Gender & Behaviour 2019 ISSN: 1596-9231

Analysis of the impact of artificial intelligence and robotics on human labour

Mbali Mfanafuthi, Jabulani Nyawo and Pfano Mashau
University of KwaZulu-Natal, South Africa

ABSTRACT

The future of human labour has been rendered uncertain recently, due to the emergence of artificial intelligence and robotics. The definition of artificial intelligence is still unclear. However, in this study, the concept is used interchangeably with others such as computerisation, automation and technological advancement. Research has demonstrated that artificial intelligence and robotics will substitute human labour, mostly in the service, production, office and administration sectors. The aim of this study is to report on some of the work achieved on the topic of automation, in order to answer the question of whether artificial intelligence and robotics will replace human labour. This a desktop study that explores different models to analyse the impact of the fourth industrial revolution on human labour. The task oriented model, diversity and specialisation method and Houthakker's model were utilised in the study. The results have revealed that computerisation will lead to the substitution of human labour, especially for occupations involving routine tasks. However, there is still more work to be achieved on the topic, in order to establish significant and valuable conclusions. It is apparent that artificial intelligence and robotics are substituting the previous generation's positions for fourth industrial evolution jobs.

***Keywords**: Intellectual intelligence, labour, computerisation, Fourth Evolution, human labour, technological improvement, automation, robotics*

INTRODUCTION

Artificial intelligence (AI) has become a topic of heated debate for many professions (Hilt, 2017). It is apparent that we live in an age of complexity, where the most impressive capabilities of AI, particularly those based on machine learning, have not been not widely dispersed thus far (Brynjolfsson et al., 2017). Like other general purpose technologies, their full effects won't be realised until waves of complementary innovations have been developed and implemented. The required adjustment costs, organisational changes and new skills can be modelled as a kind of intangible capital (Spiro et al., 2017). Its benefits are significant, as it can reach reasoned conclusions, with the potential to surpass human ability, with incomparable efficiency (Chang, 2016).

Artificial intelligence and robotics will impact either positively or negatively upon job opportunities. Currently, the world is faced with technological advances in artificial intelligence and automation, resulting in uncertainty about the future of human labour (Thirgood & Johal, 2017). It remains unclear what exactly the future of the labour markets holds. However, it appears that humans can be left to face major risks, due to excessive agitation brought about by technological advancements (Thirgood & Johal, 2017). The study will review the implications of automation and AI on the demand for labour, wages and employment. It will further note the displacement effect that automation creates as machines and AI replace human labour in tasks that humans used to perform (Boyd and Holton, 2017).

Boyd and Holton (2017) argue that this displacement effect tends to reduce the demand for labour and wages. It is counteracted by a productivity effect, resulting from the cost savings generated by automation, which increase the demand for labour in non-automated tasks (Acemoglu & Restrepo, 2017; Boyd & Holton, 2017). The productivity effect is complemented by additional capital accumulation and the deepening of automation (improvements of existing machinery), both of which further increase the demand for labour (Boyd & Holton, 2017). The more powerful countervailing force against automation is the creation of new labour-intensive tasks, which reinstate labour in new activities and tend to increase the labour share, thus counterbalancing the impact of automation. The adjustment of the economy and the labour market to automation may weaken the resulting productivity gains from this transformation, with a mismatch between the skill requirements of new technologies and the possibility that automation is being introduced at an excessive rate, possibly at the expense of other productivity-enhancing technologies (Acemoglu & Restrepo, 2017, Boyd & Holton, 2017, Brynjolfsson et al., 2017, Spiro et al., 2017). Thirgood and Johal (2017) also opine that governments need to play an important role in ensuring that risks confronted by individuals are shared, through improvements made to government policies to protect social wellbeing and investment made in workforce development for the future. They also highlight the importance of policymakers in the implementation of such policies, to ensure humans are not swept aside by the emergence of artificial intelligence. Undeniably, over the past few decades, computerisation has substituted human labour and the functions of several jobs, including bookkeepers, cashiers and telephone operators (Frey & Osborne, 2013).

