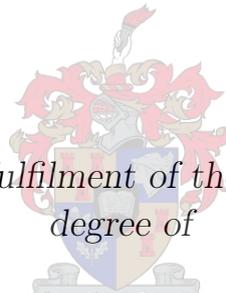


Automation and Labour Demand: South African Students' Awareness and Beliefs

by

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December 2019

Declaration

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Abstract

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The fourth industrial revolution is characterised by the integration of physical, digital, and biological technologies. We are in the beginning stages of this revolution where it is predicted that the capabilities of machines are predicted to rival and surpass some of the capabilities of human labour. It is predicted that many jobs will be automated during this revolution and human labour will need to acquire skills that will complement automation. The objective of this study is to understand the awareness of automation amongst undergraduate university students in South Africa when making career choices. With the already high unemployment rate in South Africa, it will be necessary to measure the awareness of the future of the labour market for automation. In addition to their awareness, the study investigates as to whether automation is a factor when students make their career decisions. This study is primarily exploratory and uses a quantitative research approach to gather data. A self-administered questionnaire was sent out to all undergraduate students of a research-intensive university in South Africa. The results indicate that students perceive themselves to be aware of automation, however, they do not consider automation when making career decisions. Additionally, the results indicate that external sources of influence do not significantly influence career decisions, students are primarily influenced by their interests and career-related factors.

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Chapter 1

Introduction

1.1 Background

The South African economy had an average *gross domestic product* (GDP) growth rate of 1.5% between 2013 and 2017, with GDP forecasted to grow at an average of 1.7% between 2019 and 2023 (IMF, 2018). This is a relatively low growth rate as compared to the average for emerging economies which were 4.6% and 4.8% for the respective periods. In neoclassical economics the growth of an economy is attributed to three components: capital, human labour, and technological change (Solow, 1956). An increase in any of the three components would result in an increase in the total production of an economy. Historically, the combination of capital and human labour have contributed to an increase in productivity, with technological advancements functioning as a multiplier on both of these inputs (capital and human labour). Thus far there have been three major events of technological change, named the industrial revolutions. According to Schwab (2015, p. 4) the three industrial revolutions can be identified as follows: “*The First Industrial Revolution used water and steam power to mechanize production. The Second used electric power to create mass production. The Third used electronics and information technology to automate production*”. According to Bloem *et al.* (2014), the world is now at the beginning of the fourth industrial revolution. This revolution is characterised by the integration of physical, digital, and biological technologies. This will enable technological artefacts to become more intelligent and lifelike, making them increasingly suitable replacements for many different forms of human labour. The utilisation of automation technologies is an attractive business strategy as it not only enables continuous production, but also avoids the consistently rising costs of human labour (Rifkin, 1995).

The unemployment rate in South Africa is exacerbated by its failure to grow in economic terms, and at the end of 2017 it stood at 26.7% (Statistics South Africa, 2018*b*). Over the ten-year period between 2008 and 2017 the unemployment rate has increased by 3.2 percentage points (Statistics South Africa,

2008a). Considering the already high level of unemployment, the possibility of further labour displacement as a result of automation presents a substantial challenge to workers and policy makers alike. Despite this challenge, the replacement of human labour with technology, generally termed *labour automation* or simply *automation*, also benefits the economy. It may create new work opportunities and occupation types (Rifkin, 1995; Halal *et al.*, 2016), as well as increase production levels and grow the economy. Rifkin (1995), however, indicates that there are two possible scenarios for human labour in the long-term. These scenarios, further discussed in Section 2.1.4, suggest that humans will work less due to automation technologies.

Human workers can choose to compete with or complement the emerging class of automation technologies. Brynjolfsson and McAfee (2012) warn, however, that competing with automation could prove to be fruitless as the capabilities of machines increase exponentially with every iteration. A more appropriate strategy for human workers may be to complement automation by supplementing it with capabilities that the machines are yet to acquire.

Automation technologies are already capable of replacing many of the medium-skilled occupations currently performed by South African workers. As these technologies advance, many low and high-skilled occupations will also become automatable in the near future (Frey and Osborne, 2015). However, because these occupations are often more challenging to automate, human labour will continue to be in demand for many of them. With a large portion of low and medium skills, the adoption of automation technologies could prove to be a challenge for the South African labour market which lacks in the supply of high skills (Statistics South Africa, 2018b). At the end of 2017 more than 80% of South Africa's active labour force only had a secondary school (high school) qualification (Statistics South Africa, 2018b). Although the majority of the South African labour force comprises of low-skilled workers, it is predicted that the number of youth acquiring post-secondary qualifications will rise (Department of Higher Education and Training, 2018). The youth are the future of the labour market and they are most likely to be affected by the fourth industrial revolution. In order for the future of the labour market to complement automation, the youth will need to consider automation when making career decisions. This research study aims to investigate whether the current cohort of university students are aware of automation technologies and consider them when making career decisions.

1.2 Motivation For The Thesis

There are two motivations for conducting this study. Firstly, the potential effects of the fourth industrial revolution are making it increasingly important for future participants in the labour market to consider the impact of automation on the demand for labour. By measuring the level awareness of

automation among the current cohort of university students, the thesis endeavours to develop a high-level description of the general understanding that members of this demographic have about automation. This will be beneficial as little research has focused on automation from the point of view of those who will enter the labour market in the near future. The second motivation for the thesis stems from the first one in that it is imperative to understand whether and how students' understanding of automation technologies influence their career choices. The thesis aims to identify what sources and factors do and do not influence students' career decisions, and how the automation of work feature among these.

1.3 Research Questions

The objective of this study is to understand the awareness of automation amongst undergraduate university students in South Africa when making career choices. Extending from this objective, the following primary research questions were posed:

- RQ1: *What is the level of awareness of automation amongst university students?*
- RQ2: *What are students' beliefs about the impact of automation on labour demand?*
- RQ3: *Do awareness and beliefs about automation influence career decisions?*

1.4 Research Design

To address the three specified research questions the thesis adopted a quantitative survey-based research design. The advantages of this method as opposed to others is that it can provide a numeric description of the sample, it is flexible, and could be distributed to a large number of potential respondents. In addition, this approach was selected as the thesis explored a new research area with little prior evidence existing. This suitability of the research design is further explained in Section 3.2.1.

1.5 Outline Of The Thesis

This chapter provided an overview of the research background, study motivation, research questions and the research design. The rest of this thesis consists of four chapters structured in the following order. Chapter 2 presents a narrative for the research study through a review of relevant existing literature. In

Chapter 3 an extensive description of the research design as well as the procedures for data collection and analysis is provided. Chapter 4 presents the analysis and results of the survey conducted. The final chapter provides the discussion of the findings and the conclusions reached in the thesis. Additionally, the discussion relates the findings to the existing literature as presented in Chapter 2. This chapter concluded with a consideration of, firstly, the implications of the thesis, secondly, the limitations of the present design and, finally, a number of recommendations for future research that extend from the present investigation.

Chapter 2

Literature Review

The following chapter presents a review of the literature concerning automation in the workplace, labour market trends, and the theories and factors pertaining to student career choices. The literature review establishes the basis to understand why automation is a factor that contributes to the changing landscape of the labour market, and why the future of labour supply (i.e. current and future students) should consider the possible effects of automation on the labour market.

The first section of the literature review addresses automation in the workplace. The purpose of this section is to identify the impact automation has had on the workplace and the labour market and discusses how automation affects the workplace and what the future of the workplace is predicted to become. Extending from this, the second section considers recent trends in the global labour market and presents predictions on what the future of the labour market holds. The purpose of this section is to indicate how the requirements of the labour market have changed and what they are likely to become in the future. From these changes, the question of whether the future of labour supply will meet the labour requirements of the future can be addressed. The final section of this chapter comprises of two themes related to career choices. The first theme identifies the theories that describe how students form their career choices. Extending from this, the second theme identifies factors that influence career decision making amongst students.

2.1 Automation

The following section reviews literature in relation to automation in the workplace. The section comprises of four sub-sections: the first sub-section conceptualises automation; the second discusses the history and current state of automation; the third discusses the effects of automation on the economy; and the final sub-section discusses the relationship between automation and labour demand.

2.1.1 Conceptualising Automation

To provide a foundation and understanding of automation for the remainder of this study, the following section will discuss the definition of automation, examples of automation technologies, and the reasons why automation occurs.

Groover (2008, p. 85) defines automation as “the technology by which a process or procedure is accomplished without human assistance. It is implemented using a program of instructions combined with a control system that executes instructions”. He further suggests that automation consists of three basic elements: “(1) power to accomplish the process and operate the system, (2) a program of instructions to direct the process, and (3) a control system to actuate the instructions” (Groover, 2008, p. 87). This suggests that these elements form a system which will execute an automatable process. With the definition and the basic elements, it can be deduced that automation can be presented in various forms as there are no fixed guidelines to its capabilities. It can, therefore, be presented in forms that can be used to replace the jobs of human labour (referred to as labour hereafter), and forms that do not replace the jobs of labour. The Philips Hue lighting system is one example of automation that does not replace human jobs. This system allows for an application, on a remote device, to switch or manipulate the lighting system in a home, work environment, etc. (Ur *et al.*, 2013). For the purposes of this research study, the focus will be on automation that replaces human labour. A distinction must be made between what is classified as workplace automation and what does not.

Brougham and Haar (2017, p. 213) argue that the technologies that would likely disrupt labour in the workplace are *smart technology, artificial intelligence, automation, robotics, and algorithms* (STAARA). Not all automation technologies are STAARA technology, however, the authors determined that these technologies are likely to be found commonly in the workplace.

2.1.1.1 Understanding Staara Technology

Worden *et al.* (2003, p. 1) define smart technology as technologies “with the ability to sense changes in their circumstances and execute measures to enhance their functionality under the new circumstances offer enormous benefits in performance, efficiency, operating costs and endurance”. This technology allows the users to receive information that adapts to their environment. This information is, therefore, likely to be more useful and fit for purpose. It could be argued that smart technology, accordingly, replaces the need for labour that provides custom/timely information.

Rich (1983, p. 1) states that AI “is the study of how to make computers do things at which, at the moment, people are better”. As with smart technology, AI allows for a system to provide information which could be undertaken by labour. AI, however, tries to imitate or better the capabilities of humans by

producing information that has human elements considered in the processes to a user (Rich, 1983).

Groover (2008) refer to robotics as the study of robots. The Electric Machinery Law of Japan, according to Mathia (2010, p. 8), defines an industrial robot as “an all-purpose machine equipped with a memory device and terminal device (for holding things), capable of rotation and of replacing human labor by automatic performance of movements”. Unlike smart technology and artificial intelligence which replace labour by providing information, robots replace the physical actions of labour. Robots aim to imitate and better the physical capabilities of labour (Cakmak and Takayama, 2013).

The basis for all these technologies is an algorithm, Skiena (2008, p. 3) defines an algorithm as a “procedure to accomplish a specific task”. Skiena (2008, p. 3) further explains that an algorithm is “a procedure that takes any of the possible input instances and transforms it to the desired output”. Algorithms, therefore, provide the step by step instructions for a technology to complete its set out task. An algorithm can allow for technologies to send and receive instructions, thereby replacing the need for labour to be present to operate various technologies (e.g. machinery) (Arntz *et al.*, 2016).

2.1.1.2 Drivers Of Automation

Halal *et al.* (2016, p. 87) argued that the main motivation for employing automation in the workplace is that it “reduces costs and frees up labor, which allows further economic growth and new jobs in areas of demand that were unexpected”. This suggests that the reason for automation in the workplace is profit driven. Frey and Osborne (2017, p. 268) support this argument by stating that “labour saving inventions may only be adopted if the access to cheap labour is scarce or prices of capital are relatively high”. This implies that businesses will select the form of input (i.e. capital or labour) that is cheaper to produce the same, or greater, output.

Rising wages have been found to have a positive relationship with economic growth, therefore growing economies are likely to lead to higher wages (Altman, 1998). In 2016 the global GDP growth rate was 2.49% (World Bank, 2018), this could suggest that globally, real wages have risen due to economic growth. The costs of automation also are falling, suggesting that it is becoming cheaper to automate as labour costs rise (Frey and Osborne, 2017). The falling costs are due to technological advancements, as technology advances it enables cheaper costs for its production (Frey and Osborne, 2017). With falling costs for automation and rising labour costs, labour is becoming relatively more expensive, this likely contributes to automation making labour redundant. In the United States (US) rising labour costs have been blamed for the increasing demand for machines (Rifkin, 1995).

With rising labour costs globally, automation can be considered as a more viable option for repetitive tasks as it produces far more consistent results

(Rifkin, 1995). The main advantages of automation are likely to be that machines may be better than labour at completing repetitive tasks and that the costs of automation are becoming relatively cheaper due to rising labour costs.

A working definition for automation in this study is formed from the information presented thus far. The general definition discussed is that automation is a technology by which tasks are completed without any human assistance. It has been established that the reasons for automation are to maximise profits and that the technologies of automation found in the workplace are STAARA technology. The working definition for automation in the workplace can be conceptualised for this study as a profit-maximising STAARA technology that replaces labour in completing tasks.

The different STAARA technology can operate in isolation, however, they can also be integrated. An autonomous vehicle is an example of automation in the workplace and makes use of multiple of the STAARA technology to perform its function. Duffy *et al.* (2013, p. 456) define autonomous vehicles as vehicles that “drive themselves with little to no human interaction”. Autonomous vehicles aim to drive better than humans by applying data gathered from previous occurrences and possibly live reports (Duffy *et al.*, 2013). They utilise elements from artificial intelligence and algorithms. Driving is essentially a two-part process, firstly it requires an individual to know how to operate a car, and secondly, a destination is required. Both parts of this process require a set of instructions, and algorithms can be used in this process, the artificial intelligence employed will find the best route available at the time of transit. Autonomous vehicles are emerging in the taxi industry and are likely to alter the future operations of this industry (Lutin, 2018). The demand for human taxi drivers will be reduced as these technologies become adopted. A second example of automation in the workplace is the electronic kiosk (e-kiosk). Allen *et al.* (2005, p. 1) defines an e-kiosk as a system that “provides differentiated sales-oriented interactive information services to a plurality of different classes of users such as consumers, contractors and salespersons”. This suggests that an e-kiosk replaces the need for labour to be a middleman to process data and information for a user. A commonly used example of an e-kiosk is the automated teller machine (ATM) (Narwal, 2013). With the ATM, labour is no longer required to process cash movements between the bank and its clients. The ATM provides a client with specific up-to-date information and uses robots to provide money to the client or receive money from the client (Zuboff, 1988).

According to the United States Department of Labor (2018, p. 1), industrial robots are “programmable multifunctional mechanical devices designed to move material, parts, tools, or specialized devices through variable programmed motions to perform a variety of tasks”. Industrial robots make use of algorithms, robotics, and automation to operate (Borenstein and Koren, 1985). Such technologies have replaced labour in manufacturing, agriculture, and other industries (Rifkin, 1995). These replacements are motivated by the

fact that industrial robots show, in many cases, greater production consistency and performance than human labour (Rifkin, 1995).

The technologies already discussed are not the first technologies to be heavily used by an industry, therefore, the purpose of Section 2.1.2 will be to discuss the story of automation in the workplace by analysing the history and current state of automation. The term automation will be utilised as a placeholder for all STAARA technology for the remainder of this study, as the definition of automation is applicable to each of the STAARA technology.

2.1.2 The Story Of Automation In The Workplace

The history of automation in the workplace is vast and there are many technologies which have been developed. One of the earlier technologies was the water wheel (Reynolds, 2002). The water wheel was first used a few centuries BC, this technology allowed for water power to replace some of the tasks labour was required to do (i.e. producing more flour with less labour) (Reynolds, 2002). This technology did not require computer systems as some technologies today, however, it was sufficient to impact labour demand in the flour milling industry.

Following the employment of early forms of automation, new industries have been created and others have evolved. Better technologies have been developed and employed, these technologies have not only been used in milling but other industries as well. As discussed in Section 1.1, in history, there have been three industrial revolutions which, due to technological progress, impacted the workplace, the need for labour, and economies. These technologies altered the way in which the workplace operates and they resulted in other technologies being formed (Schwab, 2015). Some examples are the by-products which were as a result of the last industrial revolution are 3-D technologies, emission control technologies, and lateral scaling (Rifkin, 2012).

One of the major changes to the workplace due to automation was found in the agricultural sector during the 20th century. With automotive technologies such as tractors and ploughs, more food could be grown with fewer resources, allowing for better planning, productivity, and output (Rifkin, 1995). An increase in agricultural output also grows economic growth and the US economy grew as a result of automation, although this form of automation ended some farm jobs other jobs were created in other industries (Rifkin, 1995). This sector managed to grow and increase output while employing less labour. Other automation technologies in history that altered the operations in the workplace include the assembly line and the computer (Groover, 2008).

Automation and technological progress are driving the fourth industrial revolution, Schwab (2015) states that this revolution is characterised “by a fusion of technologies that is blurring the lines between the physical, digital, and biological spheres”. An example of a technological change that is considered to be central in forming the fourth industrial revolution is AI (Schwab,

2015). As mentioned in the previous section AI involves developing computer programs to complete tasks which would otherwise require human intelligence. One of the goals of AI is to pass the Turing test which was defined in 1950, the test suggests that a human should not be able to tell the difference between a human and a machine (Turing, 2008). The Turing test was first passed in 2014, suggesting that the progress of AI has started to reach human intelligence (Warwick and Shah, 2016). Although the Turing test is not strictly for automation related in the workplace, it provides a basis for where AI is and where it is headed. Brynjolfsson and McAfee (2012) suggest that it may not be too long in the distant future before AI will overcome human intelligence. When AI overcomes human intelligence it is likely that labour in many, if not all tasks, will become redundant. A redundant labour force is likely to have an impact on economies, Section 2.1.3 will, therefore, indicate the effects automation is predicted to have on the economy.

2.1.3 Automation Effects On The Economy

The following subsection considers the effects of automation on the economy. It has been discussed in this study that the employment of automation in the workplace is profit driven and has the capability of raising productivity with the need for less labour. Identifying the effects automation has on the economy may indicate the benefits or losses to society.

To evaluate the state of an economy the Gross Domestic Product (GDP) is measured to indicate whether there have been changes in output compared to another period or another benchmark (Parkin, 2016). The *Solow Growth Model* expresses the factors which contribute to output, as $Y = A(t)F(K, L)$ (Solow, 1956), with Y representing output, $A(t)$ representing technological change, and $F(K, L)$ representing that capital (K) and labour (L) inputs form a function (F) for output (Solow, 1956). This model suggests that technological change has the capabilities of improving the output of an economy by multiplying the effects of input. Although automation is not the only component of technological change, it is a significant factor in the workplace and economy (West, 2015).

Bughin *et al.* (2017, p. 4) estimated that automation “could raise productivity growth globally by 0.8 to 1.4 percent annually”. An increase in productivity creates higher output and economic growth. Automation can, in this way, grow the economic pie of society (Brynjolfsson and McAfee, 2012). However, it is likely that the distribution of its gains will be distributed to a small group of its owners (Brynjolfsson and McAfee, 2012). Rifkin (1995) indicated that this was the case with the agricultural sector in the US, with automation, as fewer farms and workers were required to produce more output. He further added that the growth of food is no longer dependent on traditional farms, as technologies such as genetic engineering were used to produce food that was not easily accessible to the US. Lastly, he proposed that this resulted in the

countries reliant on exporting food to the US to experience a decrease in the demand for their agricultural goods.

Automation in the workplace can have both positive and negative effects on economies. It allows for economic growth through increased productivity, and new jobs are created through new requirements from the labour market. It can also increase the inequality of a society due to the loss of jobs, and it can allow for economies which are dependent on exporting goods to experience a diminished demand for such goods (Brynjolfsson and McAfee, 2012). Although it is predicted that automation will increase productivity, it will be at the expense of the labour force. The next subsection will consider the relationship between the labour force and automation.

2.1.4 The Relationship Between Automation And Labour Demand

Automation may lead to a reduction in labour demand, leading to a variety of further effects on the economy. However, automation may also lead to the creation of new occupations and the associated demand for human workers. Keynes (1931, p. 364) predicted that “due to our discovery of means of economising the use of labour outrunning the pace at which we can find new uses for labour”. This prediction suggested that there will be a time where labour will become redundant due to technological change. Brynjolfsson and McAfee (2012), 70 decades after Keynes’ prediction, argue that “the pace of technology has sped up so much it has left people behind” and that labour will have to catch up to the capabilities of automation or find the tasks automation is unable to do.

As mentioned in Section 1.1, Rifkin (1995) proposes that the growing capabilities and use of automation could ultimately lead to two scenarios for society, the first is that automation could lead to less work (or no work) needed to be done by labour and the second is that automation could lead to a mass unemployment of labour. Less work needed to be done suggests that there will be increased time for leisure as society will be benefiting from the output of automation. Mass unemployment suggests that a majority of labour will become unemployed and only a few will reap from the benefits of automation. Pashkevich and Haftor (2014), Roos and Shroff (2017), and Acemoglu and Restrepo (2018) indicate that there is uncertainty as to which scenario will occur. Rifkin (1995, p. 13) argues that to avoid the latter unfavourable scenario and “for productivity gains to be distributed fairly, the government would need to step in”.

For productivity to be optimised, automation and labour will need to work together (Rifkin, 1995). However, there is a growing mismatch between rapidly advancing automation and slow-changing humans (Brynjolfsson and McAfee, 2012). As automation advances labour will be required to acquire new skills in

order to collaborate with automation. In the US it was found that employment has been expanding most in high-skill areas (Brynjolfsson and McAfee, 2012). According to Frey and Osborne (2017, p. 258) this “can be explained by the falling price of carrying out routine tasks by means of computers, which complements more abstract and creative services”. Those who have high skills (defined as more than upper secondary education in Section 2.2.1) in non-routine tasks are likely to complement the benefits of automation.

With the expanding capabilities, it is possible that technologies will become fully autonomous in the future and result in labour becoming redundant in many existing tasks (Brynjolfsson and McAfee, 2012). The intelligence or capabilities of automation are growing at exponential rates. Brynjolfsson and McAfee (2012) liken these growth rates to that of Moore’s law and Kurzweil’s rice doubling theory. Moore’s law proposes that circuit complexity would double every 18 months (Schaller, 1997). This law predicted that the performance of a computer will double every 18 months. Kurzweil’s doubling theory identified that in every improvement iteration, technology doubles its capabilities (Brynjolfsson and McAfee, 2012). Moore’s law and Kurzweil’s theory suggest a doubling of the capabilities of these technologies at every iteration of processing capacity advancement.

In physical domains, it is established that automation could replace labour in agriculture and transport sectors. However, automation is still primitive in this domain as most of the work is non-routine and requires human intelligence (Brynjolfsson and McAfee, 2012). In knowledge domains automation is yet to fully replace the tasks of labour as the machine intelligence required for non-routine tasks is still inferior compared to human intelligence (Brynjolfsson and McAfee, 2012; Frey and Osborne, 2017). Technologies of automation are found to be good pattern recognisers. However, they are poor problem solvers as computers currently have weak creative abilities (Brynjolfsson and McAfee, 2012; Frey and Osborne, 2017). This suggests that labour has yet to become fully redundant in the workplace due to the lack of intelligence automation has.

