologies transform the retail value chain in the future?
   - 5.2. Please consider the framework for AI in the retail value chain [Appendix B].
     - 5.2.1. Do you think this adequately covers all the functions that AI can fulfil in the retail value chain?
     - 5.2.2. If not, what else needs to be considered?
   - 5.3. Do you have any other comments to add to this research?

University of Stellenbosch Business School
Address: PO Box 610 Bellville 7535 Carl Cronjé Drive Bellville 7530
Tel: +27 (0)21 918 4111 • Email: usbcom@usb.ac.za • Website: www.usb.ac.za

Appendix A

Traditional retail value chain



University of Stellenbosch Business School
Address: PO Box 610 Bellville 7535 Carl Cronjé Drive Bellville 7530
Tel: +27 (0)21 918 4111 • Email: usbcom@usb.ac.za • Website: www.usb.ac.za

Appendix B

AI enabled value chain

University of Stellenbosch Business School
Address: PO Box 610 Bellville 7535 Carl Cronjé Drive Bellville 7530
Tel: +27 (0)21 918 4111 • Email: usbcom@usb.ac.za • Website: www.usb.ac.za

Appendix G: Informed consent form for stage two data collection

University of Stellenbosch Business School

CONSENT TO PARTICIPATE IN RESEARCH

Title of research project	:	Artificial Intelligence in Retail: The AI-enabled value chain
Researcher	:	**Kim Oosthuizen**
Research supervisor	:	**Prof Elsamari Botha**
Department	:	**University of Stellenbosch Business School**
Qualification	:	**PhD in Business Management and Administration**

Dear (Paricipant)

You are asked to participate in this research study. You were selected as a possible participant in this study because of your expertise in working or implementation of AI technologies in Retail.

About the study

To remain competitive and survive in an ever-changing and diversified customer market, retailers need to become leaner (Campbell et al., 2020) more agile (Goworek, 2014), and innovate their value chain by adopting new technologies (Lee et al., 2018). Of the new technologies that are impacting the retail industry, AI has been earmarked as the most transformative (Kietzmann et al., 2018; Lee et al., 2018; Silva et al., 2019). Yet while there is great excitement about AI, it has yet to fully deliver on its promise (Ransbotham et al., 2017).

Traditional retailers' business models are facing disruptions by new entrants who can deliver greater value to customers more efficiently. New AI technologies are shortening the value chain by creating opportunities for manufacturers and wholesalers to sell directly to customers. The technology has given new entrants the ability to enter the market quicker than in the past. Overtime AI technologies will make the old retail value chain redundant by removing low value-added tasks and automating value chain stages in the future.

1. Purpose and benefits of the study

The purpose of this study is to explore how AI technologies are changing the retail value chain and to confirm/validate an AI-enabled retail value chain framework. Once an AI-enabled framework is confirmed, the framework can assist retail leaders to focus their AI investments in the future.

2. Procedures

Should you volunteer to participate in this study, we would request the following from you:

Firstly the researcher needs you to determine whether you are suitable to participate in the research data collection process. Once you agreed to participate, the researcher requires you to take part in a 60-minute video conference interview. The researcher will need you to sign a consent or confidentiality agreement.

During the interview, the researcher wants you to share your experiences regarding the development, implementation and usage of AI technology in Retail. The interview will follow five themed sections, namely:

- **Section A:** Knowledge and insight management: AI technologies refer to the ability to provide insights by managing, sharing, using, creating and processing information.
- **Section B**: Inventory management AI technologies: refer to those technologies in the process of balancing demand to supply over large assortments to meet customer needs and financial objectives.
- **Section C:** Operations optimisation AI technologies: help retailers operate effectively and efficiently by minimising cost and maximising operational capabilities.
- **Section D:** Customer engagement: AI technologies enable retailers to build relationships with their customers.
- **Section E:** AI in retail value chain framework.

The interviews will be conducted using Zoom software. The researcher requires 60 minutes for you to participate in the interview. The interview will be recorded using Zoom. If further time is needed, the researcher will schedule another session with you.

3. Potential risks and discomforts

If you do not want to answer a specific question, please respond by saying "unable to answer this question". You also have the right to withdraw your participation.

4. Confidentiality and protection of participants

Any information that is obtained in connection with this study and that can be identified with you will remain confidential and will be disclosed only with your permission or as required by law. Confidentiality will be maintained through anonymising all research datasets to ensure the anonymity of the participants. During the coding of the data all participants names and companies will be recorded as either consultant no 1 from Company A, retailer manager no 2 from company B , AI technologies no 3 from company C or IT retail manager no 4 from company D. All anonymised data will be encrypted and stored in a secure private cloud.

5. Payment for participation

No payment will be made for participation

6. Participation and withdrawal

You can choose whether to contribute to this study or not. If you volunteer to participate to this study, you may withdraw at any time without consequences of any kind. You may also refuse to answer any questions you do not want to answer and still contribute to the study. The investigator may withdraw you from this research if circumstances arise which warrant doing so.

7. Contact detail

If you have any questions or concerns about the research, please feel free to contact the researcher Kim Oosthuizen [kim.botes03@gmail.com; +61 477 992 422] and/or the Supervisor Dr Elsamari Botha [elsamaribotha@gmail.com or elsamari.botha@canterbury.ac.nz]

8. Rights of research subjects

Should you decide to withdraw your consent at any time and discontinue participation, you do this without penalty. You are not waiving any legal claims, rights or remedies because of your involvement in this research study. If you have questions regarding your rights as a research subject, contact Ms Maléne Fouché [mfouche@sun.ac.za; 021 808 4622] at the University of Stellenbosch Division for Research Development.

DECLARATION AND SIGNATURE OF RESEARCH SUBJECT

The information above was explained to me by Kim Oosthuizen in clear terms. I was given the opportunity to ask questions, and these questions were answered to *my* satisfaction.

I hereby consent voluntarily to participate in this study. I have been given a copy of this form.

Name of subject or participant:	....		
Signature:	....	**Date:**	....

Appendix H: Data management plan

The data management plan was created using DMPTool. The DMPTool is free, open-source software that helps researchers develop data management plans. The data management plan outlines how the interview data were treated throughout the data collection process for this study.

Data Collection	
What data will you collect or create?	The data collection method will employ unstructured interviews as an instrument. To collect the interview data, the teleconference software Zoom will be used. Zoom invite will be set up to use a secure pin code to join the meeting to ensure the privacy of the participant joining the call. The interview will be recorded using the recording functionality within Zoom. As a registered license user, the recorded Zoom meeting is saved to the Zoom cloud. The recorded audio files are stored on the cloud can be accessed on the user's desktop or from the web using a secure password of the user.
How will the data be collected or created?	To create data from the audio recordings, the data will be transcribed from speech to text using MAXQDA software. MAXQDA is a world-leading software package for qualitative and mixed methods research and the only leading QDA software to offer identical features on Windows and Mac. It is one of the most comprehensive programs in the field and is used by thousands of researchers in more than 150 countries worldwide. The transcribed data will be saved onto the MAXQDA software for coding and analysis. MAXQDA holding company VERBI takes all necessary technical and Organisational security measures to protect data from loss or misuse. MAXQDA uses encrypted connection and secures data in a secure data centre. The data is stored in a secure operating environment that is not accessible to the public. VERBI follows data protection guidelines from EU General Data Protection Regulation (Art. 4(7) GDPR)).
Documentation and Metadata	
What documentation and metadata will accompany the data?	Once all the interviews are completed and transcribed, the data will be cleaned and coded. Coding is a way to make sense of the data, by which raw data are transformed into meaningful and theoretically categories. A qualitative coding process to identify themes, categories and organise the data will be using MAXQDA software. The software facilitates the systematic coding to produce insights into qualitative coding for analysis. All interviewee data will be kept anonymous during the coding process. The coding standard will adhere to the UK language setting. All interview data will be accompanied by an informed consent form from each participant. The metadata will be stored in MAXQDA.
Ethics and Legal Compliance	
How will you manage any ethical issues?	The research involves human participants. The researcher will protect the respondent confidentiality, with obtaining informed consent. All interview participants need to sign a formal consent form prior to participating in the interview. The researcher will anonymize all research datasets to ensure the anonymity of the participants. All anonymized data will be encrypted. The data will be stored in a private cloud and backed up onto SUNScholarData.
How will you manage copyright and Intellectual Property Rights (IP/IPR) issues?	The data will be collected and created by the researcher. The researcher will own the rights to the data, and all IP belongs to Stellenbosch University. The researcher is affiliated with the University. Academic Publications will manage copyright once the data is published.

Storage and Backup	
How will the data be stored and backed up during the research?	All data will be saved on analysis platform MAXQDA. The MAXQDA data is saved onto the user's device and backed up daily on the researcher's private google drive cloud account. Updates are scheduled to run daily. The google drive account is password protected. The final dataset will be stored on data storage portal SunScholarData.
How will you manage access and security?	SunScholarData enables Stellenbosch University researchers to share and disseminate their research data in accordance with good research data management practices. This serves to facilitate the findability, accessibility and reusability of the university's research data.
Selection and Preservation	
Which data are of long-term value and should be retained, shared, and/or preserved?	The university and academic journal will retain the data.
What is the long-term preservation plan for the dataset?	The data will be stored for 5 years
Data Sharing	
How will you share the data?	Data will be shared using SunScholarData. SunScholar data uses platform figshare. Figshare is a repository where users can make all of their research outputs available in a citable, shareable and discoverable manner.
Are any restrictions on data sharing required?	The data will be restricted until the final publication is published in an academic journal.
Responsibilities and Resources	
Who will be responsible for data management?	The researcher will be responsible for managing the data.
What resources will you require to deliver your plan?	Zoom license, MAXQDA license, Google drive and collected data

Appendix I: Turnitin originality report

Please see the below Turnitin originally report showing a similarity index of 22%, however 14% is from Artificial Intelligence in retail: The AI-enabled value chain article published in the Australasian Marking Journal, and 1% is from the template used. Therefore, the similarity should only be 7%.

turnitin **Turnitin Originality Report**

Final Thesis AI enabled value chain.pdf by Kim Oosthuizen

From Turnitin Playground (Moodle PP) (PhD in Business Administration (Moodle PP))

Similarity Index	Similarity by Source	
22%	Internet Sources:	9%
	Publications:	16%
	Student Papers:	14%

