Investigating the relationship between automation and productivity in a South African firm

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Thesis presented in partial fulfilment for the degree of Master of Business Administration to the Faculty of Commerce, Law, and Management, University of the Witwatersrand

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DECLARATION

I Nobert Zvoushe declare that this research report entitled 'Investigating the relationship between automation and productivity is a South African firm' is my own unaided work. I have acknowledged, attributed, and referenced all ideas sourced elsewhere. I am hereby submitting it in partial fulfilment of the requirements of the degree of Master of Business Administration at the University of the Witwatersrand, Johannesburg. I have not submitted this report before for any other degree or examination to any other institution.

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Signed at Johannesburg on 26th July 2021

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ABSTRACT

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South African manufacturing industry productivity has been declining over the last 10 years. Automation intervention driven by advancement in manufacturing technology is becoming increasingly popular and is being touted as critical to reversing this trajectory and ensure the competitiveness of the manufacturing industry is sustained. However, in South Africa where high levels of unemployment and low-level of skills, automation interventions in the labour-intensive manufacturing industry draw mixed views due to the fears that it will lead to massive job displacement. The purpose of this study was to determine the relationship between automation and productivity in a South African manufacturing firm. It does so by critically evaluating the automation intervention of a production process by a manufacturing company. The study interrogated firm level production data looking at performance before when manual production was in use and after automation was implemented. The literature review by the researcher found that there are limited studies in South Africa evaluating automation of manufacturing process. As a result, the success of automation in South Africa has been constrained by the limited empirical evidence demonstrating the effectiveness and merits of such an intervention. Hence, an experimental study like this one is a valuable contribution to literature and addressed the contextual knowledge gap. The manufacturing industry is critical to the country and very labour-intensive. As such, understanding how automation of the manufacturing processes in the industry relates to issues such as productivity and costs is critical. The study draws from the secondary data from the company data base. The study showed that automation is an effective strategy to improve productivity, quality and reduce production costs. In addition, the immediate displacement of workers was notable, and this would have negative implications on the drive to create employment in the country.

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I am greatly indebted to the management of company X, who gave me access and allowed me to conduct the study on one of their manufacturing plants. The research would not have been possible without access to existing production facility.

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DEFINITION OF KEY TERMS AND CONCEPTS

Automation - using machines and computers to substitute for human labour in a widening range of tasks and industrial processes (Prokopenko, 1990).

Productivity - how much output is obtained from a given set of inputs (Syverson, 2010)

1 INTRODUCTION TO THE RESEARCH

1.1 Background and context

This research investigates the relationship between automation and productivity in a South African manufacturing company. The experimental study interrogates the automation intervention and how this relates to manufacturing outputs. The researcher briefly introduces the terms and concepts used in conceptualising this research in Section 1.1. The research conceptualisation in Section 1.2 provides for the research problem statement and consequently the purpose of this research as well as the research questions. The delimitations and assumptions of the research study (Section 1.3), the significance of the research study (Section 1.4) and preface to the research report (Section 1.5) close off the chapter. Thereafter, Chapter 2 focus on specific and detailed discussion on the research context.

1.1.1 The history of South African manufacturing industry

Schneider (2000) explained that the emergence of the South African manufacturing industry can be traced back to early 1920. The industry has evolved over time. The government then created an enabling environment or curtailed growth for the industry through its policies. Development of viable manufacturing industry is key to a nation's self-sustainable development. Between 1925 and 1973 the government actively pursued a policy of import substitution and investment in key sectors by the state. This saw industrialisation anchored by the relationship between the state, state owned enterprises and mining industry. Beyond 1973, apartheid unrest and disinvestment led to economic crisis hence the sector was stagnant. According to Statssa (2020) manufacturing now contributes 12.2 percent to gross domestic product. Notably, manufacturing productivity has declined since 2011 (OECD, 2019). South Africa has high levels of unemployment at 30.8 percent. Company X operate in Mpumalanga province. According to MPG (2011), approximately 23 percent of the population has no schooling and annual household income are lower than that of the country. Manufacturing represents the largest sector in the province (21percent).

1.1.2 Impact of automation on manufacturing industry in South Africa

Advances in technology meant jobs performed by about 35 percent of South African workers (roughly 4.5 million people) could potentially be automated in future (le Roux, 2018). Automation strategies in manufacturing presents opportunities and challenges. As such, there is no consensus on automation implications. For example, Chigbu and Nekhwevha (2020) view automation as improving outputs yet result in deskilling of workers. On the contrary, Jenkins (2008) view automation as having a negative impact on employment, yet it enhances the skills composition of the manufacturing sector. Williams, Cunningham and De Beer (2014) present a view automation enable direct job creation in the manufacturing sector. Despite increased use of technology in manufacturing, the debate on automation continues.

1.1.3 Frameworks for assessing performance within the South African manufacturing industry.

When investigating relationship between automation and productivity in manufacturing, the study applied industry specific frameworks. Evaluation, either formative or informative is one of the mechanisms for assessing performance. Vedung (1997, p. 3 as cited in Schoenefeld and Jordan, 2017) describe evaluation as "careful retrospective assessment of the merit, worth, and value of administration, output and outcome of government interventions, which is intended to play a role in future practical action situations". According to Khadem, Ali and Seifoddini (2008), frameworks such as overall equipment effectiveness, build to schedule, days on hand inventory etc. assess extent to which processes produce intended results though they ignore non-quantitative achievements such as quality, on-time delivery, and flexibility. Leachman, Pegels and Shin (2005) view the productivity framework as providing a closer examination of the gaps specific to the company and specific practices that explain the gaps. Sharma (2009) view the Balanced Scorecard as offering good perspective. Moreso, Chavan (2009) argue that it allows management of strategies to achieve long term goals although its suitability at production level is questionable.

1.2 Research conceptualisation

1.2.1 The research problem statement

A South African manufacturing company based in Mpumalanga province introduced automation in 2017 as a strategy for enhancing productivity. This intervention came against the backdrop of widening and increasing production losses the company was experiencing due to unstable labour relations. DOEL (2020) found that labour strikes directly result in production stoppages and increased 3.5 times more in 2018 than they were in 2014. For example, the sector lost 227,040 working days making it the second highest industry with productivity loss days in 2018. Therefore, it is not surprising that labour productivity in the South African manufacturing sector has declined since 2011 (OECD, 2019). The consequence of declining labour productivity is loss of revenue arising out of failure of manufacturing companies to mitigate rising cost base (Williams et al., 2014). Ultimately, the contribution of many companies, including the one under investigation, to economic growth has remained low (Statssa, 2020). Other consequences of low productivity include high operating costs, loss of sales and customers, and low competitiveness (Pritchard, 1990; Prokopenko, 1992). To increase its revenue and competitiveness, the company under investigation embarked on the process of automation. Perhaps introduction of automation is derived from its wide recognition as a strategy for improving productivity (Mckay, Pollak and Fitzpayne, 2019; McKinsey, 2017; Williams et. al., 2014). However, there is limited evidence on how automation addresses the question of low productivity in the South African manufacturing industry (Parschau & Hague, 2020). For example, available research on automation is dominated by international literature (Le Roux, 2018). In addition, most studies focus on the country level (Le Roux, 2018; McKinsey, 2017) and applied qualitative research strategies. As Parschau et al. (2020) point out, lack of quantitative analysis at the firm level points to a lack of rigorous empirical data on the extent and how automation affects productivity in South Africa. Therefore, this study provides a rigorous quantitative approach to determine the extent to which automation improves productivity in a South African manufacturing company context.

1.2.2 The research purpose (aim and objectives) statement

The purpose of this study is to determine the relationship between automation and productivity in a South African manufacturing firm. In doing so, the study adopted the experimental research design especially quasi-experimental research design for its relevance in measuring correlation between two important variables (Leedy and Omrod, 2019), which in this study are, (1) automation and (2) productivity. Specifically, this design will allow the researcher to measure the extent of the variation of outputs between manual and automated process in a particular manufacturing firm based in South Africa. In pursuit of this, the researcher has embarked on a series of steps. First, the researcher interrogated literature to understand the research problem in its context. Specifically, the researcher used problem analysis approach to identify the root cause, consequences as well as symptoms of low productivity at the firm level. Thereafter, the researcher reviewed literature to establish the knowledge gap. In this regard, literature review focused on research strategies, designs, procedures and methods in past and current studies on productivity issues in South Africa and beyond. Third, the researcher interrogated literature to determine appropriate variables related to productivity. As Wotela (2016) points out, reviewing literature to understand research variables and attributes provides themes and questions relevant for answering the research questions. In addition, understanding key research attributes allows the researcher to identify appropriate theories and frameworks for interpreting empirical data. Last, these aspects of literature review are summarised into what Wotela (2017) describes as a conceptual framework which is depicted in Figure 2.5.

1.2.3 The research questions as well as where applicable accompanying research hypotheses or research propositions

Limited studies on the impact of automation on productivity in South African manufacturing industry has failed to provide firm level empirical data comparing productivity between manual and automated manufacturing processes (Parschau et al., 2020). Therefore, this study seeks to generate empirical data for determining the relationship between automation and productivity in a manufacturing firm in South Africa. The need to investigate this relationship comes against the backdrop of wide recognition of automation as a strategy for improved productivity. Therefore, the researcher intends to establish if this argument holds in a particular manufacturing firm.

> **Question 1:** To what extent does automated manufacturing process in a particular firm in South Africa improve productivity as measured by production volume outputs?
>
> **Question 2:** To what extent does use of automated manufacturing processes reduce production costs in a manufacturing firm in South Africa?

1.3 Delimitations and assumptions of the research study

The study focused on a single case, manufacturing company in South Africa. Therefore, the major limitation is that findings are context specific and might be different from findings in other environments. Leedy and Omrod (2019) argue that generalisation of the findings to other situations cannot be done with certainty. Further, for quasi-experimental design, there is no control for all confounding factors hence the study can no rule out alternative explanations for the results obtained after automation.

The study interrogated literature to understand the root causes, both internal and external root causes of low productivity at firm level. Perhaps, the firm adopted automation of manufacturing processes, as a response to internal factors. Therefore, the study was limited to organisational structures and operational factors causing low productivity. This study assumes that automation is the main factor influencing the production results and other factors which can influence production such as increased demand for the company's product, ergonomics, employee skill level, motivation, experience etc. have limited impact on results. Another assumption is that the information would be available from the company X's database and that it is unaltered (integrity) and correctly represent the production information for each year.

1.4 Significance of the research study

Automation interventions in South African manufacturing industry are aimed at improving productivity and reduce costs. Despite the anticipated benefits, there are limited empirical studies at firm level on automation interventions in South Africa (Parschau et al., 2020). First, this result in limited understanding and awareness of the positive arguments and value of automation. Second, this does not enhance decision making by management teams and leadership of organisations. Lastly, this limits policy enhancement towards promoting such interventions. Hence, the success of automation in South Africa could be partly constrained by limited empirical evidence demonstrating the relationship between automation and productivity. The study is aimed at addressing the contextual knowledge gap and provide more impetus on addressing the problem of low productivity. Low productivity affects the profitability of manufacturing organisations as the cost of production is high (Pritchard, 1990; Syverson, 2011) and their ability to compete effectively (Francois & Hoekman, 2009). This impact the level of incomes paid to workers (Arnold, Mattoo & Narciso, 2006) and demand for labour (Eifert, Gelb & Ramachandran, 2006). The manufacturing industry contribute on average 12.2 percent to GDP yet continue to record job losses therefore contributing to high unemployment (Statssa, 2020). High unemployment and low wages result in increased poverty levels and inequality. Therefore, the researcher is of the view that the consequences of not addressing the problem of low productivity are far reaching if left unchecked.

1.5 Preface to the research report

To this end, the research report has six chapters. The introductory chapter covered so far discussed and put forward the research conceptualisation covering the research problem statement, research purpose and research questions as well as accompanying hypotheses. Chapter 2 provides a literature review covering the root causes, consequences, and symptoms of low productivity from past studies, the explanatory framework, and the proposed conceptual framework. Chapter 3 discusses the research strategy, design, procedures, reliability, and validity measures as well as limitations. Chapter 4 and Chapter 5 presents and discusses the research findings, respectively, and interrogating the research questions while Chapter 6 summarises and concludes the research.

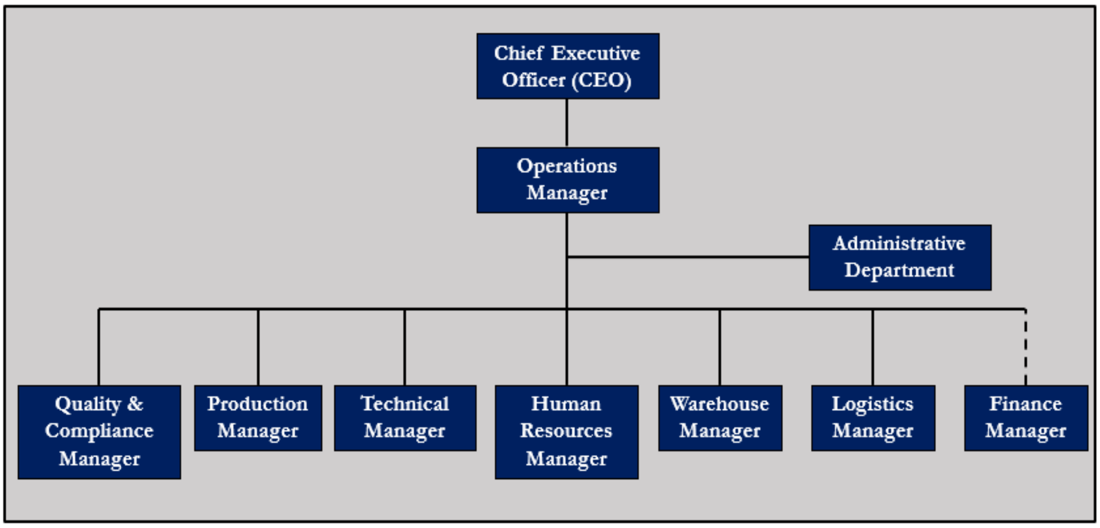
2 LITERATURE REVIEW

This chapter has three broad objectives; namely to understand the research problem, to identify the knowledge gap, and to develop a framework for interpreting the research findings. First, the researcher will discuss the research setting in Section 2.1. In Section 2.2, the researcher interrogates literature to understand how the problem of low productivity manifests within the physical context of South African manufacturing company. Thereafter, Section 2.3 highlights research strategies, designs, procedures, methods used in previous studies related to automation and productivity in different contexts. The third part of this chapter interrogates literature to identify quantitative variables (Section 2.3) as well as frameworks for interpreting empirical findings of this study (section 2.4) before proposing a conceptual framework (Section .5) showing how the study moves from conceptualisation to empirical execution.

2.1 The research setting: manufacturing company X

For ethical purposes, the researcher deliberately conceals the identity of the firm under investigation. Situated in Mpumalanga province, the firm, referred to in this study as company X, was established in early 2000. Its vision is to provide a quality product which complies with food safety and quality standards for local and international consumption. At its manufacturing plant, the company has a total compliment of 195 employees, of which 92 are in production. The manufacturing company's management structure is depicted in figure 2.2 below.

