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DEVELOPMENT OF A DATA ANALYTICS-DRIVEN SYSTEM FOR INSTANT, TEMPORARY PERSONALISED DISCOUNT OFFERS

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ABSTRACT

The innovation of targeting customers with personalised discount offers has been incorporated into business strategies in order to ensure a competitive advantage amongst peers along with ensuring customer experience. In this article, a demonstrator model was developed which provides a holistic view of an individual customer's behaviour in retail outlets. The demonstrator creates instant, temporary personalised discount offers based on the purchasing tendencies of that customer in retail outlets. The model illustrates the utilisation of customer behavioural data and data analytics to identify unique cross-selling and upselling opportunities to ultimately improve customer experience. This article also includes the architecture of the proposed model along with the results from the demonstrator model.

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1. INTRODUCTION

In the time-intensive world we live in today, one would be lost without any communication and technology. This is caused by the dependency on technology that the world has fallen into. An attitude change towards new technology has become necessary in order to accommodate the ongoing rush to achieve more.

The International Data Corporation (IDC) identified the so-called Third Platform in 2007. This platform is built on four technology pillars namely; mobile computing, cloud services, big data analytics and social networking [1]. This Platform has a series of innovation accelerators that depend on the Platform, where the Internet of Things (IoT) is one of the most promising ones. The IoT can be explained as all devices that connect and communicate with one another via the internet. This new communication channel has created new means for the creation and transfer of Big Data and with that, a new world of innovation exists.

The challenge to influence potential users and initiate a change in user attitude towards these ne innovations are ideally what industrial engineers are good at. The prospect of these new innovations creates new opportunities for industrial engineers.

In the United States of America, Walgreens partnered with Aisle 411 and Google Project Tango to create a 3D augmented reality to Walgreens. Aisle411 helps the customer map and search products to where they are located on the shelf and Project Tango can determine the user's location within the store. This proposes a game-like shopping experience and is limited to a Tango device and Walgreens store [2]. This innovation does not include personalised offers based on customer historical data and usage.

As the world became more advanced with technology and new innovations, the cost of living also increased over time. Almost all retail stores now propose discount offers and loyalty programmes to attract customers. A reason for this is the competitive attitude that started to exist among retail stores. In the past, discount offers were sufficient to still have a profitable business, but this is not so anymore. To maintain a competitive advantage, innovations must be considered to ensure customer experience is superior.

A case study provided by TM Forum [3] was the starting point of the new initiative to improve customer experience by using data analytics. In the case study, customers receive personalised discount offers (PDO) based on their buying behaviour and acceptance history. The case study was redefined according to the following scenario:

As a customer walks into a participating store, the customer will receive PDOs via a mobile device on certain items in that store. These discount offers are only valid for this specific individual at this point in time in the store mentioned. This can be made possible by analysing the purchasing behaviour of customers and determining which items they would be likely to buy or need at a specific point in time. Using historic information, customer profiles are created and personalised special offers can be determined. Along with the customer profiles, the efficiency of marketing can also be analysed and improved. To better understand the scenario described here, consider the following specific example:

Jo decides to subscribe to this personalised offer platform (which is free) and allows the tracking of his buying behaviour. Jo buys a certain brand of shampoo every time his is finished. After a certain period of time, a buying trend for Jo is identified. The trend indicates that he buys this specific shampoo every three weeks on average. One day Jo walks into one of many participating retail outlets and passes the shelf displaying all the shampoos. Jo had not gone to the store to buy shampoo since he still had a little bit left. As Jo passes this shelf, he receives a notification presenting him with a one-time PDO on his specific brand of shampoo. Jo finds this offer appealing and argues that he might as well buy shampoo now for less rather than coming back to the store in two days' time. Jo accepts this PDO and buys his shampoo for less along with his other groceries. Jo experiences a satisfied feeling towards his trip to the store and the money he saved by using his personalised offer.

Apart from being offered discount on a specific product, the client could also receive discount offers for alternative products, which are referred to as *cross-selling*. Also, discounts on similar but more expensive products could be offered, thus earning more revenue from the client if he accepts the offer. This is called *upselling* and is the ultimate goal of PDOs.

These offers must be proposed at a point in time when individuals are most susceptible to them. A large quantity of data must be processed and analysed in order to create customer profiles, track buying behaviour and specify personalised offers. The problem at hand is thus to develop a demonstrator that creates these customer profiles and determines the most suitable PDOs for specific individuals in real time. Along with this demonstrator, a simulator is necessary to generate historical, stratified data to be analysed by the demonstrator during development and testing. The authors work in the Unit for Simulation Modelling and Analysis (USMA). This research group forms part of the Department of Industrial Engineering at Stellenbosch University.

This article consists of a short literature review in Section 2. This section elaborates on customer profiling, cross-selling and upselling and offers identification, which is necessary to understand the fundamentals of this study. The proposed model for the demonstrator is described in Section 3. Section 4 presents a toy problem created by the authors. Section 5 describes the development of the simulator and demonstrator followed by the results in Section 6. A business case is provided in Section 7 and the last section concludes the research work discussed in the article.

