Geoforum 115 (2020) 120–131

Contents lists available at ScienceDirect

Geoforum

journal homepage: www.elsevier.com/locate/geoforum

Is automation stealing manufacturing jobs? Evidence from South Africa's apparel industry

Christian Parschau[b], Jostein Hauge[a,*]

[a] Centre for Science, Technology and Innovation Policy, Institute for Manufacturing, University of Cambridge, 17 Charles Babbage Road, Cambridge CB3 0FS, United Kingdom

[b] Institute for Manufacturing, University of Cambridge, 17 Charles Babbage Road, Cambridge CB3 0FS, United Kingdom

ARTICLE INFO

Keywords:
Automation
Manufacturing
Employment
Africa
South Africa
Apparel industry

ABSTRACT

There are growing fears that automation will lead to major job displacement and increasing unemployment, particularly in labour-intensive manufacturing. This is especially worrying for developing countries because of the importance of labour-intensive manufacturing to economic development. The purpose of this paper is to evaluate the threat of automation to employment, focusing on the manufacturing sector. It does so by critically reviewing studies that evaluate the current and future impact of automation on employment, as well as using industry-specific evidence from the apparel industry in South Africa. Through our literature review, we find that many studies fail to acknowledge: (1) the full range of factors that determine the net impact of automation on employment and; (2) many country-specific and industry-specific barriers to adopting new automation technologies, particularly in developing countries. A qualitative case study such as this one could therefore be a valuable contribution to the literature. The apparel industry has been chosen as a case because many forecast studies predict that the industry will suffer huge job losses due to automation. South Africa has been chosen as a case because the current literature is lacking case study evidence in the context of developing countries, and because South Africa is among those few developing countries adopting automation technologies in the apparel industry. Our evidence draws on 26 interviews with firm managers in the South African apparel industry, as well as with government and union representatives. We find that the overall impact of automation on unemployment has been negligible and is predicted to continue to be negligible. But in some instances, increased automation has and is predicted to increase employment by improving productivity at the firm level.

1. Introduction

There are growing fears that automation[1] will start displacing jobs at a faster rate than they have in the past, leaving less room for human work (Brynjolfsson and McAfee, 2014; Chang et al., 2016b; Ford, 2015; Frey and Osborne, 2017; Peck, 2017; Schwab, 2017). Some studies highlight that jobs in developing countries are at high risk (Chang et al., 2016b; Frey and Rahbari, 2016; World Bank, 2016), particularly manufacturing jobs or job creation in the manufacturing sector (Hallward-Driemeier and Nayyar, 2017; Manyika et al., 2017a; Schlogl and Sumner, 2020). This trend is especially worrying for developing countries because of the importance of labour-intensive manufacturing for economic development (Chang et al., 2016a; Hauge and Chang, 2019; Szirmai and Verspagen, 2015). In fact, the prospect of automation-related unemployment is leading some scholars to suggest that manufacturing-led economic growth may be a less feasible development model (Baldwin and Forslid, 2020; Hallward-Driemeier and Nayyar, 2017). This paper evaluates the threat of automation to employment, focusing on the manufacturing sector. It does so by critically reviewing the literature on the impact of automation on employment, as well as using industry-specific evidence from the apparel industry in South Africa.

In Section 2, we review research on how automation has impacted employment in the past, how it is impacting employment currently, and how it is expected to impact employment in the future. We argue that there is little conclusive evidence that automation is causing or will be causing overall unemployment to increase, or that it is impacting manufacturing employment in developing countries significantly. We

* Corresponding author.
E-mail address: jlh202@cam.ac.uk (J. Hauge).

[1] We understand automation as a technique, method, or system of operating or controlling a process (for example, a production process) by highly automatic means, reducing human intervention to a minimum. In present day, this is mostly done with the help of digital electronic devices, driven by advances in artificial intelligence.

https://doi.org/10.1016/j.geoforum.2020.07.002
Received 23 October 2019; Received in revised form 2 July 2020; Accepted 9 July 2020
Available online 27 July 2020
0016-7185/

highlight methodological problems with the current research on this topic. In particular, some forecast studies fail to acknowledge: (1) the full range of factors that determine levels of employment/unemployment; and (2) the many barriers to adopting new automation technologies in developing countries.

Seeing that many recent studies are global in outlook and apply opaque methodologies, which are bound to ignore many country-specific and industry-specific conditions/barriers to implementing automation technologies, we investigate a particular case: the apparel industry in South Africa. This case is the focus of Section 3 and Section 4. We focus on evaluating the employment impact of automation, barriers to adopting it, and major technical challenges to further automation. We chose to study the apparel industry because of the importance of apparel manufacturing to the industrialisation of developing countries, and the high likelihood of technical automation predicted for this industry in forecasts. We chose to focus on the South African apparel industry because it has recently shifted somewhat from a traditional labour-intensive approach to using more automation, allowing insight into the problem. The limited research on this topic carried out in developing countries also motivated us to look at a specific developing country.

We find that the overall impact of automation on unemployment in South Africa's apparel industry has been negligible and is predicted to continue to be negligible for the foreseeable future. But in some instances, increased automation has and is predicted to increase employment by improving productivity at the firm level. We also argue that numerous barriers specific to developing countries as well as the apparel industry will slow the development and adoption of automation.

Section 5 concludes by summarising the main findings and suggesting areas for additional research.

2. The impact of automation on employment: A review of the literature

This section addresses the research question – is automation posing a threat to manufacturing employment? – by critically evaluating existing literature on the topic. First we discuss how automation has affected employment in the past. To evaluate whether "this time is different", evidence from recent studies is reviewed. Towards the end of the section we consider studies that forecast/predict the impact of automation on jobs. We investigate literature that deals with the impact of automation on employment more broadly, the impact on the manufacturing sector, and, where possible, the impact on developing countries.

2.1. How has automation impacted employment in the past?

Seeing that most recent studies focus on automation driven by digital technologies, it is easy to lose sight of the fact that automation has been around for centuries. The first completely automated industrial process was developed in 1785 by Oliver Evans in the form of an automatic flour mill (Andreoni and Anzolin, 2019). The fear of job losses due to automation dates back almost as far: to the early 19th century Luddite protests, when textile workers in Great Britain destroyed machines in fear of being replaced by them. In some ways their anger was justified – industrial history shows that the introduction of automation technologies have caused disruptions to labour demand and short-term spikes of unemployment (Allen, 2009; Manyika et al., 2011, 2017b).

However, in the long run, evidence strongly supports that automation creates a multitude of jobs and unleashes demand for existing ones, more than offsetting the number of jobs it displaces (Autor, 2015; Autor et al., 2015; Manyika et al., 2017b; Muro et al., 2019). For example, while the introduction of the personal computer (PC) displaced jobs, it also created new ones. According to Manyika et al. (2017b), the PC has enabled the creation of 15.8 million net new jobs in the United States since 1980, even after accounting for jobs displaced. It should therefore come as no surprise that a vast body of literature shows that increased productivity[2] has been associated with increased overall employment in both advanced economies and developing countries (see Miller and Atkinson (2013) for an overview).

We should highlight though that automation, and technological progress more generally, has historically disrupted within-sector employment, even as overall employment has grown. In the United States, the agricultural sector's share of total employment declined from 60% in 1850 to less than 5% by 1970, and the manufacturing sector's share of total employment fell from 26% in 1960 to below 10% today (Manyika et al., 2017b). But these structural workforce shifts are not only due to technological advances. For example, while declining employment in manufacturing in advanced economies between the 1950s and 1990s has been associated with technological advances and productivity growth within the manufacturing sector (Bessen, 2017), offshoring of production to developing countries and increased international competition has become a more important factor after 1990 (Autor et al., 2015). Moreover, the restructuring of the labour force in the second half of the 20th century has been more modest than what many people think. For example, James Bessen found that among the 270 occupations in the 1950 US census, 232 of them (86%) still exist today. 37 of these disappeared either because of changes in consumer demand or technological obsolescence. Only one occupation disappeared due to automation: elevator operators (Bessen, 2016). Additionally, evidence on the impact of automation on within-sector employment is mixed. For example, during the 1st industrial revolution, machines were able to take over 98% of human work in the textile industry, but the decrease in prices that resulted from automation adoption and technological progress rapidly increased product demand and caused an overall increase in labour demand for weavers (Bessen, 2016). In fact, Bessen (2017) shows that as productivity increases and prices fall, many manufacturing sectors initially increase employment. The adoption of automation technologies also have the potential to create new jobs within the sector (e.g. people to operate new machinery).

2.2. Why is this time supposed to be different?

Despite the lack of historical precedent for widespread unemployment due to automation, fears that new technologies may disrupt these patterns should not be dismissed out-of-hand. Arguments for this view expect that new technologies, especially in the digital realm, will impact more jobs across industries, will allow more full automation and will occur more quickly than before (e.g. Brynjolfsson and McAfee, 2014; Ford, 2015; Schwab, 2017; Susskind and Susskind, 2015). Previously, computer-based automation was largely confined to manual and cognitive routine tasks involving explicit rule-based activities. This made it difficult for automation to be used in applications which involve abstract thinking, manual adaptability and/or situational awareness – often referred to as non-routine tasks in the literature (Autor et al., 2003, 2015; Autor and Dorn, 2013; Frey and Osborne, 2017). Examples of non-routine tasks are found in both both high-skilled jobs (e.g. creative design) and low-skilled manual jobs (e.g. housework).