Frey and Osborne (2013) also stated that the labour markets' outcomes due to computerisation have been well reported in numerous studies. A decrease in employment for routine, concentrated tasks has been reported – i.e. jobs primarily involving procedural tasks that can be easily done by sophisticated (or computerised) systems. Studies by Charles et al. (2013) and Jaimovich and Siu (2012) highlight that the low rates of employment are caused by a continuing decline in manufacturing employment. Autor and Dorn (2013) reported a swing in the labour market, where they highlight that workers are relocating their labour supply from middle-income manufacturing to low-income service jobs. The reason stated is, arguably, that service occupations require manual tasks that are difficult to computerise because they require more physical adaptability and flexibility (Autor and Dorn, 2013).

DeCanio (2016) supports other studies that report a decline of human labour demand and income reduction. Production and labour markets are bound to be disrupted by the introduction of new technologies; some skills will be classified as outdated, while the implementation of improved technologies may require new skills (DeCanio, 2016). However, it is predicted that there might be an increase in total productivity, due to technological change associated with new entrepreneurial opportunities and jobs (DeCanio, 2016, Autor, 2014, Goos et al., 2014, Rodrik, 2016).

Therefore, this study will explore different models and literature, so as to assess the impact of AI and robotics on the labour market. It also addresses the classification of jobs and how the new technologies will impact them. The other contributing factors to technological employment will not be discussed fully within the scope of this study, for example ethical issues, government policies and globalisation.

FOURTH GENERATION EMPLOYMENT

Revolution is the radical change of an existing order, in favour of a newer one; it is worth noting that this evolution doesn't happen until it is embraced by the people (Abdin, 2017). Industrial revolution refers "to the radical improvement of manufacturing and other technologies that have completely changed the previous scenario and established a newer version with positive shift of industrialisation" (Abdin – 2017:1). Policy makers ought to be cautious, because each individual change or shift offers something opportunistic, but also with some challenges. Therefore, we have to be careful about the opportunities and challenges of the fourth industrial revolution and prepare proper policies in order to be able to grab the opportunities and overcome challenges efficiently.

Abdin (2017:2) highlighted challenges and opportunities: The challenges of the fourth industrial revolution include: loss of jobs and disruption by lowly educated people; inequality and political instability; an end to low-cost and low-skilled labour that is based industrialisation, due to AI and robotics technology; more market access to giant global companies offering more value to customers; vulnerability of LDC countries in fighting cyber-crimes; and cyber-attacks.

Opportunities of fourth industrial revolutions could include: wealth maximisation through continual improvement of GDP growth, inclusive growth, improved performance of the SMEs, entering into an advanced stage of development, connecting disconnected people, improving environment management systems, automation of agriculture and transformation of agro production technologies, better access to healthcare and the use of modern technology to forecast about natural calamities, etc.

A study on how to survive the fourth evolution of industry determines that in the near future (2020), the fourth industrial revolution will have brought advanced robotics and autonomous transport, artificial intelligence and machine learning, advanced materials, biotechnology and genomics (Webber-Youngman, 2017). Citing the World Economic Forum 2016, Webber-Youngman (2017) highlights the 10 skills that humans need to thrive in the fourth industrial revolution, based on the use of cyber-physical systems. They are:

- Complex problem-solving
- Critical thinking
- Creativity
- People management
- Coordinating with others (group work activities)
- Emotional intelligence
- Judgement and decision-making

- Service orientation
- Negotiating
- Cognitive flexibility.

It is, however, important to note that economies are progressing at different rate, with some still in the previous generations. The economies that are lagging behind are also partly experiencing the impact of fourth generation challenges and are preparing their citizens for future jobs. Webber-Youngman (2017) also argues that academic institutions now have to think differently about the way they educate and teach the next generation of practitioners (and, in this context, how to solve complex problems).