Processed on 12-Sep-2021 12:31 SAST
ID: 1646310065
Word Count: 90637

sources:

1. 11% match (publications)
Kim Oosthuizen, Elsamari Botha, Jeandri Robertson, Matteo Montecchi. "Artificial intelligence in retail: The AI-enabled value chain", Australasian Marketing Journal (AMJ), 2020

2. 1% match (publications)
Kim Oosthuizen, Elsamari Botha, Jeandri Robertson, Matteo Montecchi. "Artificial Intelligence in Retail: The AI-Enabled Value Chain", Australasian Marketing Journal, 2021

3. 1% match (publications)
Kim Oosthuizen, Elsamari Botha, Jeandri Robertson, Matteo Montecchi. "Artificial intelligence in retail: The AI-enabled value chain", Australasian Marketing Journal, 2020

4. 1% match (Internet from 03-Sep-2020)
https://www.researchgate.net/publication/305922138_The_digitalization_of_retailing_an_exploratory_framework

5. < 1% match (publications)
Kim Oosthuizen, Elsamari Botha, Jeandri Robertson, Matteo Montecchi. "Artificial intelligence in retail: The AI-enabled value chain", Australasian Marketing Journal, 2020

6. < 1% match (Internet from 19-Apr-2021)
https://www.researchgate.net/publication/344866408_Self-service_technology_in_supermarkets_-_Do_frontline_staff_still_matter

7. < 1% match (student papers from 01-Apr-2021)
Submitted to University of Stellenbosch, South Africa on 2021-04-01

8. < 1% match (student papers from 06-Sep-2021)
Submitted to University of Stellenbosch, South Africa on 2021-09-06

9. < 1% match (student papers from 14-May-2019)
Submitted to University of Stellenbosch, South Africa on 2019-05-14

10. < 1% match (student papers from 13-Nov-2019)
Submitted to University of Stellenbosch, South Africa on 2019-11-13

11. < 1% match (student papers from 16-Nov-2017)
Submitted to University of Stellenbosch, South Africa on 2017-11-16

12. < 1% match (student papers from 01-Mar-2021)
Submitted to University of Stellenbosch, South Africa on 2021-03-01

13. < 1% match (student papers from 16-Jan-2021)
Submitted to University of Stellenbosch, South Africa on 2021-01-16

14. < 1% match (student papers from 07-Dec-2017)
Submitted to University of Stellenbosch, South Africa on 2017-12-07

Appendix J: Article one: References

Araujo, M. (2019). The Intelligent Enterprise for the Retail Industry. 32.

Begley, S., Fox, R., Lunawat, G., & MacKenzie, I. (2018, August). How analytics and digital will drive next-generation retail merchandising. https://www.mckinsey.com/industries/retail/our-insights/how-analytics-and-digital-will-drive-next-generation-retail-merchandising

Bettencourt, L. A., & Ulwick, A. W. (2008). The Customer-Centered Innovation Map. *Harvard Business Review,* 9.

Black, J. S., & van Esch, P. (2019). AI-enabled recruiting: What is it and how should a manager use it? Business Horizons, S0007681319301612. https://doi.org/10.1016/j.bushor.2019.12.001

Bolton, R. N., Chapman, R. G., & Mills, A. J. (2019). Harnessing Digital Disruption With Marketing Simulations. *Journal of Marketing Education*, 41(1), 15–31. https://doi.org/10.1177/0273475318803417

Brynjolfsson, E., Hu, Y. J., & Rahman, M. S. (2013). Competing in the Age of Omnichannel Retailing. *MIT Sloan Management Review*, 54(4), 10.

Bughin, J., Hazan, E., Ramaswamy, S., Chui, M., Allas, T., Dahlström, P., Henke, N., & Trench, M. (2017). Artificial intelligence the next digital frontier? (p. 80). Mckinsey Global Institute. www.mckinsey.com/mgi

Butler-Adam, J. (2018). The Fourth Industrial Revolution and education. *South African Journal of Science,* 114(5/6). https://doi.org/10.17159/sajs.2018/a0271

Cammett, M. (2006). Development and the Changing Dynamics of Global Production: Global Value Chains and Local Clusters in Apparel Manufacturing. *Competition & Change,* 10(1), 23–48. https://doi.org/10.1179/102452906X91993

Campbell, C., Sands, S., Ferraro, C., Tsao, H.-Y. (Jody), & Mavrommatis, A. (2020). From data to action: How marketers can leverage AI. *Business Horizons,* 63(2), 227–243. https://doi.org/10.1016/j.bushor.2019.12.002

Carlsson, C. (2018). Decision analytics—Key to digitalisation. *Information Sciences*, 460–461, 424–438. https://doi.org/10.1016/j.ins.2017.08.087

Chao, G., Cheung, J., Haller, K., & Lee, J. (2019). The coming AI revolution in retail and consumer products: Intelligent automation is transforming both industries in unexpected ways (IBM Institute for Business Value, p. 24). National Retail Federation. https://nrf.com/sites/default/files/2019-01/The%20coming%20AI%20revolution.pdf

Chen, Y., Elenee Argentinis, J., & Weber, G. (2016). IBM Watson: How Cognitive Computing Can Be Applied to Big Data Challenges in Life Sciences Research. *Clinical Therapeutics*, 38(4), 688–701. https://doi.org/10.1016/j.clinthera.2015.12.001

Christensen, C., Hall, T., Dillon, K., & Duncan, D. S. (2016). Competing against luck. The Story of Innovation and Customer Choice. First Edition. New York, NY: HarperBusiness an Imprint of HarperCollins Publishers.

Christensen CM (2003) The Innovator's Solution: Creating and Sustaining Successful Growth. Boston, Massachusetts Harvard Business School Press.

Christensen, C. M., & Raynor, M. E. (2013). The Innovator's Solution: Creating and Sustaining Successful Growth. Harvard Business Review Press. https://store.hbr.org/product/the-innovator-s-solution-creating-and-sustaining-successful-growth/16444

Chuprina, R. (2019, December 20). Artificial Intelligence for Retail in 2020: 12 Real-World Use Cases. https://spd.group/artificial-intelligence/ai-for-retail/

DalleMule, L., & Davenport, T. H. (2017, May 1). What's Your Data Strategy? Harvard Business Review, May-June 2017. https://hbr.org/2017/05/whats-your-data-strategy

Daugherty, P. R., & Wilson, J. H. (2018). Human + Machine: Reimagining Work in the Age of AI (Kindle). Harvard Business Review Press.

Day, G. S., & Schoemaker, P. J. H. (2019). See Sooner, Act Faster: How Vigilant Leaders Thrive in an Era of Digital Turbulence. MIT Press.

De Bruyn, A., Viswanathan, V., Beh, Y. S., Brock, J. K.-U., & von Wangenheim, F. (2020). Artificial Intelligence and Marketing: Pitfalls and Opportunities. *Journal of Interactive Marketing*, 51, 91–105. https://doi.org/10.1016/j.intmar.2020.04.007

de Leon, S. P. (2019, August 27). How thredUP is Driving the Circular Fashion Movement with AI. Forbes. https://www.forbes.com/sites/cognitiveworld/2019/08/27/how-thredup-circular-fashion-ai/#615d567f79a0

Djafri, L., Amar Bensaber, D., & Adjoudj, R. (2018). Big Data analytics for prediction: Parallel processing of the big learning base with the possibility of improving the final result of the prediction. *Information Discovery and Delivery*, 46(3), 147–160. https://doi.org/10.1108/IDD-02-2018-0002

Emont, J. (2018, February 16). The Robots Are Coming for Garment Workers. That's Good for the U.S., Bad for Poor Countries. *The Wall Street Journal*. https://www.wsj.com/articles/the-robots-are-coming-for-garment-workers-thats-good-for-the-u-s-bad-for-poor-countries-1518797631

Fairhurst, A. E., & Fiorito, S. S. (1990). Retail buyers' decision-making process: An investigation of contributing variables. *The International Review of Retail, Distribution and Consumer Research*, 1(1), 87–100. https://doi.org/10.1080/09593969000000007

Fiorito, S. S., Gable, M., & Conseur, A. (2010). Technology: Advancing retail buyer performance in the twenty-first century. *International Journal of Retail & Distribution Management,* 38(11/12), 879–893. https://doi.org/10.1108/09590551011085966

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, 114, 254–280. https://doi.org/10.1016/j.techfore.2016.08.019

Galer, S. (2018). Adidas Uses Machine Learning to Deliver Custom Sneakers in Just 24 Hours. *SAP News Centre.* https://news.sap.com/2018/06/adidas-uses-machine-learning-to-deliver-custom-sneakers-in-just-24-hours/

Goworek, H. (2014). An investigation into retail buying roles and responsibilities for own-label clothing: A multiple case-study. *The Journal of The Textile Institute*, 105(7), 760–769. https://doi.org/10.1080/00405000.2013.848046

Grewal, D., Roggeveen, A. L., & Nordfält, J. (2017). The Future of Retailing. *Journal of Retailing*, 93(1), 1–6. https://doi.org/10.1016/j.jretai.2016.12.008

Gupta, S. (2018). Driving digital strategy: A guide to reimagining your business. *Harvard Business Review Press*.

Haenlein, M., Kaplan, A., Tan, C.-W., & Zhang, P. (2019). Artificial intelligence (AI) and management analytics. *Journal of Management Analytics*, 6(4), 341–343. https://doi.org/10.1080/23270012.2019.1699876

Hagberg, J., Sundstrom, M., & Egels-Zandén, N. (2016). The digitalisation of retailing: An exploratory framework. *International Journal of Retail & Distribution Management*, 44(7), 694–712. https://doi.org/10.1108/IJRDM-09-2015-0140

Holweg, M., & Helo, P. (2014). Defining value chain architectures: Linking strategic value creation to operational supply chain design. *International Journal of Production Economics*, 147, 230–238. https://doi.org/10.1016/j.ijpe.2013.06.015

Ikea. (2020). Say hej to IKEA Place. Ikea. https://www.ikea.com/au/en/customer-service/mobile-apps/say-hej-to-ikea-place-pub1f8af050

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. Business Horizons, 62(1), 15–25. https://doi.org/10.1016/j.bushor.2018.08.004

Kaplan, J. (1984). The Industrialization of Artificial Intelligence: From By-Line to Bottom Line. *The AI Magazine*, 5(2), 7.