Following recent technological advances, especially within artificial intelligence (AI), automation is now spreading to domains commonly defined as non-routine (Frey and Osborne, 2017). The scale of applicability of AI in the economy is intensified by the miniaturisation of computers, increased computing power, cloud computing and continuous data collection through the so-called Internet-of-Things. Through the use of sensors, the Internet-of-Things allows data transfer

[2] In historical studies, productivity has been used to represent automation/technological advances.

over the internet between objects without requiring human-to-human or human-to-computer interaction (see UNIDO (2019) for a good taxonomy of these advanced digital technologies). Moreover, technologies hardly exist in silos any longer and can feed off one another to a greater extent. Most recent and ongoing technological advancements leverage the interactive possibilities between digital technologies to achieve desired outcomes (Banga and te Velde, 2018). Increased flexibility of technological systems mean that changes could happen in a short time frame, increasing the shock to the labour market. Even new work that arises due to technological advances could be automated.

Peck (2017) highlights a large number of business-process tasks – some of which have not existed for that long – that are immediately available for automation, including supply chain management, employee data management, invoicing, customer support, litigation support, and employee data management.

However, the adoption of AI-driven technologies and other advanced digital technologies is still slow. Surveys suggest that while businesses are interested in AI and intelligent machine technology, not many are actually rolling them out for commercial use (McKinsey, 2018). In developing countries, less than 5% of manufacturing firms use advanced digital production technologies, and in some developing countries, over 70% of manufacturing firms only use analog production technologies (UNIDO, 2019) According to Willcocks (2020), the global market for AI, worth US$4.1 billion in 2018, constitutes a very small fraction of the global market for information technology as a whole, worth roughly US$5 trillion in 2018. These figures should caution claims that AI-driven technologies will have a massive and rapid economic impact. The following sections will examine the evidence, particularly the impact on and predictions about employment.

2.3. Is new automation technology already causing unemployment?

Despite the limited adoption of advanced digital automation technologies, some of them are already in use, for example in robots, so it may be useful to investigate the recent impact of automation technologies on employment. It is not, however, straightforward to measure this impact. A particular challenge and source of variation in results between studies is the choice of proxy for automation. Some studies look at robot implementation, some look at capital formation, some look at productivity growth, some look at R&D spending, and some look at adoption of digital technologies. Beyond the challenge of finding an appropriate measure, most of these proxies will have job-creating as well as job-displacing impacts. Nevertheless, a big-picture look at studies can still give us some useful insights.

Let us first look at advanced economies. On the whole, the evidence of the impact of new automation technology on employment is mixed. While some studies find that automation has displaced labour (Acemoglu and Restrepo, 2017; Acemoglu and Restrepo, 2019; Brynjolfsson and McAfee, 2014; Chiacchio et al., 2018; Piva and Vivarelli, 2017), other studies attribute job losses to different factors (particularly in the case of the United States), such as increased international competition (Autor et al., 2015), a productivity slowdown (Miller and Atkinson, 2013), or demographic factors, such as a peak in women's participation in the labour force (Miller and Atkinson, 2013). Some studies actually find that the net effect of new automation technologies on labour demand is positive due to increasing product demand and spillover effects (Gregory et al., 2016). In the manufacturing sector specifically, studies find more robust results for decreased employment as a result of automation adoption (Acemoglu and Restrepo, 2017; Dauth et al., 2017; Mann and Püttmann, 2018). However, one of these studies point out that job losses in manufacturing were fully offset by job growth in the services sector (Dauth et al., 2017), and another one highlights that the net effect of automation on employment is positive due to job growth in the services sector (Mann and Püttmann, 2018). Moreover, the reduction in employment in most advanced economies is consistent with the overall historical trend of a decline in manufacturing employment since the 1970s, and has not accelerated since the introduction of the new automation technologies. This gives us reason to believe that other factors, such as the shift to services, offshoring of manufacturing to developing countries, and increased international competition in manufacturing – which some of the above studies highlight – have been equally, if not more important, in explaining the decline in manufacturing employment in advanced economies. There are also studies that find an increase in manufacturing employment due to automation, such as Koch et al. (2019). Using a panel dataset of manufacturing firms in Spain over 1990–2016, they found that firms that had adopted robots generated jobs because output gains were much larger than the reduction in the labour cost share.

On a global scale, UNIDO (2019) calculates that the annual growth in the stock of robots had a positive but small effect on employment growth (mostly in manufacturing activities) from 2000 to 2014. The literature investigating the employment effect of automation in developing countries is scarce. However, in the case of developing countries in Asia, the Asian Development Bank has provided some recent figures. They find that new technologies (not specifically automation technologies) had a net positive impact on employment in 2005–2015, displacing 101 million jobs but creating 134 million jobs (ADB, 2018). Similarly, a study by Dutz et al. (2018) found that manufacturing firms in Latin America that invested in new ICT technologies experienced net job gains.[3] Generally, reports from international organisations (e.g. ADB, 2018; UNCTAD, 2017; UNIDO, 2019; World Bank, 2016) note that most AI-driven automation technologies are developed and used in advanced economies, and have yet to make a significant inroad into developing countries. Ernst et al. (2018) argue that the adoption of AI-driven automation technologies in developing countries have the potential to increase opportunities for productivity growth and hence employment growth, similar to what the above studies have found with respect to digital technologies more broadly.

In summary, while some studies confirm that AI-driven automation has displaced jobs in certain industries, there is no conclusive evidence to suggest that the overall impact on employment has been significant, either in advanced economies or in developing countries. Some studies actually highlight the job-creating potential of automation technologies due to positive effects on output and productivity. It should be noted that the adoption of AI-driven technologies is still low, especially in developing countries, so empirical studies cannot capture their full effect yet.

2.4. Is new automation technology causing reshoring?

There is a concern that as new technologies reduce the need for cheap labour, offshoring of labour intensive production to developing countries may be reversed – in other words, 'reshored' (Gray et al., 2013; Hallward-Driemeier and Nayyar, 2017). Reshoring may be defined comprehensively as "re-concentration of parts of production from own foreign locations as well as from foreign suppliers to the domestic production site of the company" (Kinkel and Maloca, 2009, p. 155). Although this phenomenon is not new, the literature studying it is somewhat sparse (Stentoft et al., 2016). Evidence of reshoring is fragmented, possibly because the internal balance of production between sites and suppliers is dynamic and difficult to quantify (Fratocchi et al., 2014), and companies may fail to self-report reshoring, which some consider a failure of previous offshoring decisions (Kinkel and Maloca, 2009). Different definitions, methods and time-periods make comparisons between studies difficult.

Kinkel et al. (2017) present some of the most important findings from surveys on the topic of reshoring. Most evidence suggests that

[3] We acknowledge that 'new ICT technologies' are certainly not a perfect proxy for automation.

while reshoring does occur (Tate, 2014), it is on a smaller scale than new off-shoring activity (De Backer et al., 2016; Kinkel et al., 2017). Additionally, in those countries that have reshored some production, like the United States and the United Kingdom, it is a result of a number of factors beyond just cost-savings due to new automation technologies. Examples highlighted in the literature include: increasing fear of intellectual property theft, the rising cost of labour in many East Asian countries, and leaner supply chains associated with locating manufacturing closer to end consumers (Bailey and De Propris, 2014; Ellram et al., 2013; Tate, 2014).

Evidence that reshoring may be enabled by the use of high-tech automation and digital technology is highlighted in some studies (Arlbjørn and Mikkelsen, 2014; Dachs et al., 2019), but in practice it is still a rarity (Ancarani and Di Mauro, 2018). For example, Dachs et al. (2019) find that among 1700 manufacturing firms in Austria, Germany, and Switzerland, only 4% have reshored some activities. Given that this phenomenon was not explicitly studied before the 2000s, there is not much evidence to show that recent changes have accelerated it. And even if technology can make production in high-wage countries competitive, there are still numerous barriers to reshoring (e.g. lack of skills or suppliers) (Wiesmann et al., 2017).

In summary, while there is some evidence that reshoring is taking place, it is on a smaller scale than new offshoring. There is limited evidence to suggest that automation is accelerating reshoring. Other drivers and barriers to reshoring are highlighted as more important in the literature.

2.5. Forecasting the future impact of automation on employment

As we highlighted in earlier sections, while we have seen rapid developments in new automation technology, especially that which is AI-driven, the implementation is not yet widespread. As a result, quite a few studies have been published in recent years that estimate and/or predict the impact of automation on employment in the future – so-called forecast studies. In Table 1, we have collated key points from influential studies. The most important point we would like to highlight about these studies is that their estimates for automation and job losses in the future vary widely. An obvious explanation for this is that the studies use different data, apply different methodologies, and study different regions. Another important reason is that some studies talk more explicitly about employment impact, recognising that technical automation potential does not equate with job losses. This point often gets lost in media and hype narratives about the ’Robo-apocalypse’ (see Willcocks (2020) for a good discussion).