CONSEQUENCES OF ARTIFICIAL INTELLIGENCE AND ROBOTICS

This paper considers the consequences of AI and robotics on human labour and incomes, and addresses other inherent outcomes. Artificial intelligence can be defined as the competence of a machine in copying intelligent human behaviour (Aghion et al., 2017). Robotics is a field that refers to robots as systems that contain sensors, control systems and software that all collaborate to perform tasks (Qureshi & Syed, 2014). Concepts such as AI, automation, computerisation and technology advancements might have different meanings, but they are used interchangeably in this study, as they are all closely related.

The dependent variable being studied is human labour, which is being observed in a global framework and is not confined to certain regions. The demand for human labour is dependent on the technologies available. The rise of different technologies will lead to a reduction in the demand or displacement of human labour. Tasks that are currently being performed by humans in work settings include manual labour, which, for example, is work done in operating machinery or mopping the floor, and cognitive tasks, which are those that require more thought, logic and intellect, for example, deciding on product quality specifications.

Artificial intelligence and robotics will replace these tasks and, as highlighted by various studies (DeCanio, 2016, Autor, 2014, Bowles, 2014, Drew and Ballingall, 2015, Lamb, 2016, Lawson, 2016), the emergence of technology will render some skills obsolete, leading to a decline in the demand for human labour and, inevitably, income. Qureshi and Syed (2014) highlight that, since organisations are faced with rising labour costs and a shortage of workers, they are investing in robotics. Robots can achieve tasks that humans cannot and may be more efficient than humans, therefore organisations may substitute human labour for robots to achieve an increase in efficiency through a reduction of labour cost and total production costs (Decker et al., 2017, Qureshi and Syed, 2014).

The adoption of artificial intelligence and robotics, as reported by various studies, has resulted in a reduction in employment and incomes. However, studies by Frey and Osborne (2013) report that the impact of computerisation on employment is skill biased in their study of 702 jobs in the United States. Aghion et al. (2017), in their study of the Japanese economic environment, report labour market restructuring due to technological advancements, but also highlight skill bias. Interestingly, Ugur and Mitra (2017) used a task-oriented approach on less developed countries to study the impact of technology on employment and reported that product oriented technology has a positive impact on employment, whereas process oriented technology has a negative impact.

Beaudry et al. (2013) reported that, even with the continual increase in the supply of highly educated workers, there had been a drop in the demand for skill over the past 10 years. They determined that highly skilled employees have moved down the occupational hierarchy, because of their willingness to take on jobs usually performed by low-skilled workers, thus resulting in low-skilled workers being pushed further down the occupational ladder and even out of the labour force to some extent. DeCanio (2016) reported on the elasticity of human-robot substitution, with skill bias the main highlight.

The impact of new and more advanced technologies in industry is not a hypothetical phenomenon, but is something that is evidently occurring now. One example of this is reported by Ramaswamy (2018), who highlights that Nike and Adidas are investing in automation to reduce production costs and lower turnaround times. While other inherent factors relate to the impact of AI and robotics on employment, these variables are detrimental to understanding the fate of human labour in the technological age. Therefore, the main objective of this study is to shed light on the facilitation of AI and robotics, and its impact on human labour. To achieve the main objective, the following sub-objectives are set: classification of employee skills and how they are impacted by AI and robotics; elasticity of substitution: human and robots; impact of technology on average wages and employee educational levels, and how that impacts on their jobs.

METHODOLOGY

This is an exploratory study, with research conducted on a problem that has hitherto not been studied clearly; it is intended to establish priorities, develop operational definitions and improve the final research design (Creswell & Creswell, 2017). As we exist in complex economies, the study seeks to use different sources to explain the impact of AI and robotics on the labour market. It uses several studies and different models, as seen in the following sections. The secondary data is derived from books on topics related to robotics, websites, journals and research articles.