2. SHORT LITERATURE REVIEW

The short literature review includes information regarding customer profiles, cross-selling and upselling and offers identification.

2.1 Customer profiling and segmentation

An overview of customer profiling and segmentation is presented in this section. Approaches for developing customer profiles follows thereafter.

2.1.1 Overview of customer profiling and segmentation

Customer profiling is used to describe the customer based on some predefined attributes. Each customer has a unique profile based on their factual and behavioural data. Profiling is used to personalise individuals to better understand their needs. Customer service and satisfaction are improved by understanding the customers' desires and requirements [4], [5]. Marketers use profiling for targeted marketing strategies in which customers are presented an offer they would be interested in. The behaviour of customers is predicted by the method of discovering the similar patterns in the behavioural data. Profiling thus attempts to discover knowledge within customer data that was not known before [5]—[7].

Customer segmentation is done when customers are divided into homogeneous groups based on shared attributes and habits [5]. As in customer profiling, segmentation is used to identify certain properties for a certain group of customers. With the amount of data that must be analysed in the technological world of today, it becomes more and more tedious to segment customers based on similar traits. In order to identify the needs of each individual and choose marketing strategies appropriately, profiling individual customers seems to be the solution [8].

Bounsaythip *et al.* [5] state that customer profiling is performed after customer segmentation. The authors do not agree that this is necessarily the case. The full advantage of segmentation is done by profiling the different segments and designing marketing strategies accordingly. In the case of this study, the authors plan to go beyond customer segmentation and profile the buying behaviour of the customer.

2.1.2 Approaches to develop customer profiles and segmentations

According to Jansen [9], customer segmentation can commence without the knowledge of the data being analysed. This, unfortunately, does not apply in the case of customer profiling. Customer profiling can only commence once a complete set of individual customer data is available. The availability of data dictates which features are used for customer profiling. The factual profile is derived from the demographical data of the customer such as name, age, address, *etc*. It can also contain information derived from transactional data such as preferences. The behavioural data profile is derived from the transactional data of the customer which contains the records of the purchasing history of the customer for a certain time period [4].

Data mining is the phase where machine learning tools and techniques are used to develop customer profiles and segmentations. This is made possible by the advances in computer technology. The machine running the data mining software automatically searches large datasets to identify hidden correlations in data [6]. Machine learning techniques used for profiling differ from those used for segmentation. Customer segmentation is achieved by using unsupervised clustering models whereas customer profiling uses supervised classification models [10].

The next section describes where and how customer profiling and segmentation can be used by reviewing cross-selling and upselling.

2.2 Cross-selling and Upselling

In the domain of Customer Relationship Management (CRM), one of the core activities is customer retention. A well-known method to achieve this is by using cross-selling and upselling techniques.
Cross-selling can be defined as offering alternative products or services to customers during their current buying process. This is a strategy used to ensure an enterprise captures a large share of the consumer market. The company effectively increases the number of products the customer purchases from the company and guarantees a competitive advantage amongst its peers [11].

According to Schiffman [12], ***Upselling*** is a technique used when asking a customer who has already purchased something to purchase more of it or more of something else. This technique motivates customers to acquire more expensive versions of what is already owned. A promotion is one of the most popular upselling methods. Another method is alerting customers about alternative products by including information with the original purchase [13], [14].

Effective upselling and cross-selling occur when the needs of the customer are fully understood. This creates an opportunity for the application of customer profiling and segmentation to identify the specific needs of customers. Customer data is analysed by the practice of data mining which is an effective approach to identify cross-selling and upselling opportunities. It delivers knowledge about which products to promote and the most appropriate time to do so [13], [15].

There are three objectives of identifying cross-selling and upselling opportunities. The first is to understand the acquisition pattern of the customer. The second objective is to identify the factors which influence the repurchase decision of the customer and thirdly, forecasting the time of the possible repurchases [12]. It is important to understand these objectives as cross-selling and upselling not only ensure customer retention within the CRM domain, they also ensure profit growth for the enterprise.

In order to identify cross-selling and upselling opportunities one needs holistic information regarding customers. This was described in Section 2.1. The following section sheds light on how holistic customer segmentations are created and the process used for identifying cross-selling and upselling opportunities.

2.3 Offer identification

This subsection is an overview of RFM and Market Basket Analysis which can be used in identifying discount offers.

2.3.1 Recency, Frequency and Monetary

RFM (recency, frequency and monetary) is a common approach used for analysing customer purchase behaviour and making predictions based on the findings. The customer behaviour is usually contained within databases of enterprises and this is where the behavioural profile mentioned in Section 2.1 is developed from [10], [16].

The database must first be sorted by each attribute of RFM. After this the customers are divided into five equal segments. The different segments have different values for each RFM attribute depending on the customer's behaviour. ***Recency*** refers to the number of periods since the last purchase. The higher the number of periods (this can be days, months, *etc.*) the lower the recency variable of a customer will be, where five is the highest and one the lowest. ***Frequency*** refers to the number of purchases made in a given time period. The top quintile with the highest frequency is given the value of five. The ***monetary*** attribute is defined as the average amount of money spent during the analysed time. The more money spent on average the higher the monetary attribute will be. A combined RFM score can be calculated by adding the individual RFM attributes.