Frey and Osborne (2017, p. 262) argue that the tasks that relate to “an unstructured work environment can make jobs less susceptible to computerisation”. The current capabilities of automation allow tasks in transportation, logistics, office and administrative support, and labour in production occupations to be substituted by automation (Frey and Osborne, 2017). With the current capabilities of automation, Frey and Osborne (2017, p. 266) argue that the tasks “requiring knowledge of human heuristics, and specialist occupations involving the development of novel ideas and artefacts, are the least susceptible to computerisation”.

Bughin *et al.* (2017, p. 4) found that in the US “less than 5 percent of all occupations can be automated entirely using demonstrated technologies, about 60 percent of all occupations have at least 30 percent of constituent activities that could be automated”. This suggests that a small percentage of

labour will need to find new employment or tasks to do which have yet to be automated. Frey and Osborne (2017, p. 265) estimated that “47% percent of total US employment is in the high risk category” of being automated within an unspecified period of time in the near future. This suggests that automation will advance to be able to complete more tasks. The estimate also suggests that in the near future the occupations that will be automated will rise from 5% to 47%. An alternative to Frey and Osborne’s analysis is that the labour market will evolve to adapt to the capabilities of automation and that the scope of occupations will likely be altered to exclude redundant tasks (Bughin *et al.*, 2017).

Deming (2017, p. 3) argues that the “skills and tasks that cannot be substituted away by automation are generally complemented by it, and social interaction has proven difficult to automate”. This indicates that labour will need to acquire skills for tasks that are not, as of yet, automatable. Moravec’s paradox suggests that technological change is causing semi-skilled workers to be displaced more than high-skilled and low-skilled (defined as less than secondary education in Section 2.2.1) workers (Brynjolfsson and McAfee, 2012). The paradox suggests that high-level reasoning requires very little computation, but low-level sensorimotor skills require enormous computational resources (Brynjolfsson and McAfee, 2012). Those with mid-level skills will, therefore, need to improve their skills or find employment involving tasks for which they are over-qualified.

Technological progress has two competing effects on employment, the destruction effect and the capitalisation effect (Frey and Osborne, 2017). The *destruction effect* suggests that, as a result of automation substituting labour, jobs are lost and labour will need to reallocate its supply (Frey and Osborne, 2017). The *capitalisation effect* suggests that, due to automation, industries will thrive from productivity and, therefore, more firms will be formed and create more jobs (Frey and Osborne, 2017).

Provided for the effects of automation, there are two possible scenarios that can occur to labour and society as a whole as discussed in Section 2.1.3 . Both scenarios suggest that due to automation labour will be required to work relatively less. It was identified that for labour and automation to progress well together, labour will need to catch up to automation by acquiring more skills or education that will be complemented by automation. Frey and Osborne (2017, p. 268) found that “both wages and educational attainment exhibit a strong negative relationship with the probability of computerisation”. This suggests high skilled and high wage jobs are the least likely to be automated.

It is uncertain as to which occupations will be automated and which will exist in the future. It is, however, likely that the occupations that will exist will require tasks involving creativity and social intelligence (Pashkevich and Haftor, 2014). It is estimated that 65% of children entering primary school today will ultimately end up working in completely new job types that do not

yet exist (Schwab and Samans, 2016). Labour will need to be highly adaptive and acquire skills that will not be substituted by automation, this could result in the need for a labourer to continuously update his/her skills and education.

2.1.5 Automation In South Africa

This section considers the state of automation in South Africa. This is necessary as the present study assesses the awareness of South African students, and therefore, understanding the adoption of automation technologies by organisations within the country will provide greater relevance for the thesis.

During the first 12 years of the 21st century, there was a decrease in employment in the primary sector (mining and agriculture industries) and relatively little growth in the secondary sector (manufacturing, utilities, and construction industries) in South Africa, but there had been growth in productivity output (Bhorat *et al.*, 2015). This suggests that companies in South Africa have opted for more automation to complete tasks. Among other factors such as skill and education levels, the adoption of automation may also be a contributing factor to the high rates of unemployment in the country, among other factors. The decrease in labour employment can be attributed to the growth rate of wages rising to be greater rate than the growth rate of the GDP (Trading Economics, 2018). At the beginning of 2007, the average monthly gross wage in the country was R7 870 and at the end of 2017 this had risen to R20 060. The rising wages suggest that, among other factors, the adoption of automation technologies has become relatively more affordable for companies.

Brynjolfsson and McAfee (2012) argue that it is challenging for humans to compete with automation technologies due to their expanding capabilities. In addition, automation has become cheaper and more capable, suggesting that the probability of labour being replaced has risen. In South Africa, it was found that 67% of jobs can be automated (Frey *et al.*, 2016). With rising labour costs and a high percentage of jobs automatable in South Africa, it is likely that jobs in the country will be lost. The country's labour market will need to adapt to the effects of automation and create jobs that will complement automation.

2.1.6 Summary

This section of the literature review discussed automation in the workplace. Automation in the workplace is defined, for this study, as automation in the workplace was defined as a profit-maximising STAARA (Smart Technology, Artificial Intelligence, Automation, Robotics, and Algorithms) technology that replaces labour in completing tasks. The main reason for automation in the workplace is that it reduces costs and frees up labour, whilst allowing economic growth. The employment of automation can have two effects on society. One effect is that employment of automation will allow for productivity gains in

society, the other effect is that labour displacement will arise from this as automation will occupy tasks which were previously executed by labour. From the beginning of this century South Africa has experienced increasing productivity output whilst employing less human labour. This has occurred whilst the country has been experiencing high unemployment rates. This may be partly due to the adoption of automation technologies. Workers in the country would, therefore, have to find jobs that are not yet automatable. This would be difficult as it has been estimated that 67% of jobs in the country can be automated. The next section will address the trends of the labour market and how various factors (such as automation) have influenced changes in the labour market.

2.2 Labour Market Trends

The following section of the literature review will discuss the current and predicted trends in the South African and global labour market. As the aim of this study is to identify how automation influences university students consider when making career choices, it is necessary to review existing literature concerning the effects of automation on the labour market. Section 2.1 discussed automation in the workplace and revealed that it can have a multi-faceted effect on the demand for labour by eliminating jobs in some industries and creating jobs in other industries. The aim of this section will be to identify how jobs and the labour market have changed and are predicted to become in the future.

This section consists of four subsections; the first is to lay a foundation on which the notion that skills will be conceptualised. The second subsection will review the literature relating to the changes the labour market has experienced. In Section 2.1 it was discussed that, through processes of automation, certain tasks could be completed by machinery, therefore certain skills are required less by the labour market. This subsection will, therefore, be undertaken to comprehend what the labour market has been like in the past and what are the factors that have affected its changes. The third subsection will discuss the expectations on the future of labour demand and supply, this will give context as to how labour markets may look like in the future and what may be required of the labour force. The final subsection will discuss literature related to the trends of the South African labour market.

2.2.1 A Conceptualization Of Skills

A skill, according to Merriam-Webster (2018), is “the ability to use one’s knowledge effectively and readily in execution or performance”. To complete a task, labour will be required to have a set level of skills (Brynjolfsson and McAfee, 2012). In terms of skills, labour can be categorised as either low-

skilled, medium-skilled, or high-skilled. According to the Organisation for Economic Co-operation and Development (2011, p. 56) low-skilled “refers to less than upper secondary education; medium-skilled refers to upper secondary education; and high-skilled refers to more than upper secondary” education. This suggests that labour with education from universities and other tertiary institutions can be classified as high-skilled labourers.

The skills of the labour force have become a factor in the labour market primarily due to the argument that, for the rate of productivity to progress, automation and labour will have to work together and not against each other (Brynjolfsson and McAfee, 2012). This means that labour will need to acquire the necessary skills to complete the tasks that automation cannot complete. Tasks in the workplace can be categorised by using a two-by-two matrix, as illustrated in Table 2.1, with routine versus non-routine tasks on one axis and manual versus cognitive tasks on the other axis (Autor *et al.*, 2003). Manual tasks require physical human actions to be completed and cognitive tasks require the capacity and knowledge to process information (Frey and Osborne, 2015). In Table 2.1 it is indicated that routine tasks can be substantially substituted by automation, regardless of whether the task is manual or cognitive. For non-routine tasks, Table 2.1 indicates that these tasks are less likely to be replaced by automation. Non-routine tasks that require primarily manual input are identified to be strong complementarities to automation. This suggests that currently these tasks cannot be completed by automation, however, these tasks work well with automation to complete a job. Non-routine tasks that require primarily cognitive input are identified to be neither strongly substitutable by automation nor strongly complementary to automation. This suggests that these tasks are not as heavily influenced by automation as the other types of tasks. The labourers of these tasks are less likely to be substituted by automation, and these tasks do not necessarily need to complement automation.

Valletta (2015) proposes that the level of skill an individual possesses can be categorised into which type of tasks the individual can complete. The author mapped non-routine cognitive tasks to high-skilled labour, non-routine manual tasks to low-skilled labour, and routine (manual and cognitive) tasks to medium-skilled labour. The mapping of tasks to skill will be applied to this study. Section 2.1 revealed that the capabilities of automation are predicted to expand and that the advancements of automation are predicted to continue. These developments will likely enhance automation to have the capabilities to complete routine manual and cognitive tasks and in the near future complete non-routine manual tasks (Frey and Osborne, 2017). With advancing automation and other factors (such as macroeconomic policies, innovation, trade and foreign direct investment) influencing the labour market (Organisation for Economic Co-operation and Development, 1994), the thesis will review existing literature to consider how the labour market has changed in recent decades.

	Routine tasks	Non-routine tasks
Manual tasks	Substantial substitution	Strong complementarities
Cognitive tasks	Substantial substitution	Limited opportunities for substitution or complementarity

Table 2.1: Predictions of task model for the impact of computerisation on four categories of workplace tasks (Autor *et al.*, 2003).

2.2.2 The Changing Labour Market

In recent decades, the labour market has evolved to require cognitive skills more than manual skills (Autor, 2015). Based on the changes and the mapping used by Valletta (2015, p. 3), it would suggest that the demand for labour has shifted towards low-skilled and high-skilled labour, while there has been a diminishing demand for medium-skilled labour (Autor, 2015). In the US, in 1979 medium-skilled occupations accounted for 60% of employment, 28 years later, in 2007, this share fell to 49%, and more recently, in 2012, the share was 46% (Autor, 2014). As the demand for medium-skilled labour diminishes relative to other skill levels, it is likely that medium-skilled labourers will shift towards jobs that require lower skills. The reason for this is that high-skilled employment would require these labourers to gain further education (Organisation for Economic Co-operation and Development, 2011). These labourers are then forced to be underemployed as there are fewer jobs for medium-skilled labourers. From 2001 to 2012, the US experienced this change in demand as the underemployment rate for recent college graduates rose from approximately 35% to approximately 45% in this time period (Abel *et al.*, 2014).

Of the different skill levels, the labour market has changed to require a highly-skilled labour force. For example, in recent years 18 out of the 30 fastest growing occupations, in the US, required a form of postsecondary education (Bureau of Labor Statistics, 2017). This change in the level of skills required has likely led to the increased need for training of labour. There is a high rate of underemployment of tertiary graduates in the US, and the proportion of tertiary graduates in low-skilled employment rose between 1990 and 2012 (Abel *et al.*, 2014). During this period the rate of the underemployment of all tertiary graduates averaged 33% (Abel *et al.*, 2014). This suggests that these graduates are acquiring skills not required by the labour market.

The changes towards a greater demand for highly skilled labour that completes cognitive tasks has likely led to the skills mismatch the global labour market is currently experiencing (Leopold *et al.*, 2017). A skills mismatch suggests that there is an oversupply of low-skilled labour and an undersupply of high-skilled labour (Frost, 2001). This implies that the requirements of global labour demand may have changed at a rate that labour supply could not keep

up with. In previous decades, labour would complete a set of tasks for a single job throughout the duration of their careers. However, with the labour market predicted to evolve, it is likely that labour would be required to continuously learn new skills (Schwartz *et al.*, 2017). Continuously learning new skills will require employees to garner characteristics that enable the development of new skills such as the ability to learn, adapt, and innovate amongst others (Maurer and Weiss, 2010; Caroselli, 1994). According to Toffler (1970, p. 367), psychologist Herbert Gerjoux argued that “tomorrow’s illiterate will not be the man who can’t read; he will be the man who has not learned how to learn”. As automation advances, it is suggested that labour will be required to continuously upgrade its skills in order to progress with automation.

With the advancements of automation already contributing towards the changing requirements of the labour market and more tasks becoming automated it suggests that the impact of automation on the labour market is likely to continue growing (Schwartz *et al.*, 2017). Automation is adopted in the workplace when the costs of automation are cheaper than that of labour. The cost of automation fell rapidly in the 20th-century (Frey and Osborne, 2015). This suggests that there was possibly an increase in the adoption of automation. Between 1975 and 2012, 42 out of 59 countries, studied by Karabarounis and Neiman (2013), experienced a diminishing share of GDP by labour. This implies that a greater portion of such countries’ output was attributed to capital. Literature analysed in Section 2.1 revealed that, as automation advances, it also becomes cheaper. This likely explains why even developing nations have had greater output linked to automation (Karabarounis and Neiman, 2013). Autor (2014, p. 1) found that automation, currently, replaces the tasks that “follow explicit, codifiable procedures” (i.e., routine tasks). The capabilities have been predicted to expand and impact other skill levels.

As the demand for medium-skilled labour has diminished, the importance of specialised and social skills has risen (Pompa, 2015). The shift towards social and specialised skills could provide another explanation as to why there is a high rate of tertiary graduates that are underemployed. It is likely that the tertiary graduates have skills not required by the labour market. This creates a skills mismatch and is likely why there is a surplus of high-skilled labourers who are unable to find suitable employment (Handel, 2003). This shift towards these kinds of skills is likely to be impacted by the limitations automation currently has. Referring to Section 2.1, machinery is currently unable to complete cognitive non-routine tasks and will still be unable to complete such tasks in the near future. In the US, between 2009 and 2011, recent tertiary graduates with the lowest unemployment rates were health and education majors while the graduates with the highest unemployment rate were architecture and construction (Abel *et al.*, 2014). The US labour market valued graduates who had skills to complete tasks that have social aspects higher than those with technical aspects. Globally, it is graduates with majors in engineering, math, computing, education, and health which

are doing relatively well in the labour market (Abel *et al.*, 2014). A majority of these industries are based in the tertiary sector suggesting that the tertiary sector has become a significant employer for the labour market. Due to some skills having greater demand than other skills, it has resulted in some high-skilled labourers unable to find suitable jobs.

2.2.3 Future Of The Labour Market

As the labour market has experienced changes in recent decades it is likely that there will be further changes to the labour market in the future. The following subsection will review the literature relating to the predicted changes to the labour market from both demand and supply perspectives.

2.2.3.1 Future Of The Labour Demand

The previous subsection discussed that there is a growing need for the global labour force to obtain the skills demanded by the labour market. If the labour force does not acquire such skills it will likely lead to future economic growth driven by capital and a few workers. Economic growth driven by a few workers will lead to higher levels of unemployment, poverty, and inequality (Pompa, 2015).

With automation already having had a significant impact on the labour market, it is likely that it will continue to have an impact for a great number of years to come. It is estimated that 47% of those employed in the US are at a high risk of being automated in possibly a decade or two (Frey and Osborne, 2017). Although the rate is likely to differ in other countries, the occupations at risk are similar (Frey and Osborne, 2017). Frey and Osborne (2015, p. 58) predicted that it is those employed in “transportation, logistics, and office and administrative support” occupations that are at the highest risk of being automated. The use of automation is also anticipated to grow at rapid rates with technologies such as industrial robots anticipated to grow from just over 1.5 million in 2015 to between four and six million by 2025 (Acemoglu and Restrepo, 2017). Although this suggests that many more jobs will be automated, many companies have indicated that they will not be letting go of their labour but rather retrain it to complete other jobs (Schwartz *et al.*, 2017).

As the capabilities of automation are continuously expanding, the retraining of labour will be crucial for the labour market. Automation during the 19th century allowed for the simplification of tasks, automation during the 20th century allowed for the substitution of medium-skilled employment, and automation in the 21st century is predicted to substitute for low-skilled employment (Frey and Osborne, 2015). Although it is predicted that during the 21st-century low-skilled employment will be automated it is estimated,

that between 2016 and 2026, alongside high-skilled employment, low-skilled employment is expected to rise in the US (Chamberlain, 2017).

A commonality between the various predictions for the future of labour demand is that, in the near future, the demand for medium-skilled jobs will diminish and there will be growth of low-skilled and high-skilled jobs. The employment trends experienced by the labour market currently are likely to carry on into the near future, and significant changes to the trends of the labour market are likely to only occur after several decades (Schwab and Samans, 2016).

In the US, between 2016 and 2026, the employment growth rate is anticipated to grow at 0.7% annually with the health sector being the main driver of employment (Bureau of Labor Statistics, 2017). Pompa (2015, p. 9) predicted that, in the US, “healthcare support occupations are expected to grow more than 25% in the coming decade”. The growth of the health sector is attributed to the ageing population (Bureau of Labor Statistics, 2017). Employment in education, health, and the wider public sector are anticipated to grow in the United Kingdom (UK) by 2030 (Bakhshi *et al.*, 2017). Business and financial operations, management, computer, and mathematical sectors globally are also anticipated to have large employment growth between 2015 and 2020 (Schwab and Samans, 2016). It is predicted that between 2005 and 2025 there will be diminished employment in the primary and manufacturing sectors in the European Union (Cedeforp, 2016). During the same period the sectors of distribution and transport, business and other services, and non-marketed services are predicted to grow (Cedeforp, 2016). Frey and Osborne predicted that employment in transport would be automated in the next decade or two, whilst the European Union anticipates that there will be employment growth in the industry, leaving uncertainty in terms of the transport industry. The World Economic Forum predicted that the office and administration, the manufacturing and production, and the construction and extraction sectors are anticipated shed the most jobs between 2015 and 2020 (Schwab and Samans, 2016). One-tenth of the labour force in the US and the UK are in occupations that are predicted to grow in employment by 2030, whilst one-fifth are in occupations that will likely reduce employment (Bakhshi *et al.*, 2017). Despite this, Bakhshi *et al.* (2017) note that it is uncertain what will occur to the occupations of the remaining labourers.

Although it is predicted that the current employment trends are to continue as is, but in a more accelerated fashion, it is the demand for the content of skills that will change in the labour market. Schwab and Samans (2016, p. 20) predict that by 2020, more than a third of the desired core skill sets of most occupations will comprise of skills that are not yet considered crucial to the jobs of today. 39% of core skills required by 2020 across all occupations will be different to the requirements of 2015 (Leopold *et al.*, 2017). Schwab and Samans (2016, p. 22) argue that “social skills such as persuasion, emotional intelligence and teaching others will be in higher demand across industries

than narrow technical skills, such as programming or equipment operation and control". They predict that by 2020, a wide range of occupations will require a high degree of cognitive skills "such as creativity, logical reasoning and problem sensitivity" as part of their core skills. Bakhshi *et al.* (2017, p. 14) found that for the future of employment there is "a strong emphasis on interpersonal skills, higher-order cognitive skills and systems skills". Bakhshi *et al.* (2017, p. 14) further discuss that higher-order cognitive skills such as "originality, fluency of ideas and active learning" will grow in importance over the years to come. Bakhshi *et al.* (2017, p. 15) identify that complementary skills that are most frequently associated with higher demand are "customer and personal service, judgement and decision making, technology design, fluency of ideas, science and operations analysis". With these anticipated changes to the requirements of the labour market, it will be necessary for the future of the labour supply to be equipped with the necessary skills to diminish the current skills mismatch.

2.2.3.2 Future Of Labour Supply

The number of tertiary graduates in countries across the world has been rising in recent years (Organisation for Economic Co-Operation and Development, 2018). This could suggest that the global labour market has had a rising supply of high-skilled labour. The thesis used available OECD data to analyse the tertiary graduate trends of the United States, United Kingdom, Brazil, Russia, and South Africa. The United States and the United Kingdom were selected in the analysis as they represent powerful economies of developed nations according to International Monetary Fund (2018) data. Brazil and Russia were selected as they are nations who are a part of the BRICS (Brazil, Russia, India, China, and South Africa) association whose data was available. The analysis of the data is displayed in Table 2.2. The analysis presents three time periods and indicates that the rate of graduates in these countries has increased in recent years.

Country	2009	2012	2015
United Kingdom	53 8279	65 2174	74 0276
United States	2 417 872	2 715 337	3 855 101
Brazil	870 650	922 428	1 226 212
Russia	1 393 349	1 452 874	1 706 754
South Africa	93 274	116 341	149 787

Table 2.2: The number of degree tertiary graduates in various countries during 2009, 2012, and 2015 (Organisation for Economic Co-Operation and Development, 2018; Department of Higher Education and Training, 2018).

The proportion of fields of study taken by tertiary graduates differed greatly by the country's economic background in 2015 (Organisation for Economic Co-

Operation and Development, 2018). Table 2.3 presents the number of graduates in the United States, United Kingdom, Brazil, Russia, and South Africa for 2015. The table categorises the graduate number by fields of study, the categories are condensed from the broad categories used by the OECD. Health graduates were excluded from the STEM category as their data was provided with the welfare data. As presented in Table 2.3, graduates in the United States and the United Kingdom were more inclined to study subjects fields in humanities and other related fields. This trend is likely to be similar in other developed countries and indicates that the future labour supply in developed nations will likely consist of a large proportion of graduates with social skills. The table displays that graduates in Brazil and Russia's were more inclined to study business, administration, and law. In South Africa, the number of graduates who studied humanities and other related fields was similar to the number of those who studied in the fields of business, administration, and law. This suggests that in developing countries the future of high-skilled labour will consist mostly of labour with skills in business, administration, and law. The second most studied fields of study in Brazil and Russia differed with humanities and other related fields in the former and STEM in the latter. With both developed nations, presented in the table, it was the business, administration, and law category that had the second highest portion of tertiary graduates. This can suggest that across developed nations there will likely be a similarity of the portion of available skills, whilst across developing nations, there will likely be differences.

Country	Humanities	BAL	STEM	H&W	Total
United Kingdom	273 164 (37%)	162 590 (22%)	101 874 (14%)	98 189 (13%)	740 276
United States	1 499 113 (39%)	752 289 (20%)	433 339 (11%)	647 115 (17%)	3 855 101
Brazil	334 168 (27%)	458 948 (37%)	185 292 (15%)	169 455 (14%)	1 226 212
Russia	315 772 (19%)	647 747 (38%)	482 310 (28%)	108 855 (6%)	1 706 754
South Africa	48 984 (39%)	47 734 (38%)	18 120 (14%)	11 577 (9%)	126 514

Humanities refers to Humanities and related fields

BAL refers to Business, Administration, and Law

STEM refers to Science, Technology, Engineering, and Mathematics

H&W refers to Health and Welfare

Table 2.3: The number of degree tertiary graduates in various countries by fields of study in 2015 (Organisation for Economic Co-Operation and Development, 2018).

Trilling *et al.* (2009) estimated during the early years of the 21st century, labourers aged between 18 and 42 who had graduated high school would work in at least eleven different jobs. This is likely due to the skills mismatches, the changing labour market, and the advancements of automation among other factors. As identified with the current labour market, labour in the future will likely be required to continuously learn and adapt to new skills required by the labour market.