The models focused on are adopted from Frey and Osborne (2013), Frank et al. (2018) and DeCanio (2016). The three models are as follows:

Task-oriented model

Frey and Osborne (2013) employ the task-oriented model, where they compare routine and non-routine tasks and manual and cognitive tasks on separate plots. They studied 702 jobs in the US, using the O*NET data and the Standard Occupation Classification supplied by US Department of Labour. The model focuses on the substitution effects of recent technologies and derives factors that are expected to impact on the degree of computerisation in non-routine tasks. The researchers adopted the Cobb-Douglas production function to derive a mathematical representation of susceptible and unsusceptible labour inputs to computerisation.

Due to bottlenecks inhibiting the predictability of automation on non-routine tasks with this model, Frey and Osborne (2013) adjusted the model so that it could make predictions on any non-routine task not subject to engineering bottlenecks on computerisation. Their model predicts that most workers in transportation and logistics occupations, together with the bulk of office and administrative support workers, and labour in production occupations, are at risk. Wages and educational attainment exhibit a strong negative relationship with the probability of computerisation. The model implies that as technology races ahead, low-skill workers will reallocate to tasks that are non-susceptible to computerization – i.e., those requiring creative and social intelligence. For workers to win this race, they will have to acquire creative and social skills.

Impact of Automation in cities – Diversity and Specialisation

One study demonstrates that both small and big cities are impacted by automation (Frank et al. 2018). Its authors demonstrate that large cities exhibit increased occupational and skill specialisation, due to an increased abundance of managerial and technical professions (Frank et al. 2018). These occupations are not easily automatable and thus reduce the potential impact of automation in large cities. Cities are hubs in a modern society that effect economic productivity and innovation. However, the impact of automation on employment in cities threatens to alter urbanisation, which is largely driven by employment opportunities (Frank et al. 2018). The study quantifies relative impact and provides significant evidence for technological unemployment in cities, to show that small cities face a greater impact of automation.

Frank et al. (2018) used measures for specialisation and diversity by computing mathematical representations for specialisation and diversity, employing Shannon entropy. US Bureau of Labour statistics were used (BLS), from across 380 metropolitan areas, involving 700 different occupations. The scholars studied 230 workplace skills, for example, manual agility, finger nimbleness, difficult problem solving, management of time and negotiation. These were detailed using the BLS O'NET. O'NET skills were also detailed, for example capabilities, experience, education, training and knowledge and work activities. The raw survey responses were normalised through obtainable values between 0 and 1.

Houthakker's Model

DeCanio (2016) utilises Houthakker's model of demand, based on the deriving variable factor, probability distribution. Substitution elasticity between human labour and robotic labour is calculated using mathematical representations. A theoretical analysis and interpretation of the elasticity values is then achieved. Houthakker's method characterises aggregate production relationships, in order to estimate the effects of a change to the input of robots on the human wage, without necessitating construction of a capital aggregate (DeCanio, 2016). Data from industries in the US can be employed to estimate how large the elasticity of substitution between human and robot labour must be, such that an increase in the employment of robots will reduce the human wage (DeCanio, 2016). It is not implausible that the proliferation of AI, embodied in robots, may have negative consequences on wages (DeCanio, 2016).

POTENTIAL IMPACT OF FOURTH EVOLUTION ON EMPLOYMENT

The aim of this section is to demonstrate the impact of AI and robotics in the labour market, using the work of authors discussed above (DeCanio, 2016, Frank et al., 2018, Frey and Osborne, 2013). Results from various studies are considered and a discussion will be presented comparing numerous studies that report on the types of occupations at risk of being eliminated. Frey and Osborne (2013) used the Gaussian classifier in their unique methodology that estimated the probability of computerisation of 702 jobs in the US. They recognised constraints to the competence of computers in executing tasks originally performed by human beings, i.e. executive tasks including manipulation and perception, innovative intellect and social intellect. They reported that 47% of all jobs in the US are in danger of being phased out, mostly employment involving manual and cognitive routine tasks (Frey and Osborne, 2013).