The RFM modelling technique is commonly applied in database marketing and a known tool to be used in developing marketing strategies [10]. This is because the RFM model can predict future purchases of customers. RFM is applied in most practical areas such as financial and government organisations, online and telecommunication companies as well as marketing and retail industries.

Apart from developing marketing strategies, the ***Customer Lifecycle Value*** (CLV) can be determined from the RFM analysis. The CLV provides insight of the profitability of the customer to the enterprise. This can give an expectation of nett future revenue of the company [17]. RFM analysis is also used for clustering customers into segments based on similar traits.

RFM can be used in this initiative to create provisional customer clusters for new participating members.

2.3.2 Market Basket Analysis

Market basket analysis (MBA) is a technique used for discovering purchasing patterns of customers by identifying associations between products customers buy together [18], [19]. Association rule mining is a data mining tool with various algorithms to create association rules that are used in MBA. These rules are generated by analysing the transactional database containing customers' purchasing history. Given two products X and Y, an association rule in the form of X → Y indicates a buying pattern that if a customer purchases item X they also purchase item Y.

There are two measures needed to generate association rules, namely the *support* and the *confidence*. Support is the measure of how often the database contains both X and Y, where the confidence is a measure of the accuracy of the rule. This accuracy is defined by the ratio of the number of times both X and Y appear to the number of times only X appears in the transactional database. MBA associations between products can be used to identify cross-selling and upselling items to propose to customers. MBA results also help in marketing strategies where products having a strong association should not be placed on promotion at the same time.

According to [10] association models can be applied to selected levels of analysis. Transactional level refers to items bought at a single visit to the store. Aggregated information assesses products bought during a set time period by each customer and this is referred to as the customer level of analysis.

MBA can be used in this initiative to propose PDO to customers based on products they normally buy together. The following section provides the proposed model for this initiative.

3. PROPOSED MODEL

The proposed model gives an overall understanding of the case study that is addressed. In order to design the proposed model, the authors followed the Object-Process Methodology (OPM). OPM is an intuitive methodology that models the complex architecture of systems in a coherent way. Development and support are needed throughout the life cycle of artificial models. This calls for a comprehensive methodology that includes all challenging points in the evolution of a system [19]. Systems consist of three main aspects which are the *function*, the *structure* and the *behaviour* of the model. These aspects are alike for both artificial and natural systems, which makes OPM an unambiguous approach to gain a holistic view of a system. OPM is an ISO-certified methodology (ISO19450) which confirms that it is sufficient for practitioners to use OPM as a modelling paradigm to conceptualise systems in a varying amount of detail. The value of using OPM is within the visual graphics and semantics which make it easy to understand [20]. The proposed model created with OPM is visualised by the Object-Process Diagrams (OPD) that can be seen in Figure 1.

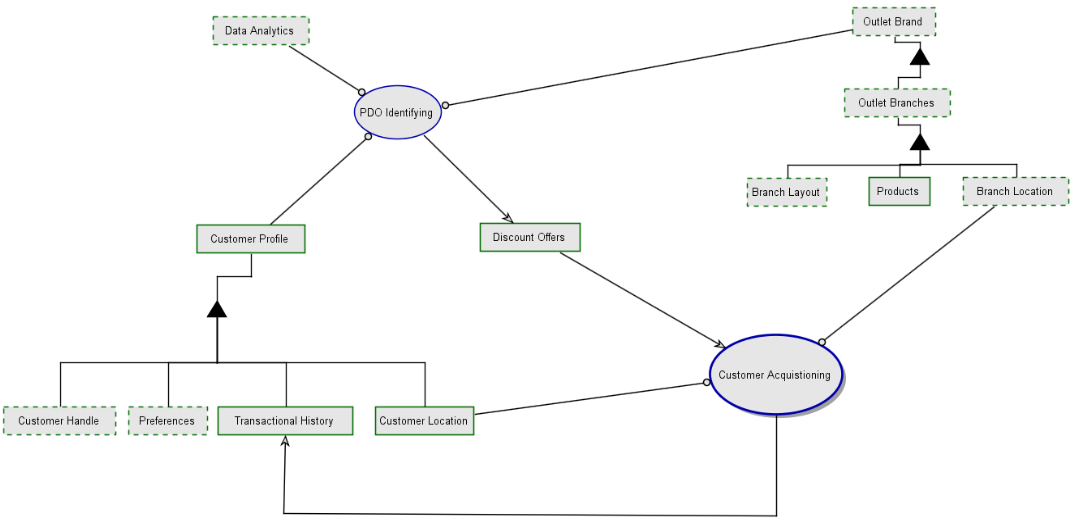


Figure 1: Architecture of the proposed model

The OPD is accompanied by the natural language description of the diagram, which makes OPM a desired approach. The natural language describing the proposed system is as follows:

Data Analytics is environmental.
Customer Profile consists of Customer Handle, Preferences, Transactional History, and Customer Location.
    Customer Handle is environmental.
    Preferences is environmental.
Outlet Brand is environmental.
Outlet Brand consists of Outlet Branches.
    Outlet Branches is environmental.
    Outlet Branches consists of Branch Layout, Products, and Branch Location.
        Branch Layout is environmental.
        Branch Location is environmental.
PDO Identifying requires Outlet Brand, Customer Profile, and Data Analytics.
PDO Identifying yields Discount Offers.
Customer Acquisitioning is physical.
Customer Acquisitioning requires Customer Location and Branch Location.
Customer Acquisitioning consumes Discount Offers.
Customer Acquisitioning yields Transactional History.

