Does automation influence career decisions among South African students?

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ABSTRACT

The potential impact of rapidly advancing automation technologies on the demand for human labour has emerged as a prominent discourse in mainstream and academic media. In this study we advance this line of inquiry by determining the extent to which automation influences the career decisions of university students. 935 undergraduate students at a large, research-oriented university completed a survey which addresses level of awareness of automation, beliefs about automation, as well as the factors and sources of influence which impact career decisions. Our findings suggest that, while most students perceive themselves to be well informed about automation, and generally believe that machines will displace human labour, they do not consider their own future occupations to be susceptible to automation. Accordingly, few students consider automation as a factor when making career decisions.

CCS CONCEPTS

• **Social and professional topics** → *Economic impact*.

KEYWORDS

automation, labour, career, work, study

ACM Reference Format:
Sakhumzi N. Mbilini, Daniel B. le Roux, and Douglas A. Parry. 2019. Does automation influence career decisions among South African students?. In *Conference of the South African Institute of Computer Scientists and Information Technologists 2019 (SAICSIT '19), September 17–18, 2019, Skukuza, South Africa.* ACM, New York, NY, USA, 10 pages. https://doi.org/10.1145/3351108.3351137

1 INTRODUCTION

The world is currently entering an industrial revolution characterised by the integration of physical, digital, and biological technologies [6]. This phase of industrial advancement, broadly termed the *Fourth Industrial Revolution* or *4IR*, has already started to impact the manner in which work is performed across industries and sectors by making it possible to automate an increasingly wide range of tasks traditionally performed by humans [16]. These developments have stirred extensive discourse in both academic and mainstream media about the potential impacts of 4IR on labour demand, raising fears of job-losses and rising inequality [8, 16, 28].

The study of automation technologies attracts interest from a wide range of disciplines. While the design and development of the relevant technological artefacts generally falls within the domain of computer science and/or engineering, the study of its effects on organisations and economies calls for interdisciplinary research approaches. It is our view that the field of Information Systems, with its tradition of interdisciplinary scholarship and close ties with reference disciplines from the economic and management sciences, is particularly well-suited to the study of automation.

While South Africa may not be at the forefront of the development and adoption of automation technologies, the country's asymmetric income distribution and high unemployment rate make it particularly vulnerable to changes in labour demand. Over the past 10 years unemployment has risen steadily, reaching 26.7% at the end of 2017 [36]. The country also experienced weak economic growth during this period with *gross domestic product* (GDP) rising by only 1.5% between 2013 and 2017, substantially lower than the average among emerging economies (4.6%) for the period.

It is against this backdrop that the small proportion of South African youth that have access to higher education make decisions about their fields of study and careers. Not surprisingly previous studies have confirmed that South African students consider potential employment opportunities as a key factor when making these decisions [2, 23, 31]. If, as has been suggested [21], the automation of work will impact the future of labour demand in South Africa, it may be argued that the degree too which an occupation is automatable would influence its attractiveness among the current cohort of university students.

The present study set out to investigate this proposition by addressing three primary research questions:

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

To address these questions a survey was conducted at a large, research-oriented university in South Africa. The survey was completed by 935 respondents and the resulting quantitative and qualitative data were analysed to address the questions posed.

The paper commences with a literature review outlining the relationships between automation and labour demand, the South African higher education landscape, and the factors that impact

SAICSIT '19, September 17–18, 2019, Skukuza, South Africa

career decisions among South African students. Thereafter we describe our method and instruments, followed by the analyses conducted and findings made. In the final section we discuss our findings, outline the study's limitations and suggest how future research can extend it.

2 LITERATURE REVIEW

In the sections which follow we provide succinct overviews of relevant literature from three knowledge domains. We consider, firstly, the relationship between automation and labour demand. Thereafter we provide an outline of the South African higher education landscape. Finally, we briefly review past studies on the factors that impact career decisions among South African students.

2.1 Automation and labour demand

As the range of technologies that enable the automation of labour expands and advances, so does the spectrum of tasks they are capable of performing. This process, often referred to as the "creative destruction" of labour [29], is a defining characteristic of industrial revolutions. Importantly, however, the automation of work also increases the demand for new types of knowledge and skills in the labour market.

Groover [18, p. 85] defines automation as "the technology by which a process or procedure is accomplished without human assistance" and it is "implemented using a program of instructions combined with a control system that executes instructions". He further argues 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" [18, p. 87]. The automation technologies that are likely to have the most substantial impact on labour demand include smart technology, artificial intelligence, automation, robotics, and algorithms —collectively termed STAARA [7, p. 213].

From a business perspective the adoption of automation technologies holds numerous benefits, most notably the potential to reduce costs and free up labour which, in turn, "allows further economic growth and new jobs in areas of demand that were unexpected" [19, p. 87]. It also offers business and capital owners a degree of freedom from the wide range of challenges associated with the appointment and management of a human workforce — an important factor in economies characterised by extensive labour legislation and a culture of unionisation. While automation may require substantial initial investment, it offers, in certain tasks, productivity benefits over human workers who are unable to match the speed, accuracy, consistency and working hours of machines. Additionally, rising wages imply that automation would become more affordable relative to human labour [28]. Moreover, recent trends indicate that the cost of automating is falling due to technological advancements that enable cheaper production of the required artefacts [17].

Despite their rapid advancement over the past decade, the current generation of commercial automation technologies remain limited in the types of tasks they are capable of performing. These tasks typically "involve physical activities in highly structured and predictable environments, as well as the collection and processing of data" Bughin et al. [9, p. 4]. Conversely, tasks which require "knowledge of human heuristics, and specialist occupations involving the development of novel ideas and artefacts, are the least susceptible to computerisation" Frey and Osborne [17, p. 266]. Analyses of the automatability of particular occupations have generally adopted this task-based perspective. Bughin et al. [9, p. 4], for example, found that in the US "less than five 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".