Figure 2.1: Organogram of Company X



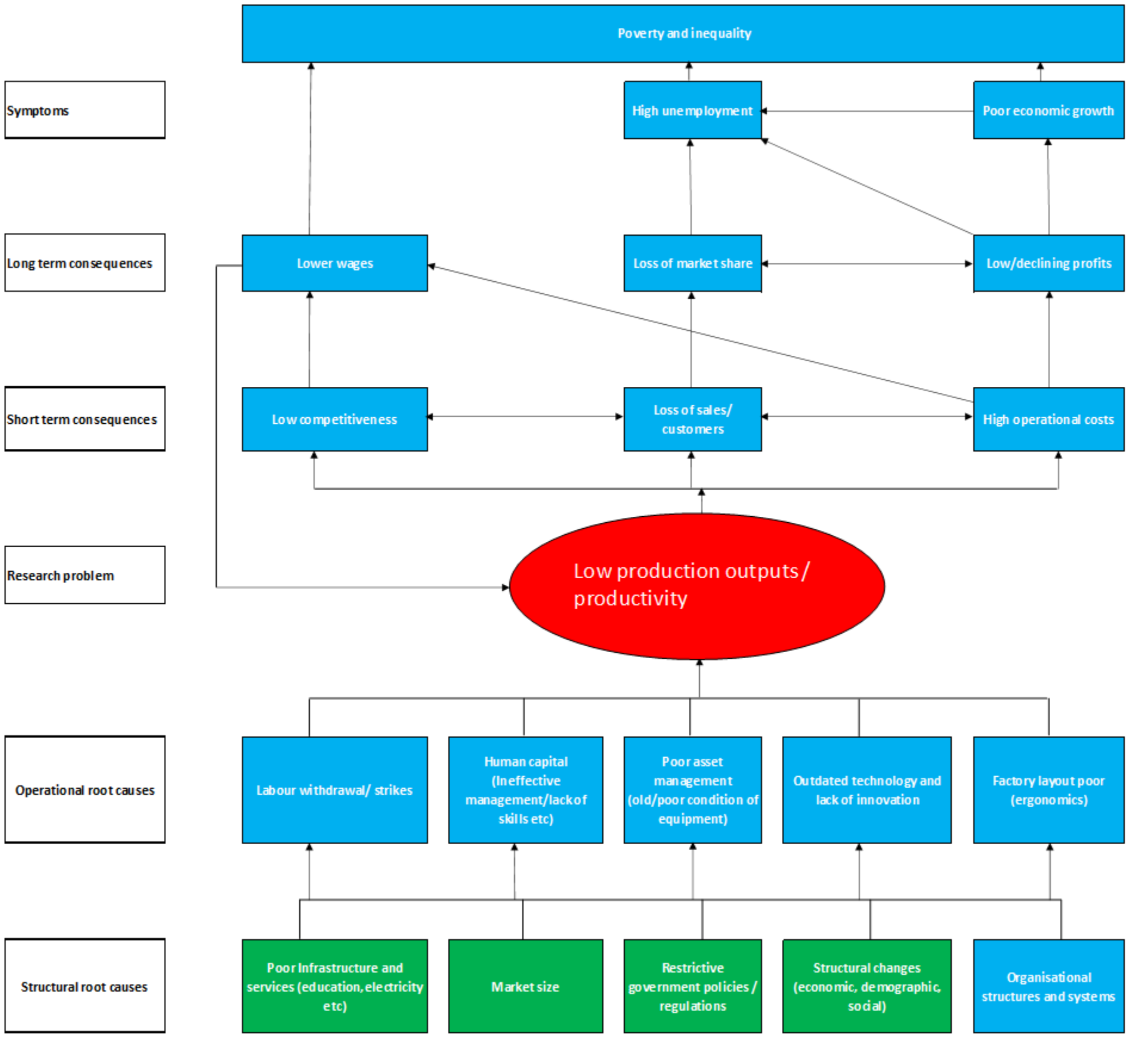
Source: Author

One of the issues that gave rise to low productivity in company X, pertains to production losses due to unstable labour relations. For example, during the period leading to implementation of the automation intervention in 2017, the company experience increased labour unrest, a phenomenon that was common in most manufacturing companies. Highlighting the extent of labour unrest in the manufacturing industry, DOEL (2020) shows that labour unrest increased 3.5 times more in 2018 compared to 2014. In addition, poor planning of the production flow and lay-out impact on productivity (Munyai, Mbonyane & Mbohwa, 2018). Therefore, automation of production processes was introduced as a strategy for improving workflow processes and enhancing productivity. However, there is shortage of empirical research on how automation leads to improved productivity in South Africa (Parschau et al., 2020). As a result, there is an opportunity for the researcher to investigate the relationship between these variables. To set the tone for this investigation, the author interrogates the issue of low productivity with particular focus on how it manifests within company X.

2.2 Understanding the problem low productivity in a South African manufacturing company

Several authors, (OECD, 2019; Prokopenko, 1992; Syverson, 2011) have discussed the concept of productivity. Despite the broad consensus on what productivity is, Pritchard (1990, p. 8) notes that productivity is "sometimes used interchangeably with such concepts as output, motivation, individual performance, organizational effectiveness, competitiveness, work quality, and what a new product will enable you to increase if you buy it". Evidence shows that manufacturing companies in South Africa registered a negative productivity growth of minus 0.3 percent between 2010 and 2016 (OECD, 2018). Earlier, Aghion et al. (2008, as cited in Kreuser and Newman, 2018) had highlighted the poor manufacturing productivity in South Africa compared to manufacturing internationally. As such, Productivity SA was established to partner and drive turnaround initiatives within the manufacturing industry (Productivity SA, 2017). Since this study is at operational level, it considers narrow and singular measures of productivity at plant level as these are suitable for day-to-day management in organisations (Harris, 1999) such as company X under study. In addition, the use of production volume outputs as measures of productivity is in line with other studies on automation and productivity. For example, Neumann, Kihlberg, Medbo, Mathiassen and Winkel (2002) have used volume outputs when interrogating the productivity impact of production process automation by comparing volume outputs between automated and semi-automated process. Therefore, the researcher considers volume outputs as appropriate measures of productivity for this study. The researcher interrogated literature and detailed the root causes of low productivity in the manufacturing firm by making use of the problem tree to demonstrate how the problem of low manufacturing productivity manifests, its results and how this perceived in the public eye.

Figure 2.2: Problem tree depicting the causes of low productivity in the South African manufacturing company.



Source: Author

2.2.1 Root causes of low manufacturing productivity in South African manufacturing company

Having introduced the problem of low productivity and how it is measured in the manufacturing firm under investigation, this section moves on to interrogate manifestations of low productivity in the firm. To this end, the author first interrogates the root causes of low productivity. A "root cause is the fundamental, underlying reason for a problem" (Tague, 2005, p. 42). In this regard, unstable power supply appears to be the main causes of low productivity in most South African firms (Arnold et al., 2006; Ateba, Prinsloo & Gawlik, 2019). Over and above power supply issues, production losses arise from continuous breakdown of machinery (Harris, 1999). This is particularly so when the machines are not effectively maintained and the poor conditions of machinery causes production losses hence cause low productivity in South African manufacturing firms (Munyai et al., 2018; Mtshali, Nyakala, Munyai & Ramdass, 2018).

Further, the poor lay-out of the production process appear to be a cause of low productivity in most South African manufacturing firms (Munyai et al., 2018). This is much so as poor lay-out of production processes likely creates a haphazard environment which causes delays in the production process and contributing to a decline in productivity (Mtshali et al., 2018). Another factor contributing to low productivity is the likely failure of manufacturing firms to attract relevant skills within the production processes particularly in a rural province where there is limited pool of highly skilled personnel (MPG, 2011). Skills shortage has been shown to cause low productivity in South African manufacturing firms (Kleynhans & Labuschagne, 2012). The scarcity of skilled technicians required to operate and service the production machines for manufacturing firms in South Africa has directly impacted productivity (Mtshali et al., 2018; OECD, 2018; Tybout, 2000).

In addition, ineffective management with respect to poor management styles and lack of control appears to be another cause of low productivity in most South African manufacturing firms (Kleynhans et al., 2012; Munyai et al., 2018; Mtshali et al., 2018). The authors have shown how this likely cause high production waste signifying poor or lack of control by management. Besides, a firms' choices of technology, inputs, and production are made by management and the low volume outputs reflect an ineffective management not capable of making decisions that correct the performance (Bartelsman & Doms, 2000). Closely linked, is the ineffective organisational structures and systems not capable and responsive enough to poor outputs and as Syverson (2011) have shown affect most South African firms. As the author have shown, organisational structures and systems set up by managers determine the productivity level of the firm. Therefore, low productivity entails such structures and system are not effective as management is responsible for the effective use of resources (Prokopenko, 1992).

Therefore, literature show that a combination of structural and operational factors contributed to the low productivity in South African manufacturing companies. The problem of low productivity transcends beyond production management. Besides management, strategic leadership is required to deal with various structural factors identified. Hence, the following section interrogates literature to understand the consequences of low productivity in a manufacturing company.

2.2.2 Consequences and symptoms of low manufacturing productivity in South African manufacturing company

Having discussed the root causes of low productivity within a particular firm under investigation in this study, the next stage involves interrogating consequences and symptoms of this problem. Before diving deep into this interrogation, it is important to note that the term consequence means expected effects or result (ILO, 1991). Based on this understanding, there are several issues resulting low productivity in South African manufacturing firms. First, high operating costs mainly driven by low outputs and high production waste has been shown to be a result of low productivity in South African manufacturing industry (Williams et al., 2014). As a result, the historical competitive edge has been eroded leading to frequent price adjustments as manufacturing companies try to compensate for high costs of production. As several authors (Francois et al., 2009; Pritchard, 1990; Syverson, 2011) have pointed out, high production costs arising out of low productivity, reduce competitiveness and profits with ultimate reduction of job opportunities. In addition, Munyai et al. (2018) show that for South African manufacturing companies, low or declining profits arises from high operating costs and reflects through low sales and decreasing production volumes. Besides the consequences, the problem of low productivity is also reflected through symptoms. A symptom "reflects an existence of something which was not there before" (Malterud, Guassora, Graungaard & Reventlow, 2015, p. 412) and how it shows up in public. For example, Eifert et al. (2006) reported high indirect costs depress labour demand and real wages. For this reason, countries such as South Africa are unable to generate adequate economic growth to take people out of poverty (Arnold et al., 2006). Low productivity in the South African manufacturing industry also manifests through retrenchments and ultimately high unemployment (Kleynhans et al., 2012). Highlighting the extent of this problem within the manufacturing industry, Statssa (2019) reported that the industry recorded employment losses of 69000 in Q1: 2019. The researcher also interrogated literature to establish the knowledge gap.

2.3 Methods, data, findings, and conclusions of studies on automation and productivity in manufacturing firms

Now that the researcher has established from literature the root causes that give rise to the problem of low productivity in a manufacturing company, its consequences and symptoms, the next step is to establish the knowledge gap. In doing so, the researcher sourced empirical journal articles that have addressed issues related to productivity and automation in South Africa and elsewhere. Specifically, the researcher applies thematic analysis to investigate research strategies, designs, methods, and procedures used in past and current studies related to the subject matter of this study.

2.3.1 Studies on issues related to automation of manufacturing processes in other countries.

Several studies on automation and productivity have focused on developed countries (le Roux, 2018), giving rise to limited empirical studies on automation and productivity in South Africa (Parschau et al., 2020). For example, Neumann et al. (2002) conducted a case study to evaluate the impact of automation on ergonomics and productivity for a Swedish electronic manufacturing company. Mixed methods strategy was used to ensure that the indicators reported by the study will be consistent with field observations made. The research design applied was a case study which crucially allowed the authors to use multiple methods to collect data. However, the disadvantage with case study design concerns the external validity or generalisability of the findings to other cases when only a single case is considered (Bryman, 2012). Sampling procedures used for the study were not explicitly stated. The sample size was one manual operator workstation and four to six automated operator workstations as well as 100 employees for general questionnaires. The small sample used enabled the authors to suggest trends, however the disadvantage was that they could not make statistical comparisons.

The data collection methods included secondary sources - company records, field observations of the process, general questionnaire for assessing working conditions, detailed video analysis and biomechanical modelling data. The authors argue that the use of production level indicators in this study helps avoid the effects of inter-individual variability. Moreso, structured observation is a method that works best when accompanied by other methods which the authors have done. However, the disadvantage is the tendency for structured observation to generate lots of fragments of data and rarely able to get at intentions behind behaviour (Bryman, 2012). The use of questionnaires is less expensive and offer greater anonymity, yet the disadvantages are that (1) there is no opportunity to clarify issues, (2) there is self-selecting bias, (3) does not allow for spontaneous responses and (4) it is possible to consult others (Kumar, 2011). Variables measured was the production volume over nine weeks, labour input, work in progress, extent of quality work, total time spend on transportation and supervision activities on machines and delivery dependability. Potential measurement error was mitigated by using the same measurement system for assessing both manual and automated systems. Similarly, this study will use production level indicators to answer similar research questions but in a different context. This will be discussed in detail in Chapter 3.

Data analysis by the author involved comparison of manual and automated data showing the percentage differences. The key findings for this study were (1) that automated production process had 51 percent higher production volumes, (2) 21 percent less labour compared to manual production and (3) lower work-in-process levels compared to manual production process. While total repetitive work was reduced by 34 percent, there was increased repetitiveness on operator movement due to layout design not considering ergonomics requirements.

Another empirical study by Sim (2001) examined the impact of automation and improvement techniques, just-in-time (JIT) and total quality management (TQM) on manufacturing performance. The objective of the study was to provide empirical evidence pertaining potential benefits of continual process improvement techniques and management of technological innovations. To achieve that, a mixed strategy was used which enabled the authors to understand why investment in manufacturing technology enhances JIT performance but inhibits TQM performance. On the other hand, the quantitative strategy enabled the authors to identify cause-and-effect relationships between variables, i.e., automation, JIT and TQM. The authors did not explicitly define the research design save for indicating that it's an empirical study focused on the USA electronics industry. The sample involved 1500 manufacturing plants randomly selected for the study by sending letter requesting their participation. From these, 126 manufacturing plants agreed to participate in the study. The sampling technique gave each plant an independent chance to participate in the study.

The data collection was done through questionnaires emailed to each of the 129 plants. The questionnaire had open-ended questions which solicited information regarding manufacturing practices and performance in multiple dimensions. A response rate of 64 percent i.e., 83 out of 129 plants, was registered. While emailing questionnaires is a less expensive method, the disadvantage though is the low response rate shown in the study. The key findings of the study show that investment in automation enhances JIT performance but inhibits TQM performance. Only 27 percent of the plants invested in automation during the period. Moreso, most plants that invested in automation exhibited a lack of attention to quality. The authors applied regression analysis and the results from multiple regression, were statistically significant ($p < 0.001$). For example, automation reduced waste from 3.66 percent to 1.65 percent when supported by high JIT. On the other hand, automation increased waste from 1.88 percent to 3.56 percent when supported by TQM. Crucially though, investment in technology on its own does not deliver improved outputs.

The limitation though is that for plants that invested in automation only the study does not give a detailed analysis of the intervention for each firm. The lack of firm level production data, detailing which process was automated, objective, its capabilities, and the outputs is a key gap. Even the quality data was presented in percentage terms and fail to capture the actual waste data from production. This study seeks to close this gap using plant level data when investigating the automation intervention.

2.3.2 Studies on issues related to automation of manufacturing processes in South Africa.

Having considered the international context on automation and productivity studies, the researcher reviewed studies done in South African context. For example, Parschau et al. (2020) conducted a case study to evaluate the threat of automation on employment in the South African apparel manufacturing sector. A qualitative strategy was used which allowed the authors to capture realities specific to the industry and region. Besides, it accommodates open-ended and emerging questions. However, a qualitative strategy does not allow for identifying cause-and-effect relationships between variables (Leedy et al., 2019). The authors used a case study research design focusing on the apparel industry since it was predicted to suffer huge job losses because of automation. However, for a case study when only a single case is involved, we cannot be sure that the findings are generalizable to other situations (Leedy et al., 2019). A purposeful sampling procedure was used. This allowed the authors to explore the perspectives of different groups and minimised potential subjectivity issues. Besides, it allowed authors to choose participants who were able to provide certain desired perspectives on the topic of automation and issues. A sample size of 26 included firm managers, government and union officials and was considered adequate to represent different viewpoints.

The authors used various data collection instruments and methods. For example, semi-structured interviews were considered conducive to this exploratory study and served as the main data source for the study. The instrument was deemed more flexible and allow important themes to emerge. In addition, open-ended questions enabled interviewees to offer own perspectives on the problem while follow up questions were used to clarify arguments. Moreso, direct observations of the production process were done and gave the authors insights into the apparel production process. In addition, it allowed the authors to verify the labour-intensity involved in the production process. Secondary data sources, such as newspapers and company websites were also used which enabled corroboration of hypotheses about impact and stage of automation. The authors used bar graphs and pie-chart to present data from the interviews. The key finding for the study was that there were no reported job losses because of automation. In addition, automation was attributed to improved productivity by 10 plants and increased sales.

However, each automation intervention was not defined and evaluated. The study did not capture and analyse firm level data to quantify productivity gains. Instead, it relied on views from firm managers which this study addressed by using actual production level data. Hence, findings by Parschau et al. (2020) are not backed by production level data. As a result, the authors recommended that the extent of productivity gains from automation and redistribution of remaining work after automation require further evaluation.

Another study by D. Hagedorn-Hansen, Steenkamp, E. Hagedorn-Hansen and Oosthuizen (2017) investigated the effects of automating production processes. The objective of the study was to determine when a company should automate its production process by comparing the performance of automated versus semi-automated production processes. A quantitative strategy was used which allowed comparison of performance between the two processes. In addition, the intent was to identify relationships among two or more variables i.e., automation and production performance which is possible through a quantitative strategy. However, the strategy was not flexible to accommodate emerging issues during the production monitoring process. The experimental design was applied for this study. It allowed the authors to monitor over a four-month period and compare the performances and identify the cause-and-effect relationship between variables, i.e., automation and production performance (Leedy et al., 2019). However, an experimental design does not rule out other factors besides automation that haven't been assessed or considered which could have affected the production performance in this study (Bryman, 2012). The sampling procedures was not explicitly defined though specific units were chosen.