As stated previously, this proposed model is a very high-level view of the desired system. The processes are shown with elliptical symbols whereas the objects are represented by rectangles. In this proposed model the two processes are the *PDO identifying* and the *Customer acquisitioning*. Customer acquisitioning consists of two lower-level OPDs. For simplicity the lower-level OPDs are not included in this article.

The process of PDO identification requires the outlet brand, customer profile, and data analytics to make this process happen. The different requirements for PDO identification consist of other objects as well. This process yields discount offers, which is consumed by the customer acquisitioning process.

The outlet brand object consists of the participating branches and these branches include information such as branch layout, location and products. The customer profile object consists of the factual information of the customer and the preferences of the customer. This information is captured when the customer subscribes to the service and cannot be changed by the model itself. The customer profile also includes the customer location and transactional history of the customer.

The customer acquisitioning process is the second process in this top-level OPD. Customer acquisitioning requires the customer and branch location. As mentioned before, this process consumes the discount offers yielded by the PDO identifying process. The transactional history is yielded from the customer acquisitioning process. This creates a feedback to the customer profile which ensures the transactional history is updated with information regarding customer acquisitions from all participating outlets.

The next section explains a toy problem the authors designed to enlighten the reader on how the proposed model will function in a real-world situation.

4. TOY PROBLEM

The toy problem is modelled on a smaller scale of data. Figure 2 visualises how the real-world system would interact with the customer.

Retail enterprises subscribe to this system in order for customers to utilise this service within their respective stores. Initially, the customer subscribes to the services of the PDOs via a mobile app. In this subscription, the factual data of the customer is captured. Along with this, the customer is also allowed to enter preferences which would help to place the new customer in a provisional customer segment. Over time, the customer builds up transactional history, which the system uses along with data mining techniques to identify offers the customer would be most susceptible to. When the customer enters one of many participating retail outlets, the system is notified of the customer's location. If the moment in time relates to the time the system estimated the customer to be most susceptible to an offer, the customer receives a notification via the app.

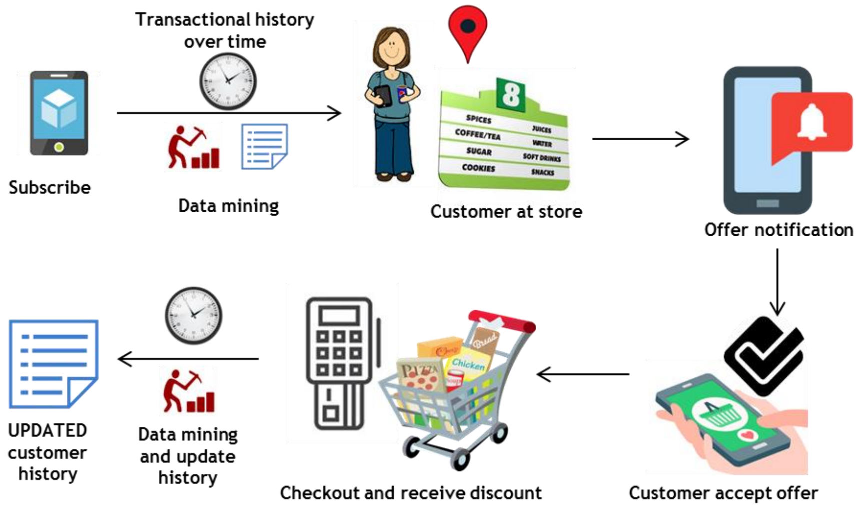


Figure 2: Schematic of the toy problem

The customer is presented with the personalised discount offer. This offer is personalised according to the purchasing behaviour of the specific customer. The offer is instant and temporary and will thus only be valid while the customer is in the store. The customer can either decide to accept the offer or to reject it. In the case of rejection, the system records the decision to improve the customer profile. If the customer decides to accept the offer, the discount is presented at the checkout point. Along with this the transactional history of the customer is updated. The customer can update the transactional history with every visit to a participating store by using the mobile app even though an offer is not presented. As time passes and the mobile app is used frequently, the customer profile will become more accurate and more appropriate offers can be identified.

The following section describes the simulator and demonstrator that was designed and developed by the authors in order to create the system that was described up until this point.

5. SIMULATOR AND DEMONSTRATOR

The proposed system consists of a:

1. simulator that creates initial customer historic data, without any PDO analysis.
2. demonstrator that uses the simulator in 1. to keep on creating customer purchases, but now the real-world process is emulated, as PDOs are identified and offered based on machine learning techniques. **Figure 3** summarises the differences between the simulator and the demonstrator in the proposed system.