The study (Autor and Dorn, 2013) is also in agreement with the above. In figure 1, as reported by Frey and Osborne (2013), using the task-oriented model, technological advancements will reduce collective demand for labour involvement in tasks that can be achieved routinely due to advancements made in machine learning. However, the demand for labour performing unsusceptible tasks will increase as technological advances increase. Frey and Osborne (2013) distinguishes occupational risks to the probability of computerisation according to high, middle and low risk and states that humans' comparative advantage over tasks requiring mobility and dexterity will diminish over time. Pajarinen et al. (2015) and Roubini (2014) report a negative impact of technology on human labour and economy respectively. Thirty-five percent of jobs in Finland are at risk of substitution by technology (Pajarinen et al., 2015). Another study (Brzeski and Burk, 2015) in Germany reports that 59% of jobs are at risk. Further research (Lamb, 2016) discovered that 42% of jobs in Canada are at risk.

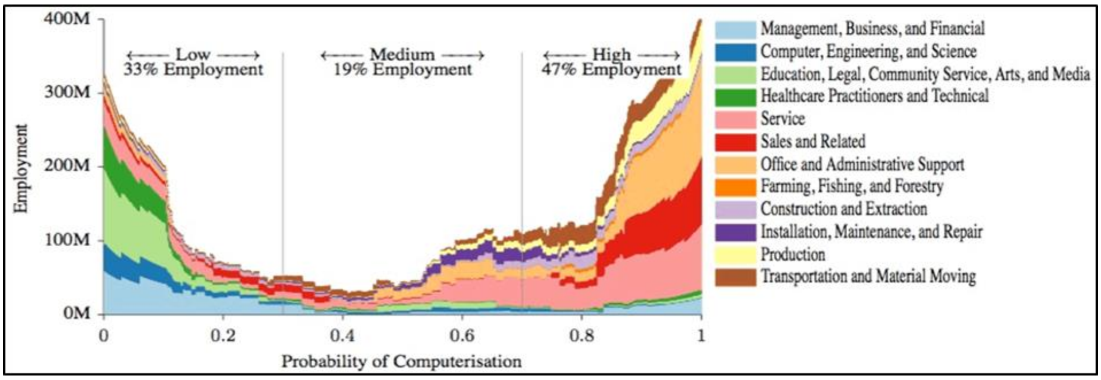


Figure 1: Computerisation probability. Source: (Frey and Osborne, 2013)

The above graph demonstrates computerisation probability, highlighting risk categorisation according to high, medium and low probability. Figure 1 shows that the jobs most susceptible to substitution are office and administrative support, service, sales and related activities, because they can be easily learned by AI technologies that have been designed to increase efficiency in the service sector. Thirty-three percent of jobs have a low risk, as they require expertise and are usually specialised; they are thus not easily substituted, but may be complemented by AI and robotics.

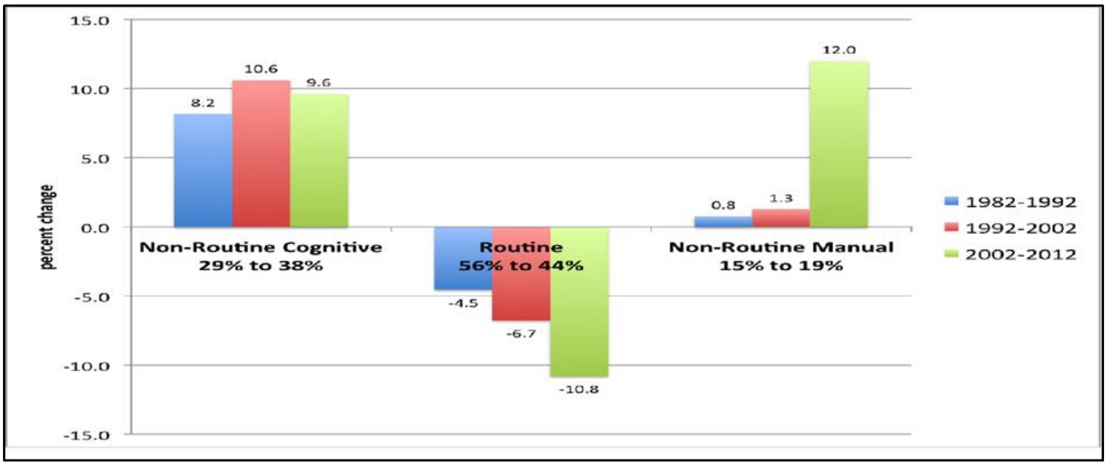
The results reported by Frank et al. (2018) on US cities reveals that each city is expected to be affected by automation, ranging from 50 to 75% of existing employment. The scholars discovered that large cities are more resistant to the damaging effects of automation than smaller cities. They also utilised the task model adopted by Frey and Osborne (2013), which determined that large cities were more resilient. The reason for this, stated by Frank et al. (2018), is that large cities can accommodate more specialised workers and the management to coordinate them, thus resulting in resilience.