The data collection involved use of OEE monitoring software which collected large amount of data. The software measured the unit's availability, performance and quality. The two processes were monitored over a period of four months. In addition, secondary sources such as company database stored on central server for the factory and documents were used as well. The advantages of using the OEE monitoring software was that it captured and provided large amount of raw production data and measured metrics. This allows for verification of the calculated metrics from the raw data. The authors used bar graphs to compare OEE data before and after automation. The key findings for the study were that automation reduced labour costs by 88.4 percent which resulted in an estimated profit increase of 177 percent. In addition, the automated process had a 6.6 percent higher availability and 3.15 percent higher OEE compared to semi-automated process. As a result, it had a higher outputs and profit margin. The quality rate decreased by 0.9 percent. However, instead of measuring quality as a percentage, this study proposes to use the actual waste data from production. In addition, performance was represented by production volume not percentage. Using actual data brings to the fore the level of the variation. For example, Hagedorn et al. (2017) findings show a 0.9% decrease in quality which sound negligible as a percentage although this might represent a substantial amount. Moreso, this study proposes to use covering a longer period of six years instead of four months to address short term issues and improve accuracy. The authors noted the numerous production losses incurred as employees take various breaks and recommended the use of additional manual labour to cover for these breaks as this is a lesser cost than automating the full production.

So far studies that have focused on automation and productivity elsewhere and South African manufacturing companies have largely adopted the case study design. In doing so the studies (Parschau et al., 2020; Sim, 2001), have failed to use firm level production indicators when evaluating automation interventions and productivity. Use of production level data directly related to the automation intervention unlike the company level information used. Besides the studies does not make use of experimental design that makes it possible to interrogate and compare data before and after automation was adopted. Also, strategies adopted are not explicitly discussed to confirm suitability. For example, Hagedorn-Hansen et al. (2017) used a quantitative strategy but the author failed to explicitly state and argue why this was the appropriate strategy. Crucially though, the author used an experimental design also proposed for this study and provided firm level empirical data on automation and OEE. The author also recommends use of manual labour to improve availability. This goes against the study's finding that automation improved labour productivity. The next section looks at the quantitative variables adopted by this study as well as accompanying hypotheses.

2.4 Quantitative variables key to the research

This quantitative study seeks to generate empirical data for determining the relationship between automation and productivity in a manufacturing firm in South Africa. Thus, the concept for this study is relationship. Relationship is "an association between two variables whereby the variation in one variable coincides with variation in another variable" (Bryman, 2012, p. 715). As Kumar (2011) indicated, a concept that could be measured is a variable where a variable is a property that takes on different values. This study has already explicitly identified the variables at the beginning of the study (Leedy et al., 2019) as the production volume and costs as measured by quality/waste generated during production and labour used to produce that volume. For this study, conversion of concepts into variables is represented in Figure 2.3 as follows:

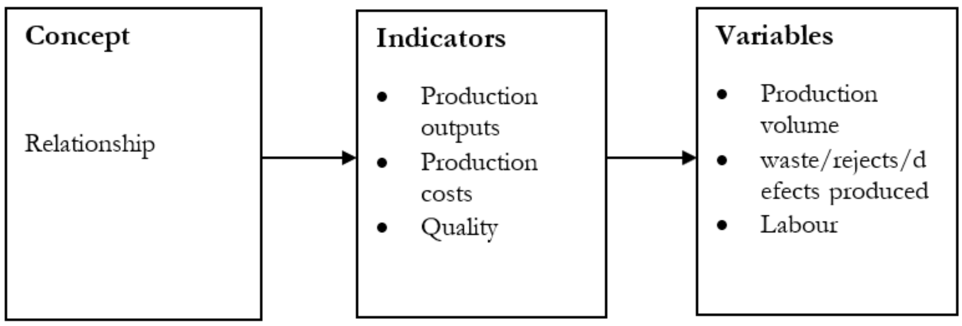


Figure 2.3: Source Author

The variables proposed for this study therefore enabled the researcher to analyse the firm level data and provide answers to the research questions through formulated hypothesis as follows:

Question 1: To what extent does automated manufacturing process in a particular firm in South Africa improve productivity as measured by production volume outputs?

> **Null hypothesis (Ho):** There will be no difference in the production volumes for automated and manual processes.
> **Research hypothesis (H1):** Automated production processes volumes are greater than manual processes outputs.

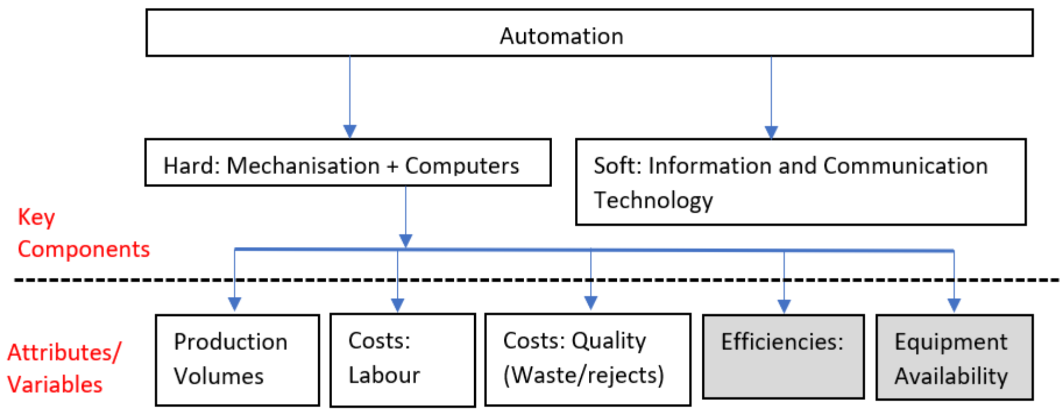
Question 2: To what extent does use of automated manufacturing processes reduce production costs in a manufacturing firm in South Africa?

> **Null hypothesis (Ho):** There will be no difference in the production costs of automated and manual process.
> **Research hypothesis (H1):** Automated production costs are lower than manual process costs.

Therefore, to provide tentative explanation for the phenomenon under study, hypothesis underlying the research need to be identified (Leedy et al., 2019). Hypothesis is "a testable proposition stating that there is a significant difference or relationship between two or more variables" (Saunders & Lewis, 2012, p. 25). The hypothesis proposed for this study are measurable, verifiable and related to previous studies (Kumar, 2011) and specifies the relationship between automation and productivity as well as automation and production costs. Hence, for research question 1, the null hypothesis, denoted by Ho deduce that there is no difference between manual and automated production volumes (Sim, 2001). Conversely, the research hypothesis proposed stipulates that automated production volumes are greater than manual production volumes (Neumann et al., 2002). In addition, for research question 2, the null hypothesis deduces that there is no difference between the automated and manual production costs (Hagedorn-Hansen et al., 2017). Conversely, the research hypothesis proposed stipulates that automated production costs are lower than manual production costs (Neumann et al., 2002). The researcher used these hypotheses when collecting and analysing data and be able to make a conclusion whether the hypotheses was true or not (Kumar, 2011).

Studies on automation and productivity used the same variables as proposed in this study. For example, Neumann et al. (2002) evaluated productivity impact of automation using production volumes when measuring productivity and labour when measuring costs of production. Similarly, Hagedorn-Hansen et al. (2017) used performance (outputs), quality, and labour costs among other variables when evaluating the effects of automating production process. As a result, the researcher chose to adopt similar variables i.e., production volumes and costs (waste and labour) as these variables enabled the researcher to answer the research question. The costs were established from the quality data as measured by waste (rejects) from the production process and the labour used in production. The data sources for these variables were drawn from existing company X's records and database. For example, to understand productivity, the researcher reviewed the three-year production volumes before the intervention (2015-2017) and after the intervention (2018-2020). This enabled the study to measure and confirm any variation in outputs due to automation. In addition, to understand costs related to production, quality data showing production waste (rejects) for the corresponding period was reviewed as well as organograms to extract and review labour (number of employees) involved in production. Similarly, Neumann et al. (2002) used secondary sources when comparing production volumes between manual and automated process when measuring extent to which automation impact productivity. In addition, the author compared labour input and quality of production between manual and automated process using number of employees and waste respectively. The link between the field of study, components and variables is shown in the figure below. While there are several variables that could be measured in a production process, this study focuses on production volumes and costs (labour and waste) in line with studies discussed.

Figure 2.4: Link between field of study, key components, and variables.



Source: Author

2.5 Using the productivity theory for interpreting the empirical results

So far, the study has interrogated literature to establish the knowledge gap and the attributes relevant for the study. This section also introduces interpretive frameworks that have been developed and applied to production process output measures and effectiveness. A framework is “a generalised type of theory that indicates relationships between constructs or latent variables” (Levy & Ellis, 2006, p. 198). This study is grounded in a production environment. As such, several theories are used for interpreting manufacturing dynamics. Fleury (2020) pointed that traditional manufacturing theories which includes Lean manufacturing, the Theory of Constraints (TOC), Materials Requirements Planning (MRP) and Six Sigma have been used when firms try to improve lead times, reduce waste and reduce inventory. However, there main weaknesses are that such theories were codified over 40 years ago and have not adapted to meet modern demands such as fragmented and elongated supply chains, products with shorter life spans and a drastic drop in customer tolerance times. Besides these traditional theories, other frameworks widely used in manufacturing is the Overall Equipment Effectiveness, OEE and Total Productive Maintenance, TPM. These theories are mostly used in production environments (Patel & Deshpande, 2016). According to De Ron and Rooda (2006) OEE was originated by Seiichi Nakajima in 1988 and the framework was developed in the context of Total Productivity Maintenance, TPM. OEE is directed towards equipment/machines and widely used as a quantitative tool essential for performance measurement. Unlike traditional metrics, the strengths of OEE are that it is clear, simple and the theory is sufficient for identifying problems and any underlying improvements required to improve performance. However, De Ron et al. (2006) noted several weaknesses of OEE. First, the description of OEE is directed towards equipment yet OEE is impacted by factors other than equipment such as operator, raw materials, recipe etc. Hence, the definition does not consider all factors which impact capacity utilisation of the equipment. Second, several authors are of the view that there is a need for a more suitable time basis compared to the loading time originally proposed by Seiichi Nakajima. Third, the accuracy of OEE largely depends on the quality of data collected. The theory has been used in the past by Hagedorn-Hansen et al. (2017) when investigating the effects of automating production processes by comparing performance of manual and automated process using quantitative measures on availability, performance and quality. However, this study considers the production outputs as measured by volumes. Since OEE does not explicitly give production outputs as a metric but present these as performance rate, the theory was considered inappropriate for interpreting results of this study.

Besides OEE, the productivity theory is one of the widely used frameworks for interpreting manufacturing dynamics. According to Schachter (1991) the theory of productivity was originated by a French mathematician, Francois Quesnay in 1750. The purpose of the productivity framework was for the analysis of input and outputs.

Quesnay provided a solid base for quantitative analysis using rudimentary numerical behaviour analysis. However, the author did not specify (1) what these inputs and outputs are, (2) how they are measured and (3) their units of measurement. In addition, "the Physiocrats, and especially Francois Quesnay through his general equilibrium scheme, were the pioneers in macroeconomic theory, econometrics and input-output analysis" (Schachter, 1991, p. 313). Early proponents to this theory included Leontief, who later perfected Quesnay's productivity theory in the 1930's. As Schachter noted, the first person to apply linear equations to the system was Leontief since Quesnay had relied on an iterative process that was difficult, but possible to follow. However, early critics of the productivity theory included Vaggi (1941-5) who argue that with relative constant prices, Quesnay's analysis would result in the share of the farmers' profits increasing at the expense the wages paid to workers' wages.

According to Steenge and Van Den Berg (2007, p. 331) many modern interpretations of Quesnay's theory have not been satisfactory and "most fundamental is a perceived discrepancy between the purpose of the Tableaux and that of traditional Input-Output (I-O) analysis". As such, the author proposed an I-O model of a Quesnaysian type which specify differing productive capacities of sectors and for disequilibrium approaches. Further, the proponent argue that this model is more aligned to Quesnay's intentions and beneficial to understanding the favourable and unfavourable directions of modern economic growth. Several authors in the 20th century have consistently defined the concept of productivity in line with Quesnay's view. There is recognition of the problem with the productivity concept. As Kumar et al. (2008) noted, productivity means several things to different people and issues pertaining to measurement of both inputs and outputs (Harris, 1999; Sharpe, 2002). Labour productivity is mostly used compared to total factor productivity.

As shown above, the productivity theory allows for input-output analysis. These aspects, outputs and inputs are relevant for interpreting the research questions for this study. This study considers the production outputs as measured by production volumes and the production inputs as measured by the costs i.e., labour and waste. Therefore, when analysing what happens to production outputs and inputs between manual and automated production processes, the productivity theory closely interpret these production measurements and variables considered for this study. As such, the productivity theory would be applied when interpreting the research results for this study. This is also in line with previous studies (Liao & Tu, 2008; Neumann et al., 2002;

Parschau et al., 2020; Waldman, 2016) that have used the productivity theory when interrogating automation and productivity. A summary of the various interpretive frameworks used by past studies for interpreting empirical results are summarised in the table below.

Table 1: Summary of the interventions, variables and frameworks used by various authors.

Author	Research strategy	Research Design	Variables	Interpretive framework
Parschau et al. (2020)	Qualitative	Case study	Productivity and job lossed	Productivity theory
Neumann et al. (2002)	Mixed	Case study	Volume (outputs); Labour; Shoulder elevation; Shoulder movement	Productivity theory and Sociotechnical theory
Hargedon-Hansen et al. (2017)	Quantitative	Experimental	Availability; performance; quality; labour costs; profit margin	OEE model
Sim (2001)	Mixed	Case study	Customer performance; quality; product development time; manufacturing lead time	Balanced scorecard
Liao and Tu (2008)	Qualitative	Case study	Delivery, Cost, Quality, Flexibility, Innovation	Productivity theory
Waldman (2016)	Quantitative method	Case study	Production costs, product quality, time to market, return on investment requirements, supply chain shortening	Productivity theory

Source: author

2.6 A conceptual framework for investigating the relationship between automation and productivity in a South African manufacturing firm

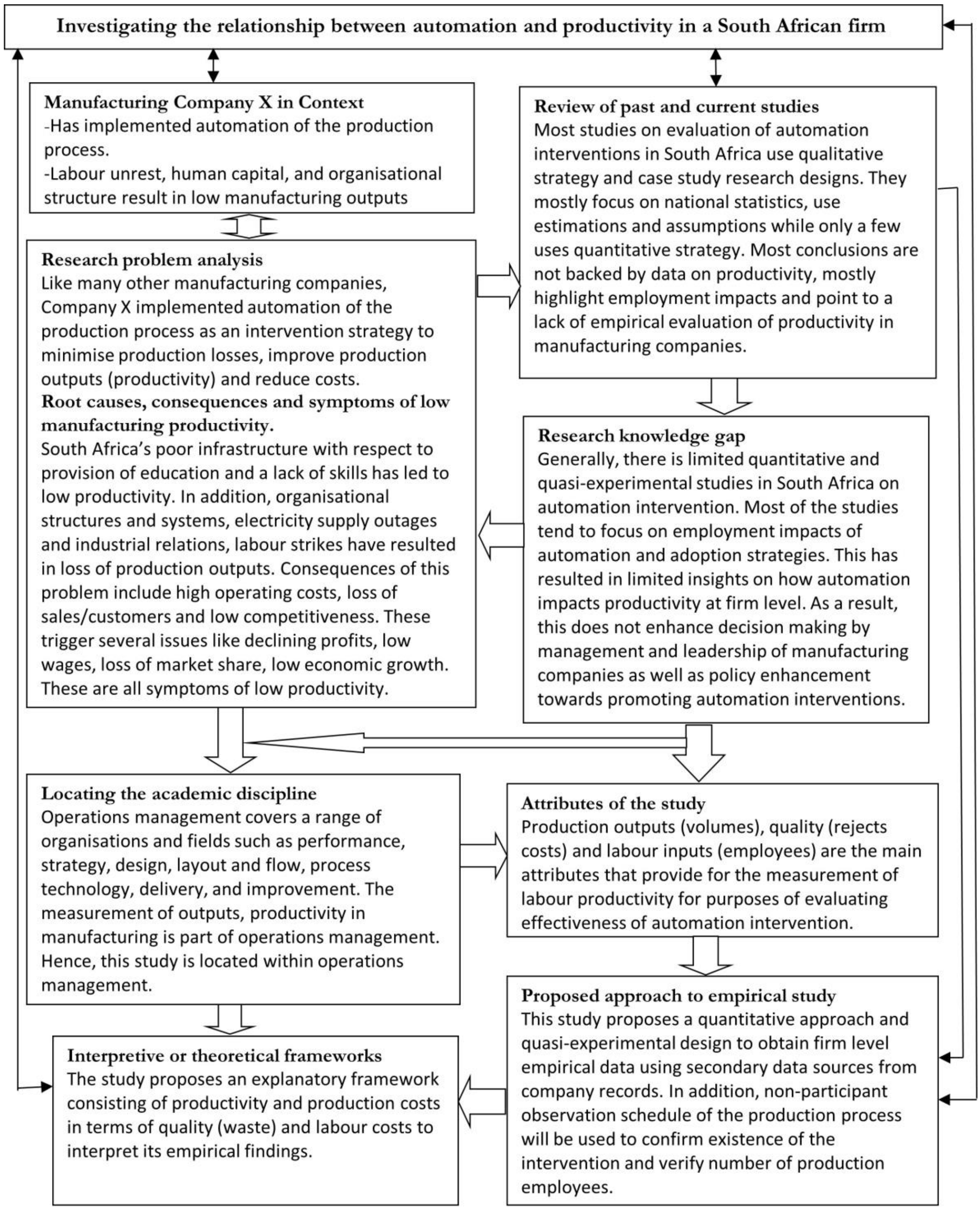
The researcher has so far interrogated literature and presented the research problem, which is low productivity which gave rise to automation of a production process by a particular company, company X. In addition, the study has through literature, established the research knowledge gap, which pertains to the general lack of firm level evidence in the context of South African manufacturing industry on evaluation of automations intervention. To address this contextual knowledge gap, the researcher has proposed a quantitative strategy to this study. Moreover, the researcher has identified appropriate variables such as production volumes and costs (labour, quality) for which data would be collected and analysed to provide answers to the research questions presented in Section 1.2.3. The researcher, therefore, has covered what Wotela (2017) describe as the introduction to the research which includes components such as research problem statement, research purpose statement, research questions and accompanying hypothesis as well as the delimitations and justification of the research. The literature review conducted by the researcher has yielded critical milestones which will be discussed and summarised in this section. In addition, the researcher would give a view of the proposed conceptual framework for the study, which is a roadmap of how the researcher has conceptualised the study and intent to undertake the empirical part of the research. The critical milestones completed are as follows:

Firstly, the researcher interrogated literature to understand the research problem, which is low manufacturing productivity. Through a systematic interrogation of textbooks, journal articles, conference papers and institutional reports, the researcher has explored in detail and discussed the problem of low manufacturing productivity. The analysis considered the root causes, consequences, and symptoms of low manufacturing productivity and shows that the South African manufacturing industry has been experiencing low productivity for several years. The journal articles identified the structural and operational factors which give rise to low manufacturing productivity for company X. The operational factors included labour strikes, asset management, condition of equipment and factory layout which are under the organisation's control. In addition, the study also presented structural factors such as infrastructure provision, skills shortages, and organisational structures and systems. The literature shows that high operating costs, loss of sales and customers low competitiveness are the short-term results which lead to higher level effects. The long-term consequences include low and declining profits, loss of market share and lower wages offered to employees.

Second, the researcher interrogated literature especially past and current studies on automation interventions to establish the knowledge gap. The interrogation considered the research strategies, designs, methods, and procedures used in previous and current studies. Automation was the intervention implemented by company X. The researcher has established that studies on automation intervention in South African manufacturing have largely used the quantitative research strategy as shown in Table 1. However, these studies except Hagedorn-Hansen et al. (2017) mostly used data at national level, assess trends and implications of advances in automation on the labour market. As such, they fail to interrogate automation intervention at firm level and interrogate how automation impact manufacturing productivity. Similarly, the researcher has also established that few studies (Parschau et al., 2020) have used the qualitative research strategy when investigating issues to do with automation of a production process yet fail to show the firm level empirical data. Therefore, the literature review has revealed a critical shortage of South African case studies addressing the relationship between automation and productivity. More so, the researcher was able to generate the important information that informs choices about the strategy, methods, and procedures to be used in undertaking this research.

Third, the researcher interrogated literature to establish the research attributes used by other studies which informs data collection and analysis. This enables the empirical execution of the theoretical concepts interrogated during literature review. By interrogating the various dimensions of manufacturing management and how performance is measured and evaluated, the researcher was able to identify the necessary attributes to operationalise the study. Therefore, production volumes, labour costs (number of employees), and quality (waste) have been presented as key attributes for collecting data that would enable understanding of low manufacturing productivity in South Africa. Fourth, the researcher interrogated literature to derive the theoretical framework by exploring several theories on manufacturing performance management. The study interrogated the various frameworks on manufacturing performance management and demonstrated that the productivity theory was the appropriate framework for interpreting the empirical findings of this study. This conclusion was also informed by previous studies (Neumann et al., 2002; Parschau et al., 2020; Sim, 2001) that have used the productivity theory when interpreting the empirical findings. To advance the observations and findings by previous studies as well as close the contextual knowledge gap, the researcher had developed a roadmap. The roadmap shows how the researcher intends to proceed with the study highlighting the study transition from research conceptualisation to empirical execution of the study. The roadmap is presented in Figure 2.5 below.

Figure 2.5: The proposed conceptual framework for investigating the relationship between automation and productivity in a South African manufacturing company.



Source: Author

3 RESEARCH STRATEGY, DESIGN, PROCEDURE AND METHODS

So far, the researcher has covered according to Wotela (2017), the research conceptualisation in Chapter 1 which posed the research questions that this study seeks to answer. In Chapter 2, the researcher interrogated literature to establish the knowledge gap and analysis of the problem of productivity. The problem tree analysis was used to show root causes, consequences, and symptoms of low manufacturing productivity. The researcher then developed the conceptual framework that will guide the choices of techniques the researcher would use for this study. Therefore, this chapter would fulfil three objectives: namely, identifying and describing the research strategy (Section 3.1), the research design (Section 3.2), as well as the procedure and methods (Section 3.3). In addition, the chapter also describes the reliability and validity measures (Section 3.4) that this research applies to make it credible as well as the technical and administrative limitations of the choices made (Section 3.5).

3.1 Research strategy

3.1.1 Broad description of research strategy

Several authors (Bryman, 2012; Creswell, 2009; Kumar, 2011) have discussed the concept of research strategy and there is consensus on what research strategy is. Research strategy is "the general approach a researcher takes in carrying out a research project" (Leedy et al., 2019, p. 371). Three different approaches exists that a researcher can adopt, namely qualitative, quantitative, and mixed (both qualitative and quantitative) research strategy. Bryman (2012) highlighted that qualitative strategy emphasis is on the inductive approach, generation of theories and ways by which individuals can interpret their social world. A quantitative approach entails a deductive approach and testing of theories while emphasising quantification in terms of collection and analysis of data. In the middle, is the mixed research strategy which combines methods associated with quantitative and qualitative research strategies.

Out of the three approaches, this study has settled for a quantitative strategy. This strategy enables the study to analyse existing quantitative data extracted from company X's records and deduce from this data the extent of variation of productivity and costs after automation intervention. Since this is a desktop study, qualitative and mixed strategies would not be appropriate since the study uses quantitative data and does not seek to explain the variation as the assumption is automation intervention drives such a change. Besides, reasonably similar studies (Hagedorn-Hansen et al., 2017; Stundziene and Saboniene, 2019) have used the same approach as will be discussed in Section 3.1.2.

3.1.2 Quantitative research strategy

A quantitative strategy adopted for this study allows for examining relationship among two or more explicitly identified variables (Cresswell, 2009) defined for this study as automation and productivity. Quantitative data extracted from company X records will be analysed using statistical procedures possible with quantitative strategy (Bryman, 2012). The study will determine the extent of the variation between manual production and automated production volumes, waste, and labour, ideal with quantitative approach (Kumar, 2011). In addition, adopting a quantitative strategy is in line with other studies that are reasonably similar. For example, Hagedorn-Hansen et al. (2017) used a quantitative strategy when comparing production level indicators for a semi-automated and automated production processes. They were able to compare and determine percentage changes and extent of variation due to automation. Similarly, le Roux (2018) adopted a quantitative approach when determining the possible implication of automation for the South African labour market. The author used quantitative data from Statistics South Africa to determine the outlook by analysing two data sets and determining trends. In addition, Stundziene et al. (2019) adopted a quantitative approach when determining if investment in tangible assets such as automation improves manufacturing productivity. The study considers quantitative data from manufacturing industries in 29 European countries employing correlation and regression analysis. However, the weakness though is that the authors (Hagedorn-Hansen et al., 2017; le Roux, 2018; Stundziene et al., 2019) did not explicitly explain why a quantitative approach was suited for their study. Despite the advantages articulated above, a quantitative strategy has limitations as well. It does not capture the realities that are specific to the case under review and does not accommodate emerging and open-ended questions (Parschau et al., 2020). Besides, it does not explain why there is a variation or the extent of the changes (Neumann et al., 2002). However, the researcher's focus is on investigating the cause-and-effect relationship between automation intervention and productivity.

3.2 Research design

To investigate the relationship between automation and productivity, an appropriate research design has been adopted for the study guided by literature. Research design is described as the "general structure that guides data collection and analysis to address a research problem” (Leedy et al., 2016, p. 371). This is guided by the “research question(s) and objectives as well as the extent of your existing knowledge, the amount of time and other resources you have available” (Saunders et al., 2012, p. 114). Various research designs can be applied. Bryman (2012) gave the five generic research designs as cross-sectional, longitudinal, case study, comparative, and experimental design. First, a cross-sectional research design entails studying variation on more than one case where data for the variables is collected at a single point in time and patterns of association between variables. Second, for a longitudinal design, a selected sample is surveyed for at least more than one occasion which requires more time and costs. Third, a case study entails an intensive and detailed analysis of a single case such as single family, single school, or a single company. Fourth, a comparative design entails comparison of two or more cases with a view to explain existing theory or use contrasting findings that might be uncovered to generate theoretical insights. Lastly, an experimental design involves at least one experimental group exposed to the treatment/intervention with a control group hence uses findings derived from the research to rule out alternative causal explanations. As such, a suitable research design for this study, supported by literature would be an experimental design.

3.2.1 Experimental (Quasi-experiment) research design

Studies that have focused on automation and productivity in South African manufacturing companies have largely adopted the case study design as discussed in Section 2.3. The cases mostly involve industry or business level data and fail to interrogate production level data before and after the automation intervention. In order to interrogate the automation intervention for company X, an experimental design would be ideal which test the impact of an intervention on the outcome (Bryman, 2012). This study seeks to identify cause-and-effect relationship between automation and productivity, which according to Leedy et al. (2019) is suited to experimental design. Hence, the central feature entails comparison in this case of productivity between manual and automated production, which typically is associated with quantitative research strategy as adopted in this study as well. Hagedorn-Hansen et al. (2017) used an experimental design when comparing semi-automated production and automated production performance. The design allowed the authors to compare performance of the two processes and determine the extent of variation between the two, which is the intention of this study as well. Different types of experimental design exist. Creswell (2009) gave these as pre-experimental design, true experiments, quasi-experiments, and single-subject designs. First, pre-experimental design entails studying a single group and providing an intervention during the experiment and does not show cause and effect relationships hence only helpful for forming tentative hypotheses. Second, true experimental designs the researcher randomly assigns participants to treatment groups and offer a greater degree of control hence greater internal validity. Third, single subject designs involve observing the behaviour of a single individual or small number of individuals over time. Fourth, quasi-experiments entail using control and experimental groups, but the researcher does not randomly assign participants to groups. They don't control for all confounding variables hence cannot completely rule out alternative explanations for results obtained.

Therefore, since the intervention has already been implemented by company X, there is no control or manipulation of the independent variable, i.e., automation. Hence, the more appropriate design for this study would be the quasi-experimental design as it does not involve random selection of the study group or presentation of the intervention (Leedy et al., 2019). Besides, automation intervention does not control all other factors involved in the production process such as systems, skills levels, communication etc. that has a potential impact on volume outputs, a key feature of quasi-experiments. However, limitations of quasi-experiments pertain to the absence of random assignments which casts certain level of doubt in the research's internal validity (Bryman, 2012). However, this applies to experiments which involve manipulation of social setting (Kumar, 2011), which is not the case in this study. In addition, external validity threats specific to this study arise due to uniqueness of the setting. As such, this might affect generalisation of the finding to other situations which cannot be done with certainty (Creswell, 2009). The resources and time availability for this researcher, means this limitation could not be addressed in this study. Therefore, more studies are required in South Africa to ensure several similar automation interventions can be compared.

3.3 Research procedure and methods

So far, the study has interrogated literature to establish the research strategy and the research design relevant for the study. This section documents the actual procedure and the methods employed in this research to collect, collate, process, and analyse empirical evidence. The researcher will detail the data and information collection instruments in Section 3.3.1 and the target population and sampling of respondents in Section 3.3.2. Thereafter, the ethical considerations during the research process would be detailed in Section 3.3.3 while data and information collection process and storage would be detailed in Section 3.3.4. The chapter would end by detailing how data and information processing and analysis would be achieved (Section 3.3.5) as well as description of the respondents who provided empirical evidence for this research study (Section 3.3.6).

3.3.1 Research data and information collection instrument(s)

Saunders et al. (2012) described a data collection instrument as a tool or device used to collect data. The data collection instruments include questionnaires, interviews, checklists, surveys, and observations. Data collection structure as described by Kumar (2011) is the process adopted by the researcher for collecting data using the tool or device chosen for the study, can be unstructured, semi-structured and fully structured.

However, this study is not going to use any of these instruments as the data already exists. The data has already been collected and what is required is extracting the required information. The study extracts raw quantitative data from company X's database. Other sources of secondary data not used in this study include government publications, personal records, mass media, earlier research etc. The other category not used in this study, is primary data which relates to data collected by the researcher or someone else directly from respondents for specific purpose as required by the study. The choice of the data collection instrument is also in line with past studies (Hagedorn-Hansen et al., 2017; le Roux, 2018; Stundziene et al., 2019). For example, Stundziene et al. (2019) used existing data from Eurostat when determining if investment in tangible assets such as automation improves manufacturing productivity. Like these studies, enough data is available over a period of six years (2015-2020) that will be considered for this study. In addition, the quantitative data exists in the right format which meets the needs of the study, and no cost will be incurred in obtaining this data which according to Saunders et al. (2012) are potential pitfalls when using secondary data. However, due to the sensitivity related to employee salaries, the labour costs would be limited to number of employees.

3.3.2 Research target population and selection of respondents

In this study, the researcher focuses on manufacturing company X as the unit of analysis. The target population is the universe of units from which the researcher selects the sample (Bryman, 2012). As such, the databases in company X constitute the target population. The various datasets exist for different purposes in the company. These include production database (ERP system), maintenance database, safety database, planning database, human resources database and inventory database. The production database consists of production volumes and quality (rejects) data. This quantitative data is input into this database by the production personnel from the shift production data and exists as daily, weekly and monthly data. The maintenance database contains the equipment registers, information on maintenance carried on each machine and the downtime associated with each machine. The safety database contains employee safety training records, inspections records, incidents and injuries recorded. The human resources contain complements per department i.e., number of employees, employee salary details, performance data etc. The planning database contains information on production plans and raw materials requirements. Therefore, these databases are defined as the target population in this study. Several authors (le Roux, 2018; Parschau et al., 2020; Stundziene et al., 2019) used secondary data sources as well. For example, Parschau et al. (2020) argues that secondary data sources such as newspaper articles and company websites enable them to corroborate hypotheses about the impact and stage of development of automation technologies. Stundziene et al. (2019) argues that availability of large secondary data (2005-2016) enables them to evaluate if the relationships between the variables is influenced by time. Therefore, the large data set available for this study would allow the study to have an accurate estimate of the dependent variables mean.

However, it is not possible to cover all databases in this study. As a result, a sample which is a subgroup of the whole population (Saunders et al., 2012) in this case the databases would be selected. The production database and the human resources database would be used in this study. These are useful as they contain the quantitative data required for answering research questions for this study. For example, the production database provides the monthly production volumes and monthly production waste (rejects) data while the human resources database provides the number of employees by department and production shift. The production volumes would be used when determining productivity while the waste data and number of employees would be used for determining production costs. Sampling was done by a non-random method and a predetermined sample size was selected. The data extracted would be for six years, consisting of three years before automation (2015-2017) and three years after automation (2018-2020). According to Kumar (2011) purposive sampling in quantitative research involves non-probability sample where the researcher selects participants in a predetermined way best positioned to provide required information relevant to the research questions. In addition, a large sample as in this study provides more accuracy on the estimate of the true population mean. Several authors (Hagedorn-Hansen et al., 2017; Parschau et al., 2020; Stundziene et al., 2019) used purposive sampling. For example, Parschau et al. (2020) argue that purposive sampling enables them to target specific manufacturing company with a particular size and producing different product ranges. Hence, the specific databases selected for this study meets this criterion.