Kelly, K. (2017). The Inevitable: Understanding the 12 Technological Forces That Will Shape Our Future. Penguin Books.

Kietzmann, J., Hermkens, K., McCarthy, I. P., & Silvestre, B. S. (2011). Social media? Get serious! Understanding the functional building blocks of social media. *Business Horizons*, 54(3), 241–251. https://doi.org/10.1016/j.bushor.2011.01.005

Kietzmann, J., Paschen, J., & Treen, E. (2018). Artificial Intelligence in Advertising: How Marketers Can Leverage Artificial Intelligence Along the Consumer Journey. *Journal of Advertising Research,* 58(3), 263–267. https://doi.org/10.2501/JAR-2018-035

Lee, C. K. H. (2017). A GA-based optimisation model for big data analytics supporting anticipatory shipping in Retail 4.0. *International Journal of Production Research*, 55(2), 593–605. https://doi.org/10.1080/00207543.2016.1221162

Lee, H., Mendelson, H., Rammoham, S., & Blake, L. (2018). Value Chain Innovation: The Promise of AI (Value Chain Innovation Initiative). *Stanford Business.*

Li, B., Hou, B., Yu, W., Lu, X., & Yang, C. (2017). Applications of artificial intelligence in intelligent manufacturing: A review. Frontiers of Information Technology & Electronic Engineering, 18(1), 86–96. https://doi.org/10.1631/FITEE.1601885

Marr, B. (2017, August 29). How Walmart Is Using Machine Learning AI, IoT And Big Data To Boost Retail Performance. Forbes. https://www.forbes.com/sites/bernardmarr/2017/08/29/how-walmart-is-using-machine-learning-ai-iot-and-big-data-to-boost-retail-performance/#35637d5e6cb1

Marr, B. (2018, August 10). How Fashion Retailer H&M Is Betting On Artificial Intelligence And Big Data To Regain Profitability. Forbes. https://www.forbes.com/sites/bernardmarr/2018/08/10/how-fashion-retailer-hm-is-betting-on-artificial-intelligence-and-big-data-to-regain-profitability/#1e4e9ef75b00

Marr, B. (2019). Artificial intelligence in practice: How 50 successful companies used artificial intelligence to solve problems (First Edition). Wiley.

McChrystal, G. S., Collins, T., Silverman, D., & Fussell, C. (2015). Team of teams: New rules of engagement for a complex world. Penguin.

Milnes, H. (2016, April 13). How Color IQ, Sephora's shade-matching skin care tool, boosts brand loyalty. https://digiday.com/marketing/color-iq-sephoras-shade-matching-skin-care-tool-boosts-brand-loyalty/

Morgan, B. (2019, March 4). The 20 Best Examples Of Using Artificial Intelligence For Retail Experiences. https://www.forbes.com/sites/blakemorgan/2019/03/04/the-20-best-examples-of-using-artificial-intelligence-for-retail-experiences/#44d8add44664

Oh, H., & Polidan, M. (2018). Retail Consulting Class: Experiential Learning Platform to Develop Future Retail Talents. *Journal of Marketing Education*, 40(1), 31–46. https://doi.org/10.1177/0273475317743015

Olanrewaju, T., & Willmott, P. (2013). Finding your digital sweet spot. McKinsey and Co., November, Available at: https://www. Mckinsey. Com/Insights/Business_ Technology/Finding_your_digital_sweet_spot

Paschen, J., Kietzmann, J., & Kietzmann, T. C. (2019). Artificial intelligence (AI) and its implications for market knowledge in B2B marketing. *Journal of Business & Industrial Marketing*, 34(7), 1410–1419. https://doi.org/10.1108/JBIM-10-2018-0295

Paschen, J., Wilson, M., & Ferreira, J. J. (2020). Collaborative intelligence: How human and artificial intelligence create value along the B2B sales funnel. Business Horizons, 63(3), 403–414. https://doi.org/10.1016/j.bushor.2020.01.003

Petropoulos, F., Kourentzes, N., Nikolopoulos, K., & Siemsen, E. (2018). Judgmental selection of forecasting models. *Journal of Operations Management*, 60, 34–46. https://doi.org/10.1016/j.jom.2018.05.005

Philips. (2020). Philips OneBlade: Trim, Edge, Shave. Philips. https://www.philips.co.za/c-m-pe/oneblade-trim-edge-and-shave

Poole, D. L., & Mackworth, A. K. (2017). Artificial intelligence: Foundations of computational agents (2nd edition). Cambridge University Press.

Porter, M. E. (1998). Competitive Advantage: Creating and Sustaining Superior Performance. SIMON & SCHUSTER.

Ransbotham, s, Kiron, D., Gerbert, P., & Reeves, M. (2017). Reshaping business with artificial intelligence- Closing the gap between ambition and action. (Research Project No. 59181). *MIT Sloan Management review*. https://sloanreview.mit.edu/projects/reshaping-business-with-artificial-intelligence/

Reddy, T. (2017, October 17). How chatbots can help reduce customer service costs by 30%. https://www.ibm.com/blogs/watson/2017/10/how-chatbots-reduce-customer-service-costs-by-30-per cent/

Reinartz, W., Wiegand, N., & Imschloss, M. (2019). The impact of digital transformation on the retailing value chain. *International Journal of Research in Marketing*, 36(3), 350–366. https://doi.org/10.1016/j.ijresmar.2018.12.002

Rieple, A., & Singh, R. (2010). A value chain analysis of the organic cotton industry: The case of UK retailers and Indian suppliers. *Ecological Economics*, 69(11), 2292–2302. https://doi.org/10.1016/j.ecolecon.2010.06.025

Romero, I., & Martínez-Román, J. A. (2015). Determinants of technology adoption in the retail trade industry—The case of SME's in spain. *Amfiteatru Economic*, 17(39), 16.

Sankaran, G., Knahl, M., Siestrup, G., & Vasileiou, I. (2019). Value of Smart Data for Supply Chain Decisions in a Data Rich, Uncertain World. CERC. https://www.semanticscholar.org/article/Value-of-Smart-Data-for-Supply-Chain-Decisions-in-a-Sankaran-Knahl/93fb75c8d51f55a71896a1a1fb64acbab6007a0c

Sicular, S., Hare, J., & Brant, K. (2019). Hype Cycle for Artificial Intelligence, 2019 (No. G00369840; p. 79). Gartner. https://www.gartner.com/smarterwithgartner/top-trends-on-the-gartner-hype-cycle-for-artificial-intelligence-2019/

Sivarajah, U., Kamal, M. M., Irani, Z., & Weerakkody, V. (2017). Critical analysis of Big Data challenges and analytical methods. *Journal of Business Research*, 70, 263–286. https://doi.org/10.1016/j.jbusres.2016.08.001

Standish, J., & Ganapathy, V. (2020, January 14). AI in Retail: Time to Stop Experimenting and Start Delivering Value at Scale. WWD.Com. https://wwd.com/business-news/technology/accenture-ai-retail-think-tank-1203422562/

Trotter, C. (2018, April 12). 50 Best AI Retail Applications. https://www.insider-trends.com/50-best-ai-retail-applications/#ixzz5DQ4CdcsH

van Esch, P., Arli, D., Gheshlaghi, M. H., Andonopoulos, V., von der Heidt, T., & Northey, G. (2019). Anthropomorphism and augmented reality in the retail environment. *Journal of Retailing and Consumer Services,* 49, 35–42. https://doi.org/10.1016/j.jretconser.2019.03.002

van Esch, P., & Black, J. S. (2019). Factors that influence new generation candidates to engage with and complete digital, AI-enabled recruiting. *Business Horizons*, 62(6), 729–739. https://doi.org/10.1016/j.bushor.2019.07.004

Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Qi Dong, J., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research*, 122, 889–901. https://doi.org/10.1016/j.jbusres.2019.09.022

Weber, F. D., & Schütte, R. (2019). State-of-the-art and adoption of artificial intelligence in retailing. *Digital Policy, Regulation and Governance*, 21(3), 264–279. https://doi.org/10.1108/DPRG-09-2018-0050

Westerman, G., Bonnet, D., & McAfee, A. (2014). Leading Digital: Turning Technology into Business Transformation. Harvard Business Review Press.

Wierenga, B. (2010). Marketing and Artificial Intelligence: Great Opportunities, Reluctant Partners. In J. Casillas & F. J. Martínez-López (Eds.), Marketing Intelligent Systems Using Soft Computing: Managerial and Research Applications (Vol. 258). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-15606-9

Wirth, N. (2018). Hello marketing, what can artificial intelligence help you with? International *Journal of Market Research,* 60(5), 435–438. https://doi.org/10.1177/1470785318776841

Xu, Y., Shieh, C.-H., van Esch, P., & Ling, I.-L. (2020). AI Customer Service: Task Complexity, Problem-Solving Ability, and Usage Intention. *Australasian Marketing Journal*, 28(4), 189–199. https://doi.org/10.1016/j.ausmj.2020.03.005

Yao, M., Jia, M., & Zhou, A. (2019). Applied artificial intelligence: A handbook for business lead

Appendix K: Article two: References

Acharya, A., Singh, S. K., Pereira, V., & Singh, P. (2018). Big data, knowledge co-creation and decision making in fashion industry. International Journal of Information Management, 42, 90–101. https://doi.org/10.1016/j.ijinfomgt.2018.06.008

Alexander, B., & Kent, A. (2021). Tracking technology diffusion in-store: A fashion retail perspective. International Journal of Retail & Distribution Management, ahead-of-print(ahead-of-print). https://doi.org/10.1108/IJRDM-05-2020-0191

Ambrogio, K. (2019, November 7). Australia's Favorite Department Store Gets More Agile with Oracle. Oracle News Connect. https://www.oracle.com/corporate/pressrelease/myer-implements-oracle-110719.html

Ameen, N., Tarhini, A., Reppel, A., & Anand, A. (2021). Customer experiences in the age of artificial intelligence. Computers in Human Behavior, 114, 106548. https://doi.org/10.1016/j.chb.2020.106548

Anica-Popa, I., Anica-Popa, L., Rădulescu, C., & Vrîncianu, M. (2021). The Integration of Artificial Intelligence in Retail: Benefits, Challenges and a Dedicated Conceptual Framework. Amfiteatru Economic, 23(56), 120. https://doi.org/10.24818/EA/2021/56/120

Arthur, R. (2018). Artificial Intelligence Empowers Designers In IBM, Tommy Hilfiger And FIT Collaboration. Forbes. https://www.forbes.com/sites/rachelarthur/2018/01/15/ai-ibm-tommy-hilfiger/

Assarroudi, A., Heshmati Nabavi, F., Armat, M. R., Ebadi, A., & Vaismoradi, M. (2018). Directed qualitative content analysis: The description and elaboration of its underpinning methods and data analysis process. Journal of Research in Nursing, 23(1), 42–55. https://doi.org/10.1177/1744987117741667

Balchandani, A., Hancock, B., Phillips, S., & Wachinger, T. (2020). How technology is disrupting the UK retail industry | McKinsey (p. 22). Mckinsey Global Institute. https://www.mckinsey.com/industries/retail/our-insights/rebooting-retail-how-technology-will-shape-the-future-of-retail#

Berg, A., Heyn, M., Rölkens, F., & Simon, P. (2018, May). Faster fashion: How to shorten the apparel calendar. Mckinsey and Co, 6.