DeCanio (2016), using the Houthakker's model, calculated the substitution elasticity between robotic and human labour. An elasticity of substitution of greater than 1.9 will result in AI technologies that cause a drop in summative wages, assuming other things remain equal (DeCanio, 2016). In the manufacturing sector, the elasticity of substitution can be even smaller, resulting in a decline of wages for industrial workers, as robots flourish (DeCanio, 2016). The service industry in Singapore is most susceptible; it is predominantly low-skilled, thereby making them likely to get reinstated should they lose their job (Fuei, 2017).

Job classification and computerisation risks

Task models were adopted by various studies, for example, Autor and Dorn (2013), Frey and Osborne (2013) and Ugur and Mitra (2017). Frey and Osborne (2013) categorised jobs according to the type of tasks performed, as shown in figure 2.

Figure 2: Employment Shares by Occupation Group. Source (Frey and Osborne, 2013).



The figure above shows the percent change in employment shares by Occupation Group. Figure 2 demonstrates the polarising effects of technology on occupations from 1982 to 2012. This task model was also expanded by Autor and Dorn (2013) to include the service sector, to describe the concept of polarising employment in the US. They pointed out that occupation changes in the US followed a U-shape in skill level. Middle-level skilled occupations reveal a decline, but those that require high skill and low skill gained. Routine tasks such as housework or caretaking services have been found to be expensive to computerise and are therefore not at high risk (Frey and Osborne, 2013). Non-routine cognitive tasks are those that require experience, expertise, abstract thinking and autonomy, and are classified as high skill (Ramaswamy, 2018). These findings are also augmented by (Thirgood and Johal, 2017), as indicated below.

The studies reveal that AI and robotics is skill biased and the projection is that it will affect labour in occupations that require routine tasks, for example, those in the service sector. Those in occupations that require non-routine cognitive tasks are likely to be complemented by technology (Thirgood & Johal, 2017).

Educational status and risk to computerisation

Arntz et al. (2017) follow the methodology adopted by Frey and Osborne (2013) and report that less educated workers are more likely to be replaced by automation. This is because they fall under the low-skilled category. Figure 3 demonstrates that the probability of automation increases with a reduction in the educational level of workers.