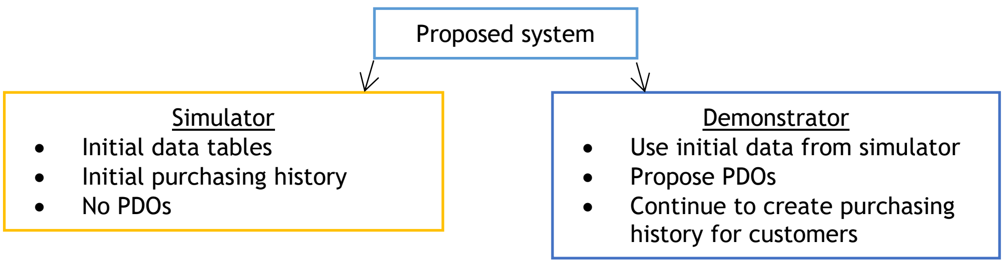


Figure 3: Summary of proposed system

5.1 Simulator

The authors developed the simulator using Matlab in order to simulate pseudo customer data that can be used for analysis purposes, thus creating historic data. For this system to be used in practice, enterprises will need to extract data in the correct format to be used in the demonstrator. The format in which the demonstrator requires the data is very specific and it is for this reason that the authors decided to simulate data in the correct format to be analysed. The simulator is not the main focus of this article and will thus not be explained in depth. The simulator simulated numerous different customers, branches, brands, products, preferences, *etc*. It was possible to create customers' transactional history using this initial information. Different statistical distributions were used to introduce variation within the initial simulated data.

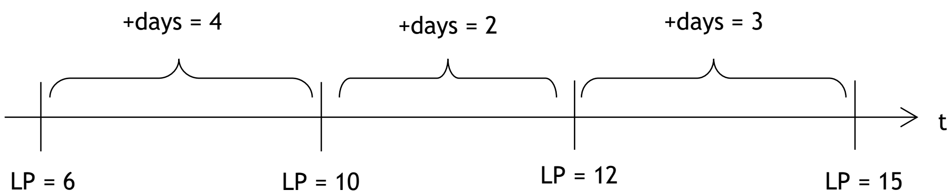
The initial orders or purchasing instances are contained within an orders table in a relational database. The orders table contains information regarding each instance a customer visits a participating store. Certain aspects need to be determined in order to populate this table for each simulated day. These aspects are:

1. The number of customers visiting stores each day.
2. The respective customers who visit the stores for the specific day.
3. The respective store each customer visits.
4. The time the customer visits a store.
5. To update the customers last purchase date.

These choices were based on using various statistical distributions in order to introduce variation within the purchasing history. The customers' last purchase dates are updated each time they visit a store again.

LastPurchase (LP)	...
~~06-01-2016~~	...
~~10-01-2016~~	...
~~12-01-2016~~	...
15-01-2016	...

Figure 4 explains visually how the last purchase date of customers is updated.



LastPurchase (LP)	...
~~06-01-2016~~	...
~~10-01-2016~~	...
~~12-01-2016~~	...
15-01-2016	...

Figure 4: Example of customer last purchase date update

Each purchasing instance that is recorded within the orders table is linked to information such as the products bought, the quantity of products and the unit price paid for them. This information is recorded in the transactional history table. These two tables are the most important tables in this study as they contain the purchasing behaviour of each customer and are used as input to the demonstrator.

All the initial information and purchasing behaviour generated by the simulator were saved in a Microsoft SQL Server database. The relevant information required for the demonstrator is extracted from this SQL database to Matlab. An ODBC data connection was created between SQL Server and Matlab using the Matlab Database Explorer Application. This connection is illustrated in Figure 5. The author used Matlab and SQL Server because it was available to the author. Alternative options can be used such as Python and MySQL.

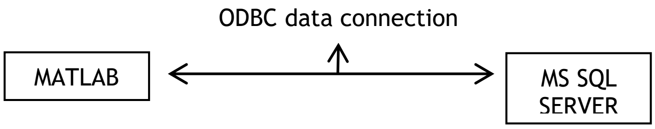


Figure 5: Data connection between Matlab and SQL Server

5.2 Demonstrator

The goal of the demonstrator is to identify patterns within the purchasing history of a customer. The demonstrator creates and presents PDOs to customers, based on the purchasing pattern of the specific customer. The demonstrator uses the simulated pseudo customer data created by the simulator explained in Subsection 5.1. The demonstrator is divided into two distinct parts or functionalities and is visualised by Figure 6.