The skills mismatch is predicted to continue with the demand for high-skilled labour rising and the labour market having an inadequate supply to meet this demand (Pompa, 2015). According to the International Labour Office (2017, p. 11) it is estimated that approximately “one fifth of the world’s young people are not in employment, education or training”. This great portion of youth not in employment, education or training (NEET) likely contributes to the global skills mismatch. Frey and Osborne (2017, p. 267) predicted that “computerisation will mainly substitute for low-skill and low-wage jobs in the near future”. With a great portion of the youth NEET and the expected growth in the capabilities of automation, it is likely that a greater portion of the world’s labour force will be unemployed.

2.2.4 The South African Labour Market

At 26.7%, South Africa has one of the highest unemployment rates in the world (Meyer, 2014; Statistics South Africa, 2018*b*). This implies that, in 2017, approximately one in four South Africans that wished to work (i.e., the active labour force) were unemployed. During 2017 employment increased by 102 000 to become 16 171 000 workers employed at the end of 2017 as compared to 16 069 000 employed at the end of 2016 (Statistics South Africa, 2018*b*). The increase in employment is, however, not entirely positive as the active labour force had increased by 202 000 during the same period (Statistics South Africa, 2018*b*). This suggests that the number of unemployed increased by 100 000 which is nearly equivalent to the number of the labour force that became employed. When analysing the employment statistics of South Africa over a 10-year period, at the beginning of 2008 there were 13 623 000 workers employed and the unemployment rate was at 23.5% (Statistics South Africa, 2008*a*). These statistics convey that over a 10-year period the number of people employed, and the unemployment rate rose, implying that the South African labour market experience difficulties absorbing the available labour (Statistics South Africa, 2018*b*).

The country, similar to the global labour market, is experiencing a significant skills mismatch with an oversupply of low-skilled labourers and undersupply of high-skilled labourers (Bhorat *et al.*, 2015). According to Reddy *et al.* (2016, p. 8), the “education level and skill base of the labour force is lower than that of many other productive economies”. With the South African labour force, 20% have a postsecondary qualification, 32% have a secondary qualification, and 48% do not possess a secondary education qualification (Reddy *et al.*, 2016). Of the unemployed, 60% do not possess a secondary education qualification (Reddy *et al.*, 2016). In terms of the changing labour market, it can be deduced that South Africa is not ready for the fourth industrial revolution and this will likely result in the labour market having greater challenges.

An in-depth analysis of the labour trends in South Africa exhibit that the labour market has been experiencing diminishing employment in low-skilled

occupations which is where the majority of the labour force can look for work (Statistics South Africa, 2018a). Between 2001 and 2012, employment in the primary sector had significant losses with agriculture and mining being the main contributors to such job losses (Bhorat *et al.*, 2015). Between 2001 and 2012, 2.5 million jobs were created with 84% of them coming from the tertiary sector, whilst the primary sector had significant net job losses (Bhorat *et al.*, 2015). During the same period, employment growth in the manufacturing sector was 0.3% per annum and employment growth in transport, finance, and community, social and personal services exceeded 2% (Bhorat *et al.*, 2015).

From the late 20th century the labour market in South Africa showed evidence of skill-biased technological change (Bhorat *et al.*, 2015). Skill-biased technological change refers to the demand of skills changing with the capabilities and requirements of technology (Rifkin, 1995). The South African labour market has undergone skill-biased technological change as the demand for a greater number of social and specialised skills that complement automation has risen. In the primary sector between 2001 and 2012, there were significant employment decreases in low- and medium-skilled occupations, however, there was growth in output. This suggests that during this period, more automation was adopted in the labour market, resulting in employment that competed with automation to become redundant (Bhorat *et al.*, 2015). During the same period, the secondary sector saw an increase in low-skilled and high-skilled employment, employment for high-skilled labour also rose in the tertiary sector (Bhorat *et al.*, 2015). This analysis conveys that the South African labour market has been transitioning to one that demands a greater portion of high-skilled labourers. The services sector has been the main contributor towards employment creation in South Africa since 2001 (Bhorat *et al.*, 2015). The financial, community and social services sectors contributed towards 73% of employment between 2001 and 2012 (Bhorat *et al.*, 2015). This likely suggests that, in terms of job creation, the South African labour market is becoming service-oriented. Reddy *et al.* (2016, p. 9) found that there “has been a structural shift towards a service economy and a high dependence on high-skilled financial services” in the country.

The public sector has, in recent years, become the main contributor towards job creation in the South African labour market (Bhorat *et al.*, 2015). Bhorat *et al.* (2015, p. 19) indicated that public sector employment has risen since 2008 and this growth was driven by “employment in national, provincial, and local government structures, as opposed to employment in state-owned enterprises”. The authors also found that public sector employment creation has been greatly concentrated in high-skilled occupations. The private sector has, however, had more employment creation concentrated in medium-skilled occupations. With the labour market having mostly low-skilled labourers unemployed, it is likely that employers are having challenges finding suitable candidates to fill in available employment.

Statistics South Africa (2018a) indicated that between 2010 and 2016, the

employment share of high-skilled jobs had fallen, whilst low-skilled jobs experienced a share gain, and medium-skilled employment remained relatively the same. It also identified that the employment share of medium-skilled employment accounted for 46.9% of all employment, high-skilled and low-skilled employment accounted for 23.4% and 29.7% respectively in 2016. This could suggest that even though the labour market has favoured high-skilled employment creation there has been insufficient labour to fill the employment due to the low-skilled labour market. Statistics South Africa (2018a) continued to indicate that between 2010 and 2016 the underemployment rate fluctuated between 3.8% and 4.6% and that the industries under-employing labour had been the private households and construction sectors. The underemployed were mainly employed as domestic workers or in elementary occupations which are low-skilled jobs. Employment in temporary employment services had nearly tripled between 1996 and 2014 (Bhorat *et al.*, 2015). This suggests that a greater proportion of the labour force are finding it more difficult to find suitable and permanent employment.

During 2017 the community and social services industry had an increase of 119 000 jobs, manufacturing jobs increased by 63 000, finance jobs increased by 44 000, and transport and communications jobs increased by 40 000 (Statistics South Africa, 2018b). Net job losses were in construction (92 000), agriculture (70 000), private households (29 000), and mining (10 000) (Statistics South Africa, 2018b). This suggests that, during 2017, employment was mainly lost in the primary and secondary sectors and gained in the tertiary sector. Overall industries in the community and social services, trade, and finance and other business services were the three largest employment sectors in South Africa during 2017 as they contributed to approximately 57.5% of all employment (Statistics South Africa, 2018b).

South Africa's youth unemployment rate was quite high during 2017, being at 50.9% for labourers aged between 15 and 24 (excluding school-going children and students that are not seeking work), and 31.9% for labourers aged between 25 and 34 (Statistics South Africa, 2018b). Approximately 64% of the unemployed labour force was between the ages of 15 and 34 (Statistics South Africa, 2018b). With the country's skills mismatches, it suggests that many of the country's young labour force have inadequate skills required by the labour market. The country has also had a history of having a large number of the labour force without a secondary education qualification, however, in recent years the proportion the labour force without a secondary qualification has diminished (Bhorat *et al.*, 2015). As of 2017, the portion labour force without a secondary qualification was approximately 50% for the active labour force (Statistics South Africa, 2018a), this is an improvement compared to the approximate 56% of the active labour force at the end of 2008 (Statistics South Africa, 2008b). Spaul (2013, p. 10) discovered that of "100 pupils that start school, only 50 will make it to Grade 12, 40 will pass, and only 12 will qualify for university". The future of the labour market will require a high-skilled

labour force, but half of the future labour force in South Africa may not even have at least a secondary qualification. Between 2010 and 2016, a great portion of the South African youth was employed in elementary, sales, craft, and clerk occupations in the trade, services, and finance industries (Statistics South Africa, 2018a). This suggests that the youth have been mainly employed in low-skilled and medium-skilled occupations, the future of the labour market is predicted to require high-skilled labour and it is likely that the South African labour supply may not be ready for the future of the labour market.

Although many of the youth are predicted to have low skills, it is predicted that the portion of those with at least a secondary qualification in the South Africa labour force will rise, the percentage of those without a secondary qualification expected to fall from 51% in 2015 to 43.6% in 2025 (Adelzadeh, 2017). There is a rising number of people enrolled in tertiary education with upward trends in the enrolment of degree programmes (Department of Higher Education and Training, 2018). In 2016, 54.3% of public university students were enrolled for undergraduate degrees and 17.5% were enrolled for postgraduate programmes (Department of Higher Education and Training, 2018). Most students in private tertiary institutions, in 2016, were enrolled in Diploma or Degree qualifications (73.4%) (Department of Higher Education and Training, 2018).

A majority of the students who were in public tertiary institutions between 2013 and 2016 were enrolled in humanities programmes at 42.5%. Following this, 18.1% of these students had the second highest enrollment in education programmes (Department of Higher Education and Training, 2018). Science, engineering, and technology programmes were the second most enrolled with 30.3% of the cohort, and business and management programmes had 27.1% of the cohort (Department of Higher Education and Training, 2018). Leopold *et al.* (2017, p. 9) predict that there will be an increased demand for a multi-skilled labour force “who can blend digital and STEM skills with traditional subject expertise”. The labour supply for such skills will likely grow as the enrolment in science, education and technology programmes have been consistently rising between 2009 and 2016 (Department of Higher Education and Training, 2018). These statistics suggest that students in South African universities were mainly enrolled in programmes which are predicted to see the most demand in the near future. Although enrolment in tertiary education has been rising between 2009 and 2016, the number of first-time entrants has stayed approximately the same throughout the period (Department of Higher Education and Training, 2018). This likely suggests that there are limited opportunities for the labour force to acquire skills and could be a contributing factor as to why many of South Africa’s labourers have low skills.

Phillips *et al.* (2018, p. 2) argue that “for countries like South Africa that are less prepared, digital may bring more job losses than gains”. For South Africa to be ready for the future of the labour market its labour force will need to be ready to work with automation. 50% of the South African population

is under 30 years old and are likely to be suited to the demands of a digitally driven economy (Phillips *et al.*, 2018). This implies that with the necessary upskilling the youth of South Africa may be able to adapt to the demands of the future labour market.

Phillips *et al.* (2018) and le Roux (2018) discovered that due to automation, 35% of all jobs that existed in recent years are at a risk of being fully automated. This high portion of automatable jobs is due to machines being able to complete most of the tasks completed by the labour force in these jobs. Phillips *et al.* (2018) predicted that this percentage will likely fall to 20% by 2025 due to the labour force evolving to the new digital demands across occupations. The authors are optimistic that a significant portion of the South African labour force will acquire skills that will complement the requirements of the labour market in the near future. Phillips *et al.* (2018) propose that to reduce this percentage even further so that only 14% of jobs will be at risk by 2025, South Africa will need to double the pace at which its workforce acquires skills that collaborate with automation. They estimate that jobs “with less than 25 percent of risk of automation will comfortably ‘run with the machine’”. The authors further estimate that of the jobs that existed in 2017 in South Africa, 31% would run with the machine indicating that 69% of the jobs does not run with the machine and have a significant portion of tasks that are automatable.

Subsequently, le Roux (2018) analysed, using labour data from StatsSA and the probability estimates for occupation automation found in Frey and Osborne (2013), that it is the workers who belong to previously disadvantaged groups whose jobs have a higher risk of being automated. Previously disadvantaged groups, in the South African context, refers to non-white people who fall into the race categories which were systematically disadvantaged during apartheid (Brown and Licker, 2003). Statistics South Africa (2018*b*) for statistical purposes categorises people into four main groups African/Black, Coloured, Indian/Asian, and White. le Roux (2018) using these categories found that for Black, Coloured, and Indian labourers the jobs at risk were above 50%, with the percentages at risk amongst the respective groups at 74.9%, 70.5%, and 53.9%. The percentage of white labourers employed is at 39.5%, which is low when compared to black and coloured labourers. These statistics do likely suggest that as a result of the effects of apartheid, it is people belonging in the previously disadvantaged groups who work in routine work. These statistics can also suggest that many labourers have a big risk of being replaced by machinery.

2.2.5 Summary

This section of the literature review discussed the recent and predicted future trends of the South African labour market as well as the global labour market. Labour can be classified by levels of skill which are low-skilled, medium-skilled,

and high-skilled. In order for labour to co-exist with automation in the labour market, they will need to acquire skills that complement automation rather than rival it. Currently, automation can complete routine tasks, therefore, labour will need to acquire skills for non-routine tasks. Non-routine (and routine) tasks can be divided further into either manual or cognitive tasks. Non-routine cognitive tasks are found to be done by high-skilled labour, non-routine manual tasks by low-skilled labour, and routine tasks (cognitive and manual) by medium labour. Internationally the share of medium-skilled jobs has fallen in recent decades and the underemployment rate has risen. This is as a result of, amongst other factors, automation and the requirements of higher education to acquire high-skills. With continuous improvements to automation, it predicted that in the near future that completed by low-skilled labour will become automatable. Labourers will, therefore, need to acquire high-skills specifically specialised and social skills. In the South African labour market more than a quarter of the labour force is unemployed, a factor towards this unemployment is the skills mismatch of the country. The skills mismatch is caused by an oversupply of low-skilled labour and an undersupply of high-skilled labour. It is predicted that, for South Africa, in the near future the share of low-skilled labour will fall and the share high-skilled labour will rise. With higher skills, amongst other factors, it is estimated that by 2025, between 14% and 20% of jobs will be automatable, down from 35% estimated for the labour market in recent years. The next section will discuss the theories and factors in relation to students' career decisions.

2.3 Career Choice Theories And Factors

This section of the literature review addresses two themes that relate to the career choices of students. The first theme, addressed in Section 2.3.1, identifies the theories that have been proposed in relation to the processes in which career choices are formed. Identifying the career choice theories will aid this study to find how students make their career choice decisions. The second theme, addressed in Section 2.3.2, identifies the factors that have been found, to influence the career choices of students. These factors will consist of both internal (subjective) and external (the environment) factors to an individual. At the end of this section, the aim is to identify who and what influences the career choices of a student and how the career decisions of students are formed.

2.3.1 Career Choice Theories

This section describes five career choice theories that explain the processes by which students form and select career choices. The theories described in this section are the *Self-concept Theory of Career Development*, *Gottfredson's Theory of Circumscription and Compromise*, *Holland's Theory of Vocational*

Personalities in Work Environment, the Theory of Work Adjustment, and the Social Cognitive Career Theory. These theories (Brown, 2002; Brown and Lent, 2005; Leung, 2008; Price, 2009) were selected based on their prominence in the body of knowledge concerning career decision making.

2.3.1.1 Self-Concept Theory Of Career Development

The self-concept theory of career development, introduced by Donald Super in 1953, is based on the relationship between the life stages of an individual and their self-concept (Brown, 2002). The theory, as with the other theories that follow, has been modified over time with additions and subtractions to the theory (Osipow, 1990; Leung, 2008). The theory is, however, still based upon the two main elements. The first element of the theory is based on the life stages (of an individual) and how these stages influence human development, the second element of the theory is about how these (life) stages interact with an individual's self-concept (Super, 1980). The self-concept, according to Leung (2008, p. 120), "is a product of complex interactions among a number of factors, including physical and mental growth, personal experiences, and environmental characteristics and stimulation". Super, therefore, suggests that career (or subject) choices are a result of the past experiences an individual has experienced and the people who were present or responsible for those experiences. Super (1980) indicated that in one's career there are five life stages growth, exploration, establishment, maintenance, and decline. Savickas (2002), one of the authors to have modified the theory, provided definitions for each of the career stages. The growth stage was defined as generally ages four to thirteen and involves forming a vocational self-concept. The exploration stage was defined, by Savickas (2002, p. 171), as generally ages fourteen to twenty-four, and involves "fitting oneself into society in a way that unifies one's inner and outer worlds". The establishment stage was defined, by Savickas (2002, p. 178), as generally ages twenty-five to forty-four, and involves "the implementation of a self-concept in an occupational role". According to Savickas (2002, p. 179), the goal of the maintenance (or management) stage is to "sustain oneself in an occupational role and preserve one's self concept". The decline (or disengagement) stage according to Savickas (2002, p. 181), generally, ages sixty-five and older involves the "vocational development tasks of decelerating", retirement planning, and retirement living.

As this study investigates the career choices of university students there will be a brief discussion about the exploration stage. According to Savickas (2002, p. 171-172) during the exploration stage, "society expects young people to learn who and what they might become". The exploration stage consists of three development tasks that an individual will likely complete, these are crystallisation, specification, and actualisation (Savickas, 2002). Savickas (2002, p. 172) defines crystallisation as the task that requires individuals to "explore broadly to form tentative ideas about where they fit into society". The specifi-

cation task, according to the author, “requires that individuals explore deeply to sift through tentative preferences in preparation for declaring an occupational choice”. Actualisation is defined by the author as the task that requires the individual to “realize a choice by converting it into actions to make it a fact”. In terms of a university student, this task is likely to be their final task before enrolling in a tertiary institution and selecting their subject choices. This theory lists the life stages that an individual will go through during their career development, however, it does not address the processes an individual experiences when making career decisions. The theory that follows discusses the processes an individual undergoes in making career decisions.

2.3.1.2 Gottfredson’s Theory Of Circumscription And Compromise

Gottfredson’s Theory of Circumscription and Compromise investigates the factors that an individual considers when making career decisions. The theory is based upon two main elements, circumscription and compromise. According to Price (2009, p. 270) circumscription “is a process of eliminating unacceptable occupations based on social criteria such as gender and class/status” and compromise “involves the modification of career choices due to barriers to successful achievement influenced by compatibility or accessibility issues”. This theory, therefore, suggests that an individual will make career choices after disqualifying other career choices. Gottfredson (1981) proposed that there are four stages of development of the self-concept and preferences that an individual experiences. These stages, according to Gottfredson (1981, p. 545), are “orientation to size and power (ages 3-5 years), orientation to sex roles (ages 6-8 years), orientation to social valuation (about ages 9-13 years), and orientation to the internal, unique self (beginning around age 14 years)”. Gottfredson (1981, p. 548) suggests that the first stage, orientation to size and power, occurs “when youngsters grasp the concept of being an adult”. The author describes the orientation to sex roles as the stage where gender self-concept is consolidated. The stage that follows is the orientation to social valuation, according to the author, this stage occurs when “the more abstract self-concepts of social class and ability become important determinants of social behavior and expectations”. According to the author, the final stage called orientation to the internal, unique self exists to “carve out a personal identity and to arrive at more specific occupational choices”. During this stage personal interests, values, and competencies are developed. This stage is where an individual can be expected to make a decision on university and career choices. This theory identifies that students make career decisions based on circumscription and compromise. It is, however, limited in indicating the factors that influence an individual when making career decisions. The theory that follows will describe the factors in more detail.

2.3.1.3 Holland's Theory Of Vocational Personalities In Work Environment

Holland's theory is a framework based on career interest and the environment (Leung, 2008; Price, 2009). The theory suggests that an individual makes a career decision through a combination of six different personality types, these are Realistic (R), Investigative (I), Artistic (A), Social (A), Enterprising (E), and Conventional (C). An assessment of an individual's personality and interest types would identify the three dominant personality types that would summarise an individual's likely career interest (Holland, 1997). The three personality types are then condensed into a three-letter code (e.g. RIC), with the first letter representing an individual's primary interest type and the other letters represent secondary interest types (Leung, 2008). Similar to the individual, the environment has a primary type from the six 'personality' types (Holland, 1997). According to Holland (1997, p. 4) "individuals search for environments that will let them exercise their skills and abilities, express their attitudes and values, and take on agreeable problems and roles". The author continues arguing that the behaviour of an individual is formed by an interaction of his/her personality and environment. This suggests that an individual that finds an environment that complements their primary personality type, will likely produce positive behaviour. Holland's theory attempts to predict what career and environment would be ideal for an individual based on their personality.

2.3.1.4 Theory Of Work Adjustment

The Theory of Work Adjustment is based on the ongoing process of adjustments individuals make in relation to their environments (Dawis, 1992). The theory proposes that an individual looks for a work environment that would match his/her requirements in terms of needs. The environment also searches for individuals who have the capabilities that meet the requirements of an organisation (Dawis, 2002). This theory is based on the presumption that an individual will make a career choice based on an environment that satisfies their needs. According to Dawis (2002, p. 430), a need is "usually defined in terms of a deficit of some kind". Therefore, the theory suggests that an individual's career choice is made by indicating what needs a work environment will likely fulfil. The author found that there are six reference dimensions that an individual would likely require from the environment in order to fulfil their needs. The dimensions are achievement, altruism, autonomy, comfort, safety, and status. The author concedes that the list of dimensions is not exhaustive and that more dimensions, through further research, could be found. This theory suggests that an individual decides on a career choice through the work environment. Similarly to Holland's theory, this theory is dependent on the external environment and does not look at the internal interests of an individ-

ual. The theory that follows discusses factors both internally and externally that influence the career decision-making process of students.

2.3.1.5 Social Cognitive Career Theory

The Social Cognitive Career Theory (referred to as the SCCT hereafter) is based on a framework comprised of three interlocking models. The three models separately identify the career-related interest, choice, and performance of an individual (Lent *et al.*, 2002). The SCCT proposes that the interest in a career is formed through a combination of self-efficacy beliefs and outcome expectations (Lent *et al.*, 2002). The theory, therefore, proposes that an individual will be interested in a career if they believe that they can perform well in it and that the career will provide desirable outcomes for the self. Aptitudes, past experiences, and exposure to learning opportunities are found to have a positive influence on self-efficacy and outcome expectations (Lent *et al.*, 2002). The second element of the theory, choice, is a three-part process following the individual's interest in a career (Lent *et al.*, 2002).

The individual initially makes a choice, which is then affected by influential and behavioural factors. After making his/her primary choice an individual will make choice actions. Choice actions refer to the individual implementing the choice with activities such as acquiring education and training related to the choice (Lent *et al.*, 2002). The final part of the choice element is the evaluation of the choice action through performance. This evaluation forms a feedback loop and affects the shape of the future behaviour of an individual (Lent *et al.*, 2002). The evaluation comes in the form of successes and failures related to the choice, the outcome of the evaluation is likely to affect the self-efficacy and outcome expectations of an individual which will likely restart the SCCT process once again. According to Lent *et al.* (2002, p. 277), the performance element is “concerned with the level (or quality) of people's accomplishments, as well as with the persistence of their behavior in career-related pursuits”. The performance the individual displays in their career actions will likely affect their perception of abilities related to the career choice and will affect self-efficacy and outcome expectations (Lent *et al.*, 2002). The SCCT is, therefore, an interconnected ongoing process in terms of career choice. The process of the SCCT is illustrated in Figure 2.1, the illustration is an adaptation of the three models joined into one figure. This theory indicates the process and factors an individual will undergo in order to make a career decision. The three-part process found in this theory is, according to Seymour and Serumola (2016), likely to be the one South African students follow when making career choices.