The studies also apply varying degrees of rigour to their calculations. The most cited paper based on rigorous and systematic calculations is Frey and Osborne (2017) (results from which were first published as a working paper in 2013). Based on 2010 data for 702 occupations in the United States, they found that 47% of occupations are under high risk of being computerised. The methodology of Frey and Osborne (2017) has come under a lot of scrutiny (see for example Borland and Coelli (2017) and Willcocks (2020)). Most importantly, the paper uses a binary distinction in their sample of occupations, labelling them “automatable” or “not automatable”. In reality, many jobs fall in between, as certain tasks and activities in a job can be automated, while others in the same job cannot. Using a task-based rather than an occupation-based approach, Arntz et al. (2016) find that only 9% of workers in the United States (and 6–12% in all OECD countries) are at high risk of automation. Another granular study taking a task-based approach has been carried out by the McKinsey Global Institute (Manyika et al., 2017a). For 800 occupations, the time spent on various activities and the required level of proficiency in 18 capabilities are estimated (relying on mostly US labour market data but constructing a global model). To determine which activities are automatable, the performance of current technology in all these capabilities are investigated as well. The study finds that while 60% of occupations worldwide contain at least 30% activities that are automatable, only 5% of occupations have >90% automatable work. The report highlights that although all skill levels contain some work activities that can be automated, automation seems to disproportionately affect lower-skilled workers, particularly in manufacturing (e.g. welders >90% and sewing-machine operators >98%). In general, economies with large manufacturing sectors face a higher risk of automation. Building on Manyika et al. (2017a,b) estimate that 75 million to 375 million workers (3–14% of the global workforce) will need to switch occupational categories by 2030. This interval does not significantly differ from the scale of historical shifts in occupational structures.

Manyika et al. (2017a,b) also go beyond simply using technical automation potential to predict the degree of automation adoption in the economy. They identify technical feasibility, financial feasibility and regulatory/social barriers as factors impacting adoption of technologies. Taking these factors into account, both early and late scenarios of adoption are estimated. The early scenario for automating over 50% of current human work is 2035, while the late scenario is 2065. Implementation challenges are very real in the context of automation: some studies have found that several organisations are slowing

Table 1
Key figures from studies estimating automation of jobs/tasks and future job losses/gains due to automation. Source: Authors’ own work.

Arntz et al. (2016)	9% of jobs in the United States (and 6–12% of workers in all OECD countries) are at high risk of automation.
World Bank (2016)	From a technological standpoint, two-thirds of all jobs in developing countries are susceptible to automation, but unemployment effects are moderated by low wages and slow technology adoption.
Chang et al. (2016b)	In ASEAN-5 countries (Cambodia, Indonesia, the Phillippines, Thailand, and Vietnam), 88% of all jobs are at either high – or medium risk of automation.
Manyika et al. (2017a) and Manyika et al. (2017b)	60% of all occupations in the world contain at least 30% technically automatable activities. However, reskilling is more likely than large-scale unemployment (Manyika et al., 2017a). By 2030, 75–375 million workers in the world will need to switch occupational categories. This does not break with historical trends of workforce restructuring (Manyika et al., 2017b).
Frey and Osborne (2017)	47% of workers in the United States are at high risk of losing their jobs to automation/computerisation over the next few decades.
PWC (2017)	The share of jobs potentially at risk of automation by the early 2030s: 30% in the United Kingdom, 38% in the United States, 35% in Germany, and 21% in Japan. Because new automation technologies will create jobs, and because of practical barriers to the implementation of automation, the net impact on employment is unclear.
World Economic Forum (2018)	In 2018–2022, 75 million jobs may be displaced by a shift in the division of labour between humans and machines, while 133 million new roles may emerge that are more adapted to the new division of labour between humans, machines and algorithms.

down in their ability to absorb further technological change, and that getting a digital technology to a workable, safe, commercial level and then engineering the technology for specific use cases can take several years (Lacity and Willcocks, 2017; Willcocks et al., 2013; Willcocks, 2020). In developing countries, practical and economic barriers to implementation are even higher. For example, UNCTAD (2017) p. 39 states that, “Most existing studies overestimate the potential adverse employment and income effects of robots, because they neglect to take account of that what is technically feasible is not always also economically profitable”. The report goes on to show that many sectors of the economy in developing countries that have a high technical feasibility of automation, like textiles/apparel and food/beverages, have a low economic feasibility of automation, largely because of the low cost of labour in those industries. Additionally, new automation technology will create jobs as well as displace jobs. This is confirmed both by studies highlighted earlier in this paper and some of the forecast studies listed in Table 1, especially those that take a global approach, such as Manyika et al. (2017b), PWC (2017), World Bank (2016), World Economic Forum (2018). The combination of barriers to adoption and the job-creating potential of some new automation technologies is why many forecast studies predict a restructuring of the labour force over time, rather than mass-scale unemployment – at least among those studies that take a global outlook and/or talk explicitly about the net effect on employment.

While some of these forecast studies are more detailed than others, all of them are bound to apply simplifications by virtue of being high-level, ignoring industry-specific and country-specific challenges and conditions. For example, Manyika et al. (2017a), although one of the more detailed studies, does not specify the level of industrial detail that the model considers (manufacturing appears to be aggregated), it only looks at wage differentials as a barrier to adoption in the case of developing countries, and does not consider shifts in global trade patterns. It is fair to say that the literature has so far provided insufficient attention to industry-specific and country-specific circumstances, particularly in developing countries. We hypothesise that the reality is likely to be highly specific to the industry and region in question. Capturing some of these specificities would be possible if the forecast studies were complemented with qualitative case study research. The rest of this paper is devoted to such a qualitative investigation, looking at the case of the apparel industry in South Africa.

3. Methodology underpinning the case study

Our literature review showed that many of the studies that have fuelled fears about the job-displacing potential of automation use questionable assumptions and, at times, opaque methodologies. And the more granular studies, like the McKinsey study, still apply high-level aggregate approaches which are bound to ignore many country-specific and industry-specific enablers and barriers to automation. In order to test how theoretically derived ‘automatability’ and adoption compare to the practical feasibility of automation and challenges of implementation, we have chosen to focus on a specific industry in a specific developing country.

Data was collected and analysed through the use of qualitative methods. Compared to quantitative methods, qualitative methods has several qualities that makes it more suitable for capturing realities that are specific to an industry or a region. Most importantly, it has a more flexible structure (e.g. it is more accommodating to open-ended and emerging questions) and focuses more on rendering the complexity of a situation (Creswell and Clark, 2000). Our qualitative approach was undertaken in an abductive manner (Charmaz, 2006; Klag and Langley, 2013), which allowed us to (a) begin our initial data collection with aforementioned theories and hypotheses as heuristic devices; (b) keep an open mind to capture events that would possibly refine or stand in contrast to initial theories; and (c) triangulate data sources and their subsequent interpretation (Jick, 1979). The point on triangulation is an important one, as qualitative data has an inevitable subjective bias.

The apparel industry has been chosen as it is a critical case[4] to test how the capability-based estimates of automatability relate to practical automation challenges. The industry is identified as one of the highest at risk of automation due to the routine manual work content of sewing machine operators (Table 2). In South Africa, the apparel sector is considered important because it could create jobs that will help address unemployment and poverty. The government has recently invested significantly in the industry, and its importance to national development makes it an interesting and useful case to study. Although South Africa could not be described as a ‘standard’ developing country in the apparel supply chain, the country’s industry has transformed from a labour-intensive structure to one using much more automation in the last two decades. Companies are trying to use as much automation as they can, backed by government funding. This process of transformation means that South African businesses are aware of what new automation is becoming available, as well as being able to present evidence of how increasing use of recent automation has impacted employment. In order to investigate how production automation technologies are expected to impact manufacturing employment in the South African apparel industry, a number of supporting questions needed to be answered: what automation is currently available, what automation is being used in South Africa, why isn’t more automation used, how has the use of automation impacted employment in the industry, and what new automation is being developed?

3.1. Data sources

Interviews are one of the most important sources of data in case study research (Yin, 2009). Semi-structured interviews are conducive to exploratory studies like this one (Saunders et al., 2009), as they are more flexible and allow important themes to emerge during the interview. Semi-structured interviews conducted with stakeholders from the industry therefore served as the main data source for our case study. Open-ended questions allowed interviewees to offer their perspective on the problem, with follow-up questions being used to clarify arguments.

Interviews were carried out during a 3-week field-trip to South Africa (21 June 2018 – 16 July 2018). Overall, 26 interviews were conducted (Table 3). Interviewees were chosen to represent different viewpoints and thereby triangulate arguments and deal with bias due to vested interests (e.g. business owners versus union representatives and government representatives).

Five of the manufacturers interviewed were large firms (>500 people), belonging to a group of about 20 larger companies in the South African apparel industry. Two smaller companies were also interviewed (<50 people). While this cannot be considered a representative sample, since the majority of the industry consists of smaller companies (TIPS, 2017), the companies chosen are expected to be more sophisticated and to be able to talk from experience about the problem being studied. Companies with a range of different product portfolios were chosen to

Table 2
Predictions of automation potential in the apparel industry. Source: Authors' own work.

Study	Prediction relating to apparel industry
Manyika et al. (2017a)	98% of work content automatable
Frey and Osborne (2017)	89% likelihood of automation for sewing machine operators

[4] A critical case is a “strategic case” which allows generalisation based on logical deduction of the type “If it is not valid for this case, then it is not valid for any (or only few) cases.” (Flyvbjerg, 2006).

Table 3
Interview sample for case study. Source: Authors' own work.