3.3.3 Ethical considerations when collecting research data.

The researcher was granted authorisation for the desktop study by Company X which requires company identity and company records be kept confidential. Therefore, the researcher will ensure confidentiality and ethical considerations relating to various stakeholders are fully understood and adhered to. Kumar (2011) describes ethics as principles of conduct which are considered correct. Unethical behaviours would include among others using information improperly, breaching confidentiality, causing harm to individuals, and introducing bias. The ethical issues relate directly to the integrity of the research (Bryman, 2012) and this study sought to maintain integrity, hence ensure no harm to various stakeholders. There is no funding body for this research and the researcher would use own resources to conduct the research. The researcher does not expect to get any direct or indirect benefits, financial or other for conducting this research. The researcher declares that there are no known competing financial interests as well as personal relationships that could potentially influence the work to be carried out by the researcher.

3.3.4 Research data and information collection process

Research data collection involves gathering information about a situation, person, problem, or phenomenon (Kumar, 2011). As discussed in Section 3.3.1 no data and information collecting instrument will be used for this study as the data is existing. Therefore, it follows that no data and information collection processes would be applied for this study. In fact, the researcher would extract data from the database mentioned in Section 3.3.2. The researcher had been given computer access and log-in credentials to the respective databases and would directly select data for the relevant period. Stundziene et al. (2019) extracted data from Eurostat database which they consider a reliable source and able to provide data for a long period, 2005-2016). The longer period enabled the authors to test for time effects and analyse various variables. Similarly, le Roux (2018) extracted data from Statistics South Africa which the author considers a reliable and house-hold database. Also, the data covers a large set of variables which allows the author to extract appropriate data and generate trends. In addition, Hagedorn-Hansen et al. (2017) extracted data from the company server and production software, which they consider reliable data and available for the period required. Therefore, data extracted from company X databases would be considered reliable data and availability of data for longer periods would enable the study to generate appropriate trends.

3.3.5 Research data and information processing and analysis

After extracting the data, it is raw and does not communicate anything unless processed (Sahu, 2013). Research data processing is when the raw data collected goes through a series of steps which includes editing, coding, and analysis (Kumar, 2011). However, for this study the quantitative data is already available in the required format i.e., monthly production volumes, monthly waste volumes and number of employees. As a result, no editing (cleaning) and coding would be required (Sahu, 2013). However, to make the data useful, we find patterns that lie beneath by conducting data analysis. This entail applying statistics in a systematic way to summarize large numerical data sets (Leedy et al., 2019). Hence, the extracted data will be entered into Microsoft excel using the computer and presented as two data sets, 2015-2017 and 2018-2020 in the form of excel tables marking the beginning of data entry (Bourque & Clark, 1992). Thereafter, the data is exported into GraphPad Prism 7.0 software to complete statistical analysis. The statistical analysis of the variables would include determining and comparison of average (mean), percentage changes, trends, two-way Anova and unpaired t test for the two data sets on production volumes and waste data. After analysing the data, then the data will be presented in Chapter 4 using bar graph and line graph over time as this allows for trending (Saunders et al., 2012). Hagedorn-Hansen et al. (2017) used bar graphs and averages when comparing manual and automated production. The author was able to determine percentage changes on the variables. Similarly, Neumann et al. (2002) used average of each variable to determine percentage changes for each variable between manual and automated production. In addition, Munyai et al. (2018) used descriptive statistics and was able to measure central tendency and the analysis show the proportion of work spend on productive work and non-productive work.

3.3.6 Description of the research respondents

The researcher focuses on a desktop study for investigating the relationship between automation and productivity using secondary data sources from the company. No interviews or questionnaires, direct/indirect engagement with company employees or managers for purposes of collecting research data would be done. Therefore, the researcher does not engage any respondents as part of this study.

3.4 Research strengthens—reliability and validity measures applied.

Several authors, (Bryman, 2012; Leedy et. al., 2019; Sahu, 2013) have discussed the concept of reliability and validity in research. For example, reliability "is the ability of a research instrument to provide similar results when used repeatedly under similar conditions" (Kumar, 2011, p. 396). As discussed in Section 3.3.1, no data collection instrument would be used for this study since the study extract existing data from company X databases. Hence, factors that threaten reliability such as subject error, subject bias, observer error and observer bias (Saunders et al., 2012) would not apply for this study. However, the validity of every aspect of the research process is also important, described by Kumar (2011, p. 402) as the "appropriateness of each step in finding out what you set out to". The four main types of validating research for quantitative research are measurement validity, internal validity, external validity, and ecological validity. According to Bryman (2012) internal and ecological validity are mostly applicable to qualitative research. Therefore, the researcher would not be pursuing internal and ecological validity in this study. The researcher proposes to apply the measurement validity to this study which entails "the degree to which a measure of a concept truly reflects that concept" (Bryman, 2012, p. 713) by using production volumes to determine productivity. Saunders et al. (2012) define external validity as the extent to which the findings can be generalisable to other research settings or the study can be replicated. This experimental study pertains to a single production line in one organisation, company X. As such, questions remain about the extent to which the conclusions are generalisable to other organisations. Similar studies would be required in South Africa.

3.5 Research weaknesses—technical and administrative limitations

The researcher has chosen the quantitative research strategy and a quasi-experimental design to interrogate the automation intervention by company X. However, quantitative strategy is less accommodating to open-ended question and emerging questions. As a result, the study would not be able to explain why the volumes change or does not change after the automation intervention. Parschau et al. (2020) argues that quantitative strategy has a less flexible structure and does not focus on rendering the complexity of a situation, something that could be achieved through a qualitative strategy. For this study, sensitive data like employees' salaries was deemed confidential and proprietary, hence could not be shared. As such, actual labour costs could not be determined. The focus of the study is on one organisation only. Therefore, external validity would always be challenged as organisations have different settings. Other factors that impact productivity and costs were not considered, hence a limitation as well. The extent to which the study could be replicated is not questionable, but internal industry realities are quite varied. From an administration point of view, the researcher is limited in the time available to complete the study. Certain data collection tools such as interviews with employees of the organisation which could enhance the study and discussion of the intervention could not be used due to time limitations.

4 PRESENTATION OF RESEARCH RESULTS

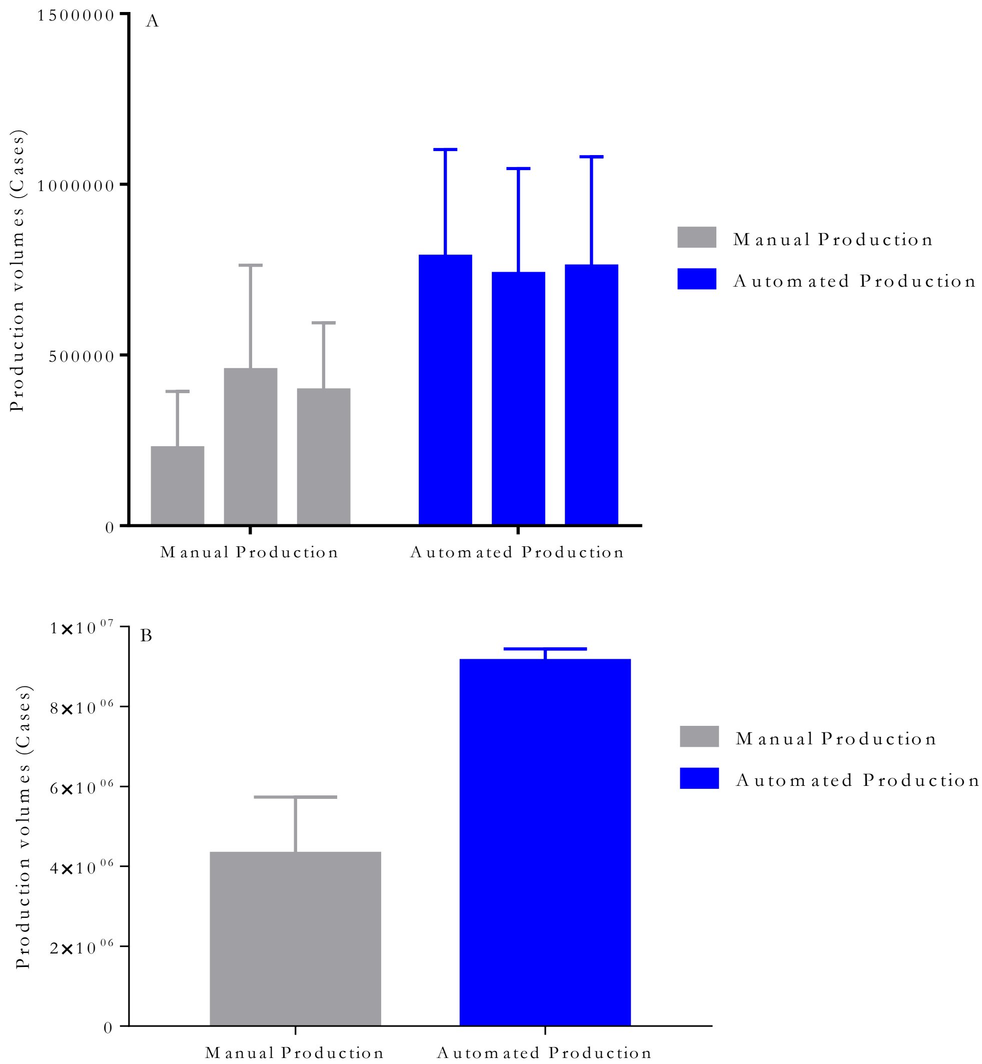
The researcher extracted data from the company records on production volumes, production employees and production waste (quality). The data extracted covers a period of 5 years. The data was entered into tables (excel), trending graphs generated, and statistical analysis done using GraphPad Prism 7.

4.1 Automation and manufacturing productivity

The first research question states, "to what extent does automated manufacturing process in a particular firm in South Africa improve productivity as measured by production volume outputs?". The research hypothesis, H1 test the interaction effect between automation and production volumes (productivity). It states that automated production processes volumes are greater than manual process volumes. This hypothesis was supported by the performances measure of production volumes. The result show that automated production volumes are 112 percent higher than manual production volumes. The evidence suggests there is synergy between automation and productivity. The null hypothesis, Ho is not supported. Ho test the non-interaction between automation and productivity i.e., there will be no difference in the production volumes for automated and manual processes.

The first three years, from 2015 to 2017 of the data pertains to production data for a period where manual palletising was being done. The three-year averaged total annual production volume during manual palletising operation was 4,307,559 cases with respective average monthly volume of 226,234: 2015; 455,056: 2016 and 395,600: 2017. On the other hand, the next three years, from 2018 to 2020 pertains to production volumes handled through automated palletising process, hence fully automated production process. The three-year averaged total annual volume from the automated palletising process was 9,132,171 cases with the respective average monthly volumes of 787,576: 2018; 736,686: 2019 and 758,780: 2020. Automated production volumes are 112 percent higher than manual production volumes. The statistical analysis of the results using 2way ANOVA show a significant ($p < 0.05$) difference between the manual and automated volumes at $p < 0.0001$. Similarly, unpaired t test analysis also shows a significant difference between the volumes at $p < 0.0001$. Therefore, the results show that there was a significant increase in production volume of cases following automation of the palletizing process ($p < 0.05$; Figure 4.1 A and B). This suggests a strong correlation between the automation and productivity as measured by the volume outputs. It is important to note that the rated capacity of the production line which includes the palletising section was the same for all the years (2015 to 2020) at 30,000BPH or 4960 cases/hour. The average annual volumes are shown in the figure below.

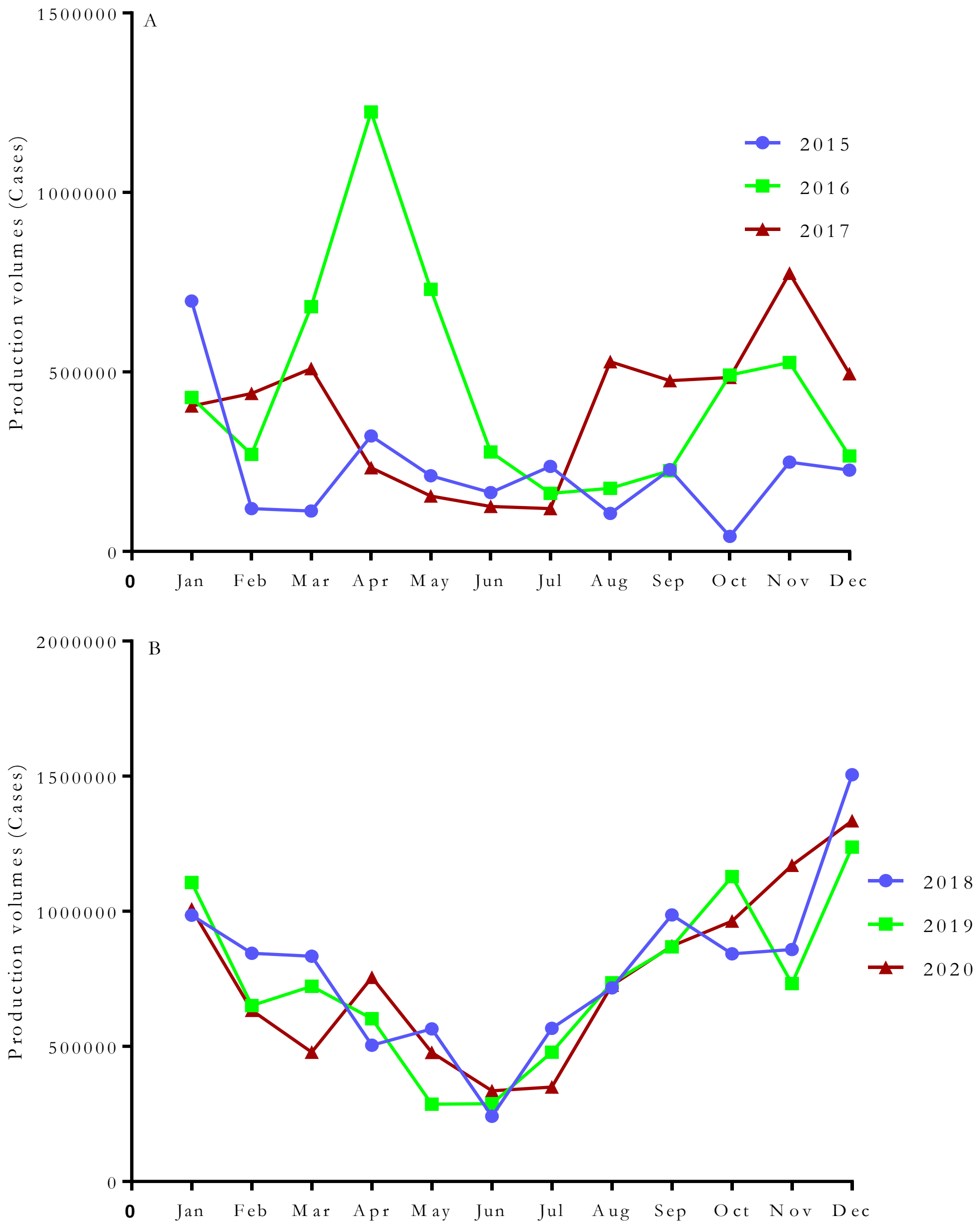
Figure 4.1: The comparison of annual production volume between manual production (2015–2017) and automated production (2018-2020).