This subsection briefly discussed five major career theories, the Self-concept Theory of Career Development, Gottfredson's Theory of Circumscription and Compromise, Holland's Theory of Vocational Personalities in Work Environment, and the Theory of Work Adjustment were found to be quite limited

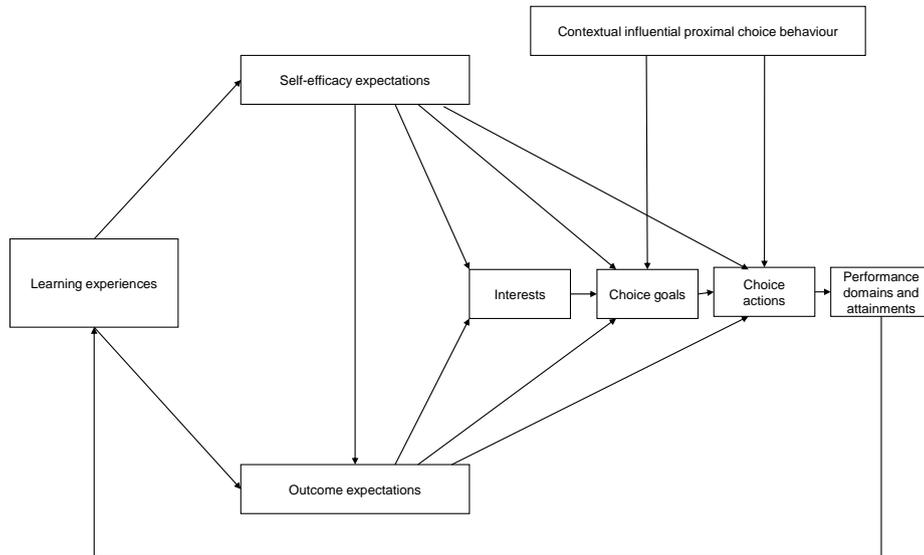


Figure 2.1: Model adapted from the three SCCT models (Lent *et al.*, 2002).

in indicating the processes that a student would undergo in terms of making career choices. The Social Cognitive Career Theory, based on self-efficacy beliefs and outcome expectations, describes the processes by which an individual makes a decision. The next section outlines the factors which have been found to influence the career choices of students.

2.3.2 Factors Affecting Career Choice

The following subsection considers the factors that influence students' career choices. In the previous subsection, it was discussed that the choices of an individual are likely influenced by the relationship between the individual and their environment. This relationship affects the self-efficacy and outcome expectations of an individual. The factors found in this subsection are either formed internally by the individual or formed externally by the environment that surrounds them. This subsection is divided into two segments, the first segment outlines the factors which have been identified in countries other than South Africa, and the second segment identifies the factors that have been found among South African students.

2.3.2.1 Career Choice Factors Identified Outside South Africa

Identifying the factors that affect students in other countries assists in benchmarking South African students and identifying the similarities and differences that exist. The factors identified can assist in determining why the career

choices of South African students differ from students in other parts of the world, as discovered in Section 2.2.3.2. This subsection provides an analysis of the internal and external factors that have been shown to affect students' career choices.

Students themselves have been discovered as the most important factor to influence their career choices (Chuang and Dellmann-Jenkins, 2010; Theresa, 2015). This suggests that there are other individuals who may influence the career choice of a student, however, it is likely that the student will be the most influential person in his/her career choice. As the student has been discovered as the most significant person in making their career choice, the internal factors that influence the student will be analysed.

The quality of life that one can acquire from a career choice is a significant influence in the career choices of students (Cleland *et al.*, 2014; Edwards and Quinter, 2011). Felce and Perry (1995, p. 60-62) defines the quality of life as "an overall general wellbeing that comprises objective descriptors and subjective evaluations of physical, material, social, and emotional wellbeing together with the extent of personal development and purposeful activity, all weighted by a personal set of values". This suggests that, when students make career choices, they greatly consider the other aspects of their lives and are likely to be less inclined to choose a career that does not give them a desired quality of life. Quality of life is much more of a significant influence than remuneration when students consider career choices (Cleland *et al.*, 2014).

In addition to the quality of life, the passion (or interest) an individual has for a particular career is a significant factor that influences the career choice of students (Roach and Sauermann, 2010; Chuang and Dellmann-Jenkins, 2010; Harnovinsah, 2017; Fizer, 2013; Owino and Odundo, 2016; Edwards and Quinter, 2011; Subait *et al.*, 2017; Weiland, 2010; Downey *et al.*, 2011). This is a consistent factor for students in both developed and developing countries. This suggests that students are more inclined to make a career choice based on what interests them. This factor is likely also a contributing factor in the quality of life, as an individual who completes tasks that interest them are likely to enjoy their careers.

Personal growth is a significant factor to student career choices as its influence varies amongst students. Chuang and Dellmann-Jenkins (2010) found that personal growth amongst students in the UK was a significant factor, whilst Weiland (2010) found that personal growth amongst students in the US was not a significant factor. These results convey that it is uncertain whether students greatly consider personal growth making career decisions.

The aptitude an individual has for a particular subject and their previous performance in relation to such a subject, are not significant factors in influencing the career choices of students (Owino and Odundo, 2016; Downey *et al.*, 2011). This suggests that the students' perceived ability in relation to a subject is less likely to be a great influence to greatly affect the career choice of a student. This could likely be as a result of the passion (or interest) one

has for a particular career being a significant factor. The relative abilities that a student has in a subject are less likely to deter from choosing a career they are passionate about.

The financial background of a student is a significant factor in influencing career choice (Rothstein and Rouse, 2011; Subait *et al.*, 2017). Students who acquired debt in order to fund their tertiary education are more inclined to choose careers with higher-salary opportunities (Rothstein and Rouse, 2011). This suggests that the weaker the financial background of a student, the more likely that they will limit the career opportunities they consider. This also suggests that career paths which are unlikely to have a great earning potential are more likely to be chosen by students with a good financial background.

Gender was, in both developed and developing nations, to be a varying factor in terms of influencing the career choice of students. Gender, as a factor, suggests that when a particular career is dominated by a particular gender it will influence a student's career choice. Research from the UK (Cleland *et al.*, 2014) and the US (Fizer, 2013) has found that gender was not a significant factor when making career choices. Ooro (2017) and Njeri (2013) found that, in Kenya, gender was a significant factor that influenced career choice, whilst Edwards and Quinter (2011) and Mtemeri (2017), who respectively conducted studies in Kenya and Zimbabwe, found that gender was not a significant factor in influencing the career choices of students. The literature, therefore, suggests that in developed countries, gender was not a significant factor influencing students making career choices, whilst in developing countries, some students consider it a significant factor and others did not consider it a significant factor.

The family of a student was also found to have a varying significance of influence amongst students' career choices with parents found to have a significant influence on a student's career choice, whilst siblings and other relatives did not have a significant influence. Parents were identified to have a significant influence on students' career choices and to be the most significant people from the external environment (Ooro, 2017; Harnovinsah, 2017; Fizer, 2013; Sarwar and Azmat, 2013; Owino and Odundo, 2016; Njeri, 2013; Subait *et al.*, 2017; Mtemeri, 2017; Theresa, 2015; Weiland, 2010). Not all the literature had identified parents as a significant factor influencing the career choices of students, Chuang and Dellmann-Jenkins (2010), for instance, found that students in the UK did not consider parents as a significant factor to have influenced their career choices. This can suggest that parents from developing countries were likely to have a greater influence on their children's career choices than parents from developed countries. The mother is the parent who was likely to have the greatest influence on a student's career choices (Mtemeri, 2017). Apart from parents the students' siblings and other relatives have been found to not have a significant influence on the career choices of students (Chuang and Dellmann-Jenkins, 2010; Harnovinsah, 2017; Njeri, 2013). This suggests that students are likely to value their parents' input far greater than other family members when making career decisions.

As with the influence of family, the influence of peers was found to vary with the level of significance amongst students' career choices. People who were considered peers in the literature were friends, classmates, or co-workers of the student. Research conducted in developed countries had a consensus that peers were not a significant influence amongst students' career decisions (Chuang and Dellmann-Jenkins, 2010; Weiland, 2010). In developing countries, the literature greatly differed, with Ooro (2017) and Harnovinsah (2017) finding that peers were not a significant influence in terms of career choice, whilst Owino and Odundo (2016), Njeri (2013), Edwards and Quinter (2011), and Mtemeri (2017) found that peers were a significant factor in terms of influence. As parents were found to have a significant influence amongst students' career choices, it can be deduced that peers are likely to have less of an influence on the career choices of students.

The influence of career counsellors was found to vary, in terms of significance, with the career choices of students. Career counsellors were found to have a greater influence on the career choices of students from developed countries than students from developing countries. Literature from developing countries indicates that career counsellors were not a significant factor to have influenced the career choices of students (Ooro, 2017; Theresa, 2015), whilst literature from a developed nation indicates that career counsellors were a significant factor in influencing the career choices of students (Chuang and Dellmann-Jenkins, 2010). It could, therefore, be deduced that, in developed countries, the influence of career counsellors on career choices is likely to be greater than the influence of peers.

The employment opportunities related to a particular career choice were found to have a varying significance on the influence of career choices. It was found that in developing countries employment opportunities were a significant factor in influencing the career choices of students (Harnovinsah, 2017; Owino and Odundo, 2016; Edwards and Quinter, 2011; Subait *et al.*, 2017). For developed nations, the results varied with students in the US indicating that they were more likely to be significantly influenced by the employment opportunities associated with a particular career (Downey *et al.*, 2011), whilst in the UK employment opportunities were identified to not be a significant factor to have influenced the career choices of students (Chuang and Dellmann-Jenkins, 2010). This suggests that, in developing nations, students are more likely to be cautious in considering careers with low employment prospects. For students in developed countries employment opportunities are likely to be less of a factor as the unemployment rates of developed countries are generally lower than those of developing countries (Central Intelligence Agency, 2018). This suggests that the state of the labour market (e.g. labour market, growth rate, *etc.*) likely has an influence on the career choice of students. The financial background of a student is likely to be a significant factor as to why some students are likely to consider employment opportunities. The financial background of a student was identified, earlier in this subsection, to have

a significant factor on career choices. It is likely that students in developing countries are less inclined to choose careers that have limited employment opportunities as employment is a significant issue in their countries.

Remuneration was identified to also have a varying significance of influence on career choice. Studies by Harnovinsah (2017) and Weiland (2010) identified that remuneration was not a significant factor to influence the career choice of students, whilst Fizer (2013) and Downey *et al.* (2011) identified remuneration as a significant factor that influenced career choices. This suggests that the earning potential associated with a career choice was not considered significant by a great portion of students. This agrees with an earlier discussion that students are more likely to be influenced by the quality of life than remuneration when making a career choice. The financial background of a student was identified, earlier in this subsection, to have a significant factor on career choices. It could, therefore, be argued that students in developing countries are less likely to choose careers that will not take them out of poverty, and will consider high-paying careers.

The prestige of a career was not a significant factor to influence the career choices of students (Ooro, 2017; Harnovinsah, 2017; Edwards and Quinter, 2011; Subait *et al.*, 2017; Downey *et al.*, 2011). The prestige of a career refers to a highly remunerating and a very notable career in society, examples of such careers are top tier career in finance, consulting, and law (Binder *et al.*, 2016). This suggests that the social status of a career is less likely to be considered when a student makes career choices. The quality of life and passion accompanied with a career were analysed, earlier in this subsection, to have a significant influence on the career choices of students. It can be deduced that students are less likely to regard the perception of society when making career choices.

Teachers and the school one attended have been identified to not have a significant factor influence on the career choices of students (Ooro, 2017; Edwards and Quinter, 2011; Theresa, 2015; Weiland, 2010; Mtemeri, 2017). Although teachers relay information about a subject to a student, the literature suggests that they are less likely to have an influence on student career choices. The perceived relationship one could have with another person could be a factor as to why alongside siblings and other relative, teachers do not have a significant factor in the career choices of students.

An individual's job or employer were found to not have a significant influence on the career choice of students (Chuang and Dellmann-Jenkins, 2010; Weiland, 2010). This factor is in relation to students with previous work experience, these students could have been employed in part-time jobs whilst studying or were previously employed in full-time employment. The literature also found that the tasks that one was completing in their job were a minimal factor in influencing the career choices students made. This could suggest that the students in these studies were making career changes.

Alongside teachers, representatives from a tertiary institution were found to

not have a significant influence on the career choices of a student (Chuang and Dellmann-Jenkins, 2010; Owino and Odundo, 2016). These representatives could be either academic staff or a marketing team from a tertiary institution that visited a school or presented at an open day. This suggests that the representatives from a tertiary institution are likely ineffective in influencing the career choices of a student. The literature review also found that the representatives were likely coming to students in their final schooling years, this may be too late to influence a student's career choices.

Race was found to not be a significant influence in the career choices of students (Fizer, 2013). Race in the literature refers to whether students were negatively or positively influenced by a dominant race in selecting career choices. The results from the study suggest that students are unlikely to consider race when making a career choice.

The media too has been identified to not have a significant influence on the career choices of students (Sarwar and Azmat, 2013). Media in the literature was in the form of newspapers, digital media, or social media. This suggests that the media is likely ineffective in influencing the career choice of students. Similar to the representatives from the university it is likely that the media addresses the students possibly at a late stage of their lives.

2.3.3 Career Choice Factors In South Africa

As the factors that influence students' career choices in other countries have been identified, the factors that influence students in South Africa will be identified in this subsection and compared to the factors found in other countries. This subsection will provide an analysis of the internal and external factors that have affected students' in selecting their career choices.

The student him/herself was discovered to be a significant influence in terms of their career choice (Shumba and Naong, 2012; Dodge and Welderufael, 2014). This was the same result for students in other countries. Students in South Africa are likely to be the greatest influence upon their career choices.

Passion (or interest) was a significant factor that influenced the career choices of students (Seymour and Serumola, 2016; Mashige and Oduntan, 2011). For example, Seymour and Serumola (2016, p. 34) surveyed Information Systems (IS) students at UCT and found that "students said they chose IS because they had a preference and interest for the major and that they felt their skills were aligned with IS". This suggests that students are more inclined to make career choices in a career they have a passion for. The significance of this factor in South Africa is consistent with that of student's in other countries. This can suggest that, globally, students are selecting career choices based on their passion. It is also possible that, as with students in other countries, South African students are likely significantly influenced by the quality of life.

Personal growth amongst South African students was found to be a significant factor influencing career choice (Abrahams *et al.*, 2015). In other countries, the level of significance varied as Chuang and Dellmann-Jenkins (2010) found that personal growth was a significant factor, whilst Weiland (2010) found it to not be a significant factor. This suggests that students in South African are more inclined to make a career choice that would allow them to further improve themselves in their chosen career.

Financial aid was found to be a significant factor to influence the career choices of students (Seymour and Serumola, 2016). The literature identified that the financial aid available to students (NSFAS, bursaries, etc.) had restrictions that limited the career choices of students. Seymour and Serumola (2016) indicated that some institutions that award bursaries limit the subjects or faculties a student may select. It is uncertain as to whether financial aid influenced the students to select career choices with a higher earning potential as was found with the studies in other countries. Financial aid, however, is likely to have a significant influence on the career choices of a student as with non-South African students. This suggests that students with a good financial background will likely have more freedom in selecting career choices than students who require financial aid. A good financial background likely suggests that a student will not have to pay back the financial aid or be lifted from poverty.

Gender was not a significant influence on the career choices of students (Mudhovozi and Chireshe, 2012). This suggests that students are less likely to be influenced by the dominant gender associated with their career choices. This is similar to the rest of the world wherein developed countries gender did not have a significant influence and in developing countries, it was a varying factor with some studies identifying that it was a significant factor and others identifying it to not be a significant factor. This suggests that students are less likely to make career choices based on the ideology that a career path is gender dominated.

The family of a student was found to have a varying influence, parents were identified to have a varying significance of influence on the choice of careers amongst students, whilst siblings and other relatives were found to not have a significant influence on career choices. Studies by Alexander *et al.* (2011), Kweyama (2016), Shumba and Naong (2012), Dodge and Welderufael (2014), Mudhovozi and Chireshe (2012), and Calitz *et al.* (2013) found that parents were a significant factor in influencing the career choices of students, whilst studies by Abrahams *et al.* (2015) and Mashige and Oduntan (2011) identified that parents were not significant factors in influencing the career choices of students. This suggests that relative to other countries, South African students are likely to be less influenced by the parents in terms of career choices. In terms of siblings and other relatives, the influence is similar to that of other countries with their influence not being significant (Alexander *et al.*, 2011; Kweyama, 2016; Mudhovozi and Chireshe, 2012).

As with family, the significance of the influence of peers on career choice varied amongst South African students. Studies by Alexander *et al.* (2011), Dodge and Welderufael (2014), and Mudhovozi and Chireshe (2012) found that peers were a significant influence on the career choices of students, whilst studies by Seymour and Serumola (2016), Kweyama (2016), and Calitz *et al.* (2013) identified that peers were not a significant influence on the career choices of students. The varying influence of peers is similar in the studies conducted in other countries. This suggests that globally the influence of peers on career choices varies amongst students as for some students it is a significant factor and for others, it is not.

Career counsellors were found to have a varying significance of influence on students' career choices. Studies by Alexander *et al.* (2011), Kweyama (2016), Abrahams *et al.* (2015) have found that career counsellors did not have a significant influence on students' career choices, whilst studies by Shumba and Naong (2012) and Dodge and Welderufael (2014) identified that career counsellors had a significant influence on the career choices of students. As with studies conducted in other countries, the significance of the influence of career counsellors varies. This suggests that the influence of career counselling is less effective than it should be, as some students consider it to not be a significant influence on their career choices.

Teachers and the school a student attended were found to have a varying significance of influence amongst students' career choices. Studies by Alexander *et al.* (2011), Kweyama (2016) and Abrahams *et al.* (2015) found that teachers did not have a significant influence on students' career choice, whilst studies by Shumba and Naong (2012), Dodge and Welderufael (2014), Mudhovozi and Chireshe (2012), Calitz *et al.* (2013) found that teachers were a significant influence on the career choices of students. The literature, therefore, suggests that teachers in South Africa are likely to have a greater influence on the career choices of students, than teachers in other countries. The school, like schools in other countries, was found to not have a significant influence towards the career choices of students (Mncayi and Dunga, 2016; Shumba and Naong, 2012; Mudhovozi and Chireshe, 2012).

Representatives from tertiary institutions were found to have a varying influence on students' career choices. Studies by Alexander *et al.* (2011), Mashige and Oduntan (2011), and Calitz *et al.* (2013) found that representatives from a tertiary institution were not a significant influence on the career choices of students, whilst Seymour and Serumola (2016) and Abrahams *et al.* (2015) found that the representatives from a tertiary institution were a significant influence. This suggests that in South Africa, representatives have a greater possibility of influencing the career choices of students than representatives in other countries do.

Remuneration was a significant factor that influenced the career choices of students (Seymour and Serumola, 2016; Abrahams *et al.*, 2015; Mashige and Oduntan, 2011). It is likely that the high poverty and inequality of South

Africa contributed to the influence of this factor. South African students are likely trying to escape their poverty by choosing careers with high earning potentials. The influence of remuneration on career choice varied amongst studies in other countries, it is likely that due to the economic background of many students in South Africa consider remuneration as a significant factor.

The prestige of a career was found to be a significant factor that influenced the career choices of students (Mashige and Oduntan, 2011). This suggests that South African students differ from students in other countries in terms of the influence the prestige of a career has. This likely indicates that South African students consider greatly the perception others have of the career choice they select.

Employment opportunities were identified to be a significant factor towards the career choices of students (Seymour and Serumola, 2016; Abrahams *et al.*, 2015; Mashige and Oduntan, 2011). This is consistent with literature from other developing countries. The significance of this factor in South Africa is likely due to the high unemployment rate in South Africa. With the high unemployment rate and high poverty, students are likely choosing careers that are less likely to result in them being unemployed.

The aptitude in relation to a career choice was found to be a significant factor that influenced the career choices of students (Seymour and Serumola, 2016; Shumba and Naong, 2012; Mashige and Oduntan, 2011). For students in other countries, it was found that the aptitude for a career was not a significant factor. This suggests that for students in South Africa their perceived abilities of self for a career greatly affected their career choice. Although students were found to be significantly influenced by their interests when making career choices, it is likely that they greatly consider their abilities in relation to that career.

Race was also found to not be a significant factor towards the influence of career choices (Abrahams *et al.*, 2015). This suggests that the past experiences of the country (such as apartheid) did not influence the career choices of students. Race is also found to not be a significant factor with other countries. This likely suggests that, globally, students do not consider race as a factor in the career choices they select.

The influence of the media amongst the career choices varied amongst students' career choices. Studies by Kweyama (2016), Dodge and Welderufael (2014), and Mudhovozi and Chireshe (2012) indicated that the media was a significant factor to influence the career choices of students, whilst Calitz *et al.* (2013) indicated that the media was not a significant influence on students' career choice. The media in other countries was not a significant factor to influence the career choices of students. This likely suggests that the media in South Africa is more effective in influencing students' career decisions than in other countries.

2.3.4 Summary

This section of the literature review discussed the theories and factors that influence students' career decisions. The five career choice theories discussed were the Self-concept Theory of Career Development, Gottfredson's Theory of Circumscription and Compromise, Holland's Theory of Vocational Personalities in Work Environment, the Theory of Work Adjustment, and the Social Cognitive Career Theory. The Self-concept Theory of Career Development suggests that career development of an individual is a result of various life stages and their self-concept. Gottfredson's Theory of Circumscription and Compromise suggests that an individual will make career decisions through a process of circumscription and compromise. Holland's Theory of Vocational Personalities in Work Environment suggests that an individual will make career decisions based on career interests and their work environment and whether their personality type matches the work environment. The Theory of Work Adjustment is similar to Holland's Theory of Vocational Personalities in Work Environment in that it is based on career interests and the environment, however, this theory suggests that career choices are an ongoing process in which individuals make ongoing adjustments to find an environment that will satisfy their needs. The Social Cognitive Career Theory suggests that an individual will make career choices based on a cycle of career interests, choices, and performance in relation to the interest and choice. The Social Cognitive Career Theory suggests that individuals decisions are influenced by various factors. The factors that influence career decisions are found internally with the individual and externally in the environment. The student is the most significant factor towards his/her career decision, followed by their career interest/passion (internal) and parents (external).

2.4 Conclusion

This literature review is presented with the purpose of establishing a reasonable argument as to why the awareness of automation amongst prospective students is necessary for their career decisions and the future of the labour market. This argument is supported by three sections in the chapter. The first section looked into automation in the workplace, from the literature it is found that automation technologies are becoming better and cheaper. When the cost of automation becomes cheaper than labour it can result in the displacement of human labour from the jobs which can be automated. The next section identified the trends in the labour market, it is found that in recent history the share of medium-skilled jobs has been falling whilst the demand for high skills has been rising. It is predicted that for the future specialised and social skills will be required. These sections indicate that in recent history automation has been able to complete tasks (previously) completed medium-skilled labour and

that in the near future automation will be able to complete more forms of tasks. Future workers will need to acquire skills that will complement automation rather than compete with it. Subsequently, the third section identifies how students form their career decisions and who influences those decisions. From the literature, it is gathered that internal factors and the external environment play a significant role in the career decisions of students. There is no mention of automation as a factor of student career decisions in the literature.

From this literature review it can be deduced that automation is becoming an increasingly important factor in the labour market, however, it has yet to be studied whether human labour considers it when making career decisions. Additionally, it has yet to be identified whether students are aware of the impact of automation in the workplace. This suggests that the research area in relation to automation and the labour market has existing gaps. This research study will, therefore, address these gaps. The thesis will identify the awareness of students in relation to automation, the believes students have about automation, and whether automation is considered when career decisions are made.