Berthiaume, D. (2019, June 4). Ulta Beauty shoppers behold new AR, AI features. Chain Store Age the Business of Retail. https://chainstoreage.com/technology/ulta-beauty-shoppers-behold-new-ar-ai-features

Bharadwaj, R. (2019, November 21). Artificial Intelligence in the Textile Industry—Current and Future Applications. Emerj. https://emerj.com/ai-sector-overviews/artificial-intelligence-in-the-textile-industry-current-and-future-applications/

Blair, A. (2018, October 29). New Sam's Club Store Will Be A Mobile-First, AI-Powered Tech Lab. Retail Touch Points. https://retailtouchpoints.com/features/news-briefs/new-sam-s-club-store-will-be-a-mobile-first-ai-powered-tech-lab

Blueprism. (2019). Inside John Lewis – How RPA is transforming retail. https://www.blueprism.com/uploads/resources/case-studies/BluePrism_JohnLewisPartnership.pdf

Boella, G., & van der Torre, L. (2006). Coordination and Organization. Electronic Notes in Theoretical Computer Science, 150(3), 3–20. https://doi.org/10.1016/j.entcs.2006.03.002

Campbell, C., Sands, S., Ferraro, C., Tsao, H.-Y. (Jody), & Mavrommatis, A. (2020). From data to action: How marketers can leverage AI. Business Horizons, 63(2), 227–243. https://doi.org/10.1016/j.bushor.2019.12.002

Canhoto, A. I., & Clear, F. (2019). Artificial intelligence and machine learning as business tools: A framework for diagnosing value destruction potential. Business Horizons, S0007681319301570. https://doi.org/10.1016/j.bushor.2019.11.003

Cao, L. (2021). Artificial intelligence in retail: Applications and value creation logics. International Journal of Retail & Distribution Management, ahead-of-print(ahead-of-print). https://doi.org/10.1108/IJRDM-09-2020-0350

Capgemini. (2018). Building the Retail Superstar: How unleashing AI across functions offers a multi-billion dollar opportunity. Capgemini Worldwide. https://www.capgemini.com/research/building-the-retail-superstar-how-unleashing-ai-across-functions-offers-a-multi-billion-dollar-opportunity/

Chao, G., Cheung, J., Haller, K., & Lee, J. (2019). The coming AI revolution in retail and consumer products: Intelligent automation is transforming both industries in unexpected ways (IBM Institute for Business Value, p. 24). National Retail Federation. https://nrf.com/sites/default/files/2019-01/The%20coming%20AI%20revolution.pdf

Chen, J.-S., Le, T.-T.-Y., & Florence, D. (2021). Usability and responsiveness of artificial intelligence chatbot on online customer experience in e-retailing. International Journal of Retail & Distribution Management, ahead-of-print(ahead-of-print). https://doi.org/10.1108/IJRDM-08-2020-0312

Chen, Y., Elenee Argentinis, J., & Weber, G. (2016). IBM Watson: How Cognitive Computing Can Be Applied to Big Data Challenges in Life Sciences Research. Clinical Therapeutics, 38(4), 688–701. https://doi.org/10.1016/j.clinthera.2015.12.001

Cho, J., & Lee, E.-H. (2014). Reducing Confusion about Grounded Theory and Qualitative Content Analysis: Similarities and Differences. The Qualitative Report. https://doi.org/10.46743/2160-3715/2014.1028

Chopra, K. (2019). Indian shopper motivation to use artificial intelligence: Generating Vroom's expectancy theory of motivation using grounded theory approach. International Journal of Retail & Distribution Management, 47(3), 331–347. https://doi.org/10.1108/IJRDM-11-2018-0251

Cosgrove, E. (2020, January 14). H&M's AI operation helps make its supply chain more sustainable. Supply Chain Dive. https://www.supplychaindive.com/news/HM-AI-supply-chain-sustainable/570400/

Daugherty, P. R., & Wilson, J. H. (2018). Human + Machine: Reimagining Work in the Age of AI (Kindle). Harvard Business Review Press.

Davenport, T. H., & Ronanki, R. (2018, January 1). Artificial Intelligence for the Real World. Harvard Business Review. https://hbr.org/2018/01/artificial-intelligence-for-the-real-world

Davis, M. (2020). Accelerating AI Deployments—Paths of Least Resistance (No. G00722711; Artificial Intelligence, p. 17). file:///Users/kimo/Downloads/Accelerating_AI_Depl_722711_ndx.pdf

de Bellis, E., & Johar, G. V. (2020). Autonomous Shopping Systems: Identifying and Overcoming Barriers to Consumer Adoption. Journal of Retailing, 96(1), 74–87. https://doi.org/10.1016/j.jretai.2019.12.004

De Bruyn, A., Viswanathan, V., Beh, Y. S., Brock, J. K.-U., & von Wangenheim, F. (2020). Artificial Intelligence and Marketing: Pitfalls and Opportunities. Journal of Interactive Marketing, 51, 91–105. https://doi.org/10.1016/j.intmar.2020.04.007

de Leon, S. P. (2019, August 27). How thredUP is Driving the Circular Fashion Movement with AI. Forbes. https://www.forbes.com/sites/cognitiveworld/2019/08/27/how-thredup-circular-fashion-ai/#615d567f79a0

Dogru, A. K., & Keskin, B. B. (2020). AI in operations management: Applications, challenges and opportunities. Journal of Data, Information and Management, 2(2), 67–74. https://doi.org/10.1007/s42488-020-00023-1

Emont, J. (2018, February 16). The Robots Are Coming for Garment Workers. That's Good for the U.S., Bad for Poor Countries. The Wall Street Journal. https://www.wsj.com/articles/the-robots-are-coming-for-garment-workers-thats-good-for-the-u-s-bad-for-poor-countries-1518797631

Eriksson, P., & Kovalainen, A. (2008). Qualitative Methods in Business Research. SAGE Publications Ltd. https://doi.org/10.4135/9780857028044

Fountaine, T., McCarthy, B., & Saleh, T. (2019). Building the AI-Powered Organization. 13.

Freddi, D. (2017). Digitalisation and employment in manufacturing: Pace of the digitalisation process and impact on employment in advanced Italian manufacturing companies. AI & SOCIETY, 33(3), 393–403. https://doi.org/10.1007/s00146-017-0740-5

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? Technological Forecasting and Social Change, 114, 254–280. https://doi.org/10.1016/j.techfore.2016.08.019

Ganapathy, V., Green, M., & Schottmiller, P. (2020, January 7). AI in Retail Transformation | Accenture. https://www.accenture.com/au-en/insights/retail/artificial-intelligence-retail-value

Gauri, D. K., Jindal, R. P., Ratchford, B., Fox, E., Bhatnagar, A., Pandey, A., Navallo, J. R., Fogarty, J., Carr, S., & Howerton, E. (2021). Evolution of retail formats: Past, present, and future. Journal of Retailing, 97(1), 42–61. https://doi.org/10.1016/j.jretai.2020.11.002

Gonzalez-Jimenez, H. (2018). Taking the fiction out of science fiction: (Self-aware) robots and what they mean for society, retailers, and marketers. Futures, 98, 49–56. https://doi.org/10.1016/j.futures.2018.01.004

Grewal, D., Noble, S. M., Roggeveen, A. L., & Nordfalt, J. (2020). The future of in-store technology. Journal of the Academy of Marketing Science, 48(1), 96–113. https://doi.org/10.1007/s11747-019-00697-z

Grill-Goodman, J. (2019, June 21). How Walmart Uses Computer Vision. RIS News. https://risnews.com/how-walmart-uses-computer-vision

Guha, A., Grewal, D., Kopalle, P. K., Haenlein, M., Schneider, M. J., Jung, H., Moustafa, R., Hegde, D. R., & Hawkins, G. (2021). How artificial intelligence will affect the future of retailing. Journal of Retailing, 97(1), 28–41. https://doi.org/10.1016/j.jretai.2021.01.005

Gupta, S., Kar, A. K., Baabdullah, A., & Al-Khowaiter, W. A. A. (2018). Big data with cognitive computing: A review for the future. International Journal of Information Management, 42, 78–89. https://doi.org/10.1016/j.ijinfomgt.2018.06.005

Hagberg, J., Sundstrom, M., & Egels-Zandén, N. (2016). The digitalization of retailing: An exploratory framework. International Journal of Retail & Distribution Management, 44(7), 694–712. https://doi.org/10.1108/IJRDM-09-2015-0140

Hardaker, A. (2017, September 18). LovetheSales.com AI 10,000 times faster than a human [BusinessCloud]. https://www.businesscloud.co.uk/news/lovethesalescom-ai-10000-times-faster-than-a-human/

Hare, J., & Andrews, W. (2019). Survey Analysis: AI and ML Development Strategies, Motivators and Adoption Challenges. 16.