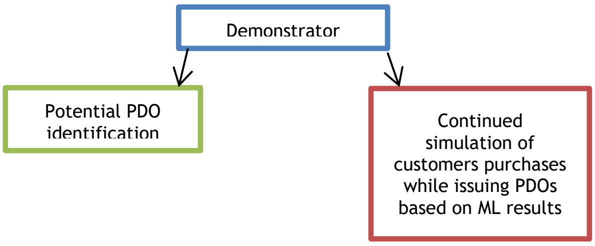


Figure 6: Summary of demonstrator functionalities

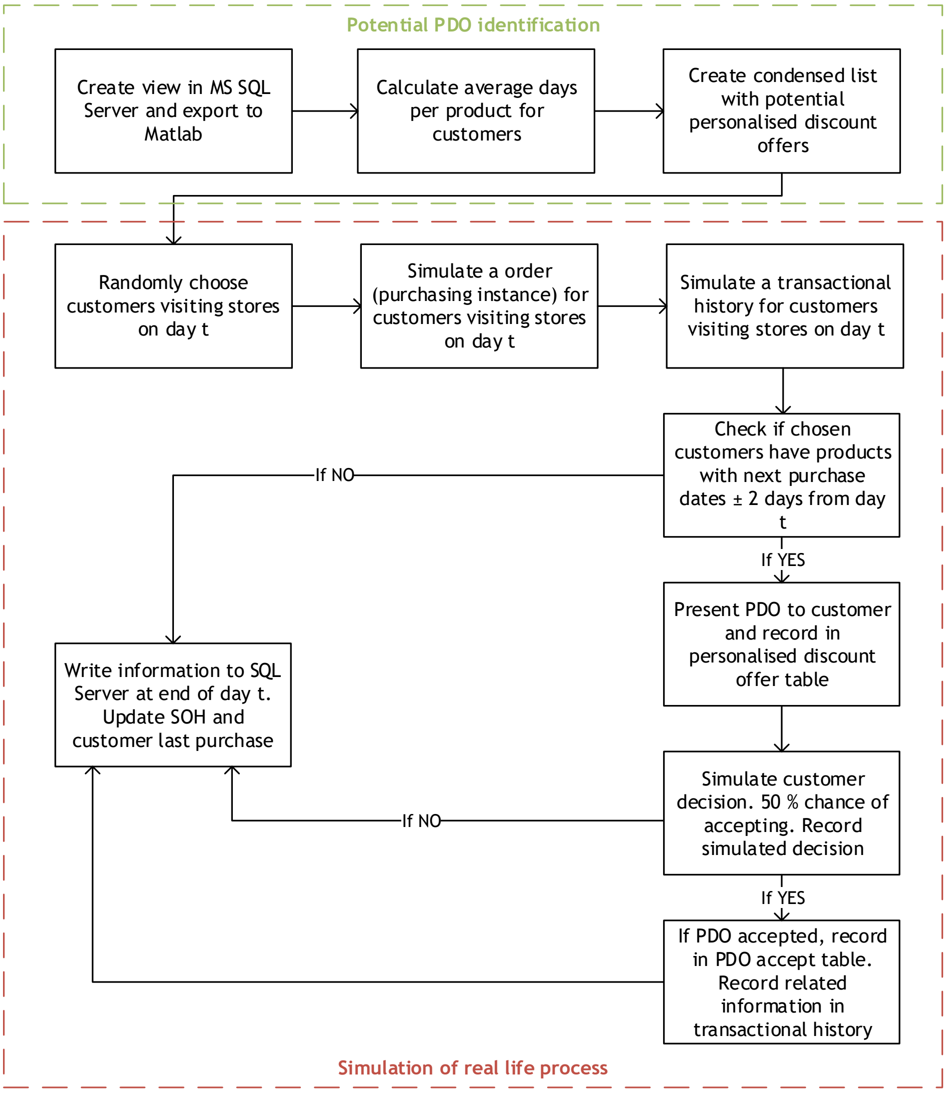


Figure 7: Conceptual schematic view of the demonstrator

The first part performs the identification of potential PDOs. The second part performs the continued simulation of the real world process where customers visit the stores, receive PDOs and continue to create a transactional history. Figure 7 is a schematic representation of the two parts.

To realise the first part of the demonstrator, the authors created a function that returns a table with products that may be potential discount items for customers. The function uses a view created in SQL Server and calculates an average days per product for products bought more than twice. This average is returned in a condensed structure along with the potential next purchase date of each product.

The average days per product was calculated taking into account the days between purchases of a specific item and the quantity that was bought. The data is updated in SQL at the end of each day to be ready for the calculation at the beginning of the next day. This explains the first part of the working of the demonstrator. Figure 8 visually explains how the function calculates the average days per product usage for example, Product X.

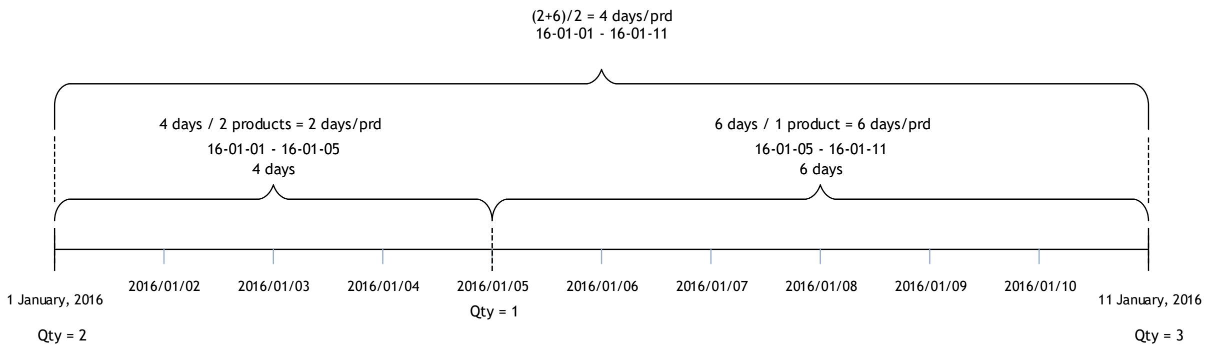


Figure 8: Calculations of average days per product

The average days per product usage for Product X was calculated as four days per product. Using the average days per product and quantity bought, the next potential purchase date for Product X is 23 Jan 2016.