Chapter 3

Research Design

The following chapter outlines the research methodology employed in this study. To provide guidance to the methodology the chapter begins by stating the objective and research questions of the thesis. This is followed by an overview of the chosen research design. Specifically, in this section the suitability and nature of the chosen method are described. This will be followed by a section on the research design employed in this study. This section will include a discussion of the research methodology employed by this study. Subsequently, there will be sections on the context and population of the thesis, as well as the ethical considerations for the thesis. The final section in the chapter will provide an outline of the data analysis procedures for the data collected.

3.1 Objective And Research Questions

The objective of this study was to understand the awareness of automation amongst undergraduate university students in South Africa when making career choices. Extending from this objective, three questions were posed in Section /refintroresearchquestions With the establishment of these questions, the sections that follow will discuss the research methodology employed to address these research questions.

3.2 Research Design

To address the objectives of this study, the research methodology selected for this study was a quantitative survey-based design. This section will, therefore, describe this research methodology, discuss the suitability of this research methodology for this study, and describe the structure of the research instrument used.

3.2.1 Suitability Of The Research Design

In this section, the suitability of the research methodology is discussed before outlining the nature of the chosen instrument. The suitability of this method will be presented with the strengths and weaknesses of this method.

3.2.1.1 Strengths Of A Survey Design

According to Creswell (1994, p. 117) the first strength of adopting a survey method is that it “provides a quantitative or numeric description of some fraction of the population—the sample—through the data collection process of asking questions”. Indicated by Babbie (2013), the second strength of a survey approach is that surveys are flexible. He suggested that they are flexible in the sense that they enable a researcher to ask many questions on a given topic, giving the researcher considerable flexibility in their analysis. The survey used in this study was hosted on a survey platform provided by the university and distributed via the university’s electronic mail system. There are two primary strengths of distributing a survey via an internet (i.e. the university’s e-mail system). The first strength is that the survey can be distributed to individuals who it may have been difficult to distribute paper-based surveys to (Wright, 2005). Paper-based surveys are, therefore, less likely to reach individuals who may not be in the same geographic place as the researcher. The university in which the thesis was being conducted consisted of various campuses and thousands of students. An online survey distributed via e-mail would, therefore, be more likely to reach a larger sample of students from various academic backgrounds. The second strength is that an Internet-based survey can save time for researchers as it can reach a larger pool of possible respondents with fewer resources being utilised (Wright, 2005). This suggests that less time and money are used when conducting research online.

3.2.1.2 Drawbacks Of A Survey Design

The first weakness of employing a survey is that due to the requirement of standardisation, a survey fails to explore the background behind a respondent’s answer (Babbie, 2013). According to Babbie (2013, p. 263) this indicates that surveys can “often appear superficial in their coverage of complex topics”. He suggested that although this weakness can be partly addressed by sophisticated analyses, the problem was inherent for this method or research.

Section 3.2.1.1 indicated that a strength of using surveys is that they are flexible, Babbie (2013), however, also suggested that a weakness in survey research is that they are inflexible in many ways. This weakness arises from the rigidity of survey research which requires the design of the initial research remain unchanged for the thesis. This limits a researcher from applying new variables which likely were not considered prior to data collection.

A subsequent weakness of surveys is that they are subject to artificiality (Babbie, 2013). Due to the objectivity of quantitative research, the interpretation of the data gathered can likely lead to assumptions behind the respondent's data, indicating a weakness in exploring the background behind the respondent's answers. This weakness indicates that survey research tends to be weak on validity. According to Drost (2011, p.114) "Validity is concerned with the meaningfulness of research components". She identified four types of validity in research: statistical conclusion validity, internal validity, construct validity, and external validity. Statistical conclusion validity relates to the relationship the research is testing; internal validity pertains to the validity of the research itself; construct validity refers to how well a researcher translates or transforms a construct into a functioning and operating reality; and external validity refers to generalising to other persons, settings, and time (Drost, 2011). According to Babbie (2013, p. 263), the lack of validity in survey research is due to that responses are gathered using "approximate indicators of what the researchers had in mind when they framed the questions". For example, a respondent strongly agreeing, agreeing, disagreeing, or strongly disagreeing to a specific statement. Survey research could, therefore, be subject to all forms of validity.

Along with the strengths of distributing a survey online, there are weaknesses that arise. Primarily the researcher can encounter problems with regards to sampling (Howard *et al.*, 2001). This arises due to researchers knowing relatively little about the characteristics of the respondents (Stanton, 1998). To mitigate this the researcher can ask questions which can relate to the background of the participant. For example, in this study the faculty for which a student is a part of was asked. This information was used to identify whether students from X faculty thought differently about automation as compared to students from Y faculty. Closely related to sampling, another weakness of distributing online is that who the survey is distributed to, can be at the discretion of administrators and organisations (Wright, 2005). This can suggest that the sample of respondents can be an inaccurate representation of the population. The final weakness of distributing survey research online is that it is subject to self-selection bias (Wright, 2005). Self-selection, in this regard, suggests that there are some individuals who are more likely than others to participate in surveys. Self-selection could lead to a bias formed via individuals with similar characteristics who are more likely than others to participate in a survey (Wright, 2005).

3.2.1.3 Conclusion On The Suitability Of The Research Design

Notwithstanding all the weaknesses identified in this subsection, this method of data collection was deemed to be capable of acquiring the data necessary in order to address the research questions of this study. Due to the topic in the thesis being relatively unknown, it was more reasonable to employ a survey

study as opposed to the other methods of data collection. Additionally, the thesis required the questions reach many students across multiple geographic locations. For these reasons a survey was found to be best suited for this study.

3.2.2 Research Approach

There are two research approaches that can be adopted for a study, a qualitative approach and a quantitative approach (Babbie, 2013; Bouma and Atkinson, 1995; Blaikie, 2009). According to Creswell (1994, p. 2) a quantitative study (or research approach) is defined as “an inquiry into a social or human problem, based on testing a theory of composed variables, measured with numbers, and analyzed with statistical procedures, in order to determine whether the predictive generalizations hold true”. This suggests that a quantitative approach is objective and based on calculated facts. A qualitative approach differs from a quantitative approach as it is subjective in nature as it emphasises meanings, experiences, description and so on (Naoum, 2012). Due to their differences, the characteristics of the data collected will also differ. Quantitative survey data, according to De Vaus (2002, p. 5), is “portrayed as being sterile and unimaginative but well suited to providing certain types of factual, descriptive information—the hard evidence”. Qualitative methods differ as they are “often regarded as providing rich data about real life people and situations and being more able to make sense of behaviour and to understand behaviour within its wider context” (De Vaus, 2002, p. 5). He, however, suggested that qualitative methods do lack in generalisability as they rely on the subjective interpretations of researchers from the respondents’ data, the researchers subjective interpretations also indicates that subsequent researchers cannot replicate qualitative studies.

According to Naoum (2012, p. 40), a quantitative research approach is selected under the following circumstances:

- When you want to find facts about a concept, a question or an attribute;
- When you want to collect factual evidence and study the relationship between facts in order to test a particular theory or hypothesis.

The purpose of this study met the criteria for both the circumstances as the thesis aimed to collect facts and evidence about students considering automation. Evidence was required to identify whether students consider automation or not when making career decisions. Gathering evidence as to opposed exploring why students do or do not consider automation when making career decisions brought about the justification for selecting the quantitative approach for this research study.

Additionally, in selecting a quantitative research approach for the thesis, the methodology was based upon a positivist philosophy. This philosophy, according to Babbie (2013, p. 60), “is grounded on the rational proof/disproof

of scientific assertions; assumes a knowable, objective reality". This suggests that the objective of this study can only be validated by proving or disproving that students do not consider automation when making career decisions.

Due to the objective nature of the thesis and the research approach, this study can be classified primarily as an exploratory study with elements of a description study. Babbie (2013) suggested that a research study typically is likely to have one of three purposes: exploration, description, and explanation. Exploration, according to Babbie (2013, p. 90), is a research purpose that "typically occurs when a researcher examines a new interest or when the subject of study itself is relatively new". According to Babbie (2013), a description purpose suggests that a researcher observes and describes what is observed, and an explanation purpose aims to explain observations. The purpose of this study was to investigate the consideration of automation amongst students, a relatively unstudied area. An exploration purpose, therefore, best described the purpose of this study. The thesis, however, also contains elements of a descriptive study as it investigated what were students' beliefs and understandings in relation to automation. This was descriptive in nature as it aimed to describe students' awareness to automation, therefore, this study contained elements of both descriptive and exploratory purposes.

This research study collected empirical evidence from primary sources, which were all the undergraduate students enrolled for a degree program at a research-intensive university. The term 'empirical' is defined in Flynn *et al.* (1990, p. 251) as "knowledge based on real world observations or experiment". The data for this study was collected directly from the students using a survey instrument as detailed in Section 3.2.3. The unit of analysis was undergraduate university students.

Following the establishment of a research strategy, the method for data collection is chosen (Naoum, 2012). The common types of methods for data collection are experiments, qualitative field research, unobtrusive research, evaluation research, and survey research (Babbie, 2013). According to Babbie (2013, p. 271) experiments are a two-step process as follows "(1) involve taking action (2) observing the consequences of that action". He suggested that both qualitative and quantitative approaches may employ this method. According to Babbie (2013, p. 324) qualitative field research is in a sense "whenever we observe or participate in social behavior and try to understand it". This implies that the current study would be more suited for qualitative research than quantitative research. The next method is obtrusive research, Babbie (2013, p. 295) defined this as a method "of studying social behavior without affecting it". Babbie suggested that these methods could be qualitative or quantitative. Evaluation research was identified, according to Babbie (2013, p. 358), as research "undertaken for the purpose of determining the impact of some social intervention". Babbie also suggested that this method could be quantitative or qualitative. He continued further by suggesting that surveys are generally used for studies that have individuals as the unit of analysis. Additionally,

survey research was indicated by Babbie (2013, p. 229) as the most appropriate method for “collecting original data for describing a population too large to observe directly”.

3.2.3 Instrumentation

The following subsection provides a brief description of the structure of the survey used in this study. The subsection will include an outline of the questionnaire employed, a discussion of the format of the questions, as well as a discussion of a pilot study conducted.

3.2.3.1 Question Format

There are two types of response formats to gather responses from survey respondents, an open-ended format or a closed-choice format (De Vaus, 2002). A closed or forced-choice question, according to De Vaus (2002, p. 99), is a response format “in which a number of alternative answers are provided from which respondents are to select one or more of the answers”. This suggests that with this response format a survey will allow a respondent to only select choices that were made available by the researcher. An open-ended question, according to De Vaus (2002, p. 99), is a response format “for which respondents formulate their own responses”. This suggests that the researcher provides the respondent with a question and likely a textbox for which the respondent can answer the question free.

The ability for respondents to answer questions freely is the main advantage of employing an open-ended format, as they are motivated to express their views (Naoum, 2012). This format allows for respondents to express their views when responding to questions. Other advantages of using this format are that the questions are easy to ask, and it can be best used when asking for sensitive information (Naoum, 2012). The open-ended format does, however, have a problem as the questions used alongside this format offer no direct clues and are broad-based. As such, according to Naoum (2012, p. 67), predictability for “this type of questionnaire is more difficult to interpret”. Another disadvantage to the open-ended format is that the responses gathered may be too broad to code and analyse (Reja *et al.*, 2003).

Unlike the open-ended format, the closed-choice response format requires respondents to provide answers via a scale. A scale allows respondents to give short responses in form of “in the form Yes or No, Agree, or Disagree, Important or Not Important, and so on” according to Naoum (2012, p. 67). This suggests that closed-choice questions are easy to ask and quick to answer. The responses from this format require no writing and the analysis for the researcher becomes straightforward for the researcher (Frankfort-Nachmias and Nachmias, 1996). The disadvantage to this response format is that the respondent can only give answers that the researcher provides, limiting other

possible answers the respondent may have (Naoum, 2012). This limitation can likely create a bias to the data collected as the responses are limited to what the researcher introduced.

The questionnaire in this study primarily made use of a closed-choice format apart from one question which made use of the open-ended format. This questionnaire structure was selected due to the nature of the research questions. Additionally, the variation to the manner for which students consider automation was likely to be too great to standardise amongst university students, therefore, making use of a fixed response format enabled the standardisation of the responses from students.

The closed-choice format sections in the questionnaire made use of a scale to collect responses from respondents and answer the research questions. A scale is defined, in De Vaus (2002, p. 180), as “a composite measure of a concept, a measure composed of information derived from several questions or indicators”. According to him the reasons for making use of a scale is that it assists in addressing the complexity of a concept, assists in increasing the number of valid measures, increases reliability, enables greater precision, and simplifies the analysis. The rating scale is the most common form of a scale used, it allows a respondent to express his/her agreement on a view with a particular scale (Naoum, 2012). This study made use of the Likert scale for data gathering. A Likert scale, according to (Naoum, 2012, p. 74), is similar to the rating scale except that “the questions consist of attitudinal statements of the survey object (say attitude to job satisfaction) ranging from one extreme of favourableness to the other”.

At the completion of this questionnaire, the various sections were used to determine the awareness of the respondents in relation to the awareness of automation. The first four sections of the questionnaire utilised a Likert scale to produce a score that will indicate the awareness of students in relation to automation awareness. Each question, in the first four sections, made use of a 5-point Likert scale with point ranging from 1 to 5. The Likert Scale adopted in this study investigated to what degree did an individual agree (or disagree) to a statement in the first two sections. The scale, therefore, was measured as follows in the first two sections: Strongly Disagree, Disagree, Neutral, Agree, and Strongly Agree. The third and fourth section also made use of a 5-point Likert scale, however, this scale evaluated how significant was the factor in influencing the career choices of students. The scale for these sections was measured as follows in relation to the influence: Not at all, Very little, Somewhat, A lot, and To a great extent. The fifth section of the questionnaire was not measured on a point scale due to the section questioning the demographics of the respondents as well as their intended careers.

3.2.3.2 Self-Administered Questionnaire

The following subsection will outline and briefly discuss the questionnaire employed by this study. Babbie (2013, p. 30) defined a questionnaire as “an instrument specifically designed to elicit information that will be useful for analysis”. Due to the nature of the study being exploratory there were no existing instruments available. The researcher, on the basis of the literature reviewed, developed the survey items inline with the research questions. The process followed involved the development of a wide range of candidate items, followed by systematic rounds of elimination and combination until a final set was produced. It is acknowledged that further testing of the instrument would be required to assess validity and reliability of the items and/or scales. The questionnaire, found in Appendix A, provided the questions to the respondent and collect data from respondents. The questionnaire consisted of five sections, with each section aimed at collecting data relative to the research questions.

The initial section of the questionnaire begins with self-reflection questions in which the respondents indicated how well-informed they were aware of automation and how exposed they were to technology growing up. The responses from these questions were useful to gather data about the awareness and perception students have of automation. There were two questions in this section. The first question presented in a matrix, consisted of four statements to which respondents indicated the level in which they agreed on a five-point Likert scale. The Likert scale consisted of five options to which respondents could select their answer. The options were Strongly Disagree, Disagree, Neutral, Agree, and Strongly Agree. Each option was assigned a value ranging from 1 to 5, with 1 assigned to Strongly Disagree and 5 assigned to Strongly Agree. As there are four statements and the highest possible value per statement being 5, the highest possible total score for this section of the questionnaire was 20 whilst the lowest total score was 4. A total score of 20 indicated that a respondent perceived himself/herself to be very aware of automation technologies, and a score of 4 indicated that the respondent perceived himself/herself to not be aware of automation. The statements used in this question were:

- I am well-informed of the tasks machines can perform.
- I am well-informed of types of jobs that can be automated.
- I am well-informed of the capabilities of artificial intelligence.
- I am well-informed of how technology affects employment levels.

The second question asked the user to indicate, through a rating scale, the level to which they agree to the following statement: Growing up I spent a lot of time on the computer playing games, exploring how it works, using advanced features, or coding algorithms/programs . This question aimed to investigate whether advanced exposure to technology affected a respondent’s awareness or

beliefs about automation. This question also made use of a five-point Likert scale with the options being Strongly Disagree, Disagree, Neutral, Agree, and Strongly Agree. As with the first question, the options were assigned values ranging from 1 to 5 with 1 assigned to Strongly Disagree and 5 assigned to Strongly Agree.

The second section investigated the beliefs students have about automation as well automation as a factor towards their studies. This section consisted of one question presented by a matrix consisting of six statements. The statements used in the question were:

- I believe that machines will replace human workers.
- I believe that there are many types of jobs machines cannot do.
- I believe that machines will soon be as intelligent as humans.
- I believe that there will always be work for humans to do.
- I believe that the work I plan to do will be automated.
- I believe that the automation of work influenced what I chose to study.

Respondents indicated the level to which they agree to a statement on a five-point Likert scale. The options on the Likert scale were Strongly Disagree, Disagree, Neutral, Agree, and Strongly Agree. The first five statements were used to determine the respondents' beliefs about automation to labour demand, the remaining question was used to determine whether the respondents considered automation when making their career decisions.

The third section investigated the factors that influenced the career choices of the respondents. The section consisted of three questions. The first question investigated which people influenced the respondent's career choice. The question was presented in a matrix consisting of five-point Likert scale and seven statements. The options on the Likert scale were: Not at all, Very Little, Somewhat, A lot, and To a great extent. The statements were as follows:

- When choosing what to study, I was influenced by the following factor: parents/guardian
- When choosing what to study, I was influenced by the following factor: other family members
- When choosing what to study, I was influenced by the following factor: career advisor/counsellor
- When choosing what to study, I was influenced by the following factor: peers

- When choosing what to study, I was influenced by the following factor: teachers
- When choosing what to study, I was influenced by the following factor: the media
- When choosing what to study, I was influenced by the following factor: university representatives

The subsequent section investigated which factors associated with the career influenced the respondent's career choice. As with the prior section, these questions were presented in a matrix consisting of five-point Likert scale and six statements. The options on the Likert scale are also: Not at all, Very Little, Somewhat, A lot, and To a great extent. The statements were as follows:

- When choosing what to study I was influenced by the following factor associated with the career: quality of life
- When choosing what to study I was influenced by the following factor associated with the career: personal growth
- When choosing what to study I was influenced by the following factor associated with the career: career aptitude
- When choosing what to study I was influenced by the following factor associated with the career: potential income
- When choosing what to study I was influenced by the following factor associated with the career: gender
- When choosing what to study I was influenced by the following factor associated with the career: passion/interest

The final question asked respondents if they have had any form of work experience in relation to their career choice. This question was presented with two radio buttons to which respondents gave their answer. The options presented by the radio buttons were Yes and No. This question investigated if work experience may have influenced the respondent's career choice in relation to automation.

The concluding section investigated the demographic profile of the respondent. There were ten questions in this section. This section asked respondents for their age, gender, population group, parents'/guardian highest level of education, the area in which they grew up in, how many years they had been a university student, whether they were receiving financial aid, if financial aid restricted their career choices, their faculty, and in which career they intended on working in.

3.2.3.3 Pilot Study

To validate the questionnaire as an instrument to use for this research study, a pilot study was conducted. A pilot study was used to eliminate any ambiguous, errors, or misunderstandings. Additionally, this enabled testing of the data formats produced by the questionnaire. The questionnaire was distributed to ten postgraduate students registered at the university several weeks prior to the thesis being distributed to the undergraduate students. The reception from the pilot study was positive from all the respondents, and the comments raised during the pilot were addressed.

3.3 Context And Population

In 2016, 975 837 students were registered in South Africa's 26 public universities (Department of Higher Education and Training, 2018). Of these students, 785 351 were enrolled in undergraduate programs and 170 666 were enrolled in postgraduate programs. The Centre of Higher Education Trust clusters the universities in South Africa into three clusters: red, blue, and green. The red cluster identifies research-intensive universities, blue cluster identifies universities focussed technical training, and the green cluster identifies universities which are focussed on both research and technical training (Van Der Schyff and Krauss, 2015).

This study focussed on undergraduate students registered at research-intensive universities in South Africa during the 2018 year. Research-intensive universities were found produce majority of postgraduates, high proportions of academic staff with PhDs, high research outputs, high income and low staff to student ratios (Van Der Schyff and Krauss, 2015). Universities considered as research-intensive universities in South Africa are the University of Cape Town, the University of Pretoria, Rhodes University, Stellenbosch University, and the University of the Witwatersrand (Erasmus, 2011). In 2016, there were 101 440 students enrolled in the research-intensive universities. Of these students, the survey was sent to 19 812 students in one of the universities.

An important question considered during the identification of a target population was whether the results obtained from surveying students at a single research-intensive university can be extrapolated to the broader student population across all research intensive universities in South Africa. It was argued that there are no conceivable properties of the institutions at which students study that would have a significant impact on their awareness of or beliefs about automation. On this basis it is reasonable to argue that the findings made in a large cross-faculty sample at one of these institutions would extrapolatable to students at other comparable institutions.

3.4 Procedure

This section discusses the procedure involved in distributing the questionnaire to prospective respondents. For the questionnaire to be distributed effectively to the largest number of prospective respondents, it was identified that the use of university's official communication channel for research would be most effective method to distribute the survey. To employ this distribution method, ethical and institutional permission was required and subsequently granted. The research was considered low risk to the respondents. For it to be considered low-risk it meant that the only risk imposed on the participant was discomfort and inconvenience. This is due to the questionnaire not having any questions that could identify or harm a participant. It was, however, required that before a respondent could participate in the questionnaire they had to provide informed consent. A consent form was, therefore, provided at the beginning of the questionnaire. The form described the nature and purpose of the thesis. Informed consent was provided by the respondents by indicating, with a tick on the relevant block, that they agree to participate in the questionnaire.

Following the approval from the university to survey students, the questionnaire was then distributed to undergraduate students registered at the university via a link in an email.

3.5 Data Analysis Procedures

The following section provides a description of the method used in processing and analysing the data acquired from the questionnaire.

As the purpose of a quantitative research approach was to collect numerical data, the data collected from the questions needed to be converted numerical figures for the closed-choice responses. This process was conducted in two stages. The first stage was that the answers from the respondents captured via the Likert scale were automatically converted into numerical values using the survey tool, SUNSurveys. At the completion of data collection and converting the values, the data was downloaded from the survey tool and stored on a computer which was synced to a cloud storage account. The data was then taken from storage and loaded on to the data manipulation tool, R-Studio. R-Studio version 1.1.456 and R version 3.5.1 were used for this procedure. The second stage included cleaning the data gathered and producing five number summaries for the responses provided from the respondents. Cleaning consisted of removing responses that were not fully completed and responses that appeared to be outliers from the rest of the respondents.

Following the conversion and cleaning of the numerical data, a detailed analysis of the data began. This analysis consisted of finding out whether students are aware of automation. The points acquired, through the Likert scale, from the various sections of the questions were tallied and given a score. These

scores were then aggregated and used for various classifications as discussed in Section 4.1. Through this procedure it became possible to identify whether the sample of students were aware of and had beliefs about automation. Additionally, it could also be identified which kind of students were likely (or less likely) to think about automation.

Subsequently, the responses from the open-ended question needed to be converted into standardised responses. The open-ended question sought to identify what careers the respondents foresaw themselves working in. This was asked in order to identify, according to the predictions conducted by Frey and Osborne (2017) and le Roux (2018), how many of respondents intended careers were predicted to be automated. This required that the responses to this question be classified according to the categories found in Frey and Osborne (2017).