Role of interviewee	Number of interviewees
International equipment manufacturers	2
Equipment suppliers (local)	2
Local consultants for industry	4
Foreign consultants for industry	2
General management consultants with focus on automation	3
Management representatives of South African manufacturers	9
Government representatives	3
Labour union representatives	1

strengthen our study as an industry-specific one. Four of the factories focused exclusively on one type of garment, while the remainder produced a mix of products (e.g. shirts, ladies fashion, and trousers). In addition to this purposeful sampling, we used a snowballing technique whereby we asked for relevant contacts at the end of interviews. Taken together, our sampling approach allowed us to explore the perspectives of different groups, thereby minimizing the potential subjectivity issues latent in qualitative research.

Multiple data sources were used to verify arguments from interviews. Direct observation of the production process and of production equipment during five shop-floor tours were an important data source and gave us insight into the apparel production process. For example, we could verify the degree of labour-intensity in the production process. Newspaper articles and company websites/policy statements were used to corroborate hypotheses about the impact and stage of development of new technologies. During the field trip, we enquired unsuccessfully with government and consulting sources about relevant quantitative data to verify arguments. Some data was proprietary and could not be shared for the purposes of this study, public data is not considered reliable by experts,[5] many of the relevant factors are not measured, and large segments of the industry are illegal/informal and cannot be assessed.

NVivo software was used to code the interview data. This approach is an example of the hypothesis pattern-matching strategy outlined by Yin (2009) (pp. 133–139). The case study is presented in the form of a question-answer format in a sequence that presents the logic of a theoretical understanding of the case (see Yin (2009), pp. 170–178). Figures which show the prevalence of opinions/arguments presented by interviewees are used as evidence. As the reader will see, the number of interviewee responses differs from figure to figure because not all interviewees responded to each question, and some questions allowed for multiple responses (e.g. Fig. 3, Fig. 4, and Fig. 5). If possible, a wider and more systematic survey should be conducted to complement this approach in future work.

4. The case of the apparel industry in South Africa

4.1. What level of automation is being used in South Africa?

The South African apparel industry has historically under-invested in capital upgrading,[6] [7] but major targeted investments have been made through recent government grants.[8] The firms chosen for the case represent the most sophisticated in the South African industry, and five out of eight firms have used government grants to purchase new equipment since 2010.

During our visits, we recorded the equipment used for various production stages and found that two of the companies were still using basic or mid-level technology for all their processes.[9] The majority of companies have adopted some advanced technologies. However, it should be noted that even the most automated factories did not use the most advanced technologies available.[10] Most of the operations in sewing assembly are still performed manually in all of the companies, with only some of the available automats being used. This shows that although the companies have adopted automation, there is still scope to adopt more.

Comparing the level of automation in South Africa to other countries is difficult because limited benchmarking has been performed and the methods are highly subjective. We therefore rely on the reported observations of the interviewees (Fig. 1). The majority of interviewees who commented on the topic felt that the firms in our sample are more advanced than most firms in low-cost countries (e.g. Bangladesh) in terms of automation, but that some other countries (e.g. China or Turkey) are considered slightly more sophisticated. China in particular appears to be investing heavily in automation.[11] There is however considerable heterogeneity between companies in other countries, with some factories in Bangladesh rivalling the best in South Africa.[12]

4.2. Why isn't more automation used?

The most important reasons for not using more automation relate to financial barriers (Fig. 2). Some non-financial barriers are also considered important (Fig. 3). Financial barriers refer to access to capital, and variables affecting sales output and the business case for the investment (e.g. consistency and volume of orders, power relationships within the value chain, investor confidence, and fashion changes). Non-financial barriers refer to limitations of currently available technology, skills and management capability shortcomings, and infrastructure issues.

Access to capital is problematic for South African firms, particularly for smaller firms or informal firms which have proliferated because of the apparel industry structure. This is typical for developing countries (Beck and Honohan, 2008). A lack of investor and business confidence in the country adds to this.[13] The apparel sector is particularly unattractive for investment on account of low margins and profitability in the global market,[14] and its recent history of decline in the country.[15] Government support in the form of grants to support capital upgrading has helped, but since it is scaled to value-added and limited to wage compliant firms, many smaller manufacturers do not receive enough money to buy new machines.

In order to make a business case for an automation decision, there

[5] One key government official noted, "I believe most of the data out there is worthless", citing self-reporting by companies, a lack of clear definitions and limited auditing of calculations as reasons.

[6] Interview with CEO, local industry consulting firm, 16/07/18. Also, assets in the clothing, textiles, footwear and leather industries only increased by 5% between 2008 and 2015 (TIPS, 2017).

[7] Capital upgrading refers to the addition of a permanent structural change or the restoration of some aspect of a property (normally capital equipment) that will enhance the property's overall value.

[8] R4.8 Billion = US$360 million have been distributed to 516 companies in the textiles value chain, and total assets have increased to R7.2 billion = US $540 in these companies since 2011 (Smith, 2017).

[9] Using the levels of technology defined in IMT (2018).

[10] Based on Atlanta Attachments product breakdown (AA, 2018).

[11] Interview with executive, American equipment manufacturer (13/07/18), claimed that most sales are now in China, agreeing with the survey results of Xu et al. (2017) which showed that Chinese garment manufacturers are more likely to upgrade technology than relocate.

[12] Interview with CEO of local manufacturing and international sourcing company, 29/06/18.

[13] DTI (2017) shows low investor confidence index.

[14] ILO (2014) and low return on assets in South African apparel value chain (TIPS, 2017).

[15] Between 2003 and 2013 the number of employees halved and the number of firms fell by 20% as a result of trade liberalisation and low-cost competition (Morris and Barnes, 2014).

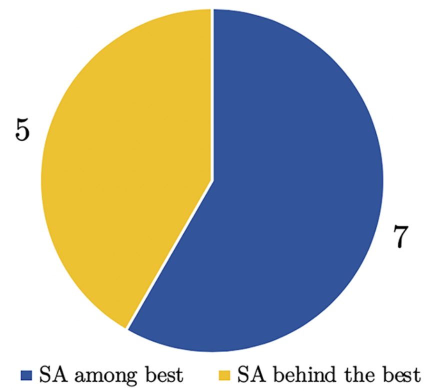

Fig. 1. Interviewees' opinions (12 responses) on level of automation in South African (SA) apparel industry relative to other producing countries.

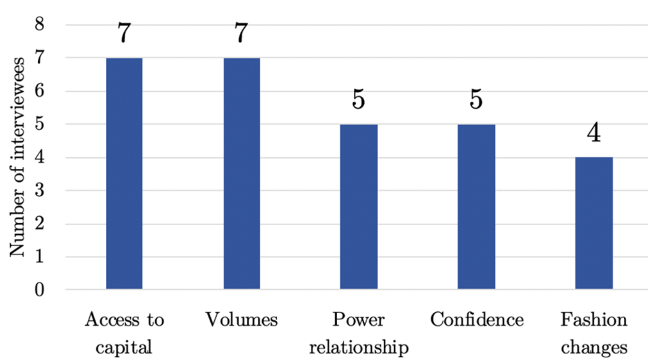

Fig. 2. Main financial barriers mentioned by interviewees.

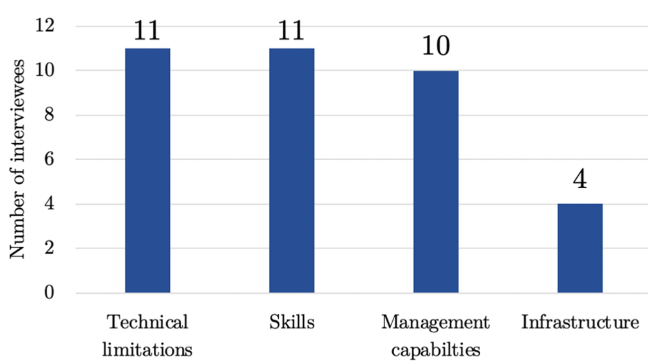

Fig. 3. Main non-financial barriers mentioned by interviewees.

needs to be enough work for the machine, which in turn requires volumes and consistency in orders. Interviewees explained that the volumes of production in the South African industry are inadequate to justify increased automation – they would be unable to utilise the equipment sufficiently. This can be attributed to the relatively small scale of the industry in the country and the strategic emphasis on flexible production, with most of the visited factories producing a large variety of different products in smaller batches, rather than long runs of the same garment/style. The difference in volumes is a major reason why more automation is thought to be more feasible in Chinese factories.

Variability of order volumes is a problem common to the apparel industry globally (ILO, 2014). This is the result of the buyer-driven supply chain structure, with a low commitment to relationship and orders to individual suppliers decided largely on a cost basis from the buyer side. Fluctuating labour costs and exchange rates mean that annual orders to individual suppliers can differ drastically. Additionally, clothing fashion and styles change frequently, particularly in the mid-range value segments in which most of the companies interviewed are active (e.g. ladies fashion). Together with the high variability in order volumes typical of the industry, this means that investing in specialised automation which is designed for a specific style or material is inherently risky.

Technical limitations of the currently available automation technology are thus a major factor in the low adoption – with machines being designed for specific styles and materials, and generally unable to adapt easily to new fabrics.[16] These limitations mean that companies tend to invest only in machines common to the majority of their products, which are robust to style changes or are used in standard products.[17] Machines for some processes cannot deal well with the variation of input materials, forcing companies to retain some manual processes (e.g. layup and cutting of checked/striped material).

The shift to digital control and computerisation require skills that most technicians in the industry do not have. Breakdowns often require support from local or overseas contractors, increasing costs and downtime. This appears most common in developing countries (Chang et al., 2016b). A number of the interviewees identified management ignorance of new technologies and a defensive vision for the growth of their businesses as a key barrier to investing in new technologies.