Hartmann, N. N., & Lussier, B. (2020). Managing the sales force through the unexpected exogenous COVID-19 crisis. Industrial Marketing Management, 88, 101–111. https://doi.org/10.1016/j.indmarman.2020.05.005

Heater, B. (2019, April 11). The startup behind Walmart's shelf-scanning robots. Tech Crunch. https://techcrunch.com/2019/04/10/the-startup-behind-walmarts-shelf-scanning-robots/?guccounter=1

Himmelreich, A. (2020, April 2). Using artificial intelligence to advance retail and consumer products to truly personalized service. Capgemini. https://www.capgemini.com/wp-content/uploads/2020/04/AI-to-Future-POV.pdf

Home Depot. (2018, August 20). 5 Technologies changing how we shop. https://corporate.homedepot.com/newsroom/5-technologies-changing-how-we-shop

Hübner, A., Amorim, P., Kuhn, H., Minner, S., & Van Woensel, T. (2018). Retail operations. OR Spectrum, 40(4), 831–835. https://doi.org/10.1007/s00291-018-0535-1

Hwang, S. (2019). A network clock model for time awareness in the Internet of things and artificial intelligence applications. The Journal of Supercomputing, 75(8), 4309–4328. https://doi.org/10.1007/s11227-019-02774-0

Ikea. (2020). Say hej to IKEA Place. Ikea. https://www.ikea.com/au/en/customer-service/mobile-apps/say-hej-to-ikea-place-pub1f8af050

Jain, S., & Gandhi, A. V. (2021). Impact of artificial intelligence on impulse buying behaviour of Indian shoppers in fashion retail outlets. International Journal of Innovation Science, 13(2), 193–204. https://doi.org/10.1108/IJIS-10-2020-0181

Johnston, R. (2017, September 26). IKEA's New Augmented Reality App Means You're Never Not At IKEA. Gizmodo. https://www.gizmodo.com.au/2017/09/ikeas-new-augmented-reality-app-means-youre-never-not-at-ikea/

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. Business Horizons, 62(1), 15–25. https://doi.org/10.1016/j.bushor.2018.08.004

Lake, K. (2018, May). Stitch Fix's CEO on Selling Personal Style to the Mass Market. Harvard Business Review. https://hbr.org/2018/05/stitch-fixs-ceo-on-selling-personal-style-to-the-mass-market

Leavitt, H. J. (1965). Applied organizational change in industry: Structural, technological, and humanistic approaches. In The handbook of organizations (RLE: Organizations) (Vol. 20). Carnegie Institute of Technology, Graduate School of Industrial Administration.

Leavitt, H. J., & Bahrami, H. (1989). Managerial Psychology: Managing Behavior in Organizations (1st edition). University of Chicago Press.

Lee, C. K. H. (2017). A GA-based optimisation model for big data analytics supporting anticipatory shipping in Retail 4.0. International Journal of Production Research, 55(2), 593–605. https://doi.org/10.1080/00207543.2016.1221162

Leung, L. (2015). Validity, reliability, and generalizability in qualitative research. Journal of Family Medicine and Primary Care, 4(3), 324–327. https://doi.org/10.4103/2249-4863.161306

Lewis-Beck, M., Bryman, A., & Futing Liao, T. (2004). The SAGE Encyclopedia of Social Science Research Methods. Sage Publications, Inc. https://doi.org/10.4135/9781412950589

Liang, Y., Lee, S.-H., & Workman, J. E. (2020). Implementation of Artificial Intelligence in Fashion: Are Consumers Ready? Clothing and Textiles Research Journal, 38(1), 3–18. https://doi.org/10.1177/0887302X19873437

Loughran, M. (2018). The promise of AI for industrial automation. The Chemical Engineer, 44–46.

Lowe's. (2020). A Helping Hand. Lowe's Innovation Lab. http://www.lowesinnovationlabs.com/lowebot/

Manyika, J., & Bughin, J. (2018, October). The promise and challenge of the age of artificial intelligence. McKinsey Global Institute. https://www.mckinsey.com/featured-insights/artificial-intelligence/the-promise-and-challenge-of-the-age-of-artificial-intelligence

Marr, B. (2018, August 10). How Fashion Retailer H&M Is Betting On Artificial Intelligence And Big Data To Regain Profitability. Forbes. https://www.forbes.com/sites/bernardmarr/2018/08/10/how-fashion-retailer-hm-is-betting-on-artificial-intelligence-and-big-data-to-regain-profitability/#1e4e9ef75b00

Marr, B. (2019). Artificial intelligence in practice: How 50 successful companies used artificial intelligence to solve problems (First Edition). Wiley.

Marshall, T. E., & Lambert, S. L. (2018). Cloud-Based Intelligent Accounting Applications: Accounting Task Automation Using IBM Watson Cognitive Computing. Journal of Emerging Technologies in Accounting, 15(1), 199–215. https://doi.org/10.2308/jeta-52095

McKinsey. (2020, October). How COVID-19 has pushed companies over the technology tipping point—And transformed business forever. McKinsey. https://www.mckinsey.com/business-functions/strategy-and-corporate-finance/our-insights/how-covid-19-has-pushed-companies-over-the-technology-tipping-point-and-transformed-business-forever

Medeiros, J. (2018, May 1). Here's How North Face Boosted Conversions Using AI. Modev. https://www.modev.com/blog/heres-how-north-face-boosted-conversions-using-ai

Milnes, H. (2016, April 13). How Color IQ, Sephora's shade-matching skin care tool, boosts brand loyalty. https://digiday.com/marketing/color-iq-sephoras-shade-matching-skin-care-tool-boosts-brand-loyalty/

Neuendorf, K. A. (2017). The Content Analysis Guidebook. SAGE Publications, Inc. https://doi.org/10.4135/9781071802878

Nike. (2020). Product Advice From Nike Experts. https://www.nike.com/membership/experts-on-demand

Olanrewaju, T., & Willmott, P. (2013). Finding your digital sweet spot. McKinsey and Co., November, Available at: Http://Www. Mckinsey. Com/Insights/Business_ Technology/Finding_your_digital_sweet_spot.

Oosthuizen, K., Botha, E., Robertson, J., & Montecchi, M. (2020). Artificial intelligence in retail: The AI-enabled value chain. Australasian Marketing Journal (AMJ), S144135822030077X. https://doi.org/10.1016/j.ausmj.2020.07.007

Paghaleh, M. J., Shafiezadeh, E., & Mohammadi, M. (2011). Information Technology and its Deficiencies in Sharing Organizational Knowledge. 2(8), 8.

Paschen, J., Kietzmann, J., & Kietzmann, T. C. (2019). Artificial intelligence (AI) and its implications for market knowledge in B2B marketing. Journal of Business & Industrial Marketing, 34(7), 1410–1419. https://doi.org/10.1108/JBIM-10-2018-0295

Paschen, U., Pitt, C., & Kietzmann, J. (2019). Artificial intelligence: Building blocks and an innovation typology. Business Horizons, 63(2), 147–155. https://doi.org/10.1016/j.bushor.2019.10.004

Pillai, R., Sivathanu, B., & Dwivedi, Y. K. (2020). Shopping intention at AI-powered automated retail stores (AIPARS). Journal of Retailing and Consumer Services, 57, 102207. https://doi.org/10.1016/j.jretconser.2020.102207

Pinterest. (2017). Pinterest Style finder and West Elm. Pinterest. https://pinterest-style-finder.westelm.com

Pizzi, G., Scarpi, D., & Pantano, E. (2021). Artificial intelligence and the new forms of interaction: Who has the control when interacting with a chatbot? Journal of Business Research, 129, 878–890. https://doi.org/10.1016/j.jbusres.2020.11.006

Poole, D. L., & Mackworth, A. K. (2017). Artificial intelligence: Foundations of computational agents (2nd edition). Cambridge University Press.

Porter, M. E. (1998). Competitive Advantage: Creating and Sustaining Superior Performance. SIMON & SCHUSTER.

Ransbotham, s, Kiron, D., Gerbert, P., & Reeves, M. (2017). Reshaping business with artificial intelligence- Closing the gap between ambition and action. (Research Project No. 59181). MIT Sloan Management review. https://sloanreview.mit.edu/projects/reshaping-business-with-artificial-intelligence/

Reinartz, W., Wiegand, N., & Imschloss, M. (2019). The impact of digital transformation on the retailing value chain. International Journal of Research in Marketing, 36(3), 350–366. https://doi.org/10.1016/j.ijresmar.2018.12.002

Rese, A., Ganster, L., & Baier, D. (2020). Chatbots in retailers' customer communication: How to measure their acceptance? Journal of Retailing and Consumer Services, 56, 102176. https://doi.org/10.1016/j.jretconser.2020.102176

Robinson, E. (2018, January 15). Morrisons implements Blue Yonder's AI stock replenishment technology. The Record. https://www.technologyrecord.com/Article/morrisons-implements-blue-yonders-ai-stock-replenishment-technology-62728

Roy, S. (2019, April 23). How Burberry is leveraging technology to lead in the digital age. Techwire Asia. https://techwireasia.com/2019/04/how-burberry-is-leveraging-technology-to-lead-in-the-digital-age/

Salento, A. (2018). Digitalisation and the regulation of work: Theoretical issues and normative challenges. AI & SOCIETY, 33(3), 369–378. https://doi.org/10.1007/s00146-017-0738-z

Schaeffer, E., Cabanes, J., & Gupta, A. (2018). Manufacturing the future. Accenture. https://www.accenture.com/_acnmedia/PDF-74/Accenture-Pov-Manufacturing-Digital-Final.pdf

Schwab, K. (2016, January 14). The Fourth Industrial Revolution: What it means, how to respond. World Economic Forum. www.weforum.org/agenda/2016/01/the-fourth-industrial-revolution-what-it-means-and-how-to-respond/

Shankar, V. (2018). How Artificial Intelligence (AI) is Reshaping Retailing. Journal of Retailing, 94(4), vi–xi. https://doi.org/10.1016/S0022-4359(18)30076-9

Sicular, S., Hare, J., & Brant, K. (2019). Hype Cycle for Artificial Intelligence, 2019 (No. G00369840; p. 79). Gartner. https://www.gartner.com/smarterwithgartner/top-trends-on-the-gartner-hype-cycle-for-artificial-intelligence-2019/

Simon, P., Tufft, C., & Zampella, P. (2020, August 28). Closing the skills gap in retail with people analytics [McKinsey & Company]. Reinventing Retail with People Analytics. https://www.mckinsey.com/industries/retail/our-insights/closing-the-skills-gap-in-retail-with-people-analytics?cid=app

Smith, C., Norton, B., & Ellis, D. (1992). LEAVITT'S DIAMOND AND THE FLATTER LIBRARY: A CASE STUDY IN ORGANIZATIONAL CHANGE. Library Management, 13(5), 18–22. https://doi.org/10.1108/01435129210020352