3.6 Summary

This chapter discussed the research methodology employed in this study. The construction of the methodology was guided by the research questions and objectives of this study. Subsequently, a survey research methodology was employed for this study in order to gather the necessary data required by the research questions and objectives. This methodology was primarily employed due to its objective nature and the ability to reach a great range of respondents. The data was then either converted into numeric values for the closed-choice responses or classified into a category for the open-ended question.

Chapter 4

Analysis And Findings

This chapter presents the key findings that emerged from the data analysis described in Section 3.5. The findings are presented in four sections. The first section provides a summary of the sample demographics. Thereafter, in relation to research question 1, the respondents' awareness of automation is considered, both overall and in relation to each of the demographic factors. Following this, based on research question 2, the respondents' beliefs about the future of automation and labour demand are analysed. The final section presents the an analysis concerning the degree to which awareness of and beliefs about automation impact career decisions among the sample.

4.1 Sample Demographics

An invitation to complete the questionnaire was distributed to 19 812 undergraduate students via email. The survey was open to the students for exactly two weeks. During this time period, the survey was initiated 1506 times. Of the students that started the survey, 948 completed it. This indicated that the survey had a 7.6% participation rate and a 63.0% completion rate. Of the 948 respondents, 547 (57.7%) were female, 399 (42.1%) were male, and two identified with other gender descriptors. The age of the respondents ranged from 17 to 39, with a mean of 20.86 ($SD = 2.05$). Outliers, in terms of age, were removed ($n = 13$, $age < Q1 - 1.5 * IQR$ or $age > Q3 + 1.5 * IQR$) resulting in a final sample size of 935 with a mean age of 20.72 ($SD = 1.58$). Of the 935 respondents, 539 (57.7%) were females, 394 (42.1%) were males, and two (0.2%) were identified as other. Given the relative proportion of the genders in the sample, the respondents who identified as other were not considered for further statistical analyses.

In terms of population group, 580 (62.0%) of the respondents were White, 167 (17.9%) were Black/African, 149 (15.9%) were Coloured, and 39 (4.2%) were Indian/Asian. Additionally, most of the respondents (52.7%) grew up in the city, 37.1% of the respondents grew up in a small town, and 9.9% grew up

Table 4.1: Parents/guardians highest level of education.

Qualification	n	%
Masters or above	88	9.4
Honours/Four-year degree	275	29.4
Three-year degree or equivalent	210	22.5
Diploma	146	15.6
Higher certificate	52	5.6
Secondary completed	114	12.2
Secondary not completed	49	5.2
Other	1	0.1
Total	935	100

Table 4.2: The number of years the respondents had been enrolled in university.

Years at university	n	%
1	277	29.6
2	265	28.3
3	198	21.2
4	117	12.5
5	60	6.4
6	18	1.9
Total	935	100

in a rural area. At 82.5%, most of the respondents' parents (or guardians) had completed a postsecondary qualification. Table 4.1 presents a summary of the parents' highest qualifications. The most common qualification that parents held was an Honours or an equivalent four-year degree.

Table 4.2 provides the statistics indicating how many years the respondents had been enrolled in the university. The largest proportion of the sample were in their first year at university, and 857 (91.7%) of the sample had not been in university for more than four years.

Within the sample, 455 (48.7%) of respondents relied upon financial aid and 480 (51.3%) did not. Of the 455 students with financial aid, 72 (15.8%) were restricted in terms of their career choices. As indicated in Table 4.3, there were respondents from all 10 faculties in the sample. Over half (58.8%) of respondents were from three of the university's large faculties: Arts and Social Sciences (17.9%), Economic and Management Sciences (21.4%), and Engineering (19.5%). Given the relative sizes of the faculties in the sample, the Education, Military Sciences, and Theology faculties were excluded from all the statistical analyses that follow.

The intended careers of the respondents varied greatly with over 638 unique

Table 4.3: Faculty representation in the sample.

Faculty	n	%
AgriSciences	54	5.8
Arts and Social Sciences	167	17.9
Economic and Management Sciences	200	21.4
Education	23	2.5
Engineering	182	19.5
Law	55	5.9
Medicine and Health Sciences	113	12.1
Military Sciences	2	0.2
Sciences	134	14.3
Theology	5	0.5
Total	935	100

responses provided. The responses were condensed to 14 career groups to enable meaningful analysis. First, the responses were standardised according to the 702 careers used in Frey and Osborne (2013) into 111 categories. Thereafter, the 111 categories were combined to form 14 higher level categories. These categories arose from grouping careers with close relation in terms of field or industry. For example, the ‘Judge’, ‘Attorney’, and ‘Lawyer’ categories were grouped into the Law category. The final set of categories are presented in Table 4.4. The table indicates that the categories with the largest proportion of students were Engineering and Healthcare, with 138 and 126 respondents respectively. The smallest category was that of Agriculture with 18 respondents. Given the relative sizes of the career categories in the sample, this category was not considered for further statistical analyses. The undecided career category refers to respondents who responded with either undecided or multiple career options. Of the sample, 602 (64.4%) of the respondents indicated that they had work experience that was related to their intended career.

In terms of exposure to technology growing up, 37.6% of the respondents indicated that they were not exposed to technology, while 41.6% indicated that they were exposed to technology.

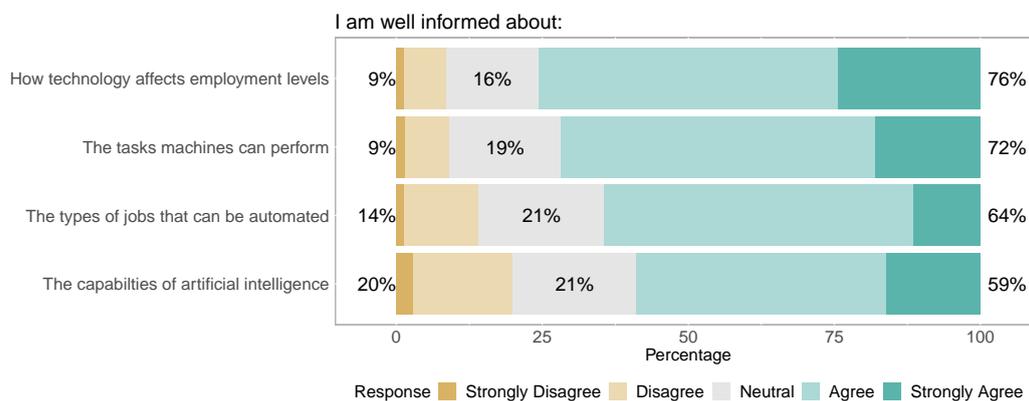
4.2 Automation Awareness Scale

To analyse respondents’ awareness of automation technology, answers to the four statements concerning their knowledge of the relevant technologies were considered. Figure 4.1 presents a summary of these responses. Skewness for awareness scale was -0.69, this means that the scale is moderately skewed. Additionally, the figure indicates that for each of the responses the majority of the sample were in agreement with each of the awareness statements. This

Table 4.4: Intended career categories.

Career Category	n	%
Accounting/Auditing	74	7.9
Agriculture	18	1.9
Biological Science	48	5.1
Business Management	86	9.2
Education (including higher education)	67	7.2
Engineering	138	14.8
Finance	58	6.2
Healthcare	126	13.5
Legal	50	5.3
Media or Entertainment	32	3.4
Physical Science	40	4.3
Social Science	96	10.3
Software Development	33	3.5
Undecided	69	7.4
Total	935	100

outcome implies that a majority of the respondents perceived themselves to be aware of the tasks machines can perform, the type of jobs that can be automated, the capabilities of artificial intelligence, and how technology affects employment levels.

**Figure 4.1:** The distribution of the awareness statements according to the samples' responses.

To calculate each respondent's automation awareness, the responses to the four questions were aggregated to generate a scale. The scale demonstrated good internal consistency (*Cronbach's alpha* = 0.82). The distribution of the

scale (ranging from 4 to 20) is presented in Figure 4.2. The scale's mean of 14.82 ($SD = 3.00$) suggests that students generally felt that they were aware of the capabilities of automation technologies and its implications for labour demand. In the sections which follow the automation awareness scale is briefly considered in relation to particular demographic variables.

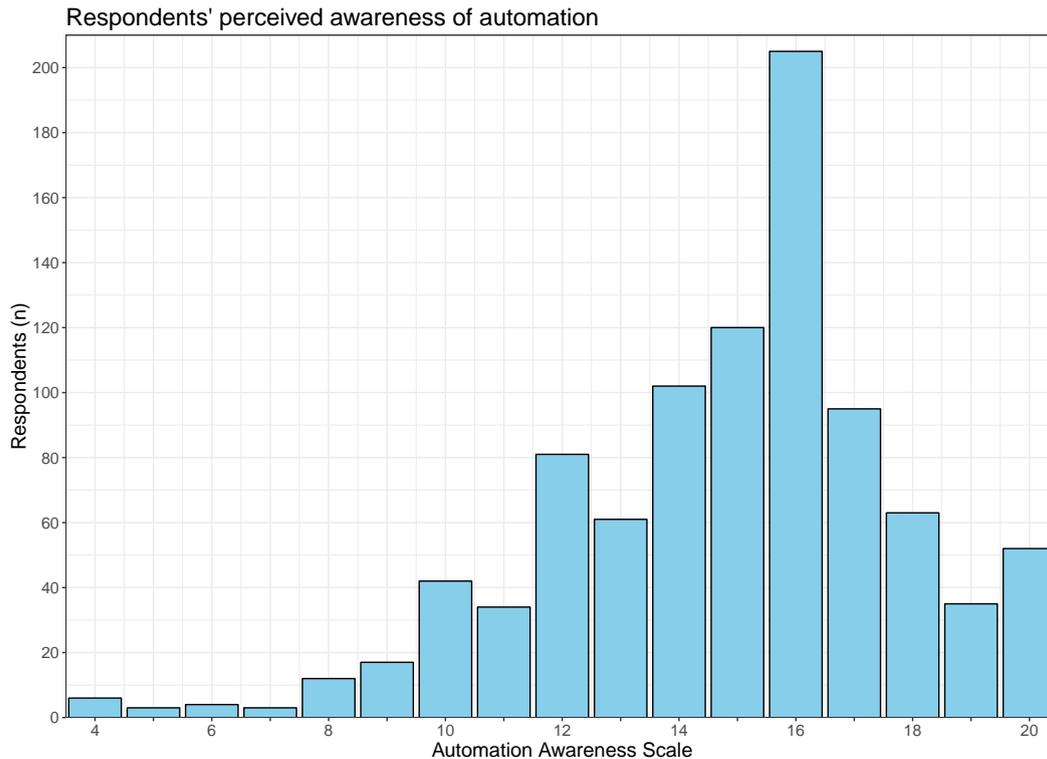


Figure 4.2: Automation awareness scale distribution

4.2.1 Demographic Differences

The following subsection details the analysis of the automation awareness scale scores by demographic factors. The demographic factors considered were gender, the type of areas the respondents grew up in, faculty, intended career, and parents' highest level of education. The predictive power of these demographic factors were tested using either an independent samples t-test or an ANOVA.

An ANOVA was used in this study as opposed to linear regressions as, according to Lazic (2008, p. 2), it enables for “greater statistical power due to more precise estimates, a simpler and more informative interpretation of the results, a more parsimonious explanation of the data with fewer parameters, and transformations of the predictor variable are possible”. A MANOVA was not employed due to the researcher following a step by step process in

Table 4.5: Automation awareness scale mean by faculty.

Faculty	M	SD
Engineering	16.05	2.86
Economic and Management Sciences	15.10	2.60
Sciences	14.92	2.74
AgriSciences	14.41	3.25
Arts and Social Sciences	14.38	3.07
Law	14.18	2.97
Medicine and Health Sciences	13.65	3.13

analysing the data. Additional motivation to use an ANOVA was that is not highly sensitive to moderate deviations from normality; simulation studies, using a variety of non-normal distributions, have shown that the false positive rate is not affected by this violation of the assumption (Glass *et al.*, 1972; Harwell *et al.*, 1992; Lix *et al.*, 1996). To test the assumption of homogeneity of variances, for all ANOVAs conducted Levene's test was separately performed and confirmed the homogeneity of variances for each independent variable.

4.2.1.1 Gender

An independent samples t-test indicated that there was a statistically significant difference in automation awareness between male and female respondents ($t(845.88) = -6.34, p < 0.05$). With a mean of 15.53 ($SD = 2.94$), the scale indicates that males had higher awareness of automation than females who had a mean of 14.30 ($SD = 2.93$).

4.2.1.2 Areas That The Respondents Grew Up In

Based on the results of an ANOVA, the area where respondents grew up was found not to be a significant predictor of variance in automation awareness ($F(2, 930) = 2.479, p > 0.05$). Respondents who grew up in cities had the highest mean level of awareness ($M = 14.99, SD = 3.08$), while those from small towns had the lowest ($M = 14.53, SD = 2.79$). Respondents from rural areas had a mean level of awareness of $M = 14.92$ ($SD = 3.25$).

4.2.1.3 Faculty

As shown in Table 4.5, respondents who were from the Engineering faculty had the highest mean level of awareness ($M = 16.05, SD = 2.86$), while those from the Medicine and Health Sciences faculty had the lowest ($M = 13.65, SD = 3.13$). Based on the results of an ANOVA, the faculty which respondents belonged to was found to be a significant predictor of variance in automation awareness ($F(6, 898) = 10.11, p < 0.05$).

Table 4.6: Automation awareness scale mean by career category.

Career Category	M	SD
Software Development	16.76	3.16
Engineering	15.88	2.68
Business Management	15.63	2.45
Biological Science	15.23	2.33
Accounting/Auditing	15.16	3.01
Finance	15.16	2.36
Physical Science	14.70	2.80
Legal	14.56	2.70
Undecided	14.55	2.99
Media or Entertainment	14.44	3.12
Education	14.40	3.31
Social Science	13.88	3.06
Healthcare	13.63	3.16

4.2.1.4 Intended Careers

Based on the results of an ANOVA, the intended career of the respondents was found to be a significant predictor of variance in automation awareness ($F(12, 904) = 6.51, p < 0.05$). As shown in Table 4.6, respondents who intended on working in Software Development had the highest mean level of awareness ($M = 16.76, SD = 3.16$), while those who intended on working in Healthcare had the lowest ($M = 13.63, SD = 3.16$). The range between these two mean levels was 3.10, with respondents intending to work in Software Development perceiving themselves to be very aware of automation whilst those intending to work in Healthcare perceived themselves to being moderately aware.

4.2.1.5 Parents/Guardians Highest Qualification Level

As shown in Table 4.7, respondents whose parents had an Honours/Four-year degree had the highest mean level of awareness ($M = 15.00, SD = 3.10$), while respondents whose parents had only a secondary qualification or did not complete a secondary qualification had the lowest (respectively as $M = 14.45, SD = 2.90$ and $M = 14.45, SD = 3.27$). As indicated by an ANOVA, this difference was not statistically significant ($F(6, 927) = 0.72, p > 0.05$).

Table 4.7: Automation awareness scale mean by parent's/guardian's highest level of education.

Qualification	M	SD
Honours/Four-year degree	15.00	3.10
Masters or above	14.95	3.24
Three-year degree or equivalent	14.93	2.78
Higher certificate	14.71	3.35
Diploma	14.68	2.82
Secondary not completed	14.45	3.27
Secondary completed	14.45	2.90

4.3 Beliefs About Automation

To analyse the respondents' beliefs about automation, their responses to the five automation belief statements about automation were considered. Figure 4.3 presents the distributions of the responses towards five belief statements. A majority of the respondents believed that there will always be work for humans to do, there are many jobs machines cannot do, and machines will replace labour. Additionally, the majority of the respondents did not believe that automation influenced their choice of study and that the work they plan to do will be automated. A scale was not used for the belief statements as the scale did not demonstrate good internal consistency (*Cronbach's alpha* = 0.11). In the sections which follow, the belief statements are considered separately in relation too.

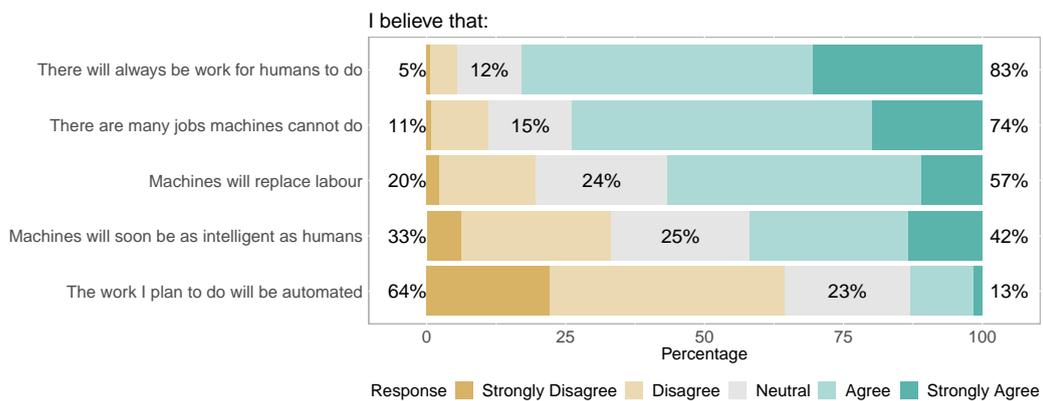
**Figure 4.3:** The distribution of the awareness statements according to the samples' responses.

Table 4.8: Belief statements mean by gender.

Beliefs That:	Females	Males
	M (SD)	M (SD)
Machines will replace labour (B1)	3.43 (0.98)	3.49 (0.96)
There are many jobs machines cannot do (B2)	3.76 (0.89)	3.90 (0.90)
Machines will soon be as intelligent as humans (B3)	3.22 (1.10)	3.07 (1.20)
There will always be work for humans to do (B4)	4.00 (0.82)	4.17 (0.81)
The work I plan to do will be automated (B5)	2.28 (0.98)	2.28 (0.99)

4.3.1 Differences In Beliefs Across Demographic Factors

The following subsection details the analysis of the belief statements by demographic factors. The demographic factors considered were gender, the types of areas which the respondents grew up in, faculty, intended career, and parents' highest level of education. These demographic factors were tested using either an independent samples t-test or an ANOVA.

4.3.1.1 Gender

Table 4.8 presents the mean values for each gender in relation to the belief statements. An independent samples t-test indicated that there was a statistically significant difference in the belief that there are many jobs machines cannot do ($t(840.43) = -2.42, p < 0.05$). With a mean of 3.90 ($SD = 0.90$), on average, males ascribed to this belief more than females, who had a mean of 3.76 ($SD = 0.89$). Another independent samples t-test indicated that there was a statistically significant difference in the belief that there will always be work for humans to do ($t(854.29) = -3.05, p < 0.05$). With a mean of 4.17 ($SD = 0.81$) males also ascribed more to this belief than females, who had a mean of 4.00 ($SD = 0.82$). For the three remaining belief statements the means did not significantly differ between the genders.

4.3.1.2 Areas That The Respondents Grew Up In

Table 4.9 presents the mean values for each area type in relation to the belief statements. Five separate ANOVAs were conducted to identify any statistically significant differences between the three area types for any of the belief statements. The findings indicated that there was no statistically significant difference between the area types for all five of the belief statements.

4.3.1.3 Faculty

Table 4.10 presents the mean values for each faculty in relation to the belief statements. Separate ANOVAs were conducted to identify any statistically significant differences between the faculties for any of the belief statements. This analysis indicated that the faculty of the respondent was a sig-

Table 4.9: Belief statements mean by the area respondents grew up in.

Beliefs That:	City	Rural	Small Town
	M (SD)	M (SD)	M (SD)
Machines will replace labour (B1)	3.43 (0.96)	3.63 (1.10)	3.45 (0.96)
There are many jobs machines cannot do (B2)	3.85 (0.91)	3.70 (0.98)	3.80 (0.84)
Machines will soon be as intelligent as humans (B3)	3.14 (1.15)	3.22 (1.28)	3.16 (1.10)
There will always be work for humans to do (B4)	4.10 (0.80)	4.07 (0.92)	4.04 (0.82)
The work I plan to do will be automated (B5)	2.24 (0.96)	2.43 (1.10)	2.29 (0.98)

nificant predictor of variance in the belief that machines will replace labour ($F(6, 898) = 2.29, p < 0.05$). Respondents from the Engineering faculty had the highest mean value ($M = 3.57, SD = 0.93$) while the respondents from the Medicine and Health Sciences faculty had the lowest ($M = 3.18, SD = 1.13$). Additionally, the results indicated that the faculty of the respondent was a significant predictor of variance in the belief that machines will soon be as intelligent as labour ($F(6, 898) = 2.53, p < 0.05$). On average, respondents from the Arts and Social Sciences faculty had the highest agreement level ($M = 3.37, SD = 1.06$) towards this belief statement and the respondents from the Medicine and Health Sciences faculty had the lowest agreement level ($M = 2.89, SD = 1.23$). Based on the results of an ANOVA, the faculty of the respondent was found to be a significant predictor of variance in the belief that the work he/she intends on doing will become automated ($F(6, 898) = 7.48, p < 0.05$). Respondents from the Economic and Management Sciences faculty had the highest mean value ($M = 2.59, SD = 0.99$) while the respondents from the Law faculty had the lowest ($M = 1.87, SD = 0.82$). The differences for the belief that there many jobs machines cannot do and the belief that there will always be work for humans to do did not significantly differ between the faculties.

4.3.1.4 Intended Careers

Table 4.11 presents the mean values for each intended career category in relation to the belief statements. Separate ANOVAs were conducted to identify any statistically significant differences between the intended career categories for any of the belief statements. Based on the results of an ANOVA, the intended career of the respondent was found to be a significant predictor of variance in the belief that there will always be work for labour to do ($F(12, 904) = 2.00, p < 0.05$). Respondents in the Engineering career category had the highest mean value ($M = 4.19, SD = 0.69$) while the respondents from the Healthcare career category had the lowest ($M = 3.85, SD = 1.00$). On average, respondents in the Accounting/Auditing career category had the highest mean value ($M = 2.73, SD = 1.06$) while the respondents from the Media or Entertainment career category had the lowest ($M = 1.84, SD = 0.92$) for the belief that work he/she intends to do will be automated. The intended career

Table 4.10: Belief statements mean by faculty.

Faculty	B1	B2	B3	B4	B5
	M	M	M	M	M
	(SD)	(SD)	(SD)	(SD)	(SD)
AgriSciences	3.52	3.80	3.28	4.11	2.41
	(1.04)	(0.71)	(1.16)	(0.69)	(0.86)
Arts and Social Sciences	3.51	3.82	3.37	4.05	2.14
	(0.93)	(0.89)	(1.06)	(0.79)	(0.89)
Economic and Management Sciences	3.52	3.80	3.09	4.13	2.59
	(0.97)	(0.91)	(1.09)	(0.79)	(0.99)
Engineering	3.57	3.80	3.06	4.15	2.25
	(0.93)	(0.92)	(1.16)	(0.74)	(1.03)
Law	3.35	3.76	3.29	4.13	1.87
	(1.00)	(0.86)	(1.20)	(0.84)	(0.82)
Medicine and Health Sciences	3.18	3.85	2.89	3.90	2.05
	(1.13)	(0.95)	(1.23)	(0.97)	(1.01)
Sciences	3.47	3.84	3.22	4.01	2.46
	(0.91)	(0.87)	(1.20)	(0.85)	(0.99)

B1 refers to the belief that machines will replace labour.