Using more advanced automation requires improved physical and digital infrastructure. In South Africa, internal company infrastructure is a big problem, particularly with smaller and less sophisticated firms who may be operating in run-down factories with minimal IT infrastructure.[18] Some interviewees mentioned energy infrastructure problems in rural areas.

In summary, financial factors are very important in preventing firms from adopting automation. While some are specific to South Africa, some are due to the highly dynamic nature of the apparel industry. Technical limitations of current automation are also a major barrier. From a developing country perspective, the lack of maintenance skills and infrastructure are also be important barriers. These findings agree with those reported in the literature on this industry (Nayak and Padhye (2017), p. 7).

4.3. Has using automation reduced employment in the industry?

Interviewees emphasised that improving productivity was the dominant motivation for using automation technologies (Fig. 4). Numerous examples were given of how a machine is able to replace many workers (e.g. an automatic cutting machine can replace up to 10 workers[19]). However, in the case of the firms interviewed this did not appear to reduce employment; the vast majority of interviewees stated that they believe increasing automation led to increased employment in their businesses and the industry as a whole (Fig. 5). Several companies emphasised that automation had enabled significant business growth, allowing them to drastically increase their employment, e.g.:

> *"[Using more automation] has allowed us to triple our business and almost triple our number of workers."*[20]

Only one company mentioned that automation led to decreased employment, and that this was related to non-production automation

[16] Interview with executive, American automation supplier, 13/07/18.
[17] The factory which specialised in denim jeans had the most automation due to standardised products.
[18] Interview with CEO, local industry consulting firm, 16/07/18.
[19] Interview with local equipment salesman, 6/07/18.
[20] Interview with manager, local manufacturer, 9/07/18.

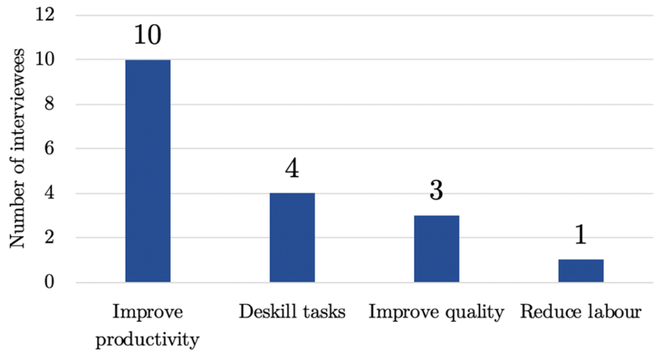

Fig. 4. Main motivations for using automation.

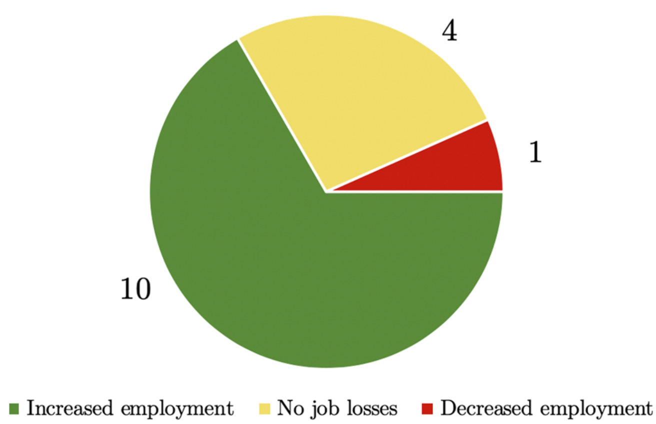

Fig. 5. Reported employment effect among interviewees (15 responses) of automation use in the South African apparel industry.

and office/administrative staff.[21] These results agree with the assessment of the government intervention measures, which include major funding for new capital equipment. The Department of Trade and Industry (DTI) claims that at least 4600 jobs have been created in the clothing, textiles, footwear and leather industries as a result of the interventions and that the job losses of the 2000s have been stabilised, pointing to recent job growth in the apparel industry since 2015.[22] Additionally, recent data and analysis show that value-added/employee and sales values have increased robustly in the firms consistently receiving government support (Smith, 2017).[23]

The explanation for why automation did not lead to job losses despite substitution was unanimously presented by all interviewees who commented on this topic. Increasing automation has allowed the firms to increase their productivity and reduce labour costs per item. This is translated into lower prices for the customer and increased product demand as a result. Seeing that the automation currently used still requires some operators and is only applicable to certain production steps, the remaining steps require additional workers to increase overall output and meet the new demand. Because the skill barriers to transferring from one task to another are low, it is easy for the substituted workers to shift to the new roles which arise.

This benign effect of automation is clearly connected with an expansionary business strategy, which may be due to the ambition of the top-tier companies sampled, or attempts to use automation to increase output and spread overhead costs. This is especially relevant in the apparel industry, where low margins drive the need to utilise assets to the maximum. Interviewees claimed that price reductions always increased sales in this market since their main customers (domestic retailers) would always choose to buy more from them and import less if their prices were competitive relative to imports. Although it is not possible to determine from aggregated data whether the growth in sales of the interviewed companies is also negatively affecting other local manufacturers, whose overall output continues to decrease (Smith, 2017), the strong perception of all stakeholders that they are substituting imports seems to lend credence to this argument. Official statistics support this view since they show that employment in the sector has stabilised since 2010, coinciding with the beginning of a government grant programme for capital upgrading, the Production Incentive intervention (Cotton, 2017). Some literature suggests that the more advanced companies using more automation are not competing with the more basic companies which focus on different garment types (Nattrass and Seekings, 2013).

The evidence seems to suggest that increased automation has slightly increased employment in the firms which have adopted it in the South African apparel industry, despite strong substitution effects. This is due to the dominating price effect which has allowed them to win market share at the expense of foreign competition. Increased product demand and expansionary business strategies have created more jobs in these companies than have been substituted by automation. None of the interviewees were aware of cases in their industry where increased automation caused significant job losses.

4.4. Does new automation threaten jobs?

Most interviewees expect that processes in apparel manufacturing will require significant human labour for the foreseeable future.[24] Arguments for this view include the expectation that technological improvements will only be incremental and the fact that new automation technologies are not applicable to many tasks. Additionally, the adoption of new technologies will be slow due to high costs relative to labour costs. In addition to all of the companies interviewed, the four technical experts we consulted unanimously shared this view.

Many sewing automation suppliers have concentrated on using new technology to incrementally improve their products, increasing the speed of operation, designing solutions for an extended range of specific operations, as well as modifying machines to deal with new style and material requirements. The ability to fully automate processes and to automate the sewing assembly of garments is limited primarily by the complexity of handing fabric. Unlike stiff materials (e.g. metal) which can be easily gripped and moved by robotic handling devices, fabric is difficult to handle because it is flexible and distorts. The sewing process involves a number of complex manipulation tasks (e.g. guiding material through a machine process) that require variable input from the operator (e.g. different forces on parts being joined) which cannot yet be automated (Nayak and Padhye (2017), pp. 18–20). Robotic systems currently in use are highly bespoke and still limited to a few simple process steps.[25]

This evaluation of the technology stands in contrast to some of the literature we reviewed (e.g. Chang et al., 2016b; Frey and Osborne, 2017; Manyika et al., 2017a) and media coverage on this topic, which expects widespread automation of whole-garment sewing in the near future. One company in particular is highlighted by these source: Softwear Automation, a start-up that uses computer-vision systems and micro-robotics to assist the sewing, and vacuum panels to handle fabric (Guizzo, 2018). The start-up has a US$7.5 million grant, venture capital funding and 30 employees (Softwear, 2018). It claims that it will be able to produce a t-shirt every 22 s using one operator, and has signed

[21] Interview with CEO, local manufacturer, 18/07/18.

[22] Private correspondence with local government grant-fund manager, also Smith (2017).

[23] It should be noted that a major criticism of the grants is that they only support the best performing businesses.

[24] Only the labour union representative expressed fears of job losses as a result of increased automation.

[25] Interview with executive at American equipment manufacturer, 13/07/18.

development agreements with a number of multinational companies. However, an initial implementation project seems to have been delayed, no evidence of successful t-shirt prototypes currently exists, and the publicly available information is vague as to the specifics of the process and how the 3D handling of garments will be managed. The production of t-shirts is much more complex than what available information suggests the system is currently capable of producing.

While the full automation of garment sewing would obviously have major implications for jobs in developing countries, the above-mentioned studies seem to exaggerate the impact, insufficiently accounting for the significant technical and commercial challenges that need to be overcome before these automation technologies can be widely adopted.[26] It should also be noted that these technologies focus on t-shirts, which are among the simplest garments.

The whole-garment knitting machine, however, is one piece of technology that can automate aspects of sewing. The automation literature has surprisingly not paid much attention to it. This machine knits pieces of garments together into one piece, avoiding the need to assemble a garment by sewing. The technology has been commercially available for more than 20 years and is being used by several manufacturers. However, its adoption is limited by high machinery cost, limited style flexibility, and slow knitting speeds. It is primarily used in high-cost novelty and fashion production, although it appears to be entering mainstream retail.[27] This technology was perceived by two industry experts and several company managers that we interviewed as a serious threat to sewing in developing countries in the mid- to long-term, although significant investment and supply chain readjustments (e.g. changing design styles) will be needed.