(Author: 2021)

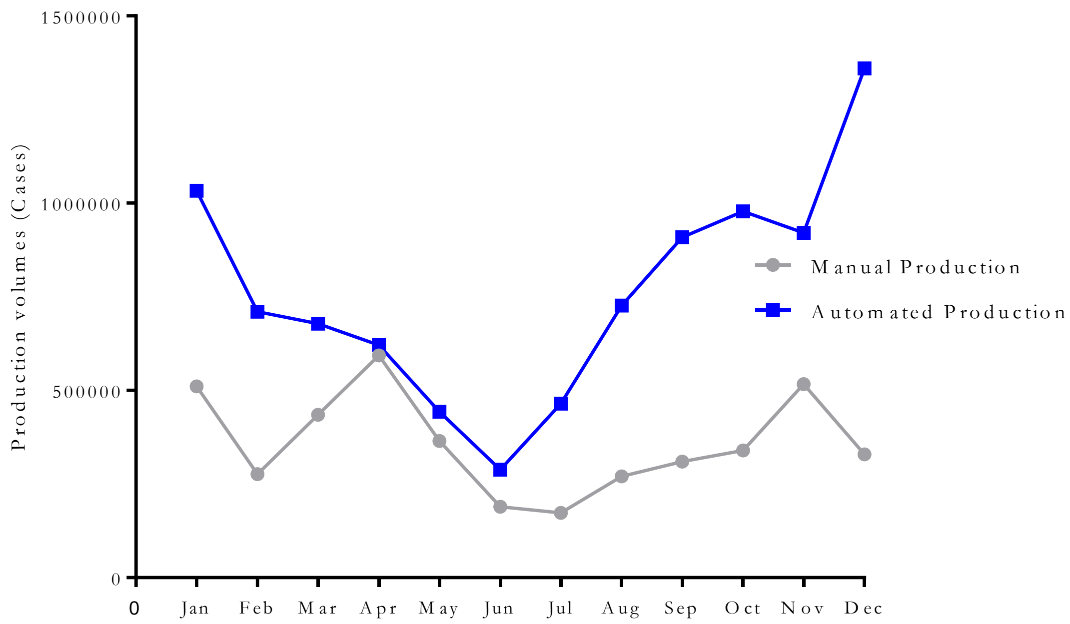
The analysis of the annual trends of the production volumes also shows the significant difference between the annual production volumes produced using manual and automated palletising process. The average monthly volumes for automated production are higher than the average monthly volumes for manual production for the three-year period. The cyclical nature of the business as measured by the monthly volumes shows yearly low demand periods during the winter months from May to August. This does not mean manual palletising or automated palletising was ineffective during this period. Other monthly spikes in volumes could be related to demand movement for the products, hence increased volumes. Alternatively, the company has three manufacturing plants in South Africa and possibly one plant might produce volumes for the other plant/s depending on circumstances. The monthly trends are shown in figures below.

Figure 4.2: The comparison of annual production volume between manual production (2015–2017) and automated production (2018-2020).



(Author: 2021)

Figure 4.3: The comparison of average monthly production volume between manual production (2015–2017) and automated production (2018-2020).



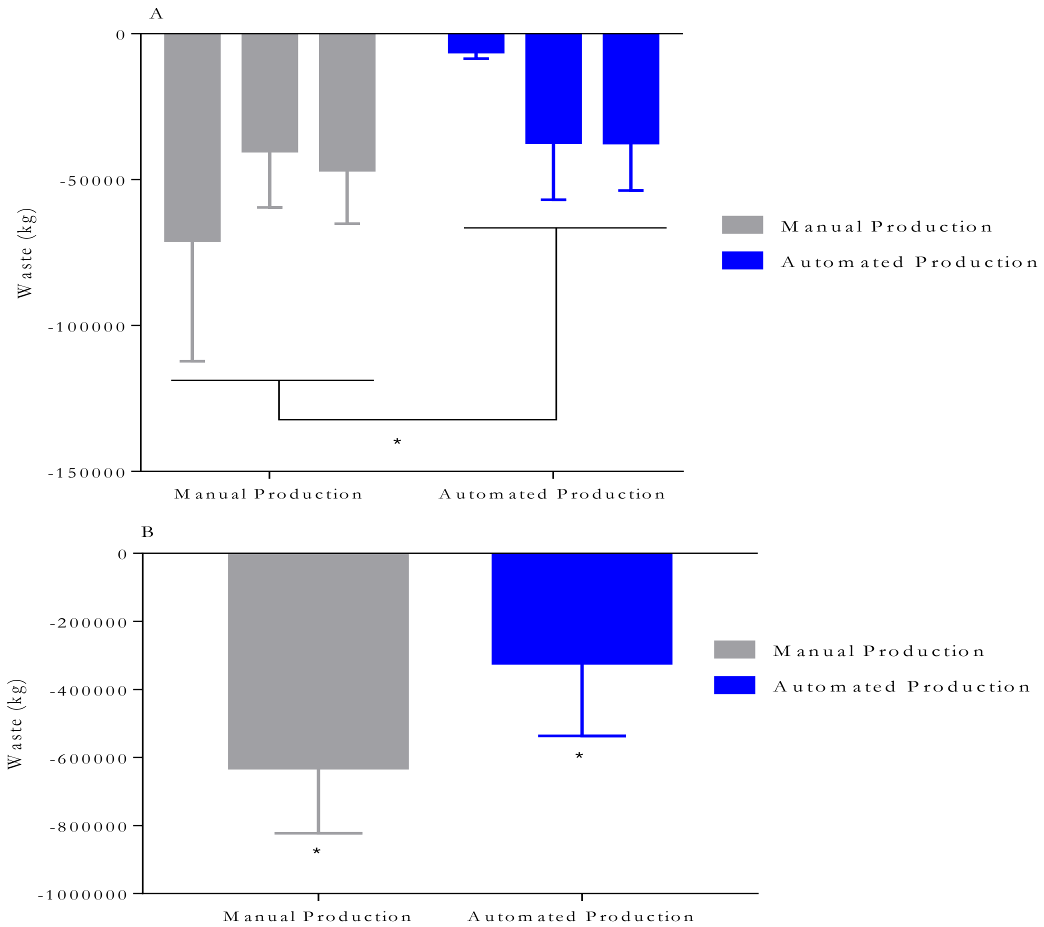
(Author: 2021)

4.2 Automation and manufacturing costs

The second research question states, "to what extent does use of automated manufacturing processes reduce production costs in a manufacturing firm in South Africa?". Two forms of waste (rejects) data were collected and analysed. Type 1 waste is directly related to palletising process while type 2 waste is produced before palletising and is partly influenced by the palletising process. Type 1 waste is due to breakages in palletising of the final product due to such issues as manual mishandling, impact from throwing product, falling, and machine damage, among others. The research hypothesis, H1 test the interaction effect between automation and production costs i.e., automated production costs are lower than manual process costs. This hypothesis was supported by both the waste and production labour measures. The results show that automation reduced direct waste by 49 percent and production labour by 73 percent. Waste and labour directly contribute to costs. Therefore, the result show that the automated production costs as measured by the quality (rejects) and number of employees are lower than manual production costs. As such the null hypothesis, Ho is not supported. Ho test the non-interaction between automation and cost i.e., there will be no difference in the production costs of automated and manual process. The results suggest there is a difference between the costs.

The quality performance results as measured by waste (rejects) show that the average total rejects, Type 1 waste was a 49 percent reduction from 52,443 kilograms (2015-2017) to 26,769 kilograms (2018-2020). This is significant considering the volume produced were far higher between 2018-2020 compared with 2015-2017. The three-year averaged total waste (kilograms) produced by manual palletising operation was 629,318 kilograms with respective average monthly volume of 70,668: 2015; 40,054: 2016 and 46,607: 2017. On the other hand, the three-year averaged total rejects for automated palletising process were 321,226 kilograms and the respective average rejects was 6,027: 2018; 37,079: 2019 and 37,200: 2020. The statistical analysis of the results using two-way ANOVA show a significant (i.e., $p<0.05$) difference between the manual and automated rejects at $p<0.0001$. Similarly, unpaired t test analysis also shows a significant difference between the rejects at $p<0.0013$. Therefore, the results show that there was a significant reduction in rejects following automation of the palletizing process ($p < 0.05$; Figure 4.4 A and B). This suggest that the extent to which automation reduce production was found to be significant in this study. The results are shown in figure below.

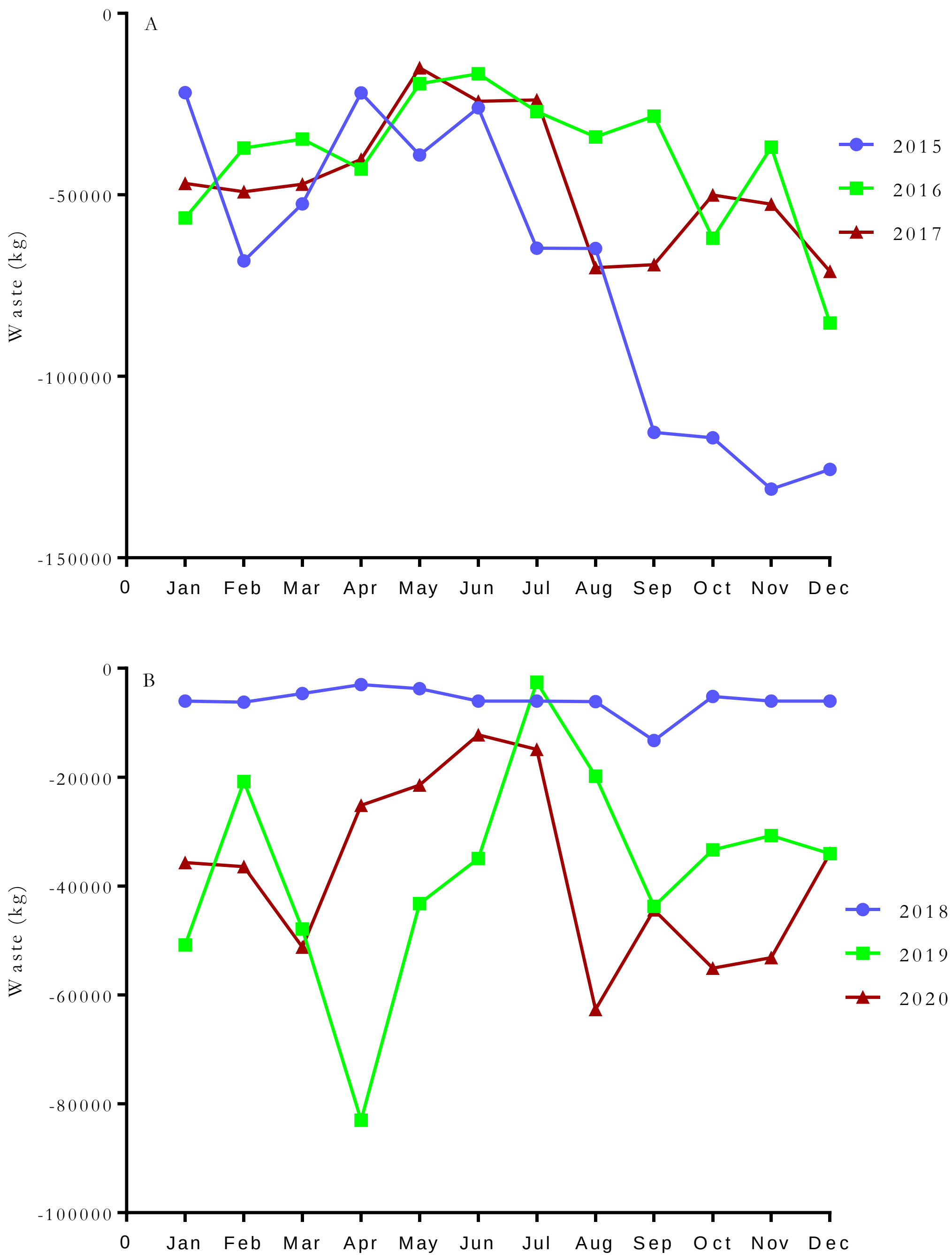
Figure 4.4: The comparison of annual waste 1 between manual production (2015–2017) and automated production (2018-2020).



(Author: 2020)

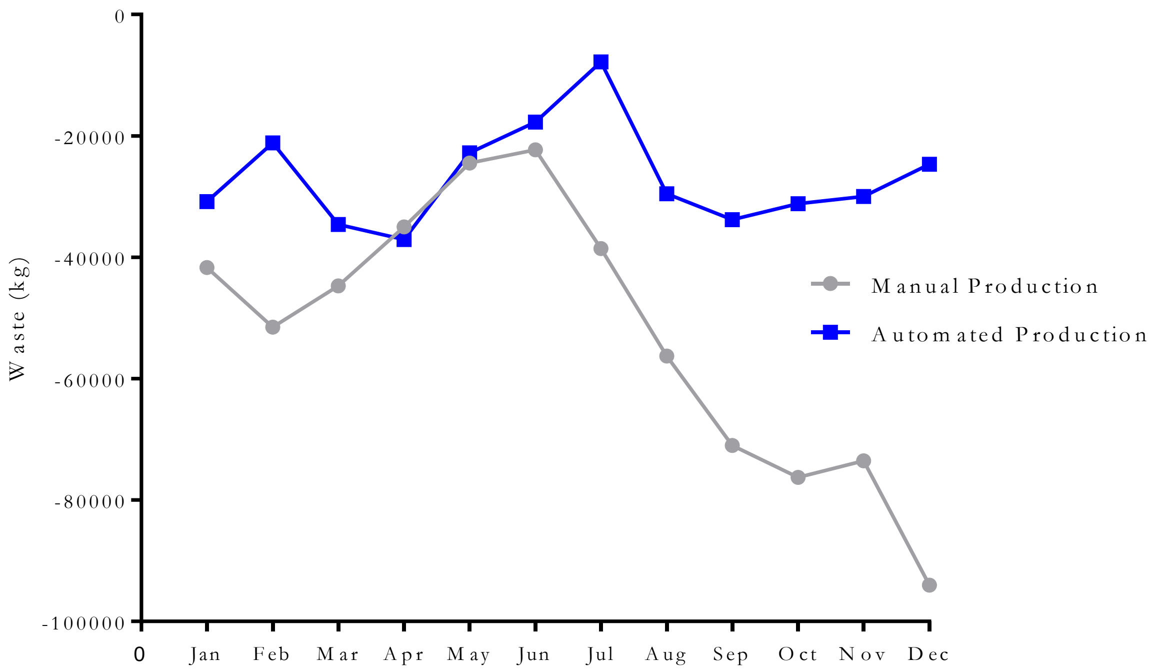
The monthly waste trends are shown in the figures (Figure 4.5 and Figure 4.6) below. The result show automated production waste is consistently lower than manual waste throughout the year except for the month of April when manual waste was lower than automated waste. This is consistent with the results of the average waste volumes in Figure 4.4 above.

Figure 4.5: The comparison of monthly waste 1 between manual production (2015–2017) and automated production (2018-2020).



(Author: 2021)

Figure 4.6: The comparison of average monthly waste 1 between manual production (2015–2017) and automated production (2018-2020).



(Author: 2021)

The 3-year trend (Figure 4.6) shows that automation process waste in consistently lower than manual process waste with only one period showing otherwise. This suggest company X was able to significantly improve the quality of the production process through automation.

The labour costs as measured by the number of the employees on the production process, showed a 73 percent reduction. The automated production process had less employees compared to manual process. Information on salary rates for each employee could not be accessed since the company did not authorise such access. In addition, the results show a 45 percent reduction in the number of technical employees responsible for maintenance of the production line. On the other hand, there was no change on the quality employees. Overall, the result shows a 63 percent reduction in number of employees when all departments are considered as shown in Table 2 below.

Table 2: Comparison of employees between manual production (2015-2017) and automated production (2018-2020)

Company X Production Employees

Department	Company Documents (Manual)	Company Documents (Automation)	Change (Manual Vs Automation)	Percentage Change (Manual vs Automation)
Production	**45**	**12**	**33**	**73%**
Technical	**11**	**6**	**5**	**45%**
Quality	**4**	**4**	**0**	**0%**
Total Employees	**60**	**22**	**38**	**63%**

Source: Author

The number of production employees reduced from fourty five (45) to fourteen (12). In addition, the number of technical employees doing maintenance on the lines was reduced from eleven (11) to six (6). On the other hand, the number of quality employees performing quality checks and measurements on the line remained constant at four (4). Overall, the total number of employees working on the production line reduced from sixty (60) to twenty-two (22). The company records indicate that the affected employees were retrenched rather than being absorbed in other sections of the organisation.

5 DISCUSSION OF RESEARCH FINDINGS

5.1 Introduction

The study by the researcher has managed to present the empirical results of the automation of the production line by company X. The results were analysed, and trends were established over a five-year period. Firm level secondary data was used to analyse the outputs of this intervention. The results of the quantitative analysis of the attributes such as production volumes, quality and costs as measured by the waste (rejects) and number of employees was presented in Section 4. The implemented automation intervention had lower production costs and higher production volumes compared to the manual production process. This section discusses the results of each analysis done on these attributes.