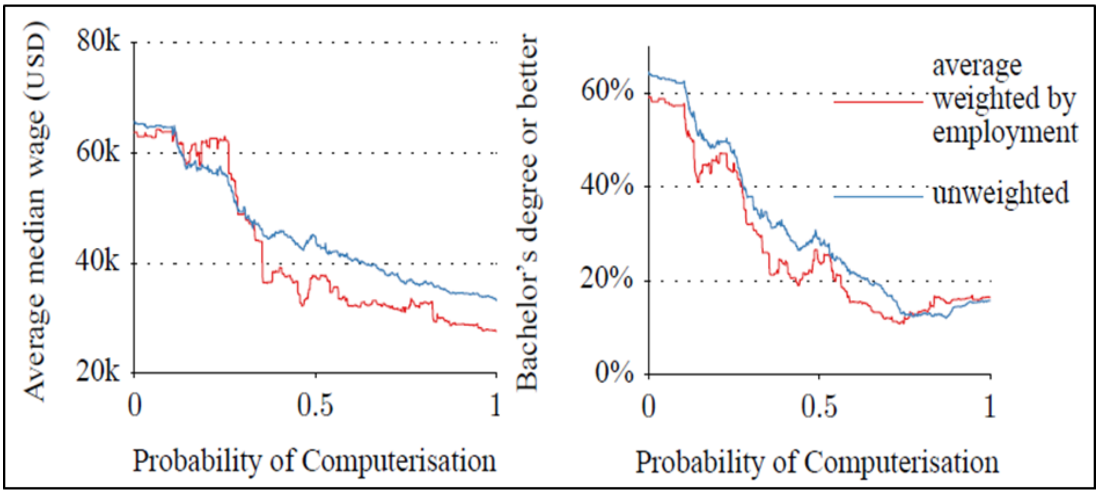


Figure 3: Average median wage and educational level (Frey and Osborne, 2013)

The figure above shows the relationship between probability of computerization, and two dependent variables, i.e. average median wage and educational level. The trend reported has been attributed to the fact that technological adoption eliminates routine occupations, since these are entry-level, process-driven tasks that don't require much abstract thinking

(Ramaswamy, 2018). Highly educated employees, as reported by Frey and Osborne (2013), are usually employed in specialised occupations that require high skills, for example, physicians and engineers. Therefore, computerisation will not substitute human labour in this regard, but human labour and technology may act as complements (DeCanio, 2016). The skill bias shown by technological change is the attributing factor for this trend, as also shown by Cirillo (2017), who asserts that humans will always be an important element of jobs in the future.

Impact of computerisation on average wages

The adoption of technology results in a decline in income, as reported by DeCanio (2016). A similar trend is reported by Frey and Osborne (2013), as shown in figure 3. Similar trends were reported in the study of the United Kingdom and US, which reported wage inequality due to technology adoption (Van Reenen, 2011). Zhang et al. (2017), in their study of China, also reported the wage inequality with technological innovation. As the cost of robots decreases and technological competencies develop, as a consequence, robots can be expected to steadily substitute human labour in a wide range of low-wage service jobs, where the growth of most US jobs has previously occurred (Autor and Dorn, 2013). The implication of this is that many low-wage, labour-intensive jobs that had been safe from computerisation could be reduced over time (Autor and Dorn, 2013).

Type of technology and labour substitution

Frey and Osborne (2013) report that the type of technology is significant in human labour substitution and state that product-oriented technology adoption is expected to have positive outcomes on employment, due to an increase in production output brought about by technology , resulting in more labour required to deliver the products to consumers. However, process-orientated technology is likely to yield negative effects on employment, due to the routine nature of process-related tasks that can be easily automated (Frey & Osborne, 2013, Autor & Dorn, 2013, DeCanio, 2016, Fuei, 2017).

Age and gender in technological change

Fuei (2017) reported that more females are in a high-risk category, compared to males – i.e. 55%, compared to 45%. The majority are in the service industry (84%) and in other industry positions that fall under the service industry, for example, retail trade, wholesale and public administration (Fuei, 2017). In a US study conducted by Wanberg et al. (2016), it has also been reported that age matters in terms of automation, with older workers in the US having a tendency to stay unemployed 10.6 weeks longer than younger workers, for example, those aged between 20 and 29. There was a 2.6% drop in the chance of older workers being re-employed for each yearly increase in age.

SUMMARY

To summarise, artificial intelligence and robotics are affecting negatively upon certain occupations, rather than all occupations, but there will be a reduction in total employment across industries. However, studies that will clearly define the relationship between Artificial Intelligence and robotics and human labour are still required, due to a high misconception between study heterogeneity of 75-selection bias by the researchers that advocates technological innovation. The issue of inhibiting factors to technological change should be considered as well, for example, government policies that might be implemented to protect humans and ethical issues that arise as a result of the adoption of new technologies. The generalisability of data presented by various studies is uncertain, however, especially in the southern African context, with strong laws and labour regulations in place that protect employees.