Importantly, occupations that require low-skilled human labour are not, as a matter principle, easier to automate. Rather, the nature of the particular skills should be considered based on the computational resources required to automate them. Moravec's paradox suggests that semi-skilled workers are more likely to be displaced by automation technologies than high-skilled and low-skilled workers [8]. The paradox is based on the principle that the automation of reasoning requires less computational resources than the automation of low-level sensorimotor skills [8]. Accordingly, to remain relevant in the labour market, semi-skilled workers need to obtain more advanced skills or perform low-skilled work that requires dexterity. This line of reasoning is supported by the finding that a rising proportion of tertiary graduates in the US are occupied in low-skilled positions [1].

While demand for specific skills may decline due to automation, the adoption of the STAARA technologies in industry creates new business opportunities and, as a result, demand for labour with the appropriate skill set. This is generally referred to as the *capitalisation effect* of automation [17] and it is estimated that, as a result, 65% of children entering primary school today will ultimately work in completely new job types [37]. Importantly, however, the newly created occupations are likely to require high-level skills, favouring individuals that have access to tertiary education [21, 28]. This *skills-bias* which is inherent to technological advancement is broadly recognised as a driver of economic inequality [27].

An important question following from this, is which jobs would be more or less in demand in future. The World Economic Forum's most recent *Future of Jobs* report [22] argues that occupations likely to experience an increase in demand are those which are "significantly based on and enhanced by the use of technology" [22, p. 20]. This includes established roles like "Data Analysts and Scientists, Software and Applications Developers, and E-commerce and Social Media Specialists", but also emerging roles like "AI and Machine Learning Specialists, Big Data Specialists, Process Automation Experts, Information Security Analysts, User Experience and Human-Machine Interaction Designers, Robotics Engineers and Blockchain Specialists" [22, p. 20]. Importantly, however, it is not only tech-oriented occupations that expected to experience higher demand. Occupations that require social skills such as "Customer Service Workers, Sales and Marketing Professionals, Training and Development, People and Culture, Organisational Development Specialists and Innovation Managers" are also expected to grow. Occupation expected to become "increasingly redundant over the 2018âĂŞ2022 period" typically involve routine-based tasks executed in well-structured (often white-collar) work environments. These include, for example, "Data Entry Clerks, Accounting and Payroll Clerks, Secretaries, Auditors, Bank Tellers and Cashiers" [22, p. 21].

South Africa, due to its already high rate of unemployment and levels of economic inequality, faces particularly complex challenges in this regard. Analyses by Phillips et al. [26] and le Roux [21] suggest that around 35% of the South African workforce currently perform occupations that will be automatable in the near future. le Roux [21]'s analysis indicated that, due to the skills-bias associated with automation, South African workers that were previously disadvantaged due to a lack of access to higher education are more at risk to be displaced than well-qualified (predominantly white) workers. This raises the possibility that automation technologies may further entrench the race-based economic inequality that characterises the country's economy. Phillips et al. [26], accordingly, argue that an intensive skills-development programme is required to produce a workforce that is able to harness automation technologies effectively and reap the benefits.

2.2 Labour supply in South Africa

Approximately 64% of South Africa's unemployed labour force are between the ages of 15 and 34 [36]. While this partly reflects the general lack of labour demand, it is also indicative of a structural mismatch between the knowledge and skills available in the market and those employers are seeking. This mismatch highlights the considerable shortcomings of the country's education system. The portion of the country's active labour force without a secondary (high school) qualification is approximately 50% [35], a slight improvement from 56% at the end of 2008 [34]. [33, p. 10], accordingly, found 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". Consequently, most South African youth are employed to perform low-skill work in elementary, sales, craft, and clerical occupations in the trade, services, and finance industries [35].

In contrast to this oversupply of low-skilled labour, South Africa is also experiencing an under-supply of high-skilled labour [5]. It is predicted that the portion of the labour force with at least a secondary qualification will rise [3] and, in real terms, the number of degree tertiary graduates have grown from 93 274 in 2009 to 149 787 in 2015. However, as a proportion of all new labour market entrants, those with tertiary qualifications remain a significant minority. In 2016, for example, fewer than 8% of employed South African workers or business owners had bachelors or higher degrees from universities [35]. As technological advancement increases demand for high-skilled workers, this small group of graduates becomes a critical economic resource.

Table 1 presents the distribution of 2015 graduates across fields of study in South Africa and other countries. Based on 2016 figures from the Department of Higher Education and Training, 54.3% of public university students were enrolled in undergraduate degree programmes while 17.5% were enrolled in postgraduate programmes [12]. Most students in private tertiary institutions were enrolled in Diploma or Degree qualifications (73.4%) [12]. A majority of students (42.5%) enrolled in public tertiary institutions between 2013 and 2016 were studying programmes in humanities, with 30.3% in STEM (Science, engineering, and technology) programmes, 27.1% in business and management programmes, and 18.1% in education programmes [12]. When considered in relation to the distributions of other countries represented in Tables 1, South Africa's proportion of humanities graduates is similar to those of the US and UK. However, South Africa, Brazil and Russia have larger proportions in Business, Administration and Law programmes. With 14% of graduates in STEM programmes, South Africa is comparable with developed countries, though substantially lower than Russia.

2.3 Factors that influence career decisions among South African students

In the section which follows we briefly consider studies that have analysed the factors that impact career decisions among South African students. In general, the findings of these studies align with those conducted in other countries.