5.2 Automation and productivity

The results of the study show that automation of the production line had higher volumes than manual process. Therefore, the researcher argues that automation would be an effective way for improving manufacturing productivity. As highlighted earlier, the automation of the palletising process did not alter the rated throughput (capacity) of the line. The rest of the production process was already automated with only the palletising section operating manually. The design capacity of the line remains at 4960 cases per hour. The volume outputs of the automated production process are 112 percent higher than manual process. According to the productivity theory,

$$\textbf{PRODUCTIVITY} = \frac{\textbf{OUTPUT}}{\textbf{INPUT}}$$

In this case the outputs are the measured by the production volumes. Since productivity is directly proportional to the outputs, an increase in production volumes by implication increases the productivity assuming inputs do not increase at a faster rate than outputs. Therefore, automation would have reduced production losses due to line stoppages caused by strikes, sick days (insufficient labour), meetings, comfort breaks (tea breaks, toilet breaks, lunch breaks) for the manual palletising employees, fatigue, and morale issues among other things. Machine on the other hand can operate for long periods of time without need for breaks unless there is a technical breakdown which requires maintenance repair to be done. While the increased production volume over the years might also be attributed to other factors such as increased demand for the company's products, increased market share as well as increased efficiencies, it is likely that automation played a key role. This much so since the rated production throughput for the line was the same for both manual and automated palletising.

The results are consistent with existing body of knowledge. For example, Neumann et al. (2002) investigated the productivity impact of automation and recorded 51 percent increase in production volumes between manual and automated production process. They found faster transfer of production and from carts and machinery resulted in less task variability. Besides, the faster repetitions due to automation provided production-ergonomic trade-off resulting in improved production volume outputs. Similarly study by Hagedon-Hansen et al. (2017) in a South African manufacturing company shows that automated production process had a 6.6 percent higher availability and 3.15 percent higher OEE of machines hence outputs. This directly translated to 28 percent and 11 percent increase in profit respectively. In addition, Parschau et al. 2020 study in South Africa found that automation of manufacturing process increases productivity. While the author did not provide figures, the study found that manual process outputs are lower than automated process.

However, other studies had different outcomes to the researcher's study. For example, study by Sim (2001) show that investment in technology on its own does not deliver improved outputs, despite its importance to the long-term success of the organisation. It is however important to note that this was in the context of a developed country and not a company specific case study. Therefore, the results support the widely held view that automation improves manufacturing productivity. This is vital for the South African manufacturing industry which has recorded productivity decline over the years and seen its contribution to the economic growth and employment decline over the years.

5.3 Automation and production costs

The results of the study show that automation of the production line had higher quality results, hence low rejects compared to manual process. Therefore, the researcher argues that automation is an effective way of improving quality of the production process hence reduce costs of production. The significant reduction, 49 percent in waste demonstrate the difference between machines and human when it comes to repetitive tasks. Moreso, the manual palletising is physically demanding due to the nature of the products produced by company X. While humans are subject to tiredness, the same cannot be said of machines. This shows product breakages due to mishandling and damage from impacts (throwing) are minimised where machines are set-up for smooth handling and transfer. In addition, build-up of product on the production line in minimised hence reduce the likelihood of product falling off machines and pressing against each other. This directly translate to less rejects and effective conversion of raw materials to good product. This is against the volume produced between 2018-2020 being 112 percent higher than the volume produced between 2015-2017. Therefore, besides handling significantly higher volume, automated process effectively converted the raw materials to finished product. As the volume increased, the costs were reduced due to lower rejects.

The results of the study are consistent with findings from other studies. For example, Sim (2001) show that automated process had a higher quality performance compared to manual process. Similarly, Waldman (2016) show reduction in production costs and improvement in quality as one of the key drivers in automation investment. Therefore, the findings of this study provide empirical evidence at firm level on how automation impacts quality and costs. This addresses the gap identified by Parschau et al. (2020) in terms of lack of firm level studies in South Africa on automation interventions. As a result, the study enhances the existing literature and enables the gaps identified for developing countries to be closed. However, other studies had different outcomes to the researcher's study. For example, Hagedorn-Hansen et al. (2017) study show a slight decrease in quality due to automation, albeit insignificant at 0.9 percent between automated process and semi-automated process.

Labour costs for automated production process are significantly less than manual process. The company was able to produce more with less labour since the automated production process had a 73 percent reduction in number of employees and by extension, the labour costs. This bodes well for the company to be competitive in a market where consumers have various options and choices. The results are consistent with several findings from other studies in the rest of the world. For example, a study by Neumann et al. (2002) shows that the 51 percent increase in production volume after automation of a production process was achieved with 21 percent less labour input. Similarly, studies in South Africa by Hagedorn-Hansen et al. (2017) shows that labour costs for the automated production process was considerably less that semi-automated process recording an 88.4 percent reduction. However, the authors argue that to promote labour in South Africa, companies must prioritise effective use of equipment which increases the quality compared to efficient use of resources. Similarly, Parschau et al. (2020) study show automation improves labour productivity in the South African apparel industry.

Productivity is critical for economic growth which in turn would create sustainable jobs (Parschau et al., 2020). This becomes more pertinent in Mpumalanga province where manufacturing is the biggest employer. The result of this study show that jobs are lost due to productivity improvement because of automation, however there could be gains in other industries or national level. Therefore, for an organisation whose primary strategic vision is improve outputs and reduce costs, introduction of automation as an intervention would be ideal. However, when specifically, looking at technical department responsible for the maintenance of the equipment, the findings of this research go against the predominantly held view that automation result in increased number of more skilled employees (Mckay et al., 2019; McKinsey, 2017). The number of technical employees responsible for maintenance reduced by forty-five percent. This is despite the increased number of assets (equipment) on the production line. This could be explained by the fact that the production process was already automated except the end part of the process, which is palletising. As a result, the existing skills would have been high-level and experienced enough.

Overall, automation of the manufacturing process was effective in improving productivity by 112 percent, reducing costs as measured by waste and labour by 49 percent and 69 percent respectively. The net effect is that productivity increased since outputs increased while inputs decreased. The automation intervention was effective as a strategy for cost reduction and improving productivity.

6 SUMMARY, CONCLUSIONS, LIMITATIONS, AND RECOMMENDATIONS

6.1 Summary

The researcher had raised an argument that the success of automation in South Africa has been constrained by the limited empirical evidence demonstrating the relationship between automation and increased productivity in manufacturing. This was supported by literature pointing to a general lack of firm level case study evidence in South Africa evaluating automations intervention. To address this problem, the researcher adopted company X as a case study and interrogated firm level company production data. The automation of the production process as an intervention by company X was interrogated in this study. The research conceptualisation was grounded in literature. Accompanying research questions were proposed in Section 1.2.3. The researcher completed a literature review in Section 2 to understand the root causes, consequences, and symptoms of low productivity in manufacturing industry. The problem tree was adopted to demonstrate how the problem of low productivity manifests, its results and how this problem is perceived in the public eye. The researcher was able to show that the underlying causes of low manufacturing productivity include structural as well as operational issues. After interrogating literature, the researcher concluded that organisational structures and systems are at the centre of low manufacturing productivity in South Africa. In addition, the researcher was able to draw the link between the factors affecting productivity in a manufacturing company, the consequences, and symptoms of low productivity and how these manifests in South Africa. The results of low productivity included high manufacturing costs and loss of market share. On the other hand, the symptoms included low wages, poverty, and high unemployment in South Africa, which Statssa (2020) show picked at 30.1 percent.

Once the low productivity problem was understood, the researcher further interrogated literature (Section 2.2) to understand the methods, data, findings, and conclusions of studies on evaluating automation interventions in manufacturing. The researcher was able to discuss how other companies have addressed the problem of low productivity in the rest of the world as well as looking at the South African context. The researcher then proposed a conceptual framework for evaluating effectiveness of automation in a South African manufacturing company. In addition, the productivity theory was adopted from literature for interpreting the effectiveness of the automation intervention.

The study considered two research questions and the interrogation of company X secondary data was carried out to provide answers to those questions. The researcher presented the results of the study in Section 4. First, the study considered extent of variation in productivity due to automation of a production process. The results of the 3-year trends and statistical analysis of the production volumes were presented in Section 4.1. The results show that automation volumes are 112 percent higher than manual volumes. In addition, both 2way ANOVA and unpaired t-test analysis show a significant difference ($p<0.05$) between automation and manual production volume. Therefore, the results confirmed that there was relationship between automation of the production process and automation. Second, the study considered the extent to which automation impact production costs. The 3-year trends and statistical analysis of the waste data was presented in Section 4.2. The results show a 49 percent reduction in waste after automation while the statistical analysis shows a significant difference ($p<0.05$) between the automation and manual waste. In addition, the labour costs were also interrogated. There was a 73 percent reduction in labour from 45 employees to 12 employees between manual production and automated production process. The employees' salaries as well as unit costs of waste (rejects) could not be accessed as per condition of case study authorisation from company X. Therefore, the costs associated with waste and labour while not presented explicitly, were deduced using the waste and labour data. The results presented are consistent with previous and current studies done in South Africa and elsewhere.

The researcher completed a discussion of the results presented in Section 4. The discussion was completed in Section 5. The researcher first considered automation and productivity in Section 5.2 by interrogating why automation volumes are higher than manual production volumes. The researcher considered both human and machine factors and how the key differences between automation and manual production relate to the increased volume from automation. The ability of machines to operate continuously without breaks and fatigued were noted as some of the key aspects driving these improved volumes. On the other hand, it was shown that employees would require breaks, leave, and suffer from fatigue which impact on outputs. Section 5.3 discussed the automation intervention and the associated costs related to waste and labour. The researcher was able to show that automation the factors such as handling, stoppages and consistence as contributing to improved quality for the automated production line, hence reducing costs associated with waste (rejects). In addition, the researcher considered and discussed the implications of a reduction in labour due to automation of the manual production process. While manufacturing companies pursue productivity enhancing solutions and competitiveness, the researcher was able to show that the immediate displacement of workers remains a cause for concern in a high unemployment country such as South Africa.

6.2 Conclusions

The study interrogated the effectiveness of automation as an intervention to address the problem of low manufacturing productivity by company X. The data was collected from the company's records and data base. This was achieved by critically evaluating the intervention where the secondary data was analysed using quantitative techniques and processed in GraphPad Prism 7. The manual palletising process on the production line was compared to automated palletising process in terms of performance, outputs as measured by production volumes, quality, and labour requirements. The researcher was able to draw several key conclusions from the case study.

First and critical conclusion is that automation is effective in improving productivity and reducing production costs. This is because automation intervention led to higher production outputs (volumes). Higher volumes entail the company can meet the forecasted volumes hence customer orders on time. This is significant since South African manufacturing productivity has been declining over the years. By adopting carefully thought automation solutions, manufacturing companies can stem the tide. Second, the higher production outputs were achieved with less costs. While the outputs increased, there was a reduction in waste and labour. As a result, the manufacturing costs are reduced, and the company can position itself to compete in the market. However, the retrenchment of workers would be notable in this study, the employment impact is far from simple and causal. Automation interventions in other manufacturing industries have shown that the employment impacts are very limited. For example, study by Parschau et al. (2020) have shown no job losses in the apparel industry from automation adoption. This would entail labour impacted by other manufacturing companies adopting automation is able to be absorbed in other manufacturing companies. Third, automation requires skilled employees to perform maintenance and machine set-up tasks. The reduction in technical skills observed in this study might be considered an isolated case when compared to other studies. This is particularly so considering the increased asset base which demands more maintenance activities.

Lastly, automation was effective in improving the quality performance of the production line. The number of product rejects was significantly reduced by the automation intervention. Product rejects is waste and has a cost. This entails a reduction in waste directly reduced the production costs for the company. When this is added to the low labour input, the cumulative benefits become more significant. Therefore, the productivity benefits of automation are derived from several factors making such an intervention critical for companies looking to improve productivity. While volume outputs increased, the inputs as measured by labour costs and waste costs were reduced. Overall, the study shows that automation is effective in reducing production costs. The researcher is of the view that adoption of automation by the South Africa manufacturing industry might slow the declining productivity and employment contribution as well as reposition the industry to compete effectively.

6.3 Limitations

Several limitations existed for this study. First, the researcher is a full-time employee hence time was limited to conduct the study. This narrowed the focus of the study. In addition, the resources required to conduct a full industry study were not available.

Second, the major limitation of quasi-experiment study, according to Leedy et al. (2019) is that when only a single case is considered, generalisation of the findings to other situations cannot be done with certainty. The researcher has shown that the results of the study pertaining to productivity and quality are consistent with outcomes of other studies in South Africa and elsewhere. However, in terms of labour impacts, the interpretation of the results of this study should be done with caution as shown by outcomes from studies by Parschau et al. (2020). Hence, extrapolation of the employment impact results due to automation across industries and countries would need to be informed by evidence from various studies not just one study.

Third, the company chosen for the case study opted to remain anonymous. As a result, the researcher had to adapt and carefully avoid stating certain production level parameters as this would make it obvious which company it is. Resorting to high level descriptors like waste without stating the exact definition of that production parameter might take away the whole essence of a case study and limit adoption of the automation intervention. In addition, access to some critical information such as employee salaries was not possible. As a result, labour costs could only be assumed from the number of employees on the production line, yet employee salaries might be adjusted in line with skills and automation requirements. In addition, the cost of raw materials could also not be accessed. Hence calculation of the cost associated with waste data and rejects could not be ascertained.

Lastly, the researcher used a quantitative strategy. The approach does not capture or explain the reasons besides automation why results obtained were achieved as well as management decisions taken. For example, reduction of technical employees responsible for the maintenance of the production line which goes against increased assets on the production line and by implication increased requirements for maintenance. Therefore, to increase confidence in the quantitative analysis, Neumann et al. (2013) argue that a mixed strategy, quantitative and qualitative would have been effective in addressing such gaps.

6.4 Recommendations

The results have shown that automation is effective as a strategy to address the problem of low manufacturing productivity. As such companies must continuously weigh the benefits of automation against the costs and compare to the cost of manual labour. South African manufacturing industry must accelerate adoption of automation to remain competitive particularly in the global market where competition might not be regulated by national borders. However, where manual labour achieves the productivity levels offered by automation and a company can sustain its position in the market, then automation might be not the right strategy hence the need for continuous evaluation.

On the other hand, a carefully crafted mix and package of manufacturing activities are required per province supported by incentives and good infrastructure investments by the government. For certain manufacturing companies, demand for semi-skilled labour which is in abundance in South Africa remain high despite automation as shown by Parschau et al. (2020). Labour impacted by other manufacturing companies such as company X adopting automation would be absorbed by other manufacturing companies in the same province. Province with low levels of education and high poverty levels would benefit hence stop the migration and reduce pressure on provinces like Gauteng.

Further studies are required that interrogate firm level production data for manufacturing firms in South Africa on automation and productivity due to the limited body on knowledge highlighted, especially impact on technical skills shown in by this study.

7 REFERENCESREFERENCES

Arnold, J. M., Mattoo, A., & Narciso, G. (2006). *Services inputs and firm productivity in Sub-Saharan Africa: Evidence from firm-level data.* Paris: World Bank.

Ateba, B. B., Prinsloo, J. J., & Gawlik, R. (2019). The significance of electricity supply sustainability to industrial growth in South Africa. *Journal Energy Reports*, 1324-1338.

Bartelsman, E. J., & Doms, M. (2000). Understanding Productivity: Lessons from Longitudinal Microdata. *Journal of Economic Literature*, 569-594.

Bourque, L. B., & Clark, V. A. (1992). *Processing data: The survey example.* California: Sage Publications.

Bryman, A. (2012). *Social research methods* (4th ed.). New York: Oxford University Press.

Chavan, M. (2009). The Balnced Scorecard: A New Challenge. *Journal of Management Development*, 393-406.

Chigbu, B. I., & Nekhwevha, F. H. (2020, September 30). *The Conversation*. Retrieved from The Conversation Web site: https://theconversation.com

Creswell, J. W. (2009). *Research design* (3rd ed.). California: Sage Publications.

De Ron, A. J., & Rooda, J. E. (2006). OEE and Equipment Effectiveness: An Evaluation. *International Journal of Production Research*, 4987-5003.

DOEL. (2020). *Strikes in 2018 reaches a high in the past five year.* Pretoria: Department of Employment and Labour (DOEL).

Eifert, B., Gelb, A., & Ramachandran, V. (2006). Business environment and comparative advantage in Africa: Evidence from the investment climate data. *Annual World Bank Conference on Development Economics: Growth and Integration* (pp. 195-233). Washington, DC: The World Bank.

Fandel, G. (1991). *Theory of production and cost.* Hagen: Springer.

Fleury, R. (2020, May 16). *Why traditional manufacturing theories don't work.* Retrieved from Manufacturing Global Web site: https://manufacturing global.com

Francois, J. F., & Hoekman, B. (2009). *Services, trade and policy.* Paris: World Bank.

Hagedorn-Hansen, D., Steenkamp, L., Hagedorn-Hansen, E., & Oosthuizen, G. (2017). Investigating the Effects of Automation Process Chains Towards Sustainable Manufacturing in South Africa. *Procedia Manufacturing*, 262-268.