The study has been conducted to produce further insight into the issue of AI and the effect of robotics on human labour. Researchers report that automation has been restricted to routine tasks, including obvious procedural activities (Autor & Dorn, 2013). Today, big data systems are rapidly moving into fields that rely upon pattern recognition and can readily substitute labour. This can be spread widely across all non-routine cognitive tasks (Frey & Osborne, 2013). Advancement in robotics means that robots are gaining superior senses and agility, which enable them to perform an ever-widening range of labour-intensive tasks (Decker et al., 2017).

This paper attempts to expound upon whether AI and robotics will make a positive or negative impact upon human labour. Three models were used: the task-orientated model, adopted by Frey and Osborne in their study of 702 occupations in the US (2013); the diversity and specialisation method, employed by Frank et al. (2018), in their study of 700 different occupations; and a study examining 230 work skills in the US, whereby Shannon entropy was utilised to measure diversity and specialisation. DeCanio (2016) employed Houthakker's model, which is based on the probability of a variable factor to be substituted by automation. Substitution elasticities were calculated between robotics and human labour.

Jobs were ranked based on their probability of computerisation as low, medium and high risk. Studies report estimates that reveal that 47% of overall employment in the US lies in the high-risk category and it is anticipated that these positions will be automated soon. The results further report that occupations in the service industries, production and office and administration support, are at high risk of computerisation. DeCanio (2016) uses elasticities of substitutions between humans and robots to explain the substitution effect. He reports that an elasticity above 1.9 will result in a negative impact upon employment and average wages. However, he highlights that, in the manufacturing occupations, the substitution elasticity is expected to have a negative impact at even lower values.

Another dimension, diversity and specialisation, introduced by a study by Frank et al. (2018), supports research by Fuei (2017), who reported that specialisation associated with high skill level is more resilient to the negative effects of technological change. This can be attributed to the fact that big cities have more careers that are unique and industries that can accommodate employees with high skill levels (Frank et al., 2018).

Other research also reports that both routine and non-routine task occupations are susceptible, however, non-routine cognitive tasks are difficult to automate, due to them requiring more abstract thinking (Frey & Osborne, 2013). Reports by Frey and Osborne (2013), and Arntz et al. (2017), state that the educational status of employees determines susceptibility to technological change, where the probability of automation increases with a decrease in the educational level of employees.

Gender and age effects have also been reported by Fuei (2017) and Wanberg et al. (2016), who highlight that females are more at risk of substitution compared to males, due to the fact that women hold more positions in the service, office and administrative fields; they have a 55% chance, compared to a 45% chance of substitution, compared to males. Age also has an impact, according to Wanberg et al. (2016), who report upon the difficulty of older adults becoming re-employed after losing their jobs, compared to younger employees aged between 20 and 29.

However, some authors believe that the emergence of technology will only have a short-term negative impact (Qureshi & Syed, 2014). In other studies, the researchers are of the opinion that the high efficiency brought by robotics, i.e. minimisation of labour costs and reduction of total production costs, will result in increased output that will create new entrepreneurial opportunities and employment (Qureshi & Syed, 2014, DeCanio, 2016). Studies by Fuei (2017) report that the technology industry will generate more employment, as human labour will be required to create new advances.

CONCLUSION

It is clear that the automation trend across all industries has the potential to disarm many jobs, especially those that concern repetitive tasks and minimal cognition. However, automation gives rise to fourth industrial revolution jobs. The first movers to the fourth industrial evolution are a testimony to its impact and there is much more to learn and avoid for the following countries. Despite the fear of losing value of human capital to robotics and computerisation there are benefits that the economies can drive from the fourth evolution. The study assert that human will remain the in center as the world progresses but for the organisations to remain competitive and relevant in tomorrow's market, it is vital that they reach successful and significant levels of automation and readiness.

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