Shumba and Naong [32] and Dodge and Welderufael [13] found that, while other sources of influence also play a role, South African students, like their peers abroad, tend to rely significantly on their personal opinions and views when making career decisions. Accordingly, the students' passions and areas of interest are key factors [23, 31], as well as their perception's of their own strengths and weaknesses. Seymour and Serumola [31, p. 34], for example, after surveying Information Systems (IS) students at the University of Cape Town, found that "they chose IS because they had a preference and interest for the major and that they felt their skills were aligned with IS".

Many studies have investigated the sources of influence that impact career decisions of South African students. Family members have been found to have varying degrees of influence. A number of studies found that parents significantly influence students' decisions [4, 11, 13, 20, 24, 32], while others found this not be the case [2, 23]. However, there seems to be agreement between studies that siblings and other relatives do not impact students' decisions [4, 20, 24]. Findings about the impact of career counsellors also vary across studies. Some have found evidence supporting the significance of their impact [13, 32], while others differ [2, 4, 20]. A similar pattern emerges when considering the impact of school teachers, with some studies finding their influence to be significant [11, 13, 24, 32], and others not [2, 4, 20]. Finally, Kweyama [20], Dodge and Welderufael [13], and Mudhovozi and Chireshe [24] found that the media was a significant source of influence impacting career choices of students, whilst Calitz et al. [11] found this not be the case.

In addition to passion, interest and personal strengths, Abrahams et al. [2] found that the desire for personal growth was a significant factor that students considered when choosing a field of study. Abrahams et al. [2] and others [23, 31] also found employment opportunities and remuneration to be key factors. Mashige and Oduntan [23], in addition, identified the prestige associated with a career as something many students consider. Because many South African students rely on financial aid programmes to fund their studies, the restrictions imposed by these programmes have been found to impact students' choices [31]. Mudhovozi and Chireshe [24] found that gender did not have a significant impact on career choices, while Abrahams et al. [2] made the same finding for race.

To the best of our knowledge no previous studies have specifically considered automation as a factor in career decisions among students.

Table 1: The number of graduates in various countries by fields of study in 2015 [25].

Country	Humanities	Business, Administration and Law	STEM	Health and Welfare	Total
United Kingdom (UK)	273 164 (37%)	162 590 (22%)	101 874 (14%)	98 189 (13%)	740 276
United States (US)	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

3 METHOD

The objective of the present study was to investigate the awareness of and beliefs about automation among the current cohort of undergraduate university students in South Africa. Additionally, we aimed to determine the extent to which these factors influenced students' career choices. To this end we developed a self-administered, web-based survey. This section outlines the design of the survey and its distribution to the sample frame.

3.1 Instrumentation

The first section of the survey consisted of four statements to which respondents indicated their level of agreement on a five-point Likert scale ranging from *Strongly Disagree* (1) to *Strongly Agree* (5). Responses to these statements were summed to produce a scale ranging from four to 20 representing a respondent's level of awareness of automation technologies. The statements 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 section considered respondents' beliefs about the automation of work. Again, respondents were asked to indicate their level of agreement with different statements through a five-point Likert scale ranging from *Strongly Disagree* (1) to *Strongly Agree* (5). The statements 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.

In the third section of the survey respondents were asked to indicate the degree of influence different people had on their career decisions. This was done through a five-point Likert scale ranging from *Not at all* (1) to *To a great extent* (5). Respondents were asked to indicate the degree of influence of parents/guardian, other family members, career advisor/counsellor, peers, teachers, the media, and university representatives.

In the fourth section respondents were asked to indicate to what extent different factors influenced their career choices. This was done through a five-point Likert scale ranging from *Not at all* (1) to *To a great extent* (5) in relation to the following seven factors: quality of life, personal growth, aptitude, potential income, gender, passion/interest, and automation.

The final section elicited the demographic profile of the respondent. This included age, gender, population group, parents'/guardian's highest level of education, faculty, intended career (open ended), the area in which they grew up (city/small town/rural), the number of years they had been a university student, whether they were receiving financial aid, and, if so, whether their financial aid source restricted their career choice.

3.2 Ethical considerations

Ethical clearance and institutional permission was obtained for the distribution of the survey from the relevant parties at the institution where the research was conducted. All respondents completed the survey voluntarily and anonymously.

3.3 Pilot study

A pilot study was conducted to eliminate any ambiguities and/or errors in the questionnaire. Additionally, it enabled testing of the data formats produced. The questionnaire was distributed to 10 postgraduate students registered at the university. The reception from the pilot study was positive from all the respondents, and all comments raised during the pilot were addressed.

3.4 Target population

The target population for our study was undergraduate students registered at research-intensive universities in South Africa in 2018. In 2016, 975 837 students were registered at South Africa's 26 public universities [12]. Of these students, 785 351 were enrolled in undergraduate programmes and 170 666 were enrolled in postgraduate programmes. Universities considered as research-intensive were the University of Cape Town, the University of Pretoria, Rhodes University, Stellenbosch University, and the University of the Witwatersrand [14]. A combined total of 101 440 undergraduate students were enrolled in these universities in 2016. An invitation to complete the survey was sent, via e-mail, to 19 812 undergraduate students at one of these universities and the survey was available for completion for two weeks thereafter. During this period the survey was initiated 1 506 times and completed 948 times, producing a response rate of 4.8% and a completion rate of 62.9%.

4 FINDINGS

In the sections which follow we outline our findings based on the analysis of data collected through the survey. We commence with a description of the sample population in terms of demographic variables, thereafter we address each of the research questions by reporting the analysis procedures followed and their results.