B2 refers to the belief that there are many jobs machines cannot do

B3 refers to the belief that machines will soon be as intelligent as humans

B4 refers to the belief that there will always be work for humans to do

B5 refers to the belief that the work I plan to do will be automated

of the respondent was found to be a significant predictor of variance for this belief ($F(12, 904) = 4.65, p < 0.05$). The differences for the three remaining belief statements did not significantly differ between the career categories.

4.3.1.5 Differences Across Parents' Highest Qualification

The following subsection presents an analysis of the difference in the qualifications that the respondents parents (or guardians) held in relation to the belief statements. Table 4.12 presents the mean values for each qualification in relation to the belief statements. Separate ANOVA's were conducted to identify any statistically significant differences between the qualifications for any of the belief statements. A parents qualification was found to be a significant predictor of variance for a respondents belief that their intended career will be automated ($F(6, 927) = 2.11, p < 0.05$). Respondents who parents held a Higher Certificate had the highest mean value ($M = 2.54, SD = 1.21$) while the respondents from the Honours/Four-year degree had the lowest ($M = 2.19, SD = 0.93$). The differences for the four remaining belief statements did not significantly differ between the parent or guardian qualifications.

Table 4.11: Belief statements mean by career category.

Intended Career	B1	B2	B3	B4	B5
	M (SD)	M (SD)	M (SD)	M (SD)	M (SD)
Accounting/Auditing	3.47 (1.06)	3.76 (0.99)	3.14 (1.14)	4.05 (0.87)	2.73 (1.06)
Biological Science	3.67 (0.91)	3.83 (0.75)	3.33 (1.19)	3.96 (0.74)	2.48 (0.95)
Business Management	3.58 (0.98)	3.72 (0.92)	3.19 (1.11)	4.20 (0.73)	2.52 (1.03)
Education	3.19 (0.96)	3.84 (0.93)	2.93 (1.08)	4.03 (0.87)	2.06 (0.90)
Engineering	3.51 (0.88)	3.79 (0.88)	3.09 (1.14)	4.19 (0.69)	2.25 (0.98)
Finance	3.59 (0.86)	3.76 (0.82)	3.19 (1.16)	4.16 (0.70)	2.53 (0.78)
Healthcare	3.28 (1.14)	3.84 (0.93)	2.96 (1.22)	3.85 (1.00)	2.12 (1.04)
Law	3.42 (1.07)	3.88 (0.85)	3.28 (1.16)	4.12 (0.82)	1.94 (0.91)
Media or Entertainment	3.53 (0.84)	4.06 (0.67)	3.56 (1.01)	3.81 (0.86)	1.84 (0.92)
Physical Science	3.35 (0.95)	4.00 (0.85)	3.25 (1.19)	4.08 (0.89)	2.40 (1.13)
Social Science	3.34 (0.93)	3.93 (0.89)	3.10 (1.11)	4.21 (0.75)	2.02 (0.83)
Software Development	3.82 (0.85)	3.97 (0.68)	3.46 (1.23)	3.88 (0.89)	2.27 (1.01)
Undecided	3.58 (0.90)	3.49 (1.09)	3.29 (1.11)	4.10 (0.77)	2.38 (0.91)

Table 4.12: Belief statements mean by parent's/guardian's highest level of education.

Qualification	B1	B2	B3	B4	B5
	M (SD)	M (SD)	M (SD)	M (SD)	M (SD)
Masters or above	3.40 (0.98)	4.05 (0.92)	3.10 (1.25)	4.30 (0.66)	2.21 (0.97)
Honours/Four-year degree	3.43 (1.03)	3.75 (0.91)	3.07 (1.18)	4.08 (0.80)	2.19 (0.93)
Three-year degree or equivalent	3.51 (0.93)	3.86 (0.83)	3.17 (1.13)	4.09 (0.80)	2.20 (0.95)
Diploma	3.47 (0.93)	3.78 (0.92)	3.23 (1.13)	4.00 (0.80)	2.33 (0.98)
Higher Certificate	3.37 (0.95)	3.62 (1.01)	3.15 (1.18)	4.10 (0.89)	2.54 (1.21)
Secondary completed	3.47 (0.97)	3.82 (0.84)	3.31 (1.05)	4.00 (0.85)	2.45 (1.05)
Secondary not completed	3.55 (1.02)	3.92 (0.89)	3.14 (1.08)	3.92 (0.98)	2.43 (0.96)

4.3.2 The Effect Of Awareness On Beliefs

An ANOVA was used to identify the effect of automation awareness on beliefs. As the respondents' score on the automation awareness scale ranged from 4 to 20, the respondents were divided into tertiles to analyse differences in beliefs between those who were relatively unaware, moderately aware, and very aware. Those who scored between 4 and 14 on the scale were classified as relatively unaware ($n = 365$), those who scored between 15 and 16 were moderately aware ($n = 325$), and those who scored between 17 and 20 were very aware ($n = 245$). Table 4.13 presents the mean values for each awareness classification. Additionally, Table 4.14 presents the results of each ANOVA for the belief statements.

Based on the results of an ANOVA, awareness of automation was found to be a significant predictor of variance in the belief that machines will replace labour ($F(2, 932) = 9.01, p < 0.001, \eta_p^2 = 0.02$). With a mean value of $M = 3.64$ ($SD = 0.99$), respondents who were very aware had the highest mean value, whilst respondents who were unaware had the lowest mean value ($M = 3.31, SD = 0.98$). The results also indicated that the awareness of automation was found to be a significant predictor of variance in the belief that machines will soon be as intelligent as humans ($F(2, 932) = 7.40, p < 0.001, \eta_p^2 = 0.02$). Respondents who were very aware had the highest mean value ($M = 3.36, SD = 1.22$) and respondents who were unaware had the lowest mean value ($M = 3.00, SD = 1.12$). Finally, a respondent's awareness of

Table 4.13: Belief Statements Mean By Awareness Of Automation.

Belief that:	Unaware	Moderately Aware	Very Aware
	M (SD)	M (SD)	M (SD)
Machines will replace human labourers	3.31 (0.98)	3.49 (0.93)	3.64 (0.99)
There are many types of jobs machines cannot do	3.75 (0.90)	3.88 (0.80)	3.84 (1.00)
Machines will soon be as intelligent as humans	3.00 (1.12)	3.17 (1.10)	3.36 (1.22)
There will always be work for humans to do	3.98 (0.85)	4.05 (0.76)	4.23 (0.81)
The work I plan to do will be automated	2.25 (0.96)	2.35 (0.96)	2.24 (1.05)

Table 4.14: Relationship between awareness and beliefs of automation technologies.

Belief that:	df	F	η_p^2	p
Machines will replace labour	2	9.01	0.02	0.00***
There are many types of jobs machines cannot do	2	1.96	0.00	0.14
Machines will soon be as intelligent as humans	2	7.40	0.02	0.00***
There will always be work for humans to do	2	6.83	0.01	0.00**
The work I plan to do will be automated	2	1.11	0.00	0.33

* refers to $p < 0.05$; ** refers to $p < 0.01$; *** refers to $p < 0.001$.

automation was found to be a significant predictor of variance in the belief that there will always be work for labour ($F(2, 932) = 6.83, p < 0.01, \eta_p^2 = 0.01$). With a mean value of $M = 4.23$ ($SD = 0.81$), respondents who were very aware had the highest mean value, whilst respondents who were unaware had the lowest mean value ($M = 3.98, SD = 0.85$). The differences for the two remaining belief statements did not significantly differ between the awareness classifications.

4.4 Predictors Of Career Decisions

The following section presents findings in terms of the predictors of the career decisions of the respondents. The first subsection presents a brief analysis of the responses related to the sources of influence. The subsequent subsection presents a brief analysis of the responses related to the factors of influence.

4.4.1 Sources

To analyse the influence that particular sources had on the career choices of the respondents, the responses related to the sources of influence were considered. Figure 4.4 presents the distributions for the responses for each source. The figure indicates that the largest proportion of the sample indicated that they were influenced by their parents/guardians with 25% of the sample agreeing or strongly agreeing that they were influenced by this source. Career advisors/counsellors had the second highest proportion with 18% of the sample agreeing or strongly agreeing that they were influenced by this source. Peers had the lowest proportion of the sample's with 8% agreeing or strongly agreeing that they influence by this source. No source had more than 25% of the sample agreeing to its influence on their career decisions.

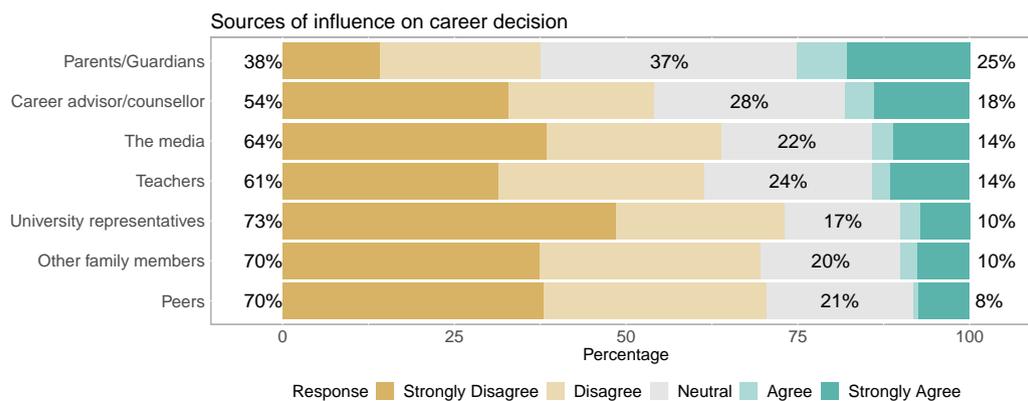


Figure 4.4: Response distribution for the sources.

4.4.2 Factors

To consider the effect of particular factors on the respondents' career choices, the responses related to the factors considered were analysed. Figure 4.5 presents the distribution of responses for each factor. A majority of the respondents indicated that they were influenced by passion/interest, personal growth, career aptitude, quality of life, and personal income when making their career decisions. Additionally, a majority of the respondents indicated that they were not influenced by gender when making their career decisions.

4.4.2.1 The Automation Of Work As A Factor

Figure 4.5 indicates that 59% of the sample did not feel that the automation of work influenced their choice of study. In contrast, 22% of the sample indicated that they felt that the automation of work influenced their choice of study. This sub-subsection analyses the effects that demographic factors

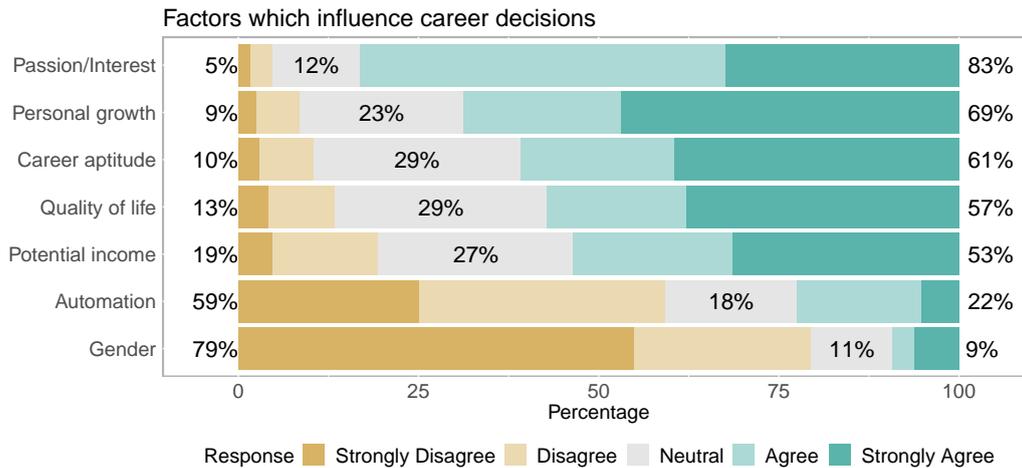


Figure 4.5: Response distribution for the factors of influence.

had on automation as a factor on the career decisions of the respondents. An independent samples t-test indicated that there was a statistically significant difference in the belief that automation influenced the choice of study between male and female respondents ($t(834.64) = -2.86, p < 0.05$). With a mean of 2.57 ($SD = 1.20$), males agree more than females ($M = 2.34, SD = 1.17$) that they were influenced by this factor. An ANOVA indicated that there was a statistically significant difference between the respondents from the three area types ($F(2, 930) = 6.83, p < 0.01, \eta_p^2 = 0.01$). On average, respondents from a rural area had the highest agreement level that they were influenced by automation when making career decisions ($M = 2.53, SD = 1.19$). Respondents from a small town were second to those from a rural area with mean of 2.45 ($SD = 1.16$), with a mean of 2.41 ($SD = 1.21$) respondent from the city had the lowest level of agreement.

Figure 4.6 presents the mean values of the respondents' belief levels by faculty. Based on the results of an ANOVA, the faculty of the respondent was found to be a significant predictor of variance in the belief that automation influenced his or her choice of study ($F(6, 898) = 8.03, p < 0.05$). Respondents from the Engineering faculty had the highest mean value ($M = 2.86, SD = 1.22$) while the respondents from the Law faculty had the lowest ($M = 2.06, SD = 1.19$). The mean values of the respondents' belief levels by intended career group are presented in Figure 4.7. Using an ANOVA, the intended career of the respondent was found to be a significant predictor of variance in the belief that automation influenced his/hers choice of study ($F(12, 904) = 8.91, p < 0.05$). Respondents in the Software Development career category had the highest mean value ($M = 3.76, SD = 1.06$) while the respondents from the Education career category had the lowest ($M = 1.88, SD = 0.91$). Based on the results of an ANOVA, a parent's level of education was not a significant predictor of variance in the belief that

automation influenced choice of study.

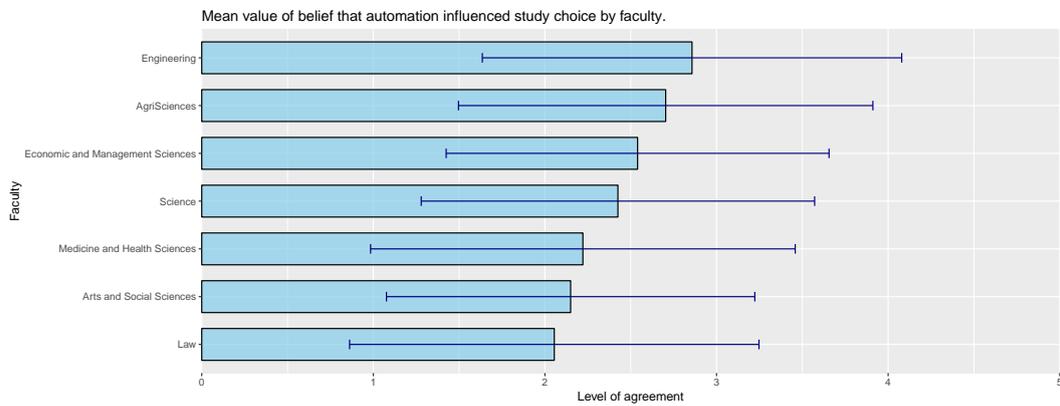


Figure 4.6: The mean level of agreement for the belief that automation influenced the respondents' choice of study by faculty. The faculties presented are ordered by mean value in descending order and the errors bars illustrate the standard deviation.

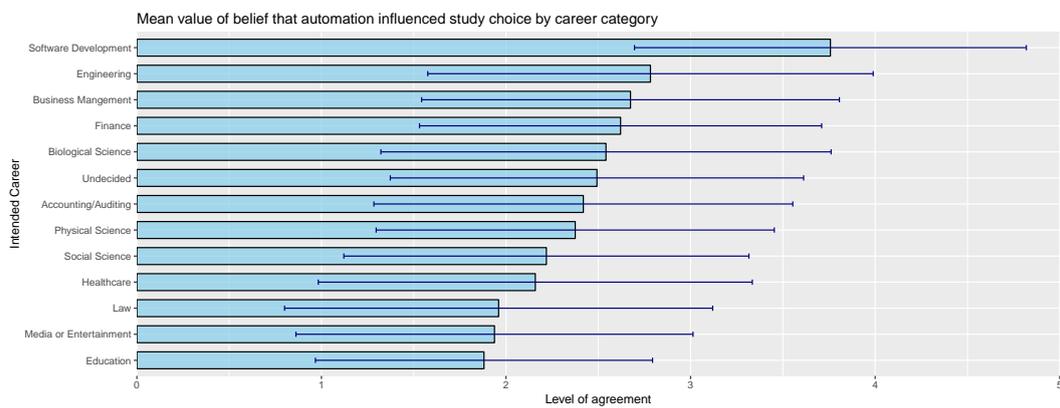


Figure 4.7: The mean level of agreement for the belief that automation influenced the respondents' choice of study by intended career. The career groups presented are ordered by mean value in descending order and the errors bars illustrate the standard deviation.

Chapter 5

Discussion And Conclusions

In this chapter the findings of the reported study are discussed, thereafter conclusions are drawn and presented. The chapter contains two sections. The first section addresses the research questions posed in Section 3.1. The second section presents the implications of the thesis and outlines a number of limitations present in the current study. Finally, extending from the findings presented and the limitations discussed, a number of recommendations for future research are provided.

The objective of this research study was to understand the awareness of automation amongst undergraduate university students in South Africa, and to determine whether perceptions of labour automation had an impact on their career decisions. Based on the findings of the literature reviewed it was determined that current and future workers will need to acquire skills that enable them to complement automation technologies in the workplace. University students, who will, in the future, become a key component of the labour force, were the target population considered in this study. At the time of this investigation automation has not been considered as a factor that impacts students' career decisions. Rather, previous investigations have considered perceptions about labour automation among individuals already in the workforce (Brougham and Haar, 2017) or, for career decisions, focused on other personal and environmental factors (e.g. career interest, gender, and family members). To address the objective of the thesis the following three research questions were posed:

- RQ1: *What is the level of awareness of automation amongst university students?*
- RQ2: *What are students' beliefs about the impact of automation on labour demand?*
- RQ3: *Do awareness of and beliefs about automation influence career decisions?*

The thesis was exploratory-descriptive in nature and a quantitative, survey-based research approach was adopted. A self-administered questionnaire was utilised as this was reasoned to be the most effective method to reach a large number of university students. Additionally, the questionnaire primarily utilised a closed-choice question format which provides the advantages of standardisation and the comparison of responses as opposed to the open-choice format. The questionnaire was distributed to the entire undergraduate student population of a large, residential research university in South Africa via email.

5.1 Research Questions Addressed

In the following section, three sub-sections are presented in which the findings are discussed in relation to each of the three research questions posed in this research study.

5.1.1 What Is The Level Of Awareness Of Automation Amongst University Students?

The first research question in the thesis was aimed at identifying the level of awareness of labour automation amongst the current cohort of university students in South Africa. An automation awareness survey instrument was developed to address this aim. The findings for this scale indicated that a majority of students perceived themselves to be well informed about automation. Although the scale does not provide substantial insight into the accuracy level or quality of the respondents' awareness of automation, it provides an indication of their subjective estimation of their degree of awareness. Further research into assessing the construct validity of the scale is required to determine the extent to which the questions posed accurately represent levels of automation awareness. It is argued, however, that, in its present form, the scale presents a useful and internally consistent method to assess perceptions of automation awareness for a large sample of university students and, given the complex nature of labour automation and awareness thereof, presents a suitable reflection of automation awareness for the purposes of this investigation.

The findings indicate that, on average, male students had higher levels of automation awareness than their female counterparts, with the former averaging 15.53 on the scale and the latter averaging 14.30 on the scale. This could be due to differences in the subject choices in prior years of learning among male and female students. This could be due to differences in the subject choices in prior years of learning among male and female students. Buser *et al.* (2014) identified that, in secondary school, males are more likely than females to select more math and science intensive academic careers than their female counterparts. It is possible that male students gain a degree of awareness of automation while completing these subjects. This may also account

for the finding that that students who are most aware of automation tend to select the math, science, and commerce-related choices of study fields and subsequent careers. The three faculties with the highest scores on the automation awareness scale were Engineering, Economic and Management Sciences, and Sciences. These faculties are generally concerned, to a greater or lesser degree, with managing, building, or implementing automation or aspects thereof. The faculties whose respondents had the lowest scores on average —were from the Arts and Social Sciences, Law, and Medicine and Health Sciences— faculties. The outcomes for the participants' intended careers seem to corroborate those of the faculty analysis. The findings indicate that, on average, the students who perceive themselves to be most aware of automation are those who intend to work in the Software Development, Engineering, and Business Management career categories. The students who perceive themselves to be least aware of automation are those who intend to work in Education, Social Science, and the Healthcare career categories. This is possibly explained by the content covered when studying for these careers. Students who intend to work in Software Development and Engineering are more likely to be exposed to automation technologies and their capabilities than students intending to work in other career categories. For Business Management students, their awareness is likely due to their exposure to concepts that examine the labour market from courses they have taken at school or university. These students are more likely than other students to be aware of the effects machines have on the labour market and the economy.

The awareness of students was found not to be influenced by the area in which they grew up nor the level of education their parents held. These findings, together with the findings from the sources of influence, suggest that the external environment where one grew up is not a significant predictor on their awareness of automation. In contrast, South African students experience a high degree of freedom from external factors (e.g., government, parents, schools etc.) in terms of their career decisions (Shumba and Naong, 2012; Dodge and Welderufael, 2014). As seen with the sources of influence, the majority of the students are not influenced by other people, their awareness is more influenced by internal interests and the education they receive. With this lack of influence from external sources, the area the students grow up in, the level of knowledge their parents have, and their socioeconomic background are less likely to have an influence on their awareness of automation. Another explanation for the lack of influence by the external environment to students' awareness could be due to the changing labour market and the advances in automation. The people who influenced the students' career decisions may have not needed to consider automation when making career decisions in the past, and therefore did not consider it when influencing the students.

5.1.2 What Are Students' Beliefs About The Impact Of Automation On Labour Demand?

The second research question was presented to determine the beliefs that university students hold in relation to the impact of automation on labour demand. To address this question responses were elicited for five key belief statements. At a high-level, these beliefs related to the role of humans in the labour force, the intelligence and capabilities of machines, the replacement of labour by machines and, importantly, the automation of a respondents' intended job. Rifkin (1995), Brynjolfsson and McAfee (2012), and Acemoglu and Restrepo (2018) have indicated that human labour will need to 'run' with automation, this means that labour will need to acquire skills that will complement automation as machine capabilities continuously expand. These questions, therefore, intend to understand whether students' beliefs about automation are in line with the predictions of the labour market by scholarly experts. The responses received indicate that, on average, university students are optimistic about the role humans will play in the future labour force, with over 80% believing that there will always be work for humans to do and less than 5% disagreeing. This also occurred with the previous industrial revolutions whereby some human jobs were replaced with machines and other jobs were created for human labour. For instance when people moved from horses and carriages and onto motorised cars, the labour employed for servicing carriages and horse grooming lost their jobs. This shift, however, resulted in the emergence of car mechanics and other jobs in the automobile industry (Bedi, 2018). Rifkin (1995) identified that throughout all the industrial revolutions job elimination and job creation was a common trend.