The second part of the demonstrator is the simulation of the real world process of customers visiting retail stores and receiving potential PDOs. The condensed structure obtained by the Matlab function in the first part is used in this part of the demonstrator to evaluate whether the specific customers visiting the stores on the specific day qualify for a PDO. The demonstrator was developed so that it still created pseudo customer transactional data for those customers visiting the store on the specific day.

For each day, the demonstrator randomly chooses customers visiting stores that day. After the customers are chosen, the purchasing instance and transactional history are created as the simulator created it. Using the condensed list of potential PDOs, the demonstrator evaluates whether the customers entering a store that day have a product with a next purchase date ± two days from the current date. If any of the customers entering the store encompass products with a next purchase date within this date range, they will be presented with a PDO. The information regarding the specific PDO is recorded in a personalised discount offer table. This table also includes the acceptance or rejection of offers.

The demonstrator was developed to have an acceptance rate for PDOs of 50%. This was used as a starting point. It is inadequate to assume that the probability of a customer accepting offers based on their acceptance history. The offer could be a cross-sell or upsell offer and based on the customer's experience of the new product they might not accept it again. In practice this percentage will be determined by the customers' acceptance and rejection rate by analysing the customer historical data.

If the demonstrator simulates the customer to accept the PDO, the relevant information is documented in the acceptance table. The product bought, including the discount, is also recorded in the transactional history table along with the other products the customer bought during the particular purchasing instance.
At the end of each day, all relevant information recorded is exported to the SQL Server database. Except for the tables already mentioned, the stock on hand of products and the particular customers' last purchase dates are also updated during this event. The information regarding the purchasing history of customers is continuously

updated by the feedback to the SQL Server database at the end of each day. This ensures that PDOs are estimated based on the current buying behaviour of customers.

The following section sheds light on the experiments and results that were obtained from the demonstrator.

6. RESULTS

The authors simulated a dataset containing historical purchasing data of customers using the simulator developed in Subsection 5.1. This simulated purchasing history was used as the initial input in the demonstrator in order to predict customers' PDOs.

The authors first simulated a smaller dataset to ensure the model is correct before attempting the simulation and analysis of a large dataset. After a validation and verification of the simulator and demonstrator, no evidence of errors was found in the development of the simulator and demonstrator. Any latent errors must still be observed within the model. The demonstrator presented PDOs to customers based on their historical purchasing behaviour. In order to show the result of this, the purchasing behaviour of Customer 2 toward Product 7 is used as an example.

Table 1: Purchase history of Customer 2 for Product 7

Purchase instance	Date of purchase	Quantity
1	06-03-2016	3
2	26-03-2016	2
3	15-04-2016	3

Based on the purchase history displayed in Table 1, the demonstrator predicted the next purchase dates for Product 7. Table 2 shows when Customer 2 bought Product 7. The table also includes the date on which Customer 2 was presented a PDO for Product 7 along with the customer decision of acceptance or rejection.

Table 2: Demonstrator predictions for Customer 2's Product 7

Purchase instance	Date of purchase	Quantity	Offered as PDO	Accepted/ Rejected	Expected NPD
4	01-07-2016	2	No	-	27-07-2016
5	14-07-2016	2	No	-	31-07-2016
6	02-08-2016	1	No	-	11-08-2016
	12-08-2016	-	Yes	Rejected	13-08-2016
	14-08-2016	-	Yes	Rejected	17-08-2016
7	15-08-2016	1	No	-	18-08-2016
8	16-08-2016	1	Yes	Accepted	28-08-2016
	30-08-2016	-	Yes	Rejected	10-09-2016
9	21-09-2016	1	No	-	02-10-2016
	04-10-2016	-	Yes	Rejected	05-10-2016
	07-10-2016	-	Yes	Rejected	09-10-2016
10	08-10-2016	3	Yes	Accepted	22-11-2016
	24-11-2016		Yes	Rejected	25-11-2016
11	25-11-2016	1	Yes	Accepted	30-11-2016
12	29-11-2016	1	No	-	15-11-2016
13	13-12-2016	2	Yes	Accepted	06-01-2017
14	02-01-2017	2	No	-	27-01-2017

After each purchase instance of Product 7 by Customer 2 the next purchase date is updated as explained in Subsection 5.2. This example shows an extraction of the purchasing behaviour of Customer 2 in order to illustrate the working of the demonstrator. The authors are in the process of investigating using survival analysis for the prediction of the next purchase dates. The next section presents the business proposition for this initiative.