Table 2: 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

4.1 Sample description

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%) identified with other gender descriptors. The largest proportion of the sample were in their first (29.6%) or second (28.3%) year at university, and 91.7% of the sample had completed four years or less at the university. 455 (48.7%) of the respondents relied upon financial aid, of which 72 (15.8%) were restricted in terms of their career choices. As indicated in Table 2, 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%).

We used a bottom-up coding strategy to standardise the 638 unique responses provided to the question of what career the respondent intended to follow. In the first step each response was associated with one of the 702 occupations used in Frey and Osborne [15]. This resulted in 111 unique occupations across our sample. To enable meaningful analysis we sorted these into 14 higher level categories by grouping the occupations based on field or industry. For example, the 'Judge', 'Attorney', and 'Lawyer' categories were grouped into the Law category.

4.2 Students' level of awareness of automation

To determine respondents' awareness of automation technology, answers to the four statements concerning their familiarity with the relevant technologies were considered. Figure 1 presents a summary of these responses.

Respondents' scores for the four statements were aggregated to generate an *Automation Awareness Scale* (range 4 to 20). The scale demonstrated good internal consistency (*Cronbach's alpha* = 0.82), the distribution is presented in Figure 2. The scale's mean of 14.82 ($SD = 3.00$) suggests that students generally perceive themselves to be well-informed about automation technologies.

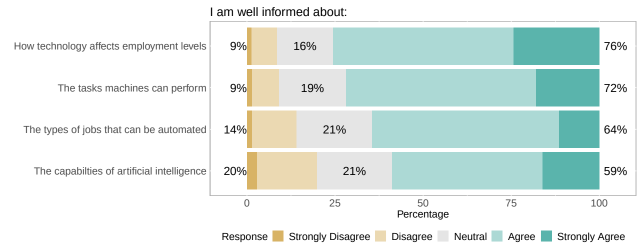

Figure 1: The distribution of the awareness statements according to the samples' responses.

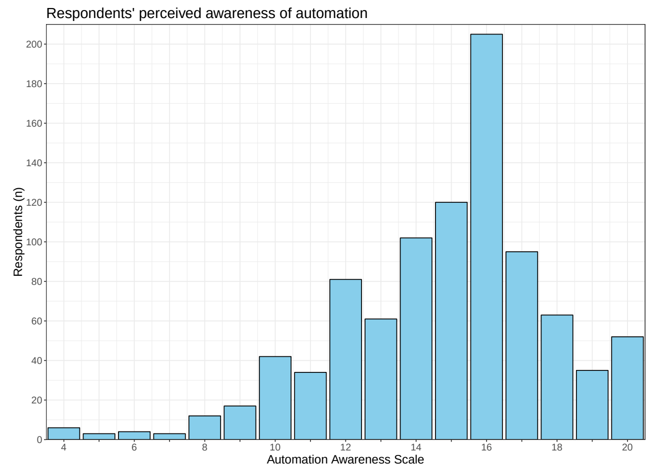

Figure 2: Automation awareness scale distribution

A multiple linear regression model was produced to test if the combined effect of demographic factors and sources of influence significantly predicted the respondents' awareness of automation. The model used the respondents' scores on the automation awareness scale as the dependent variable. Additionally, for the independent variables the model considered all the sources of influence and the following demographic factors: gender, the area the respondents grew up in, faculty, intended career group, and parents' level of education. The results of the regression indicated that the combined effect of the demographic factors and sources of influence explained 9% of the variance in the awareness of the respondents ($R^2 = 0.09, F(41, 893) = 3.35, p < 0.001$). The model indicated that the gender of a respondent significantly predicted their awareness of automation with male respondents predicted to have higher awareness of automation ($\beta = 0.85, p < 0.001$). The type of area in which a respondent grew up in was identified to be a significant predictor of their awareness with respondents from a small town predicted to have a lower level of awareness than respondents from other area types ($\beta = -0.45, p < 0.05$). The respondent's faculty was identified as a significant predictor of their awareness. Respondents in the faculty of Law are predicted to have a lower level of automation awareness than respondents from the other faculties ($\beta = -1.88, p < 0.05$). The final demographic which was found to be a predictor of the awareness of a respondent was their intended career. Respondents from Healthcare ($\beta = -1.76, p < 0.05$), Social Science ($\beta = -1.35, p < 0.05$), and the Undecided ($\beta = -1.31, p < 0.05$) career groups are predicted to have a lower level of automation awareness than respondents intending to do other careers.

4.3 Students' beliefs about automation

Figure 3 presents the distributions of the responses to the five belief statements. A majority of the respondents believe that there will always be work for humans to do, that there are many jobs machines cannot do, and that machines will replace labour. Additionally, the majority of the respondents believe that the work they plan to do will not be automated.

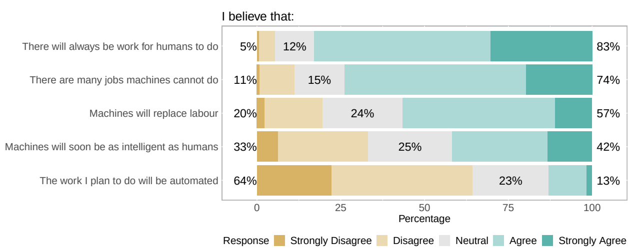

Figure 3: The distribution of the awareness statements according to the samples' responses.

The overall distribution of responses to the five belief statements suggests that students generally hold a nuanced view of automation — i.e., while the technologies are rapidly advancing, human workers will remain relevant in particular types of tasks. Perhaps most interesting is the distribution of beliefs about the realisation of machine-based general intelligence, with a majority of respondents indicating that they believe machines will soon be as intelligent as humans.