Spicer, R. (2020, March 2). Growing Fashion Retailer Taps Oracle Retail Solutions to Increase Focus on Customers [Oracle retail blog]. Best Practices and Trends.

https://blogs.oracle.com/retail/growing-fashion-retailer-taps-oracle-retail-solutions-to-increase-focus-on-customers-v2

Standish, J., & Ganapathy, V. (2020, January 14). AI in Retail: Time to Stop Experimenting and Start Delivering Value at Scale. WWD.Com. https://wwd.com/business-news/technology/accenture-ai-retail-think-tank-1203422562/

Target. (2017, September 25). Finding the Perfect Product Is As Easy As Taking a Pic, Thanks to This New Target + Pinterest Collab. Target. https://corporate.target.com/article/2017/09/pinterest-lens

Tupikovskaja-Omovie, Z., & Tyler, D. (2020). Clustering consumers' shopping journeys: Eye tracking fashion m-retail. Journal of Fashion Marketing and Management: An International Journal, 24(3), 381–398. https://doi.org/10.1108/JFMM-09-2019-0195

van Esch, P., Cui, Y. (Gina), & Jain, S. P. (2021). Self-efficacy and callousness in consumer judgments of AI-enabled checkouts. Psychology & Marketing, 38(7), 1081–1100. https://doi.org/10.1002/mar.21494

Vargo. (2020, January 7). Vargo designs solutions for GAP Inc facilities in Arizona and the UK. Vargo Solutions. https://vargosolutions.com/vargo-designs-solutions-for-gap-inc-facilities-in-arizona-and-the-uk/

Vincent, J. (2018, May 8). Welcome to the automated warehouse of the future. The Verge. https://www.theverge.com/2018/5/8/17331250/automated-warehouses-jobs-ocado-andover-amazon

Weber, F. D., & Schütte, R. (2019). State-of-the-art and adoption of artificial intelligence in retailing. Digital Policy, Regulation and Governance, 21(3), 264–279. https://doi.org/10.1108/DPRG-09-2018-0050

Wirth, N. (2018). Hello marketing, what can artificial intelligence help you with? International Journal of Market Research, 60(5), 435–438. https://doi.org/10.1177/1470785318776841

World Economic Forum. (2018). The Future of Jobs Report 2018. https://www.weforum.org/reports/the-future-of-jobs-report-2018

Xu, Y., Shieh, C.-H., van Esch, P., & Ling, I.-L. (2020). AI Customer Service: Task Complexity, Problem-Solving Ability, and Usage Intention. Australasian Marketing Journal, 28(4), 189–199. https://doi.org/10.1016/j.ausmj.2020.03.005

Yao, M., Jia, M., & Zhou, A. (2019). Applied artificial intelligence: A handbook for business leaders

Appendix L: Article three: References

Agresti, A. (2002). Categorical data analysis (2nd ed). Wiley-Interscience.

Ameen, N., Tarhini, A., Reppel, A., & Anand, A. (2021). Customer experiences in the age of artificial intelligence. Computers in Human Behavior, 114, 106548. https://doi.org/10.1016/j.chb.2020.106548

Ammanath, B., Jarvis, D., & Hupfer, S. (2020, July 14). Thriving in the era of pervasive AI. Deloitte Insights. https://www2.deloitte.com/us/en/insights/focus/cognitive-technologies/state-of-ai-and-intelligent-automation-in-business-survey.html

Assarroudi, A., Heshmati Nabavi, F., Armat, M. R., Ebadi, A., & Vaismoradi, M. (2018). Directed qualitative content analysis: The description and elaboration of its underpinning methods and data analysis process. Journal of Research in Nursing, 23(1), 42–55. https://doi.org/10.1177/1744987117741667

Balchandani, A., Hancock, B., Phillips, S., & Wachinger, T. (2020). How technology is disrupting the UK retail industry | McKinsey (p. 22). Mckinsey Global Institute. https://www.mckinsey.com/industries/retail/our-insights/rebooting-retail-how-technology-will-shape-the-future-of-retail#

Begley, S., Fox, R., Lunawat, G., & MacKenzie, I. (2018, August). How analytics and digital will drive next-generation retail merchandising. https://www.mckinsey.com/industries/retail/our-insights/how-analytics-and-digital-will-drive-next-generation-retail-merchandising

Blair, A. (2018, October 29). New Sam's Club Store Will Be A Mobile-First, AI-Powered Tech Lab. Retail Touch Points. https://retailtouchpoints.com/features/news-briefs/new-sam-s-club-store-will-be-a-mobile-first-ai-powered-tech-lab

Blueprism. (2019). Inside John Lewis – How RPA is transforming retail. https://www.blueprism.com/uploads/resources/case-studies/BluePrism_JohnLewisPartnership.pdf

Bryant, A., Bryant, A., Bryant, A., & Casper, M. (2007). The SAGE Handbook of Grounded Theory. In pages 1-28, The SAGE Handbook of Grounded Theory. SAGE Publications Ltd. https://doi.org/10.4135/9781848607941

Bughin, J., Hazan, E., Ramaswamy, S., Chui, M., Allas, T., Dahlström, P., Henke, N., & Trench, M. (2017). Artificial intelligence the next digital frontier? (p. 80). Mckinsey Global Institute. www.mckinsey.com/mgi

Burkett, M. (2013). Future Supply Chain 2028: Four Factors to Watch (p. 27). Gartner.

Cao, L. (2014). Business Model Transformation in Moving to a Cross-Channel Retail Strategy: A Case Study. International Journal of Electronic Commerce, 18(4), 69–96. https://doi.org/10.2753/JEC1086-4415180403

Cao, L. (2021). Artificial intelligence in retail: Applications and value creation logics. International Journal of Retail & Distribution Management, ahead-of-print(ahead-of-print). https://doi.org/10.1108/IJRDM-09-2020-0350

Chao, G., Cheung, J., Haller, K., & Lee, J. (2019). The coming AI revolution in retail and consumer products: Intelligent automation is transforming both industries in unexpected ways (IBM Institute for Business Value, p. 24). National Retail Federation. https://nrf.com/sites/default/files/2019-01/The%20coming%20AI%20revolution.pdf

Choi, T.-M., Hui, C.-L., Liu, N., Ng, S.-F., & Yu, Y. (2014). Fast fashion sales forecasting with limited data and time. Decision Support Systems, 59, 84–92. https://doi.org/10.1016/j.dss.2013.10.008

Chuprina, R. (2019, December 20). Artificial Intelligence for Retail in 2020: 12 Real-World Use Cases. https://spd.group/artificial-intelligence/ai-for-retail/

Daugherty, P., Ghosh, B., & Wilson, J. (2020). Your legacy or your legend? A CEO's guide to getting the most out of new technologies (Future Systems, p. 34) [Research Report]. Accenture. https://www.accenture.com/_acnmedia/Thought-Leadership-Assets/PDF-2/Accenture-Legacy-or-Legend-PDF-Report.pdf#zoom=50

Day, G. S., & Schoemaker, P. J. H. (2019). See Sooner, Act Faster: How Vigilant Leaders Thrive in an Era of Digital Turbulence. MIT Press.

Deloitte. (2021). The age of with: Leveraging AI to connect the retail enterprise of the future. Deloitte. https://www2.deloitte.com/ca/en/pages/consumer-industrial-products/articles/age-of-with-ai.html

Elliot, B., & Andrews, W. (2017). A Framework for Applying AI in the Enterprise. Gartner.

Fan, X., Chai, Z., Deng, N., & Dong, X. (2020). Adoption of augmented reality in online retailing and consumers' product attitude: A cognitive perspective. Journal of Retailing and Consumer Services, 53, 101986. https://doi.org/10.1016/j.jretconser.2019.101986

Fiorito, S. S., Gable, M., & Conseur, A. (2010). Technology: Advancing retail buyer performance in the twenty-first century. International Journal of Retail & Distribution Management, 38(11/12), 879–893. https://doi.org/10.1108/09590551011085966

Gauri, D. K., Jindal, R. P., Ratchford, B., Fox, E., Bhatnagar, A., Pandey, A., Navallo, J. R., Fogarty, J., Carr, S., & Howerton, E. (2021). Evolution of retail formats: Past, present, and future. Journal of Retailing, 97(1), 42–61. https://doi.org/10.1016/j.jretai.2020.11.002

Goworek, H. (2014). An investigation into retail buying roles and responsibilities for own-label clothing: A multiple case-study. The Journal of The Textile Institute, 105(7), 760–769. https://doi.org/10.1080/00405000.2013.848046

Grill-Goodman, J. (2019, June 21). How Walmart Uses Computer Vision. RIS News. https://risnews.com/how-walmart-uses-computer-vision

Hagel, J., Seely Brown, J., Wooll, M., & de Maar, A. (2016, January 11). Shorten the value chain: Transforming the stages of value delivery. https://www2.deloitte.com/insights/us/en/focus/disruptive-strategy-patterns-case-studies/disruptive-strategy-value-chain-models.html

Hayes, A. (2019, September 2). Big-Box Retailers: What You Should Know. Investopedia. https://www.investopedia.com/terms/b/big_box_retailer.asp

Heater, B. (2019, April 11). The startup behind Walmart's shelf-scanning robots. Tech Crunch. https://techcrunch.com/2019/04/10/the-startup-behind-walmarts-shelf-scanning-robots/?guccounter=1

Hollebeek, L. D., Sprott, D. E., & Brady, M. K. (2021). Rise of the Machines? Customer Engagement in Automated Service Interactions. Journal of Service Research, 24(1), 3–8. https://doi.org/10.1177/1094670520975110

Kaplan, A. (2020). Retailing and the Ethical Challenges and Dilemmas Behind Artificial Intelligence. In Retail Futures: The Good, the Bad and the Ugly of the Digital Transformation (Kindle Edition). Retailing and the Ethical Challenges and Dilemmas Behind Artificial Intelligence Retail Futures . Emerald Publishing Limited.