In summary, advances in automated sewing are incremental, largely because many technical challenges in handling of materials remain unresolved, even with new developments within AI. The literature underestimates the major commercial challenges that lie ahead of attempts to fully automate garment sewing, not sufficiently considering the start-up nature of the firms behind these efforts". A more serious threat may be posed by whole-garment knitting machines, which are already in use and eliminates the need for sewing. But we will need to see substantial investments and reconfiguration of supply chains (i.e. evolution of new companies to serve the market, development of new capabilities for the retailers/brands) before this technology can displace traditional methods of production.

4.5. Discussion

The apparel industry is still labour-intensive. Current automation technology is only able to automate some of the tasks in this industry, is constrained to specific styles/materials, and still requires operators. However, although South African firms have adopted automation, they are not using all of the available technology. This is due to barriers specific to either South Africa, the global apparel industry, and/or developing country contexts. In Table 4, we identify a number of barriers specific to different contexts, based on our data analysis and literature review as a whole. We use the categories of financial and non-financial barriers introduced earlier. The identification of the importance of these barriers is a key finding of our study.

Most of these barriers are not considered by the forecast studies, despite their importance. For example, in the McKinsey study (Manyika et al., 2017a) developing countries are assumed to have the same technology adoption behaviour as advanced economies, with only wage differentials being the exception. The significance of additional barriers suggests that automation adoption will be on the lower end of the spectrum of predictions for this industry, particularly for developing countries. It is expected that some additional barriers will exist in every manufacturing industry due to the particularities of supply chains.

A major limitation of our study is that the level of automation in our sample of firms cannot be compared rigorously to other developing countries. However, the opinion of interviewees suggests that our sample of firms have adopted more automation than most developing countries. This suggests, as highlighted by the World Bank (World Bank, 2016) and McKinsey (Manyika et al., 2017b), that the use of automation technologies in developing countries is unlikely to be causing significant job losses in these countries.

The most significant finding of our case study is that none of the interviewees reported job losses as a result of automation. This was attributed to increased productivity and increased sales. The case therefore illustrates a mechanism by which increasing productivity in a sector can increase employment in that sector, aligning with the arguments of Bessen (2017) and highlighting the role of demand elasticity and price flexibility (Chang et al., 2009). However, rather than increasing consumer demand, the South African industry is increasing employment by 'winning' more sales from foreign competition in the market by offering lower prices, illustrating the trend suggested by the model of Rodrik (2016). This trade-competition effect and demand-response role of supply chain intermediaries should be considered in addition to the concept of 'demand evolution', general demand and price elasticity, and inventory practises (Bessen, 2017; Chang et al., 2009) in determining whether automation will increase/decrease within-country employment in a sector. The positive effect of automation on employment in this industry appears to be enabled by the buyer-driven supply chain which leads to a high level of demand-mobility and price-driven competition. The extent of productivity gains from automation and how the remaining work is redistributed need to be evaluated and compared to increased demand in order to determine the impact on overall employment in a sector.

These findings illustrate the importance of differentiating between different sectors in manufacturing, since the way demand responds is highly dependent on the product and supply chain. This is not done in the McKinsey forecast (Manyika et al., 2017b). Given the experience of the South African apparel industry, we expect that countries which adopt more automation in their apparel industries will be able to increase their market share and employment, all other factors remaining constant.

The case also highlights the importance of firm strategy in determining the employment impact of automation: in addition to the price-reduction strategy, automation was mostly part of an expansionist strategy which intended to increase overall production and employment. It is conceivable that in firms with a less strategic vision, whose primary aim of introducing automation is to maintain output but reduce labour costs, the effect would be different.

Advances in automated sewing appear to be incremental and it is unclear how AI capabilities will solve the technical challenges related to handling fabrics. The likelihood of sewing machine operators losing their jobs due to automation appear far less likely than predicted by some forecast studies (e.g. Frey and Osborne, 2017; Manyika et al., 2017a). More detailed capabilities that capture the challenges related to handling fabric are needed for accurate predictions.

Additionally, much of the literature and the broader media have failed to emphasise the prototype nature of the technologies/companies that they view as a threat to the industry, and should likewise be read with some caution. The research also revealed that a technology which will render sewing obsolete rather than automate it is perceived as a more serious threat to the industry. However, widespread adoption for mainstream retail is expected to be slow due to the required supply chain reconfiguration; many types of garment can still not be produced using this technology (e.g. woven shirting). While this is a single industry case, it illustrates the potential shortcomings of high-level

[26] Technical experts interviewed were sceptical about how commercially ready Softwear's products are.

[27] E.g. Max Mara (high end fashion, Italy), Adidas 'knit-for-you' (experimental in-store knitting) in 2016/2017, Uniqlo U line (mainstream retail) 2017/2018. Machines are produced by Stoll and Shima Seiki.

Table 4
Barriers to automation adoption in various contexts. Source: Authors' own work.

Barriers		Causes common to:		
		South Africa	Developing Countries	Global Apparel Industry
Financial barriers	Access to capital	Negative industry sentiment	High cost and difficulty for small businesses	Low margins, proliferation of small sub-contractors
	Low order volumes	Small market size, flexible production model	–	Subcontracting leads to smaller orders
	Inconsistency of orders	Focus on fashion segment	–	Changing fashions, buyer-driven supply chain
Non-financial barriers	Technical limitations	–	–	Automation constrained to style/fabric
	Skills	–	Lack of trained maintenance people	–
	Management attitude	Defensive and ignorant of technology	–	–
	Infrastructure	–	Unreliable energy infrastructure	Small subcontractors have poor company infrastructure

capability based forecast studies and suggests that predictions by such studies should be interpreted cautiously, as similar issues may arise in other industries.

We can also gain insight into the question of reshoring in the apparel industry. Growth in employment in South African companies is thought to be import-substituting and winning back market share previously lost to imported goods.[28] While this reshoring represents an opportunity for South African firms, it also reveals that reshoring of apparel manufacturing to Western countries is unlikely to happen at a large scale in the near future. South Africa is currently only able to partially reshore production despite high tariffs (currently at 45%, the maximum permitted by the World Trade Organisation), government subsidised equipment and relatively cheap labour. Based on these findings, the reshoring of production is not thought to be a major challenge to developing countries in the near term, although emerging technologies like whole-garment knitting may change this in the future. It seems more likely that increased use of automation in China will allow it to remain competitive against low-cost countries for longer, slowing labour-intensive industrialisation (cf. Chang et al., 2009; Xu et al., 2017).

4.6. Limitations

In light of our findings, it is important that we clearly spell out the limitations of our study. First, while we are predicting unemployment due to automation to be at the lower end of the forecast scenarios, this is a prediction about the future, just like the forecast studies. Any future prediction about socio-economic change in the long term should be read with caution, including our own, due to the highly uncertain nature of how social and economic change unfolds in the long term. Especially in light of the fact that much of the available automation technology has not been rolled out fully for commercial use, our findings should be interpreted with some caution. We cannot exclude the possibility that reshoring to the West will increase as new automation technology becomes more accessible. More importantly, we highlighted that South Africa, and many other developing countries, have not adopted all available automation technology due to various barriers. If (some of) these barriers were to fall, the results could be different.

Second, while our paper is intended to inform the general debate on the impact of automation on jobs, research so far shows that this impact is highly context-specific. For example, in the United States, advances in AI-driven automation technology has undeniably played a role in stagnating labour demand, declining labour share in national income, rising inequality and lower productivity growth (Acemoglu and Restrepo, 2019). But other countries have not experienced the same impact of automation, or seen the same inroad of automation technologies, as a recent paper by (Gentili et al., 2020) shows, which concludes that the process of robotisation is highly country - and industry-specific. Therefore, we must caution against a generalisation of our results across countries and industries.

Third, our study looked at national employment and did not account for possible jobs lost in other countries as a result of increased productivity (due to automation) in one country. If/when the implementation of automation technology in the apparel industry increases in South Africa, this is not necessarily a win-win regionally as South African apparel companies might simply be stealing jobs from neighbouring countries, such as Lesotho and Mauritius, if we assume a within-firm positive correlation between the level of automation, productivity and employment. As the integration of developing countries in global trade increases (Horner and Nadvi, 2018), and African countries in particular are looking to gain shares of global manufacturing output (Hauge, 2019; Giannecchini and Taylor, 2018), we might see more jostling between countries in an attempt to secure the productive jobs. Then, it is not inconceivable that those countries that are able to rapidly implement new automation technologies will actually increase employment levels at the expense of other countries (i.e. a new type of reshoring debate). However, this discussion extends beyond automation technology, as it is more generally about global competition in manufacturing trade.

Fourth, while our study investigates the impact of automation on levels of employment and job displacement, looking at other aspects of automation's impact on the labour market are equally important. For example, jobs in certain income categories or at certain skill levels might be more susceptible to automation than others, which has consequences for inequality. Especially in the context of developing countries, there is ample scope to further the research agenda on inequality and the distributional consequences of automation.

Finally, due to the nature of qualitative research, in particular that which is based on semi-structured interviews, bias in findings are unavoidable. While we triangulated our sources of evidence to account for this, we cannot completely control for the fact that some interviewees might have vested or political interests underlying some of their answers. For example, a firm representative could have reported inaccurate employment figures to justify an investment in new capital equipment. And, as mentioned, due to our limited sample, we hope that a wider and more systematic survey is carried out in the future to complement this approach.