To investigate the interplay between awareness of and beliefs about automation, we divided the sample into tertiles based on their level of awareness. Those who scored between 4 and 14 on the awareness 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 3 presents the mean scores for each belief statement across the tertiles.

Based on the results of ANOVAs, level of awareness of automation was found to be a significant, but small, predictor of variance in (a) the belief that machines will replace labour ($F(2, 932) = 9.01, p < 0.001, \eta_p^2 = 0.02$); (b) the belief that machines will soon be as intelligent as humans ($F(2, 932) = 7.40, p < 0.001, \eta_p^2 = 0.02$); and (c) the belief that there will always be work for labour ($F(2, 932) = 6.83, p < 0.01, \eta_p^2 = 0.01$). When considering Table 3 it is noteworthy that respondents who claim to be most informed about automation technologies (i.e., the *very aware* tertile), also agree most with the belief that machines will soon be as intelligent as humans. However, they also subscribe to the belief that there will always be work for humans to do.

4.4 The impact of awareness of and beliefs about automation on career decisions

We now consider the factors which influenced respondents' career decisions. Figure 4 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. In contrast, a majority (59%) of the respondents indicated that automation did not influence their career decisions, while only 22% either agreed (n=162) or strongly agreed (n=49) that it did.

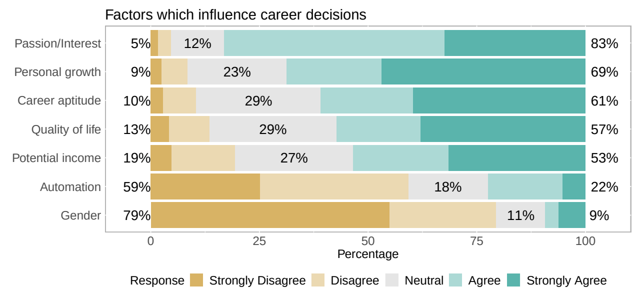

Figure 4: Response distribution for the factors of influence.

An independent samples t-test indicated that there was a statistically significant difference in the influence of automation on 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.[1] 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 ($M = 2.06, SD = 1.19$). Figure 5 provides the summary statistics for all faculties.

The mean values of the respondents' belief levels based on their intended career categories are presented in Figure 6. Using an ANOVA, career category was found to be a significant predictor of variance in the belief that automation influenced his/hers choice of study ($F(12, 904) = 8.91, p < 0.05$).[2] 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 ($M = 1.88, SD = 0.91$).

Finally, we performed a bivariate correlation (Spearman's rank order correlation) to determine the association between respondents' level of awareness of automation and the influence thereof on their career decisions. The result ($r_s = 0.01, p < 0.01$) indicated a small but statistically significant positive correlation. Hence, while the effect size is negligible, the finding suggests that students with higher levels of automation awareness are more likely to consider this as a factor when choosing careers.

[1] Given the relative proportion of the genders in the sample, the respondents who identified as other were not considered in this analysis.
[2] The Agriculture career category was not considered in this analysis due to its small size (n=18).

Table 3: 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)

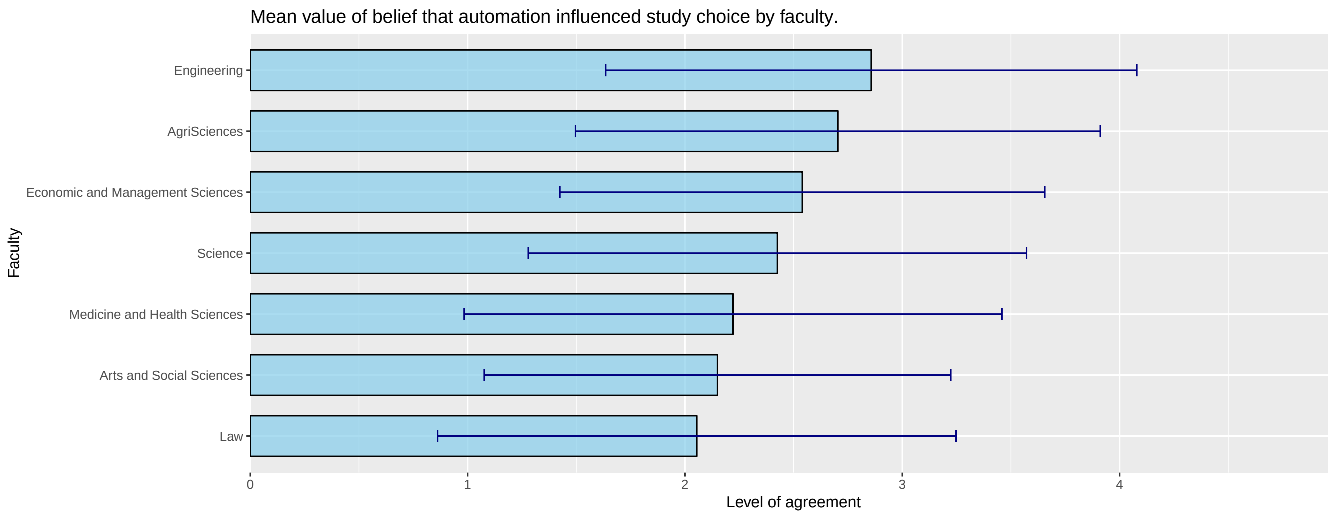

Figure 5: The mean level of agreement for the belief that automation influenced the respondents' choice of study by faculty. Given the low number of respondents from the faculties of Education, Military Sciences, and Theology, these were not considered in this comparison.