Kapner, S. (2021, May 16). Not Qualified for a Job? These Companies Will 'Reskill' You. Wall Street Journal. https://www.wsj.com/articles/retailers-try-to-solve-labor-imbalances-by-reskilling-staff-11621157407

Lai, K.-H., Cheng, T. C. E., & Tang, A. K. Y. (2010). Green Retailing: Factors for Success. California Management Review, 52(2), 6–31. https://doi.org/10.1525/cmr.2010.52.2.6

Lake, K. (2018, May). Stitch Fix's CEO on Selling Personal Style to the Mass Market. Harvard Business Review. https://hbr.org/2018/05/stitch-fixs-ceo-on-selling-personal-style-to-the-mass-market

Lewins, A., & Silver, C. (2011). Using Software in Qualitative Research. SAGE Publications, Ltd. https://doi.org/10.4135/9780857025012

Marr, B. (2019). Artificial intelligence in practice: How 50 successful companies used artificial intelligence to solve problems (First Edition). Wiley.

Meticulous Research. (2020, July). Artificial Intelligence in Retail Market—Global Opportunity Analysis and Industry Forecast (2020-2027). Meticulous Research. https://www.meticulousresearch.com/product/artificial-intelligence-in-retail-market-4979/

Mills, A., Durepos, G., & Wiebe, E. (2010). Encyclopedia of Case Study Research. https://doi.org/10.4135/9781412957397

Milnes, H. (2016, April 13). How Color IQ, Sephora's shade-matching skin care tool, boosts brand loyalty. https://digiday.com/marketing/color-iq-sephoras-shade-matching-skin-care-tool-boosts-brand-loyalty/

Nadkarni, S., & Prügl, R. (2020). Digital transformation: A review, synthesis and opportunities for future research. Management Review Quarterly. https://doi.org/10.1007/s11301-020-00185-7

Oosthuizen, K., Botha, E., Robertson, J., & Montecchi, M. (2020). Artificial intelligence in retail: The AI-enabled value chain. Australasian Marketing Journal (AMJ), S144135822030077X. https://doi.org/10.1016/j.ausmj.2020.07.007

O'Reilly, K. (2009). Key Concepts in Ethnography. SAGE Publications Ltd. https://doi.org/10.4135/9781446268308

Parida, V., Sjödin, D. R., Lenka, S., & Wincent, J. (2015). Developing Global Service Innovation Capabilities: How Global Manufacturers Address the Challenges of Market Heterogeneity. Research-Technology Management. https://doi.org/10.5437/08956308X5805360

Paschen, J., Kietzmann, J., & Kietzmann, T. C. (2019). Artificial intelligence (AI) and its implications for market knowledge in B2B marketing. Journal of Business & Industrial Marketing, 34(7), 1410–1419. https://doi.org/10.1108/JBIM-10-2018-0295

Poole, D. L., & Mackworth, A. K. (2017). Artificial intelligence: Foundations of computational agents (2nd edition). Cambridge University Press.

Porter, M. E. (1998). Competitive Advantage: Creating and Sustaining Superior Performance. SIMON & SCHUSTER.

Ransbotham, s, Kiron, D., Gerbert, P., & Reeves, M. (2017). Reshaping business with artificial intelligence- Closing the gap between ambition and action. (Research Project No. 59181). MIT Sloan Management review. https://sloanreview.mit.edu/projects/reshaping-business-with-artificial-intelligence/

Reinartz, W., Wiegand, N., & Imschloss, M. (2019). The impact of digital transformation on the retailing value chain. International Journal of Research in Marketing, 36(3), 350–366. https://doi.org/10.1016/j.ijresmar.2018.12.002

Robinson, E. (2018, January 15). Morrisons implements Blue Yonder’s AI stock replenishment technology. The Record. https://www.technologyrecord.com/Article/morrisons-implements-blue-yonders-ai-stock-replenishment-technology-62728

Satell, G. (2018). How to Make an AI Project More Likely to Succeed. 5.

Shechtman, R., Spitz, C., Wimbish, R., & Thyagaraj, S. (2018). Merchandising of the future [Accenture].

Shi, M., & Yan, X. (2017). Heterogeneous consumers, search and retail formats. Frontiers of Business Research in China, 11(1), 18. https://doi.org/10.1186/s11782-017-0017-3

Sicular, S., Hare, J., & Brant, K. (2019). Hype Cycle for Artificial Intelligence, 2019 (No. G00369840; p. 79). Gartner. https://www.gartner.com/smarterwithgartner/top-trends-on-the-gartner-hype-cycle-for-artificial-intelligence-2019/

Simon, P., Tufft, C., & Zampella, P. (2020, August 28). Closing the skills gap in retail with people analytics [McKinsey & Company]. Reinventing Retail with People Analytics. https://www.mckinsey.com/industries/retail/our-insights/closing-the-skills-gap-in-retail-with-people-analytics?cid=app

Sklyar, A., Kowalkowski, C., Tronvoll, B., & Sörhammar, D. (2019). Organizing for digital servitization: A service ecosystem perspective. Journal of Business Research, 104, 450–460. https://doi.org/10.1016/j.jbusres.2019.02.012

Smith, L., Maull, R., & C.L. Ng, I. (2014). Servitization and operations management: A service dominant-logic approach. International Journal of Operations & Production Management, 34(2), 242–269. https://doi.org/10.1108/IJOPM-02-2011-0053

Smith, T. J., & McKenna, C. M. (2013). A Comparison of Logistic Regression Pseudo R2 Indices. 39, 10.

Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines. Journal of Business Research, 104, 333–339. https://doi.org/10.1016/j.jbusres.2019.07.039

Trotter, C. (2018, April 12). 50 Best AI Retail Applications. https://www.insider-trends.com/50-best-ai-retail-applications/#ixzz5DQ4CdcsH

Vargo. (2020, January 7). Vargo designs solutions for GAP Inc facilities in Arizona and the UK. Vargo Solutions. https://vargosolutions.com/vargo-designs-solutions-for-gap-inc-facilities-in-arizona-and-the-uk/

Vargo, S. L., & Akaka, M. A. (2009). Service-Dominant Logic as a Foundation for Service Science: Clarifications. Service Science, 1(1), 32–41. https://doi.org/10.1287/serv.1.1.32

Vargo, S. L., & Lusch, R. F. (2004). Evolving to a New Dominant Logic for Marketing. Journal of Marketing, 68(1), 1–17. https://doi.org/10.1509/jmkg.68.1.1.24036

Wadhawan, N., & Seth, D. A. (2016). Technology Revolutionizing Retail Practices in Digital Era. Conscientious and Unimpeachable Technologies 2016, 60–62.

Zentes, J., Morschett, D., & Schramm-Klein, H. (2012). Retail Formats – General Merchandise. In J. Zentes, D. Morschett, & H. Schramm-Klein (Eds.), Strategic Retail Management: Text and International Cases (pp. 49–69). Gabler Verlag. https://doi.org/10.1007/978-3-8349-6740-4_4

Zeta. (2020, February 20). The RealReal Boosts ROAS by 57% by partnering with Zeta. Zeta Global. https://zetaglobal.com/case-studies/case-study-the-realreal-boosts-roas/

Zolkiewski, J., Story, V., Burton, J., Chan, P., Gomes, A., Hunter-Jones, P., O'Malley, L., Peters, L. D., Raddats, C., & Robinson, W. (2017). Strategic B2B customer experience management: The importance of outcomes-based measures. Journal of Services Marketing, 31(2), 172–184. https://doi.org/10.1108/JSM-10-2016-0350

Appendix M: Article four: References

Acharya, A., Singh, S. K., Pereira, V., & Singh, P. (2018). Big data, knowledge co-creation and decision making in fashion industry. International Journal of Information Management, 42, 90–101. https://doi.org/10.1016/j.ijinfomgt.2018.06.008

Ammanath, B., Jarvis, D., & Hupfer, S. (2020, July 14). Thriving in the era of pervasive AI. Deloitte Insights. https://www2.deloitte.com/us/en/insights/focus/cognitive-technologies/state-of-ai-and-intelligent-automation-in-business-survey.html

Araujo, T., Helberger, N., Kruikemeier, S., & de Vreese, C. H. (2020). In AI we trust? Perceptions about automated decision-making by artificial intelligence. AI & SOCIETY, 35(3), 611–623. https://doi.org/10.1007/s00146-019-00931-w

Balchandani, A., Hancock, B., Phillips, S., & Wachinger, T. (2020). How technology is disrupting the UK retail industry | McKinsey (p. 22). Mckinsey Global Institute. https://www.mckinsey.com/industries/retail/our-insights/rebooting-retail-how-technology-will-shape-the-future-of-retail#

Barredo Arrieta, A., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., Garcia, S., Gil-Lopez, S., Molina, D., Benjamins, R., Chatila, R., & Herrera, F. (2020). Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. Information Fusion, 58, 82–115. https://doi.org/10.1016/j.inffus.2019.12.012

Begley, S., Hancock, B., Kilroy, T., & Kohli, S. (2020, February). Automation in retail: An executive overview for getting ready. McKinsey. https://www.mckinsey.com/~/media/McKinsey/Industries/Retail/Our%20Insights/Automation%20in%20retail%20An%20executive%20overview%20for%20getting%20ready/Automation-in-retail-An-executive-overview-for-getting-ready-FINAL.pdf

Boella, G., & van der Torre, L. (2006). Coordination and Organization. Electronic Notes in Theoretical Computer Science, 150(3), 3–20. https://doi.org/10.1016/j.entcs.2006.03.002

Bryant, A., Bryant, A., Bryant, A., & Casper, M. (2007). The SAGE Handbook of Grounded Theory. In pages 1-28, The SAGE Handbook of Grounded Theory. SAGE Publications Ltd. https://doi.org/10.4135/9781848607941

Burström, T., Parida, V., Lahti, T., & Wincent, J. (2021). AI-enabled business-model innovation and transformation in industrial ecosystems: A framework, model and outline for further research. Journal of Business Research, 127, 85–95. https://doi.org/10.1016/j.jbusres.2021.01.016

Campbell, C., Sands, S., Ferraro, C., Tsao, H.-Y. (Jody), & Mavrommatis, A. (2020). From data to action: How marketers can leverage AI. Business Horizons, 63(2), 227–243. https://doi.org/10.1016/j.bushor.2019.12.002

Canhoto, A. I., & Clear, F. (2019). Artificial intelligence and machine learning as business tools: A framework for diagnosing value destruction potential. Business Horizons, S0007681319301570. https://doi.org/10.1016/j.bushor.2019.11.003

Capgemini. (2018). Building the Retail Superstar: How unleashing AI across functions offers a multi-billion dollar opportunity. Capgemini Worldwide.