5. Conclusions

This paper sought to evaluate the threat of automation to employment, focusing particularly on the manufacturing sector in developing countries. We examined this question by critically evaluating the literature and testing predictions made in it through a case study of the

[28] A key limitation is that we cannot assess how many jobs are lost in developing countries as a result of this.

South African apparel industry.

In our literature review, we highlighted that automation not only displaces jobs but also creates jobs through a number of mechanisms. Historically, the jobs created and the new demand unleashed for existing jobs have outweighed job losses, so that increasing automation and productivity have led to increased wealth and overall employment. However, automation can lead to within-sector job displacement and de-industrialisation as we have seen in the case of advanced economies in the last few decades – although the evidence points to factors beyond automation for job losses in advanced economies as well, such as increased international competition.

Many studies predict that the next wave of automation technology, driven in particular by advances in AI, will allow more jobs in a wider range of industries to be fully automated, causing a rise in unemployment. However, the adoption of such technologies so far has been slow, and there is no conclusive evidence yet to show that this is dramatically disrupting the historical pattern of automation's effect on employment. Likewise, claims that new technology is reversing the trend of offshoring to developing countries (i.e. reshoring) are not supported by strong evidence, and it appears that offshoring of production still dominates. Additionally, while many studies predict job losses, other studies cation against such claims, instead predicting workforce restructuring or reskilling.

Seeing that many recent forecast studies are global in outlook and apply opaque methodologies, which are bound to ignore many country-specific and industry-specific conditions/barriers to implementing automation technologies, our project used a case study to explore the specific drivers and barriers to using automation in an industry in a developing country. The apparel industry was chosen because it is important to many countries' industrialisation, and because high technical automation is predicted in many of the forecasts. South Africa was chosen as it is among those few developing countries adopting new automation technologies in the apparel industry. Stakeholders in South Africa therefore have an awareness of how automation impacts employment, what new automation is becoming available and what barriers there are to using more automation, allowing us to gather insights about the problem. The limited research on this topic carried out in developing countries also motivated us to look at a specific developing country.

Data was collected by interviewing 26 stakeholders in the industry. The augmented data were then analysed using qualitative techniques and coded in NVivo for common themes. A number of important conclusions were drawn from the case study.

The first and most interesting conclusion is that increasing automation is not leading to reduced employment in the South African apparel industry. This is because automation has led to higher productivity, which in turn has led to lower prices and increasing demand from retailers. Second, financial and non-financial barriers specific to South Africa and the apparel industry there prevent or slow the adoption of automation. Third, forecast studies seem to underestimate the challenges of automating sewing work; it is unclear how new technologies will solve the problems related to handling fabric. Predictions do not consider the possibility of occupations becoming obsolete, which appears to be a bigger threat to this industry. These points suggest that the forecasts may be inaccurate for many individual industries and countries, and should therefore be interpreted with caution. Finally, reshoring of apparel production to the West does not seem likely due to the high labour intensity still required in apparel manufacturing. New technologies like 3D knitting may change this for certain product types in the mid- to long-term if the technology matures and can be widely adopted in the apparel industry. Adoption of automation in China may slow the relocation of production to other developing countries.

We also emphasised that the results of our study should be interpreted with caution. Just like the forecast studies, our study's predictions about the future are inherently uncertain. And while this article is intended to inform the general debate on the impact of automation on jobs, it made claims specific to a country and an industry. Therefore, extrapolation across countries and industries needs to be informed by more evidence than just our article.

The literature in this field is still underdeveloped and rich opportunities for further research became apparent during the course of our project. The case study has shown the value of focusing on specific industries, and we think that considering different industries (e.g. automotive) may highlight further barriers and specificities not covered in forecasts and may allow for more realistic predictions of the future impact of automation. This would also allow cross-industry analyses to further explore how supply-chain power relationships and pricing strategy affect growth opportunities and the employment impact of automation. While it is not possible to predict the future with certainty, our paper suggests that unemployment levels will most likely be at the lower end of the forecast scenarios, particularly in developing countries. Automation seems to pose a smaller threat to labour-intensive industrialisation in the near future compared to the greater forces shaping overall global demand/supply and globalisation: demographic, geopolitical, environmental, and health-related developments.

CRediT authorship contribution statement

Jostein Hauge: Conceptualization, Methodology, Validation, Resources, Writing - original draft, Writing - review & editing, Supervision, Project administration, Funding acquisition. **Christian Parschau:** Conceptualization, Methodology, Software, Investigation, Data curation, Writing - original draft, Formal analysis, Data curation, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

We would like to thank all interview partners for sharing their time and insights. We would also like to thank Neeraja Bhamidipati, Karishma Banga, Jennifer Castañeda-Navarrete, and three anonymous reviewers for reading earlier versions of the paper and providing useful feedback that helped improve the paper. Discussions at a workshop on African countries' role in the global economy held at the London School of Economics in January 2020 also helped improve the paper. Julie MacLeavy at Geoforum provided excellent editorial support, handling the submission and review process with great care and attention. The project benefitted from funding support from the Gatsby Charitable Foundation and Christ's College Cambridge. The Institute for Manufacturing at the University of Cambridge provided invaluable institutional support.

References

AA, 2018. Product index. Atlanta Attachments Co. http://atlatt.com/apparel/manufacturers-products.

Acemoglu, D., Restrepo, P., 2017. Robots and jobs: Evidence from US labor markets. National Bureau of Economic Research (NBER) working paper no. w23285 URL http://www.nber.org/papers/w23285.

Acemoglu, D., Restrepo, P., 2019. The wrong kind of AI? Artificial intelligence and the future of labour demand. Cambridge J. Regions Econ. Soc. https://doi.org/10.1093/cjres/rsz022.

ADB, 2018. Asian development outlook 2018 - How technology affects jobs. Asian Development Bank, Manila.

Allen, R.C., 2009. Engels' pause: Technical change, capital accumulation, and inequality in the british industrial revolution. Explor. Econ. Hist. 46, 418–435.

Ancarani, A., Di Mauro, C., 2018. Reshoring and industry 4.0: how often do they go together? IEEE Eng. Manage. Rev. 46, 87–96.

Andreoni, A., Anzolin, G., 2019. A revolution in the making? Challenges and opportunities of digital production technologies for developing countries. URL https://www.unido.org/idr-2020-background-papers.