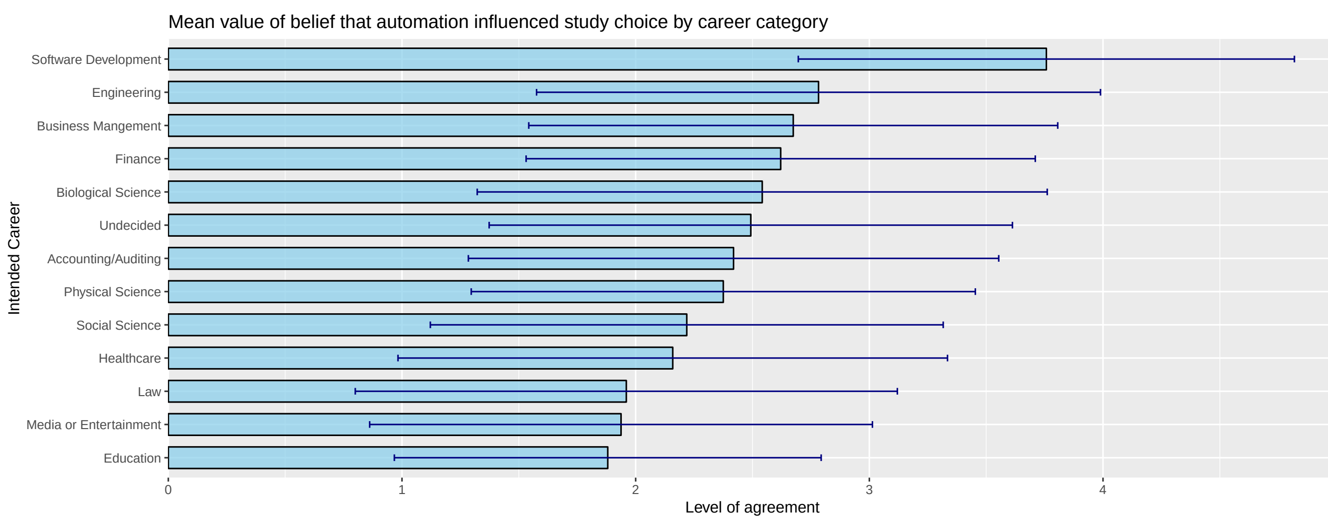

Figure 6: The mean level of agreement for the belief that automation influenced the respondents' choice of study by intended career category.

5 DISCUSSION

In the section which follows we briefly discuss our findings and provide suggestions for future research. The section ends with consideration of the limitations of our study.

The first research question in the study 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 question. The findings for this scale indicated that a majority of students perceive themselves to be well informed about automation. Although the scale does not provide substantial insight into the accuracy or quality of the respondents' awareness, it provides an indication of their subjective estimation thereof. 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.

Based on our analysis, none of the sources of influence we considered significantly predicted automation awareness. Our data therefore provide limited insight into the manner through which students become informed about the potential impact of automation on career paths. Buser et al. [10] found that, in secondary school, males are more likely than females to select more math and science intensive subjects. It is possible that male students' greater awareness of automation, as reflected in our data, results from the completion of these subjects. This may also account for the finding that students who are most aware of automation tend to select the math, science, and commerce-related choices of study fields and subsequent careers. However, we suggest that future research extend this study by identifying the sources of information that shape students' perceptions of automation.

The second research question concerned students' beliefs about automation. Our data revealed an interesting trend in this regard. In general, students seem to be quite optimistic about the rapid advancement of artificial intelligence with a majority of our sample agreeing with the statement that machines will soon be as intelligent as humans. However, this optimism is countered by strong agreement with the belief that human workers will remain relevant in the labour market. Two interpretations of these findings are worth considering. Firstly, it may be the case that students' appreciation of the complexities involved in, for example, the automation of basic sensorimotor skills enables them to have a nuanced understanding of the current limitations to the technological displacement of labour. This view seems to be supported by the finding that 74% of the sample agreed that there are many jobs that machines cannot do. However, an alternative interpretation of the data is that students are experiencing a degree of confusion about the potential and limitations of automation technologies. This interpretation is supported by the finding that only 13% of the respondents felt that their intended careers are automatable. Brougham and Haar [7] make a similar observation in their analysis of workers' awareness of automation technologies. They argue that, while people may be aware of the relevant technologies, they may not have an accurate understanding of how these impact the automatability of their own occupations. This aligns with observations from our own data. For example, of the 74 students who intend to work as accountants or auditors, almost half ($n = 34$) believe that these careers will not be automated. Of course, Frey and Osborne [16]'s analysis suggest that these occupations have a 94% probability of being automatable in the near future.

Lastly, we consider the impact of awareness of and beliefs about automation on career decisions. Our data indicate that only 22% of the current cohort of students considered automation when making their career decisions. Importantly, this is not purely due to a lack of awareness — while significant, the strength of the correlation between these variables is negligible. It is reasonable to deduce, on this basis, that a majority of students do not believe that the automation of work poses a substantial risk to the demand for labour in their chosen careers. However, this deduction should be weighed against the finding that 57% of our sample agreed that machines will replace labour. When considering these two findings together, it seems that many students believe that their chosen careers will, in some way or other, resist automation. While this line of reasoning is supported by the argument that those with tertiary qualifications may be less at risk than semi-skilled workers [8, 27, 30], we find it difficult to reject the argument that this belief is frequently based on limited knowledge of and false assumptions about the actual state and potential of STAARA technologies. Future studies should investigate this proposition by extending our study to consider, in addition to level of awareness, the quality and accuracy of students' perceptions of automation.