7. BUSINESS CASE

This section provides the business proposition this initiative has. A business model for this service was proposed by the authors by applying the Business Model Canvas designed by Osterwalder to explicitly state and refine the business model of this initiative [21]. shows the nine building blocks suggested by Osterwalder. The authors populated the nine building blocks with the focus on this project.

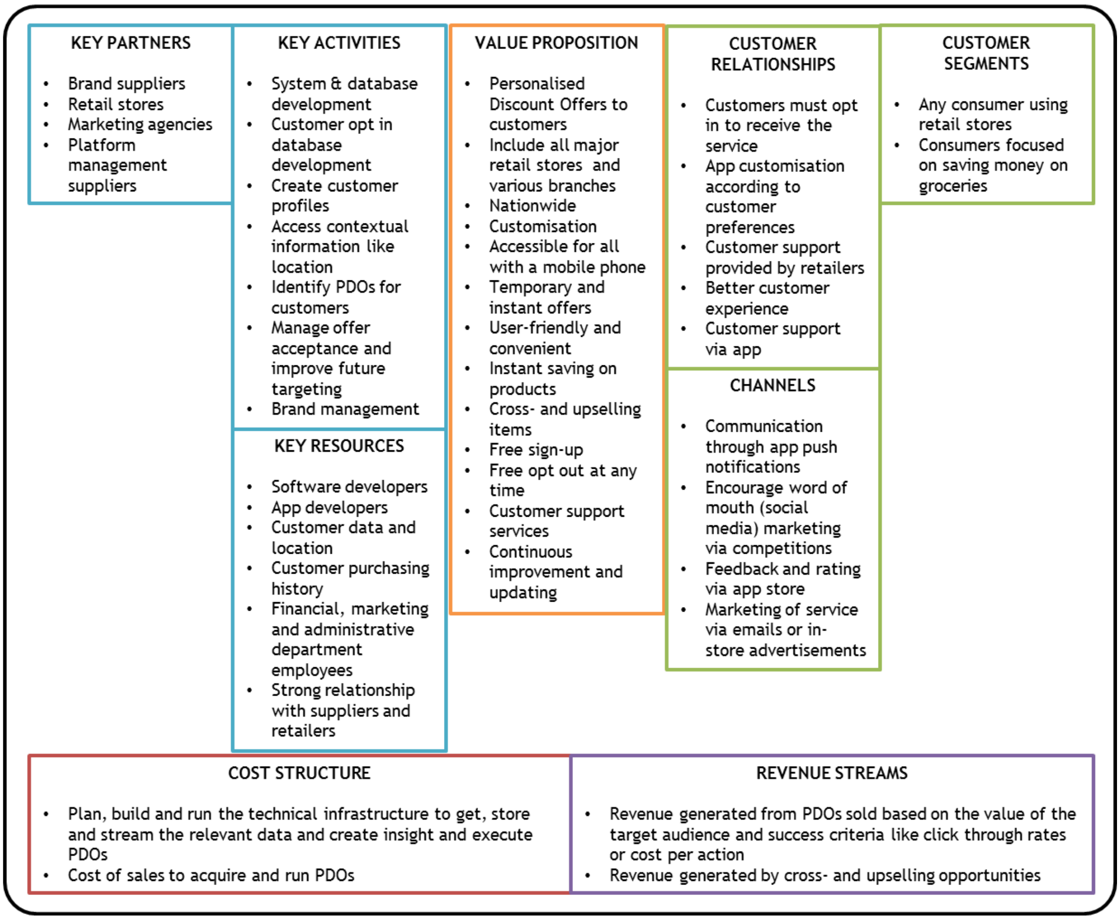


Figure 9: Business Model Canvas (adapted from [21])

This innovation suggests a new way of thinking and conducting business within the retail domain. The current relationship between retailers and suppliers in terms of creating promotions is a difficult and unpleasant task. With this new service, both retailers and suppliers can gain information regarding purchasing behaviour of potential customers along with ensuring low customer churn ratios. Promotions are personalised ensuring higher acceptance and including cross-selling and upselling offers based on purchasing behaviour, enterprises can expect an alternative revenue stream.

8. CONCLUSION

This article reflects on the work done by the authors as well as the mutual research done by the USMA Workgroup [22]. The literature study is considered fundamental to this study specifically. The literature review is followed by a proposed model. This article proposed a customer-centric marketing system in the context of data analytics where many customers with buying history can be targeted individually to enable cross-selling and upselling.

The proposed model visualises the architecture of the model and demonstrates how data mining will be used within the model. The study is explained by means of a toy problem. The toy problem is based on a smaller set of data and describes the interaction with the system. This illustrates precisely how the personalised discount offers are to be identified and how the customer will interact with the system.

The system was designed and developed in the form of a simulator and demonstrator. The simulator created pseudo customer historical data which was used as the input for the demonstrator. The demonstrator identified the personalised discount offers and proposed them to customers visiting the participating stores. Industrial engineers are system integrators who can see the detail but also the big picture. We are ideally positioned to engineer systems of the nature described in this article, i.e. systems that integrate to improve our lives, as dictated by the fourth industrial revolution.

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