Arlbjørn, J.S., Mikkelsen, O.S., 2014. Backshoring manufacturing: Notes on an important but under-researched theme. J. Purchasing Supply Manage. 20, 60–62.
Arntz, M., Gregory, T., Zierahn, U., 2016. The risk of automation for jobs in OECD countries. OECD iLibrary.
Autor, D., 2015. Why are there still so many jobs? the history and future of workplace automation. J. Econ. Perspect. 29, 3–30.
Autor, D.H., Dorn, D., 2013. The growth of low-skill service jobs and the polarization of the us labor market. Am. Econ. Rev. 103, 1553–1597.
Autor, D.H., Dorn, D., Hanson, G.H., 2015. Untangling trade and technology: Evidence from local labour markets. Econ. J. 125, 621–646.
Autor, D.H., Levy, F., Murnane, R.J., 2003. The skill content of recent technological change: An empirical exploration. Quart. J. Econ. 118, 1279–1333.
Bailey, D., De Propris, L., 2014. Manufacturing reshoring and its limits: the UK automotive case. Cambridge J. Regions Econ. Soc. 7, 379–395.
Baldwin, R.E., Forslid, R., 2020. Globotics and development. Technical Report. National Bureau of Economic Research.
Banga, K., te Velde, D.W., 2018. Digitalisation and the future of manufacturing in Africa. Overseas Development Institute, London.
Beck, T., Honohan, P., 2008. Finance for All? Access to Finance and Development: Theory and Measurement. World Bank, Washington DC.
Bessen, J.E., 2016. How computer automation affects occupations: Technology, jobs, and skills. Boston Univ. School of Law, Law and Economics Research Paper.
Bessen, J.E., 2017. Automation and jobs: When technology boosts employment. Boston Univ. School of Law, Law and Economics Research Paper.
Borland, J., Coelli, M., 2017. Are robots taking our jobs? Austral. Econ. Rev. 50, 377–397.
Brynjolfsson, E., McAfee, A., 2014. The second machine age: Work, progress, and prosperity in a time of brilliant technologies. WW Norton & Company.
Chang, H.J., Hauge, J., Irfan, M., 2016a. Transformative industrial policy for africa. Economic Commission for Africa, Addis Ababa, Ethiopia.
Chang, J.H., Rynhart, G., Huynh, P., et al., 2016b. ASEAN in transformation: textiles, clothing and footwear: refashioning the future. ILO Regional Office for Asian and the Pacific, Geneva.
Chang, Y., Hornstein, A., Sarte, P.D., 2009. On the employment effects of productivity shocks: The role of inventories, demand elasticity, and sticky prices. J. Monet. Econ. 56, 328–343.
Charmaz, K., 2006. Constructing grounded theory: A practical guide through qualitative analysis. SAGE Publications.
Chiacchio, F., Petropoulos, G., Pichler, D., et al., 2018. The impact of industrial robots on EU employment and wages: A local labour market approach. Bruegel.
Cotton, S.A., 2017. Outlook on the South African Cotton Textile Industry. Cotton SA.
Creswell, J., Clark, V., 2000. Designing and conducting mixed methods research.
Dachs, B., Kinkel, S., Jäger, A., 2019. Bringing it all back home? Backshoring of manufacturing activities and the adoption of industry 4.0 technologies. J. World Bus. 54, 101017.
Dauth, W., Findeisen, S., Südekum, J., Woessner, N., 2017. German robots - The impact of industrial robots on workers. SSRN.
De Backer, K., Menon, C., Desnoyers-James, I., Moussiegt, L., 2016. Reshoring: Myth or reality? OECD Science, Technology and Industry Policy Papers, No. 27 doi:https://doi.org/10.1787/5jm56frbm38s-en.
DTI, 2017. State of Manufacturing 2017. Presented at the Briefing to Portfolio Committee on Trade and Industry.
Dutz, M.A., Almeida, R.K., Packard, T.G., 2018. The jobs of tomorrow: Technology, Productivity, and Prosperity in Latin America and the Caribbean. The World Bank.
Ellram, L.M., Tate, W.L., Petersen, K.J., 2013. Offshoring and reshoring: an update on the manufacturing location decision. J. Supply Chain Manage. 49, 14–22.
Ernst, E., Merola, R., Samaan, D., 2018. The economics of artificial intelligence: Implications for the future of work. ILO Future of Work Research Paper Series 5, 41.
Flyvbjerg, B., 2006. Five misunderstandings about case-study research. Qualit. Inquiry 12, 219–245.
Ford, M., 2015. The rise of the robots: Technology and the threat of mass unemployment. Simon and Schuster.
Fratocchi, L., Di Mauro, C., Barbieri, P., Nassimbeni, G., Zanoni, A., 2014. When manufacturing moves back: Concepts and questions. J. Purchasing Supply Manage. 20, 54–59.
Frey, C.B., Osborne, M.A., 2017. The future of employment: How susceptible are jobs to computerisation? Technol. Forecast. Soc. Change 114, 254–280.
Frey, C.B., Rahbari, E., 2016. Do labor-saving technologies spell the death of jobs in the developing world? Prepared for the 2016 Brookings Blum Roundtable.
Gentili, A., Compagnucci, F., Gallegati, M., Valentini, E., 2020. Are machines stealing our jobs? Cambridge J. Regions Econ. Soc.
Giannecchini, P., Taylor, I., 2018. The eastern industrial zone in Ethiopia: Catalyst for development? Geoforum 88, 28–35.
Gray, J.V., Skowronski, K., Esenduran, G., Johnny Rungtusanatham, M., 2013. The reshoring phenomenon: what supply chain academics ought to know and should do. J. Supply Chain Manage. 49, 27–33.
Gregory, T., Salomons, A., Zierahn, U., 2016. Racing with or against the machine? Evidence from Europe. Evidence from Europe (July 15, 2016). ZEW-Centre for European Economic Research Discussion Paper.
Guizzo, E., 2018. Your next t-shirt will be made by a robot. IEEE Spectr. Technol. Eng. Sci. News. https://spectrum.ieee.org/robotics/industrial-robots/your-next-tshirt-will-be-made-by-a-robot.
Hallward-Driemeier, M., Nayyar, G., 2017. Trouble in the Making? The Future of Manufacturing-led Development. World Bank Publications.
Hauge, J., 2019. Should the African lion learn from the Asian tigers? a comparative-historical study of fdi-oriented industrial policy in Ethiopia, South Korea and Taiwan. Third World Quart. 40, 2071–2091.
Hauge, J., Chang, H.J., 2019. The role of manufacturing versus services in economic development. In: Transforming Industrial Policy for the Digital Age. Edward Elgar Publishing, pp. 12–36.
Horner, R., Nadvi, K., 2018. Global value chains and the rise of the global south: unpacking twenty-first century polycentric trade. Global Netw. 18, 207–237.
ILO, 2014. Wages and working hours in the textile, clothing and footwear industries. Issues Paper for Discussion.
IMT, 2018. Annexures to the study on garment sector to understand their requirement for capacity building. Industry benchmarking study, Indian Ministry of Textiles.
Jick, T.D., 1979. Mixing qualitative and quantitative methods: Triangulation in action. Administr. Sci. Quart. 24, 602–611.
Kinkel, S., Dewanti, R.T., Zimmermann, P., Coates, R., 2017. Measuring reshoring trends in the EU and US. MAKERS Deliverable No. 4.1.
Kinkel, S., Maloca, S., 2009. Drivers and antecedents of manufacturing offshoring and backshoring-a German perspective. J. Purchasing Supply Manage. 15, 154–165.
Klag, M., Langley, A., 2013. Approaching the conceptual leap in qualitative research. Int. J. Manage. Rev. 15, 149–166.
Koch, M., Manuylov, I., Smolka, M., 2019. Robots and firms. Robots and Firms.
Lacity, M., Willcocks, L.P., 2017. Robotic process automation and risk mitigation: The definitive guide. SB Publishing.
Mann, K., Püttmann, L., 2018. Benign effects of automation: New evidence from patent texts. Available at SSRN 2959584 doi:https://doi.org/10.2139/ssrn.2959584.
Manyika, J., Chui, M., Miremadi, M., Bughin, J., George, K., Wilmott, P., Dewhurst, M., 2017a. A future that works: AI automation employment and productivity. McKinsey Global Institute Research, Tech. Rep.
Manyika, J., Hunt, D., Nyquist, S., Remes, J., Malhotra, V., Medonca, L., Auguste, B., Test, S., 2011. Growth and renewal in the United States: Retooling America's economic engine. J. Appl. Corp. Financ. 23, 8–19.
Manyika, J., Lund, S., Chui, M., Bughin, J., Woetzel, J., Batra, P., Ko, R., Sanghvi, S., 2017b. Jobs lost, jobs gained: Workforce transitions in a time of automation. McKinsey Global Institute.
McKinsey, 2018. Digital manufacturing - escaping pilot purgatory. McKinsey & Company.
Miller, B., Atkinson, R.D., 2013. Are robots taking our jobs, or making them? ITIF, September 2.
Morris, M., Barnes, J., 2014. The challenges to reversing the decline of the apparel sector in South Africa. In: International Conference on Manufacturing-Led Growth for Employment and Equality in South Africa.
Muro, M., Maxim, R., Whiton, J., 2019. Automation and Artificial Intelligence: How machines are affecting people and places. Brookings India.
Nattrass, N., Seekings, J., 2013. Job destruction in the South African clothing industry: How an unholy alliance of organised labour, the state and some firms is undermining labour-intensive growth. Centre for Social Science Research, University of Cape Town, working paper no. 323.
Nayak, R., Padhye, R., 2017. Automation in Garment Manufacturing. Woodhead Publishing.
Peck, J., 2017. Offshore: Exploring the worlds of global outsourcing. Oxford University Press.
Piva, M., Vivarelli, M., 2017. Technological change and employment: Were Ricardo and Marx right? IZA discussion paper no. 10471.
PWC, 2017. UK economic outlook. Price-Waterhouse-Coopers, London.
Rodrik, D., 2016. Premature deindustrialization. J. Econ. Growth 21, 1–33.
Saunders, M., Lewis, P., Thornhill, A., 2009. Research methods for business students. Financial Times/Prentice Hall, Essex.
Schlogl, L., Sumner, A., 2020. Disrupted development and the future of inequality in the age of automation.
Schwab, K., 2017. The fourth industrial revolution. Crown; Penguin Portfolio, USA; London.
Smith, G., 2017. CTCP monitoring and evaluation. Presented at the Sector Seminar: Clothing, Textiles, Leather and Footwear.
Softwear, 2018. SoftWear automation. Crunchbase https://www.crunchbase.com/organization/softwear-automation.
Stentoft, J., Olhager, J., Heikkilä, J., Thoms, L., 2016. Manufacturing backshoring: a systematic literature review. Oper. Manage. Res. 9, 53–61.
Susskind, R.E., Susskind, D., 2015. The future of the professions: How technology will transform the work of human experts. Oxford University Press, USA.
Szirmai, A., Verspagen, B., 2015. Manufacturing and economic growth in developing countries, 1950–2005. Struct. Change Econ. Dyn. 34, 46–59.
Tate, W.L., 2014. Offshoring and reshoring: US insights and research challenges. J. Purchasing Supply Manage. 20, 66–68.
TIPS, 2017. Manufacturing subsectors: Clothing, footwear, leather and textiles. In: Trade and Industrial Policy Strategies.
UNCTAD, 2017. Trade and development report 2017–beyond austerity: Towards a global new deal.
UNIDO, 2019. Industrial Development Report 2020: Industrializing in the digital age. URL https://www.unido.org/resources-publications-flagship-publications-industrial-development-report-series/idr2020.
Wiesmann, B., Snoei, J.R., Hilletofth, P., Eriksson, D., 2017. Drivers and barriers to reshoring: a literature review on offshoring in reverse. Eur. Bus. Rev. 29, 15–42.
Willcocks, L., 2020. Robo-apocalypse cancelled? Reframing the automation and future of work debate. J. Inform. Technol 0268396220925830.
Willcocks, L., Venters, W., Whitley, E., 2013. Moving to the Cloud Corporation: How to face the challenges and harness the potential of cloud computing. Springer.
World Bank, 2016. World development report 2016: Digital dividends. World Bank Publications.
World Economic Forum, 2018. The future of jobs report 2018. World Economic Forum Geneva.
Xu, J., Gelb, S., Li, J., Zhao, Z., 2017. Adjusting to rising costs in Chinese light manufacturing. Overseas Development Institute.
Yin, R., 2009. Case study research: designs and methods, fourth ed. Sage Publications.