Our data suggest that, among students that consider automation when making career decisions, the dominant strategy is to choose an area of study in which they obtain advanced technical knowledge and skills. Underpinning this strategy is the argument that, as automation technologies infiltrate industry, demand for the associated technical expertise (e.g., software development) will increase. This strategy is inline with the World Economic Forum's projection that high-skill, tech-oriented roles are expected to expand in coming years [22]. However, it does not necessarily consider the automatability of these technical expertise — e.g., many aspects of software development may be more automatable than non-technical work such as primary school education or creative writing. Interestingly, those respondents choosing predominantly non-technical careers that are likely to resist automation (e.g., education, media or entertainment) generally did not consider automation when making their career decisions. Hence, we cannot define this as a specific strategy followed, but it should be noted that, as automation technologies advance, it may be pragmatic to choose a career which involves tasks that are more difficult to automate (e.g., social interaction, sensorimotor skills and creativity). It is possible that the demand for these types of skills will increase as automation technologies advance to satisfy the demand for technical, cognitive labour.

5.1 Limitations

Four limitations of our study are worth mentioning. Firstly, by using a survey with few open-ended questions, we did not provide respondents with the opportunity to express or describe their perceptions of or beliefs about automation beyond the statements and questions provided. This naturally limits our data and, by extension, our ability to address the research questions posed. Secondly, by using self-reported perceptions to determine automation awareness, our measurement instrument is not sensitive to the objective accuracy or meaningfulness of respondents' perceptions. Future studies should consider developing a more appropriate measurement instrument by asking respondents to answer test-type questions about automation technologies. Automation awareness can then be calculated based on the accuracy of their responses. Thirdly, the survey was only completed by students enrolled at a research-intensive university. The same survey may produce different results if conducted at some of South Africa's other tertiary institutions. Finally, by limiting our study to university students we naturally ignore the career decisions of a majority of the labour force.

6 CONCLUSION

In conclusion we turn our attention to the question of whether the finding that less than a quarter of our sample considered automation when choosing their careers should be a matter for concern. It may be the case that the impact of automation on the structure of labour demand has been overhyped, in which case ignoring it as a factor is non-problematic. Conversely, the argument can be made that ignorance of automation is setting many students up for failure, and that career advisers, parents and universities should take greater responsibility by guiding prospective students to career paths which enable them to "run with the machines" [8] rather than compete against them. There is, at this point in time, a lack of evidence to provide a definitive answer to this question. However, there is strong agreement among scholars and industry leaders that automation technologies will, firstly, disrupt the status quo and, secondly, require workers in a wide spectrum of occupations to adopt intelligent machines to increase work performance. We believe that, as these processes play out, researchers and industry leaders have an important responsibility to communicate the implications of automation for labour demand to prospective students and job seekers.

REFERENCES

[1] Jaison R. Abel, Richard Deitz, and Yaqin Su. 2014. Are Recent College Graduates Finding Good Jobs? *Current Issues in Economics and Finance* 20, 1 (2014), 1–8.

[2] Fatima Abrahams, Rukhsana Jano, and Burger van Lill. 2015. Factors Influencing the Career Choice of Undergraduate Students at a Historically Disadvantaged South African University. *Industry and Higher Education* 29, 3 (jun 2015), 209–219. https://doi.org/10.5367/ihe.2015.0253

[3] Asghar Adelzadeh. 2017. *Modelling Future Demand and Supply of Skills in South Africa.* Technical Report. Department of Higher Education and Training, Pretoria, South Africa. 1–220 pages.

[4] P. M. Alexander, M. Holmner, H. H. Lotriet, M. C. Matthee, H. V. Pieterse, S. Naidoo, H. Twinomurinzi, and D. Jordaan. 2011. Factors Affecting Career Choice: Comparison Between Students from Computer and Other Disciplines. *Journal of Science Education and Technology* 20, 3 (2011), 300–315. https://doi.org/10.1007/s10956-010-9254-3

[5] Haroon Bhorat, Karmen Naidoo, Morné Oosthuizen, and Kavisha Pillay. 2015. Demographic, employment, and wage trends in South Africa. (2015), 39 pages.

[6] J. Bloem, M. van Doorn, S. Duivestein, D. Excoffier, R. Maas, and E. van Ommeren. 2014. *The Fourth Industrial Revolution.* Technical Report. Sogeti. 1–40 pages. https://doi.org/10.3903/gtp.2008.1.3 arXiv:arXiv:1011.1669v3

[7] David Brougham and Jarrod Haar. 2017. Employee assessment of their technological redundancy. *Labour and Industry* 27, 3 (2017), 213–231. https://doi.org/10.1080/10301763.2017.1369718

[8] Erik Brynjolfsson and Andrew McAfee. 2012. *Race Against the Machine: How the Digital Revolution is Accelerating Innovation, Driving Productivity, and Irreversibly Transforming Employment and the Economy.*

[9] Jacques Bughin, James Manyika, Jonathan Woetzel, Frank Michael Mattern, Susan Chui, Anu Lund, Sree Madgavkar, Jaana Ramaswamy, Andres Cadena, Richard Dobbs, Katy George, Rajat Gupta, Eric Hazan, Eric Labaye, Acha Leke, and Scott Nyquist. 2017. *A future that works: automation, employment, and productivity.* Technical Report. McKinsey Global Institute. 1–135 pages.

[10] Thomas Buser, Muriel Niederle, and Hessel Oosterbeek. 2014. Gender, Competitiveness, and Career Choices. *The Quarterly Journal of Economics* 129, 3 (2014), 1409–1447. https://doi.org/10.1093/qje/qju009

[11] André Calitz, Jean Greyling, and Margaret Cullen. 2013. The Influencers of Scholars' ICT Career Choices. *Educational Research for Social Change (ERSC)* 2, 1 (2013), 64–81.