https://www.capgemini.com/research/building-the-retail-superstar-how-unleashing-ai-across-functions-offers-a-multi-billion-dollar-opportunity/

Chopra, K. (2019). Indian shopper motivation to use artificial intelligence: Generating Vroom's expectancy theory of motivation using grounded theory approach. International Journal of Retail & Distribution Management, 47(3), 331–347. https://doi.org/10.1108/IJRDM-11-2018-0251

Daugherty, P., Ghosh, B., & Wilson, J. (2020). Your legacy or your legend? A CEO's guide to getting the most out of new technologies (Future Systems, p. 34) [Research Report]. Accenture. https://www.accenture.com/_acnmedia/Thought-Leadership-Assets/PDF-2/Accenture-Legacy-or-Legend-PDF-Report.pdf#zoom=50

de Bellis, E., & Johar, G. V. (2020). Autonomous Shopping Systems: Identifying and Overcoming Barriers to Consumer Adoption. Journal of Retailing, 96(1), 74–87. https://doi.org/10.1016/j.jretai.2019.12.004

Deloitte. (2017). Bullish on the business value of cognitive. https://www2.deloitte.com/content/dam/Deloitte/us/Documents/deloitte-analytics/us-da-2017-deloitte-state-of-cognitive-survey.pdf

Deloitte. (2021). The age of with: Leveraging AI to connect the retail enterprise of the future. Deloitte. https://www2.deloitte.com/ca/en/pages/consumer-industrial-products/articles/age-of-with-ai.html

Dogru, A. K., & Keskin, B. B. (2020). AI in operations management: Applications, challenges and opportunities. Journal of Data, Information and Management, 2(2), 67–74. https://doi.org/10.1007/s42488-020-00023-1

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data – evolution, challenges and research agenda. International Journal of Information Management, 48, 63–71. https://doi.org/10.1016/j.ijinfomgt.2019.01.021

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., … Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. International Journal of Information Management, 57, 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Elliot, B., & Andrews, W. (2017). A Framework for Applying AI in the Enterprise. Gartner.

Feuerriegel, S., Dolata, M., & Schwabe, G. (2020). Fair AI: Challenges and Opportunities. Business & Information Systems Engineering, 62(4), 379–384. https://doi.org/10.1007/s12599-020-00650-3

Fountaine, T., McCarthy, B., & Saleh, T. (2019). Building the AI-Powered Organization. 13.

Ganapathy, V., Green, M., & Schottmiller, P. (2020, January 7). AI in Retail Transformation | Accenture. https://www.accenture.com/au-en/insights/retail/artificial-intelligence-retail-value

Haines, V. Y., & Lafleur, G. (2008). Information technology usage and human resource roles and effectiveness. Human Resource Management, 47(3), 525–540. https://doi.org/10.1002/hrm.20230

Hartmann, N. N., & Lussier, B. (2020). Managing the sales force through the unexpected exogenous COVID-19 crisis. Industrial Marketing Management, 88, 101–111. https://doi.org/10.1016/j.indmarman.2020.05.005

Jüttner, U., Christopher, M., & Baker, S. (2007). Demand chain management-integrating marketing and supply chain management. Industrial Marketing Management, 36(3), 377–392. https://doi.org/10.1016/j.indmarman.2005.10.003

Kaplan, A., & Haenlein, M. (2020). Rulers of the world, unite! The challenges and opportunities of artificial intelligence. Business Horizons, 63(1), 37–50. https://doi.org/10.1016/j.bushor.2019.09.003

Kapner, S. (2021, May 16). Not Qualified for a Job? These Companies Will 'Reskill' You. Wall Street Journal. https://www.wsj.com/articles/retailers-try-to-solve-labor-imbalances-by-reskilling-staff-11621157407

Leavitt, H. J. (1965). Applied organizational change in industry: Structural, technological and humanistic approaches. In The handbook of organizations (RLE: Organizations) (Vol. 20). Carnegie Institute of Technology, Graduate School of Industrial Administration.

Leavitt, H. J., & Bahrami, H. (1989). Managerial Psychology: Managing Behavior in Organizations (1st edition). University of Chicago Press.

Lee, C. K. H. (2017). A GA-based optimisation model for big data analytics supporting anticipatory shipping in Retail 4.0. International Journal of Production Research, 55(2), 593–605. https://doi.org/10.1080/00207543.2016.1221162

Lee, I., & Shin, Y. J. (2020). Machine learning for enterprises: Applications, algorithm selection, and challenges. Business Horizons, 63(2), 157–170. https://doi.org/10.1016/j.bushor.2019.10.005

Lewins, A., & Silver, C. (2011). Using Software in Qualitative Research. SAGE Publications, Ltd. https://doi.org/10.4135/9780857025012

Lyytinen, K., & Newman, M. (2008). Explaining information systems change: A punctuated socio-technical change model. European Journal of Information Systems, 17(6), 589–613. https://doi.org/10.1057/ejis.2008.50

Mahroof, K. (2019). A human-centric perspective exploring the readiness towards smart warehousing: The case of a large retail distribution warehouse. International Journal of Information Management, 45, 176–190. https://doi.org/10.1016/j.ijinfomgt.2018.11.008

Makarius, E. E., Mukherjee, D., Fox, J. D., & Fox, A. K. (2020). Rising with the machines: A sociotechnical framework for bringing artificial intelligence into the organization. Journal of Business Research, 120, 262–273. https://doi.org/10.1016/j.jbusres.2020.07.045

Manyika, J., & Bughin, J. (2018, October). The promise and challenge of the age of artificial intelligence. McKinsey Global Institute. https://www.mckinsey.com/featured-insights/artificial-intelligence/the-promise-and-challenge-of-the-age-of-artificial-intelligence

Manyika, J., Chui, M., Miremadi, M., Bughin, J., George, K., Willmott, P., & Dewhurst, M. (2017). Harnessing automation for a future that works. Mckinsey Global Institute. https://www.mckinsey.com/featured-insights/digital-disruption/harnessing-automation-for-a-future-that-works

MAXQDA. (2020). What is MAXQDA. Maxqda.Com. https://www.maxqda.com/what-is-maxqda

McCormick, J. (2020, August 7). AI Project Failure Rates Near 50%, But It Doesn't Have to Be That Way, Say Experts. Wall Street Journal. https://www.wsj.com/articles/ai-project-failure-rates-near-50-but-it-doesnt-have-to-be-that-way-say-experts-11596810601

McKinsey. (2008). Enduring Ideas: The 7-S Framework | McKinsey. https://www.mckinsey.com/business-functions/strategy-and-corporate-finance/our-insights/enduring-ideas-the-7-s-framework

Mills, A., Durepos, G., & Wiebe, E. (2010). Encyclopedia of Case Study Research. https://doi.org/10.4135/9781412957397

Oosthuizen, K., Botha, E., Robertson, J., & Montecchi, M. (2020). Artificial intelligence in retail: The AI-enabled value chain. Australasian Marketing Journal (AMJ), S144135822030077X. https://doi.org/10.1016/j.ausmj.2020.07.007

Paghaleh, M. J., Shafiezadeh, E., & Mohammadi, M. (2011). Information Technology and its Deficiencies in Sharing Organizational Knowledge. 2(8), 8.

Paschen, J., Kietzmann, J., & Kietzmann, T. C. (2019). Artificial intelligence (AI) and its implications for market knowledge in B2B marketing. Journal of Business & Industrial Marketing, 34(7), 1410–1419. https://doi.org/10.1108/JBIM-10-2018-0295

Paschen, U., Pitt, C., & Kietzmann, J. (2019). Artificial intelligence: Building blocks and an innovation typology. Business Horizons, 63(2), 147–155. https://doi.org/10.1016/j.bushor.2019.10.004

Peters, T. J., & Waterman, R. H. (2012). In Search of Excellence: Lessons from America's Best-Run Companies. Harper Collins.

Poole, D. L., & Mackworth, A. K. (2017). Artificial intelligence: Foundations of computational agents (2nd edition). Cambridge University Press.

Preece, A. (2018). Asking 'Why' in AI: Explainability of intelligent systems - perspectives and challenges. Intelligent Systems in Accounting, Finance and Management, 25(2), 63–72. https://doi.org/10.1002/isaf.1422

Press, G. (2019, July 19). This Week In AI Stats: Up To 50% Failure Rate In 25% Of Enterprises Deploying AI. Forbes. https://www.forbes.com/sites/gilpress/2019/07/19/this-week-in-ai-stats-up-to-50-failure-rate-in-25-of-enterprises-deploying-ai/

Sanders, N. R., Boone, T., Ganeshan, R., & Wood, J. D. (2019). Sustainable Supply Chains in the Age of AI and Digitization: Research Challenges and Opportunities. Journal of Business Logistics, 40(3), 229–240. https://doi.org/10.1111/jbl.12224

Sanders, N. R., & Wood, J. D. (2020, August 24). The Secret to AI Is People. Harvard Business Review. https://hbr.org/2020/08/the-secret-to-ai-is-people

Satell, G. (2018). How to Make an AI Project More Likely to Succeed. 5.

Shin, D. (2021). The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI. International Journal of Human-Computer Studies, 146, 102551. https://doi.org/10.1016/j.ijhcs.2020.102551

Simon, P., Tufft, C., & Zampella, P. (2020, August 28). Closing the skills gap in retail with people analytics [McKinsey & Company]. Reinventing Retail with People Analytics. https://www.mckinsey.com/industries/retail/our-insights/closing-the-skills-gap-in-retail-with-people-analytics?cid=app

Smith, C., Norton, B., & Ellis, D. (1992). LEAVITT'S DIAMOND AND THE FLATTER LIBRARY: A CASE STUDY IN ORGANIZATIONAL CHANGE. Library Management, 13(5), 18–22. https://doi.org/10.1108/01435129210020352

Vial, G., Jiang, J., Giannelia, T., & Cameron, A.-F. (2021). The Data Problem Stalling AI. 9.

Vidgen, R., Shaw, S., & Grant, D. B. (2017). Management challenges in creating value from business analytics. European Journal of Operational Research, 261(2), 626–639. https://doi.org/10.1016/j.ejor.2017.02.023

Weber, F. D., & Schütte, R. (2019). State-of-the-art and adoption of artificial intelligence in retailing. Digital Policy, Regulation and Governance, 21(3), 264–279. https://doi.org/10.1108/DPRG-09-2018-0050