The beliefs of the students can indicate that they believe that new jobs will be created as existing jobs are automated. Students believe that new jobs will be created as existing jobs are automated, implying optimism from the students with the belief that there will still be jobs for humans in the future. Further supporting this optimistic perspective, 74% of respondents indicated that they believe that there are many jobs that machines cannot do. This is inline with previous predictions of the proportion of automatable jobs in South Africa. For instance, Phillips *et al.* (2018) and le Roux (2018), on the basis of investigating the portion of jobs that are highly automatable in the country, predicted that only 35% of jobs in South Africa are potentially automatable in the near future. The reason for this percentage of automatable jobs is due to the present capabilities of automation. Brynjolfsson and McAfee (2012), Autor *et al.* (2003), and Autor (2015) identify that automation technologies can currently complete manual-routine tasks, thereby unable to complete cognitive and non-routine tasks. Due to the nature of the instrumentation employed, the thesis was unable to question the students about the specific jobs that machines cannot do. Future research should investigate this aspect further.

In contrast to this optimistic perspective for the future role of human

labour, when asked if machines will replace labour, a majority of respondents agreed, with only a small minority disagreeing. In considering this finding, it is important to consider the phrasing of the item presented. The item read: “machines will replace labour”. It did not state “all labour” or “most labour”. Consequently, while students may have agreed with the indication that *some* labour will be replaced, they may still have been generally optimistic about the future role of humans in the labour force relative to machines. When asked about machine intelligence relative to human intelligence no clear majority emerged, with only slightly more respondents agreeing than disagreeing. This indicates that students are divided on this belief, there could be differentiating factors which may have contributed to those that agreed with this belief statement, therefore, further exploration is required to identify the differentiating factors.

While the findings for these four beliefs seem to indicate that, in general, students are optimistic about the future role of humans in the labour market, demographic differences were found for these beliefs. For instance, the belief that there are many jobs that machines cannot do and the belief that there will always be work for humans to do, were ascribed to more by males than by females. This indicates that males, who have higher levels of automation awareness, are less optimistic about the capabilities of machines. This could be driven by the awareness of the current limitations of automation technologies such as not being able to complete cognitive and non-repetitive tasks. While students’ beliefs about automation did not differ based on whether a respondent grew up in a rural, peri-urban or urban area, faculty was found to be a significant predictor of the belief that machines will soon be as intelligent as humans and that machines will replace labour. This was a similar result for the awareness of the students, with the area they grew up found to be a significant predictor. This indicates that whether a student grew up in a city or a rural area, seemingly, their automation awareness is the same and their beliefs are generally the same as well. This means that the area where one grew up is not a differentiating factor to their awareness and beliefs of automation.

For the belief that machines will soon be as intelligent as humans, students enrolled in programmes in the Arts and Social Sciences faculty had the highest level of agreement, while those from the Medicine and Health Sciences faculty had the lowest. This outcome may be indicative of the knowledge one acquires from his/her study field. With Arts and Social Sciences students more involved with social behaviour they are likely to perceive human intelligence than students in other faculties. The belief of Medicine and Health Sciences students is likely affected by their low awareness of automation. This may be attributed to the content they cover in their studies. As medical and health-related studies focus on maintaining health, they are less likely, than students in other studies, to be aware of automation and its capabilities.

For the belief that machines will replace labour, again, students from the Medicine and Health Sciences faculty had the lowest level of agreement while

those from the Engineering faculty reported the most support for this belief. The outcome for those studying medical and health-related degrees supports the earlier interpretation that due to the content of their studies, the students in these degrees are less likely to be aware of automation. Engineering students, in contrast, are more likely to study about automation technologies than students from other studies. The finding that engineering students, on average, believe that machines will replace labour may be interpreted as an indication that due to their awareness and exposure to such technologies, they believe that the capabilities of machines will rival and surpass the capabilities of humans.

Supporting these findings, the analysis considering the respondents' intended careers further indicated stark differences between students intending to work in engineering jobs, students intending to work in health-related jobs, and those from the remaining career categories. Specifically, those who intended on working in engineering-related careers, on average, were in agreement that there will always be work for labour to do, more so than any other intended career category. On the other end of the spectrum, those intended on working in healthcare had the lowest level of agreement with this statement. This finding seems to contradict the earlier indication that those in the engineering faculty believed that machines will replace labour. This contradiction indicates that although engineering students believe that machines will replace labour, they likely believe that more jobs will be created for humans. This belief is supported by Brynjolfsson and McAfee (2012) and Acemoglu and Restrepo (2018), who suggest that embracing technology will create more jobs for humans. The relatively low agreement levels by the students intending to work in health-related jobs for the beliefs that machines will replace labour and that there will always be jobs for humans to do may imply that these students are unclear about the possible effects automation may have on the labour market. The lack of clarity is likely driven by their low level of awareness of automation.

The fifth belief statement related directly to the students' own intended career. Only 13% of respondents believed that the work they plan to do will be automated. In contrast, 64% of respondents indicated that they disagreed with this statement, presumably, considering their intended career to be safe from automation. This sentiment does, to some extent, correspond to the overwhelming majority who indicated that they believe that there will always be work for humans to do and, as a consequence, support the generally optimistic perspective that students seem to have adopted about labour automation in the future. While this belief did differ, on the whole, based on faculty, specifically, those in the Economic and Management Sciences and Law faculties differed markedly from the rest. Students in programmes in the Economic and Management Sciences faculty, on average, agreed more than others that their intended careers will be automated. This could be due to the careers associated with this faculty (e.g. Accountancy and Business Managers)

having a relatively high probability of being automated (Frey and Osborne, 2013). The students in this faculty are thereby likely to have an idea of the automatability of their intended careers, and their awareness of the possible automation of their intended careers is likely superseded by other factors such as remuneration or career prestige. Seymour and Serumola (2016), Abrahams et al. (2015), and Mashige and Oduntan (2011) indicated that poverty and inequality contribute largely to the reasons as to why students choose careers with high remuneration and career prestige. The students in this faculty likely considered these factors more than automation when making their choices. This finding supports the lack of consideration for automation by students, with students considering other factors more when making career decisions. In contrast, those registered for programmes in the law faculty were least likely to support the suggestion that their intended jobs would be automated. This is likely due to the nature of the associated careers, as indicated in Frey and Osborne (2013) careers such as Lawyer, Attorney, and Judge have relatively low probabilities of being automated. These low probabilities are due to the social, cognitive, and non-repetitive attributes of law-related careers. As indicated in Deming (2017), Autor *et al.* (2003), and Frey and Osborne (2015) careers with such attributes are the most difficult to automate, implying that the students in this faculty likely believe that automation technologies will not gain the capabilities to automate law-related tasks.

A students' awareness of automation was found to have an effect on their beliefs that machines will replace labour, machines will soon become intelligent as humans, and that there will always be work for humans to do. Similarly, to the students' consideration of automation on their study choices, their awareness of automation has an impact on their beliefs about automation. The analysis indicated that the more they were to believe that machines will replace labour, that machines will soon become as intelligent as humans, and that there will always be work for humans to do. This implies that the more aware students are of automation the more they are optimistic that its capabilities will expand and replace human labour. The optimism also extends to human labour with the belief that there will be other jobs created for humans to do. This implies that students believe that the automation of the fourth industrial revolution will have similar effects to previous industrial revolutions where machines replaced some jobs, while creating other, new occupation categories (Rifkin, 1995; Brynjolfsson and McAfee, 2012).

5.1.3 Do Awareness And Beliefs About Automation Influence Career Decisions?

The third research question concerned the influence of students' awareness of and beliefs about labour automation on their career decisions. This section has thus far indicated that the students who are most aware of automation

were more likely to choose fields of study and careers in fields involving technology or business and, conversely, those students who were least aware of automation chose fields of study and careers that were more social in nature such as education, social science, or healthcare. As a first step in considering the influence of automation beliefs on career decisions the analysis considered the sources from which students received their career advice. Following this, the factors that they considered were elicited. Amongst these, specifically, automation as a factor was investigated in addition to the factors emerging from Roach and Sauermann (2010), Chuang and Dellmann-Jenkins (2010), Harnovinsah (2017), Fizer (2013), Owino and Odundo (2016), Edwards and Quinter (2011), Subait *et al.* (2017), Weiland (2010), Downey *et al.* (2011), Seymour and Serumola (2016), Mashige and Oduntan (2011), Abrahams *et al.* (2015), Shumba and Naong (2012), Cleland *et al.* (2014) and Mudhovozi and Chireshe (2012). In the following section the discussion will first concern the sources of career advice, followed by the factors considered in general and, finally, automation as a specific factor.

Across the seven sources considered (parents/guardians, other family members, career advisor/counsellor, media, teachers, university representatives, and peers), the largest portion of respondents indicated that they were influenced by their parents or guardians when making their study and career decisions. Despite being the largest source, less than a third of respondents indicated that they were influenced by their parents or guardians when choosing what to study, with a greater number indicating that this source did not influence them. This finding is similar to a study in the United Kingdom conducted by Chuang and Dellmann-Jenkins (2010) who found that parents were not a significant factor in influencing students' study choices. An explanation for this finding may relate to the socio-economic background of the student as studies conducted by Ooro (2017), Harnovinsah (2017) and Njeri (2013) in other developing regions indicated that parents played a significant role in career choices. A majority of the students in this study had parents who had a postsecondary education. Assuming that higher level of education indicates a higher socio-economic status (Houthakker, 1959), the findings indicate that socio-economic background has an impact on a parents influence on a students career choice. Of the seven sources assessed, none were identified to influence the majority of students' career choices. This is likely due to students considering having a high degree of freedom from external factors when making career decisions (Chuang and Dellmann-Jenkins, 2010; Theresa, 2015; Shumba and Naong, 2012; Dodge and Welderufael, 2014). The students were likely influenced more by their internal factors as opposed to the influences of other people. Although most of the respondents were not influenced by the sources of influence when making career decisions, they were aware of automation. This implies that sources of influence considered here are less likely to have an influence on students' awareness of automation. Any awareness gained, therefore, comes from other factors in a students' life.

Of the general factors analysed, a majority of respondents indicated that passion/interest was a factor that they considered when making their career decisions. Only 5%, the smallest proportion, indicated that they did not consider passion or interest. This was followed by personal growth and career aptitude with both factors influencing more than 60% of the students sampled. This supports the previous interpretation that internal, personal factors play a greater role in career and study decisions than factors emanating from various external sources of influence (e.g. parents or teachers). Amongst the internal factors it was found that a greater number of respondents' reported passion or interest as an important factor when making career decisions than the benefits associated with a given career path. This finding is consistent with a number of previous studies in this regard (e.g., Roach and Sauermann, 2010; Chuang and Dellmann-Jenkins, 2010; Harnovinsah, 2017; Fizer, 2013; Owino and Odundo, 2016; Edwards and Quinter, 2011; Subait *et al.*, 2017; Weiland, 2010; Downey *et al.*, 2011). In addition to passion/interest, a majority of the students indicated that they were influenced by the following internal factors personal growth, career aptitude, quality of life, and potential income when making their career decisions. The influence of these internal factors is also consistent with the current body of knowledge on career-selection (e.g., Roach and Sauermann, 2010; Chuang and Dellmann-Jenkins, 2010; Harnovinsah, 2017; Fizer, 2013; Owino and Odundo, 2016; Edwards and Quinter, 2011; Subait *et al.*, 2017; Weiland, 2010; Downey *et al.*, 2011; Seymour and Serumola, 2016; Mashige and Oduntan, 2011; Abrahams *et al.*, 2015; Shumba and Naong, 2012; Cleland *et al.*, 2014).

Finally, in addition to internal and external factors, the survey asked respondents whether automation of labour was a factor that influenced their career decisions. Although a majority of the students perceive themselves to be aware of automation, a similar majority indicated that they did not consider automation when making career or study decisions. Less than a quarter of respondents indicated that, when considering their future careers and, consequently what to study programmes to register for, they considered the automation of labour as a factor. In contrast, close to 60% of respondents indicated that they did not consider labour automation when making these decisions. This can be attributed to the students' beliefs about automation. As discussed previously and as shown in the analysis of beliefs about automation, students likely believe that the skills they will acquire in university will not be automated. This interpretation is supported by Valletta (2015), Brynjolfsson and McAfee (2012), Pompa (2015) and Schwab and Samans (2016) who suggest that machines cannot yet replicate social and specialised skills which are primarily taught in tertiary institutions. With this belief students will likely not be concerned about their intended careers becoming automated. Instead this could make them believe that tertiary skills are less susceptible to automation.

The students who perceived themselves to be most aware of automation

were the ones who were most likely to consider automation when making career decisions. This lack of consideration from other students likely arises from the external environment only influencing the career decisions of a small portion of the students. Additionally, a parent's level of education did not explain differences in automation as a factor, implying that the socio-economic background of a student was not a differentiating factor in the awareness of students. With internal factors related to career having the most impact on the career decisions, it is likely that the students are unaware that they need to consider automation when making career decisions. Another factor indicated in the findings was faculty. Students who were studying engineering were the most aware of automation as opposed to law students who were found to be the least aware of automation. It is unknown whether the contents of these degree programs or other external factors contributed to this result. It is, however, striking that such differences exist along faculty lines. Moreover, the students' intended careers affected whether they considered automation or not. Students who intended to become software developers considered automation as a factor far more than students who intended to work in other careers. As software development is closely related to the intelligence of machinery, it is likely that this consideration is driven by their awareness of automation. This awareness could be driven by interest in the career field and the studies the students are involved in. It may however, also reflect retrospective justification with students in engineering or related degrees who intend on working in software development justifying the previous choices on the basis of their current knowledge. To determine whether this the case future investigations should seek to understand students' awareness of automation and the effects this has on their study and career choices, prior to their registration at a higher education institution. In this way, such beliefs can be isolated from any content taught at university level.

5.2 Conclusions

To understand the awareness of automation amongst undergraduate university students in South Africa, and to determine whether perceptions of labour automation had an impact on their career decisions a survey-based study was executed. Addressing three specific research questions, the findings from this study indicate that students do not consider labour automation when making career decisions. Students do perceive themselves to be aware of automation, however, they do not consider it to be a factor that could possibly replace their intended careers in the future or a major consideration when deciding what to study. There is, however, some nuance to this finding. While differences were small, it was also evident that students primarily studying Engineering considered automation as a factor to a greater extent than students in other fields. This may be due to the content in their studies as they are the students

most likely to learn about it extensively. The awareness of automation amongst all the students indicates optimism amongst the students, however, it also indicates naivety amongst the students. As students are more inclined to believe that machines will not become as intelligent humans, it can indicate that they believe that machines will not be able to replicate high-level or cognitive skills which are primarily obtained in tertiary institutions. This likely reassures students that their intended careers will not be automated. Studies mentioned in Section 2.2.1 support this by indicating that automation is less likely to replace those with cognitive skills than is the case for those without tertiary education. In the literature, it is identified that cognitive skills present more of a challenge to automate in comparison to manual skills. This, however, could hold true in the short term as other studies, mentioned in Section 2, have predicted that many jobs that currently exist will no longer exist in the coming decades.

Although it appears that students do not consider automation when making career decisions, they do believe that automation will replace labour. Students do believe that machines will replace labour, they do also believe that there are many jobs that machines cannot do and that there will always be work for humans to do. This indicates that students are optimistic that humans can run with automation and not oppose it or be left behind by it. This may also be attributed to the students' not believing that machines will soon become as intelligent as humans. The awareness of automation was found to have an influence on the career choices of a student, but the beliefs the student has about automation is less likely to have an influence on their careers choices. The students who are most aware of automation are likely to be intending to work in the Science, Commerce, and Engineering careers, whilst those who are less aware of automation are likely to study for more social careers such as Social Sciences, Healthcare, and Education. This means that those who know more about automation are more likely to work in fields related to it, and those who are less aware of it are less likely to work in field related to it. The beliefs about automation not having an impact on their choices of study is likely due to the current low probability of automation replacing labour with tertiary skills. With this factor, students are less likely to be concerned that automation will at some time replace them in their careers.

Notwithstanding the value of the present findings and interpretations for research and practice, a number of limitations present in the current study merit consideration. To follow, such limitations are briefly considered before recommendations for future research are provided.

5.2.1 Limitations Of The Thesis

As with all research endeavours, there are several limitations that exist in the present thesis. These limitations primarily relate to the research design adopted and the extent to which findings can be generalised to other popu-

lations. As this thesis was exploratory in nature the scope of the thesis was limited. Additionally to the scope of the thesis, limitations of the chosen research approach as acknowledged in Section 3.2 do exist. A brief discussion of limitations existing within this thesis is provided.

1. The survey used to acquire the data was of a quantitative approach. With this approach, the respondent can only respond to the answers using the options that have been given to them. The respondent cannot give an explanation or describe the answer they have given, the answer from this approach thereby assume that the respondents are identical in their background and thinking.
2. The survey was only completed by students from a research-intensive university. This could thereby influence their awareness and beliefs of automation as research-intensive universities provide more cognitive skills than the other types of universities.
3. This thesis focused only on university students whose skills are the least likely to be automated in the near future. As literature has indicated that manual jobs are more likely to be automated in the near future. The research was thereby limited by the type of respondents involved in the thesis.

5.2.2 Recommendations

From the findings produced in this thesis several recommendations for future research and practice are proposed. In this subsection, these recommendations are briefly presented. The findings in the thesis have indicated that a majority of students do not consider automation when making career decisions. Although at present automation does not replace cognitive skills, Rifkin (1995) and Brynjolfsson and McAfee (2012) past studies have indicated that the capabilities of automation are increasing exponentially. Additionally, Schwartz *et al.* (2017), Maurer and Weiss (2010) and Caroselli (1994) have also indicated that humans in the future will need to constantly re-skill themselves when automation acquires the capabilities to complete more skills. The offerings of universities will, therefore, have to be constantly updated to provide skills that complement automation as opposed to competing with it. Additionally, with the large proportion of the South African labour force having low to medium skills the public and private sectors will need to work together in order provide more avenues for the labour force to re-skill itself and for job creation that will complement automation and the skills of the labour market. Before making career decisions, students should be made aware and exposed to automation and other factors which may affect their careers. As sources of influence were found not to have a great impact on students' career decisions, students can be exposed through course content in secondary school.

In addition to these recommendations for educational practice, extending from the findings presented in this study, a number of suggestions for future research are proposed.

1. In this study, both the automation awareness scale and the specific automation belief items were newly constructed. While the internal consistency of the automation awareness scale was demonstrated, the construct validity of the scale and the individual items remains a concern. On this basis, it is proposed that future investigations, firstly, explicitly consider the validity of instruments designed to elicit students' awareness and beliefs in relation to labour automation and, secondly, seek to determine if such instruments hold value with other populations (e.g., those in the working world). Additionally, as the automation awareness scale was based on subjective perceptions of awareness, the relative awareness of individual participants was difficult to elicit. In future research investigators should seek to experimentally account for differences in subjective perceptions by, for example, providing participants with example cases or scenarios to rate or judge.
2. Conduct the thesis before the students begin university courses. When the study is conducted before the students begin university courses, the responses they provide are less likely to be influenced by what they learned in their fields of study.
3. Conduct the study on more spheres of the labour force, not just university students. University students are part of the future of the labour market, but they are a small component as compared to their less educated counterparts. A study analysing both educated and uneducated people would prove to be more beneficial to compare differences in awareness and beliefs between these types of labourers.
4. Identify what factors and sources contribute to the awareness of automation. Students perceive themselves to be aware of automation, however, there is currently no explanation as to how they acquire their awareness of automation. A study exploring the source of their awareness could be beneficial to them considering it when making career choices.
5. Investigate students' awareness and beliefs about automation through qualitative techniques. This is due to the limitations of the quantitative techniques employed in the present investigation. One limitation of a quantitative study is that it does not seek to understand the background or motivations that lead to students' awareness and beliefs. A qualitative study can, therefore, be used to add more nuance and texture to the findings of this study. In particular qualitative techniques such as interviews and focus groups can be used to understand students' beliefs

in more detail and understand what skills they think will be in demand as a result of the effects of automation.

Appendices

Appendix A

Survey Instrument

The following Appendix presents the survey instrument discussed in Section 3.2.3 of the research design chapter. Section A.1 presents the questions in relation to the awareness of automation technologies. Thereafter, Section A.2 presents the questions in relation to the beliefs about automation technology and technology demand. In the survey sent out to the students the questions were presented in a five-point Likert scale. The responses for the Likert scale were: Strongly Disagree, Disagree, Neutral, Agree, Strongly Agree. The sections which follows, Section A.3, presents the questions in relation to the sources and factors. Question 1 and 2 in this section were present in five-point Likert scales, the options for these scales were: Not at all, Very little, Somewhat, A lot, To a great extent. The remaining questions did not use Likert scales and the possible responses for each question is listed below the question.

A.1 Awareness Questions

1. I am well informed of:
 - the tasks that machines can perform.
 - types of jobs that can be automated.
 - the capabilities of artificial intelligence.
 - how technology affects employment.
2. Growing up I spent a lot of time on the computer playing games, exploring how it works, using advanced features, or coding algorithms/programs.

A.2 Beliefs Questions

1. I believe that:
 - machines will replace human labour.

- there are many types of jobs machines cannot do.
- machines will soon be as intelligent as human beings.
- there will always be work for humans to do.
- the work I plan to do will be automated.
- the automation of work influenced what I chose to study.

A.3 Sources And Factors Questions

1. When choosing what I chose to study, I was influenced by the following factor:
 - parents/guardians.
 - other family members.
 - career advisor/counsellor.
 - peers.
 - teachers.
 - the media.
 - university representatives.
2. When choosing what I chose to study, I was influenced by the following factor associated with the career:
 - quality of life.
 - personal growth.
 - career aptitude.
 - potential income.
 - gender.
 - passion/interest.
3. Have you had any form of work experience (e.g. Internship, Job Shadowing, Vacation Work, etc.) in relation to your career?
 - Yes
 - No

A.4 Demographic Questions

1. Year Of Birth:

- Before 1980, 1980, 1981, 1982, 1983, 1984, 1985, 1986, 1987, 1988, 1989, 1990, 1991, 1992, 1993, 1994, 1995, 1996, 1997, 1998, 1999, 2000, 2001, 2002, 2003, After 2003

2. Gender:

- Male
- Female
- Other

3. Population Group:

- Black/African
- White
- Coloured
- Indian/Asian

4. Parents'/Guardian's highest level of education:

- Doctorate/PhD, Masters, Honours/4-year degree, 3-year degree or equivalent, Diploma, Higher certificate, Secondary completed, Secondary not completed, Primary completed, Less than primary completed, No schooling, Other

5. In which type of area did you grow up in:

- Rural
- Small Town
- City
- Other

6. How many years have you been a university student:

- 1, 2, 3, 4, 5, 6 or more

7. Are you receiving any form of financial aid (e.g. bursary, loan, etc.):

- Yes
- No

8. If you are receiving financial aid, did it restrict the career choices you had:

- Yes
- No

9. In which faculty is your programme under:

- AgriSciences, Arts and Social Sciences, Economic and Management Sciences, Education, Engineering, Law, Medicine and Health Sciences, Military Sciences, Sciences, Theology

10. In which career do you foresee yourself working?

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