[12] Department of Higher Education and Training. 2018. *Statistics on Post-School Education and Training in South Africa Statistics on Post-School Education and Training in South Africa: 2016.* Technical Report. Department of Higher Education and Training, Pretoria, South Africa. 1–138 pages.

[13] Emily Ann Dodge and Martha Welderufael. 2014. *Factors that Influence Career Choice in South African Township High School Students.* Ph.D. Dissertation. University of Carlifornia.

[14] Norman Erasmus. 2011. *The impact of the Intellectual Property Rights Act for Publicly Funded Research and Development on Technology Transfer Offices at South African Universities.* Ph.D. Dissertation. University of Pretoria.

[15] Carl Benedikt Frey and Michael Osborne. 2013. The Future of Employment. (2013), 78 pages. http://sep4u.gr/wp-content/uploads/The{_}Future{_}of{_}Employment{_}ox{_}2013.pdf

[16] Carl Benedikt Frey and Michael Osborne. 2015. *Technology at work: the future of innovation and employment.* Technical Report. 1–107 pages.

[17] Carl Benedikt Frey and Michael A. Osborne. 2017. The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting & Social Change* 114 (2017), 254–280. https://doi.org/10.1016/j.techfore.2016.08.019

[18] Mikell P. Groover. 2008. *Automation, production systems, and computer-integrated manufacturing.* Prentice Hall. 815 pages.

[19] William Halal, Jonathan Kolber, and Owen Davies. 2016. *Forecasts of AI and Future Jobs in 2030: Muddling Through Likely, with Two Alternative Scenarios.* Technical Report 2. 83–96 pages. https://doi.org/10.6531/JFS.2016.21(2).R83

[20] Nqobile I. Kweyama. 2016. *Factors influencing career choice among students at the University of Zululand.* Ph.D. Dissertation. University of Zululand.

[21] Daniel B. le Roux. 2018. Automation and employment: The case of South Africa. *African Journal of Science, Technology, Innovation and Development* (jun 2018), 1–11. https://doi.org/10.1080/20421338.2018.1478482

[22] Alexander Till Leopold, Vesselina S. Ratcheva, and Saadia Zahidi. 2018. *The Future of Jobs Report 2018.* Technical Report. World Economic Forum, Centre for the New Economy and Society, Geneva, Switzerland. 147 pages. http://www3.weforum.org/docs/WEF{_}Future{_}of{_}Jobs{_}2018.pdf

[23] K. P. Mashige and O. A. Oduntan. 2011. Factors influencing South African optometry students in choosing their career and institution of learning. *African Vision and Eye Health* 70, 1 (dec 2011), 21–28. https://doi.org/10.4102/aveh.v70i1.90

[24] Pilot Mudhovozi and Regis Chireshe. 2012. Socio-demographic Factors Influencing Career Decision-making among Undergraduate Psychology Students in South Africa. *Journal of Social Sciences* 31, 2 (2012), 167–176. https://doi.org/10.1080/09718923.2012.11893025

[25] Organisation for Economic Co-Operation and Development. 2018. Graduates by field of education.

[26] Roze Phillips, Yusof Seedat, and Stephan van der Westhuizen. 2018. *Creating South Africa's Future Workforce: Digital puts one in three jobs at risk.* Technical Report. 1–27 pages.

[27] Claudia Pompa. 2015. *Jobs for the Future.* Technical Report. Overseas Development Institute. 1–42 pages.

[28] Jeremy Rifkin. 1995. *The end of work : the decline of the global labor force and the dawn of the post-market era.* Putnam, New York. 1–350 pages.

[29] Anna Sabadash. 2013. *ICT-induced Technological Progress and Employment : a Happy Marriage or a Dangerous Liaison ? A Literature Review.* Technical Report. European Commission Joint Research Centre Institute for Prospective Technological Studies, Luxembourg. 62 pages. https://doi.org/10.2791/2141

[30] Klaus Schwab and Richard Samans. 2016. *The Future of Jobs: Employment, Skills and Workforce Strategy for the Fourth Industrial Revolution.* Technical Report. World Economic Forum, Geneva, Switzerland. 1–157 pages.

[31] Lisa F Seymour and Thabang Serumola. 2016. Events that lead university students to change their major to Information Systems: A retroductive South African case. *SACJ* 28, 1 (2016), 18–43. https://doi.org/10.18489/sacj.v28i1.367

[32] Almon Shumba and Matsidiso Naong. 2012. Factors Influencing Students' Career Choice and Aspirations in South Africa. *Journal of Social Sciences* 33, 2 (nov 2012), 169–178. https://doi.org/10.1080/09718923.2012.11893096

[33] N. Spaull. 2013. *South Africa's Education Crisis: The Quality of Education in South Africa 1994-2011.* Technical Report. Centre for Development and Enterprise.

[34] Statistics South Africa. 2008. *Quarterly Labour Force Survey Quarter 4, 2008.* Technical Report. Statistics South Africa. 29 pages.

[35] Statistics South Africa. 2018. *Labour Market Dynamics in South Africa, 2016.* Technical Report. Statistics South Africa, Pretoria, South Africa. 1–189 pages.

[36] Statistics South Africa. 2018. *Quarterly Labour Force Survey.* Technical Report. Statistics South Africa. 1–126 pages.

[37] World Economic Forum. 2016. *The Future of Jobs Employment, Skills and Workforce Strategy for the Fourth Industrial Revolution.* Technical Report january. 2–3 pages. https://doi.org/10.1177/1946756712473437 arXiv:0803.1716