Harris, R. G. (1999). Determinants of Canadian Productivity Growth: Issues and Prospects. *CSLS-Industry Canada Conference on Canada in the 21st Century:* (pp. 1-46). Ottawa: Centre for the Study of Living Standards.

ILO. (1991). *Prevention of major industrial accidents.* Geneva: International Labour Office.

Khadem, M., Ali, S. A., & Seifoddini, H. (2008). Efficacy of Lean Matrics in Evaluating the Performance of Manufacturing Systems. *International Journal of Industrial Engineering*, 176-184.

Kleynhans, E. P., & Labuschagne, J. R. (2012). Human Capital Constraints in South Africa: A Firm-Level Analysis. *Journal of Managing Global Transitions*, 69-86.

Kreuser, C. F., & Newman, C. (2018). Total Factor Productivity in South African Manufacturing Firms. *South African Journal of Economics*, 1-178.

Kumar, R. (2011). *Research methodology: a step-by-step guide for beginners.* London: Sage Publications.
Kumar, S., & Suresh, N. (2008). *Production and operations management.* New Delhi: New Age International.
Kusek, J. Z., & Rist, R. C. (2004). *Ten steps to a results-based monitoring and evaluation system : a handbook for development practitioners.* Washington, DC: The World Bank.
le Roux, D. B. (2018). Automation and Employment: The Case of South Africa. *African Journal of Science, Technology, Innovation and Development, 10*(4), 507-517.
Leachman, C., Pegels, C. C., & Shin, S. K. (2005). Manufacturing Performance: Evaluation and Determinants. *International Journal of Operations and Production Management*, 851-874.
Leedy, P. D., & Ormrod, J. E. (2019). *Practical research: planning and design* (12th ed.). New York: Pearson.
Levy, Y., & Ellis, T. J. (2006). A Systems Approach to Conduct an Effective Literature Review in Support of Information Systems Research. *Informing Science: The International Journal of an Emerging Transdiscipline*, 181-212.
Liao, K., & Tu, Q. (2008). Leveraging Automation and Integration to Improve Manufacturing Performance Under Uncertainty. *Journal of Manufacturing Technology Management*, 38-51.
Malterud, K., Guassora, A. D., Graungaard, A. H., & Reventlow, S. (2015). Understanding Medical Symptoms: A Conceptual Review and Analysis. *Theoretical Medicine and Bioethics*, 411-424.
Mckay, C., Pollack, E., & Fitzpayne, A. (2019). *Automation and a changing economy.* Washington, DC.: The Aspen Institute .
McKinsey & Company. (2017). *A future that works: automation, employment and productivity.* San Francisco: McKinsey Global Institute.
MPG. (2011). *Mpumalanga Economic Growth and Development Plan.* Nelspruit: Mpumalanga Provincial Government, MPG.
Mtshali, E. P., Nyakala, S. K., Munyai, T. T., & Ramdass, K. (2018). Identifying causes of low productivity in the printing industry. *International Conference on Industrial Engineering and Operations Management* (pp. 933-944). Pretoria: IEOM Society International.
Munyai, T., Mbonyane, B., & Mbohwa, C. (2018). *Productivity Improvement in Manufacturing SMEs: Application of work study techniques.* Florida: CRC Press.
Neumann, W. P., Kihlberg, S., Medbo, P., Mathiassen, S. E., & Winkel, J. (2002). A Case Study Evaluating the Ergonomic and Productivity Impacts of Partial Automation Strategies in the Electronics Industry. *International Journal of Production Research*, 4059-4075.
OECD. (2018). *OECD Jobs Strategy.* Paris: OECD Publishing.
OECD. (2019). *OECD Compendium of productivity indicators 2019.* Paris: OECD Publishing.
Parschau, C., & Hauge, J. (2020). Is Automation Stealing Manufacturing Jobs? Evidence from South Africa's Apparel Industry. *Geoforum*, 120-131.
Patel, C., & Deshpande, V. (2016). A Review on Improvement in Overall Equipment Effectiveness. *International Journal for Research in Applied Science & Engineering Technology*, 642-650.

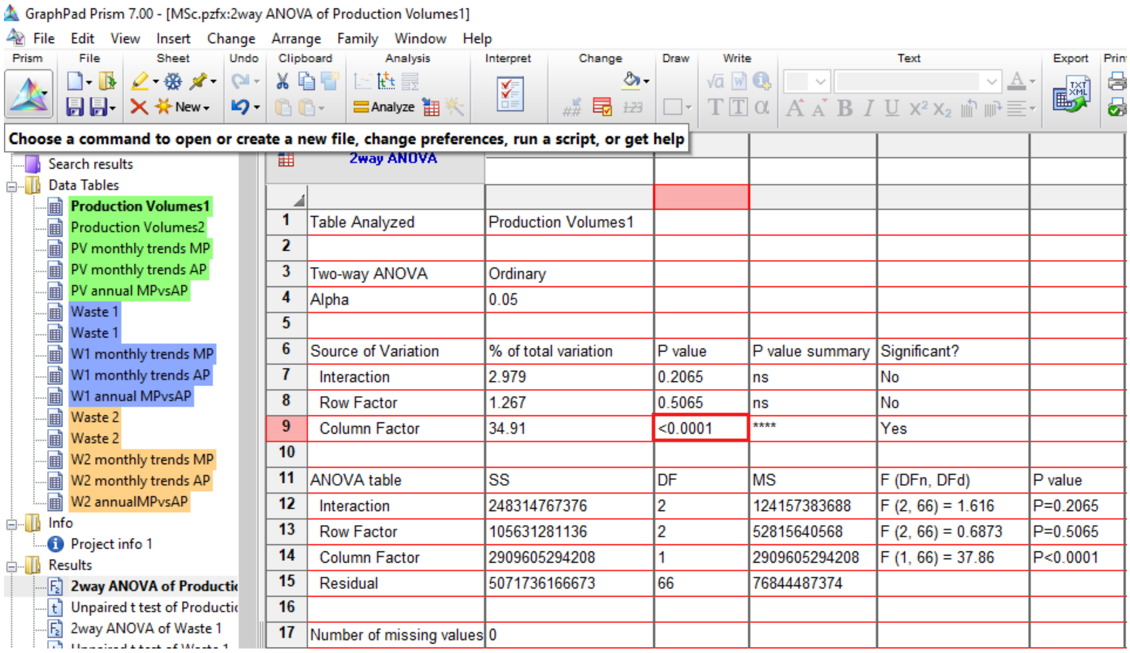
Pritchard, R. D. (1990). *Measuring and improving organizational productivity: A practical guide.* New York: Praeger Publishers.
Productivity SA. (2017). *Annual report 2015/16.* Johannesburg: Productivity SA.
Prokopenko, J. (1987). *Productivity Management: A practical handbook.* Geneva: International Labour Organisation.
Rosenthal, R., & Rosnow, R. L. (2008). *Essentials of behavioral reseacrh: Methods and data analysis.* New York: McGraw Hill.
Sahu, P. K. (2013). *Research methodology: A guide for researchers in agricultural science, social science and other related fields.* New Delhi: Springer.
Saunders, M., & Lewis, P. (2012). *Doing business in resarch and management: An essential guide to planning your project.* London: Pearson .
Schachter, G. (1991). Francois Quesnay: Interpreters and Critics Revisited. *The American Journal of Economics and Sociology*, 313-322.
Schneider, G. E. (2000, June). The Development of the Manufacturing Sector in South Africa. *Journal of Economic Issues, 34*(2), 413-424.
Schoenefeld, J., & Jordan, A. (2017). Governing Policy Evaluation: Towards a New Typology. *Evaluation*, 274-293.
Schwab, K. (2016). *The Fourth Industrial Revolution: what it means and how to respond.* Cologny: World Economic Forum.
Sharma, A. (2009). Implementing Balanced Scorecard for Performance Measurement. *The IUP Journal of Business Srategy*, 7-16.
Sharpe, A. (2002). Productivity Concepts, Trends and Prospects: An Overview. In A. Sharpe, F. St-Hilaire, & K. Banting, *The review of economic performance and social change 2002: Towards a social understanding of productivity* (pp. 31-56). Montreal: The Institute of Research on Public Policy.
Sim, K. (2001). Am Empirical Examination of Successive Increamental Improvement techniques and Investment in Manufacturing Technology. *International Journal of Operations & Production Management*, 373-399.
Statssa. (2018). *Men, Women and Children: Findings of the Living Conditions Survey 2014/15.* Pretoria: Statistics South Africa.
Statssa. (2019). *Inequality trends in South Africa: A multidimensional diagnostic of inequality.* Pretoria: Statistics South Africa.
Statssa. (2020). *Gross domestic product: Second quarter 2020.* Pretoria: Statistics South Africa.
Statssa. (2020). *Quarterly labour force survey, Quarter 3.* Pretoria: Statistics South Africa.
Steenge, A. E., & Van Den Berg, R. (2007). Transcribing the Tableau Economique: Input-Output Analysis A La Quesnay. *Journal of the History of Economic Thought*, 331-358.
Stundziene, A., & Saboniene, A. (2019). Tangible Investment and Labour Productivity: Evidence from European Manufacturing. *Economic Research*, 3519-3537.
Syverson, C. (2011). What Determines Productivity? *Journal of Economic Literature*, 326-364.
Tague, N. R. (2005). *The quality toolbox.* Wisconsin: American Society for Quality.
Tybout, J. R. (2000). Manufacturing firms in developing countries: How well do they do, and why? *Journal of Economic Literature*, 11-44.
Waldman, C. (2016). The Evolving Contours of Productivity Performance and Automation Investment in U.S. Manufacturing. *Business Economics*, 213-238.

Williams, G., Cunningham, S., & De Beer, D. (2014). Advanced Manufacturing and Jobs in South Africa: An Examination of Perceptions and Trends. *International Conference on Manufacturing-Led Growth for Employment and Equality,* (pp. 1-36). Johannesburg.

Wotela, K. (2017). Conceptualising Conceptual Frameworks in Public and Business Management Research. *Proceedings of the 16th European Conference on Research Methods in Business and Management* (pp. 370-379). Dublin: Academic Conferences and Publishing International Limited.

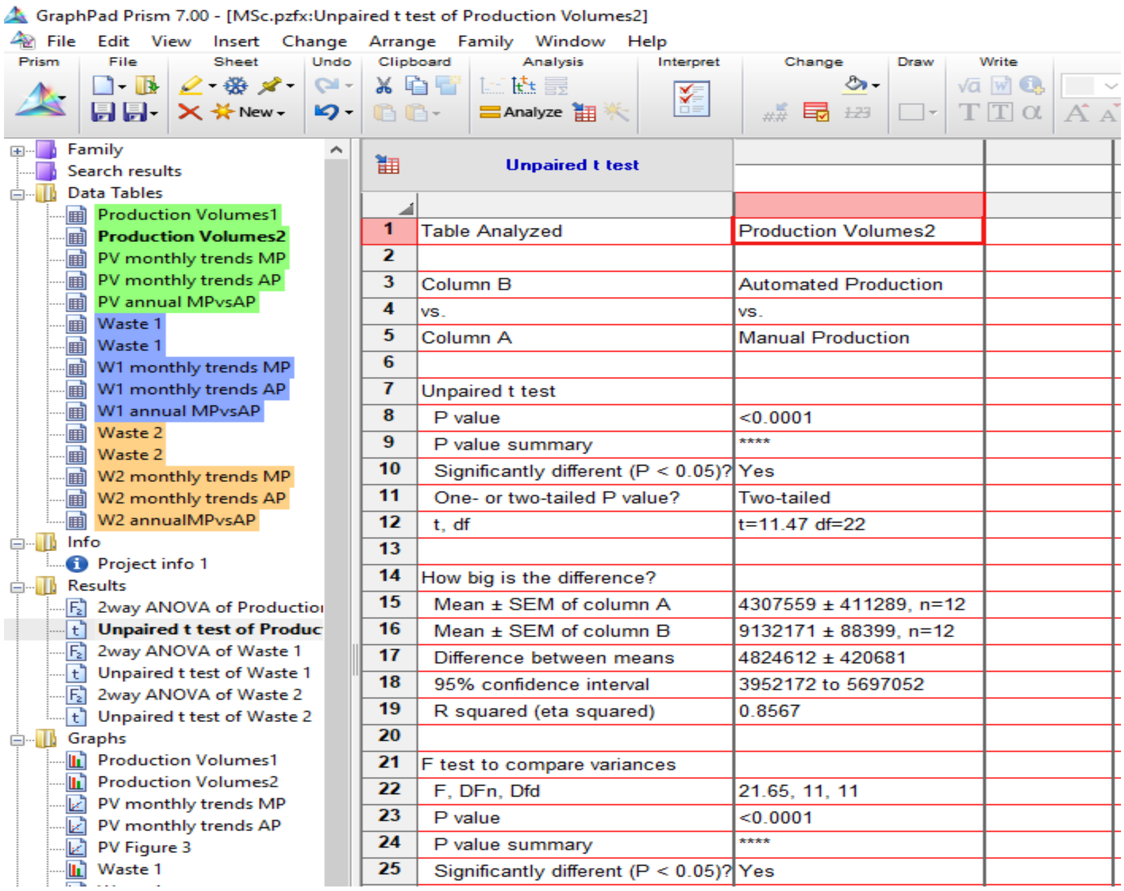
APPENDICES

Table 5: Two-way ANOVA of production volumes.



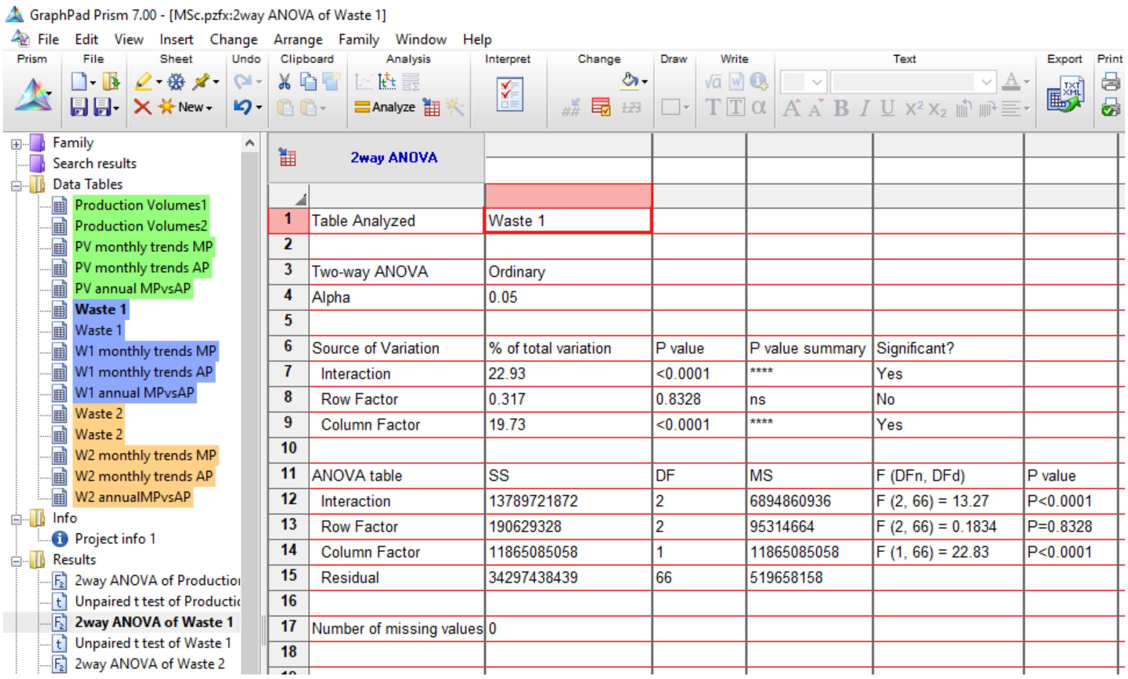
1	Table Analyzed	Production Volumes1				
2						
3	Two-way ANOVA	Ordinary				
4	Alpha	0.05				
5						
6	Source of Variation	% of total variation	P value	P value summary	Significant?	
7	Interaction	2.979	0.2065	ns	No	
8	Row Factor	1.267	0.5065	ns	No	
9	Column Factor	34.91	<0.0001	****	Yes	
10						
11	ANOVA table	SS	DF	MS	F (DFn, DFd)	P value
12	Interaction	248314767376	2	124157383688	F (2, 66) = 1.616	P=0.2065
13	Row Factor	105631281136	2	52815640568	F (2, 66) = 0.6873	P=0.5065
14	Column Factor	2909605294208	1	2909605294208	F (1, 66) = 37.86	P<0.0001
15	Residual	5071736166673	66	76844487374		
16						
17	Number of missing values	0				

Table 6: Unpaired t test of production volumes.



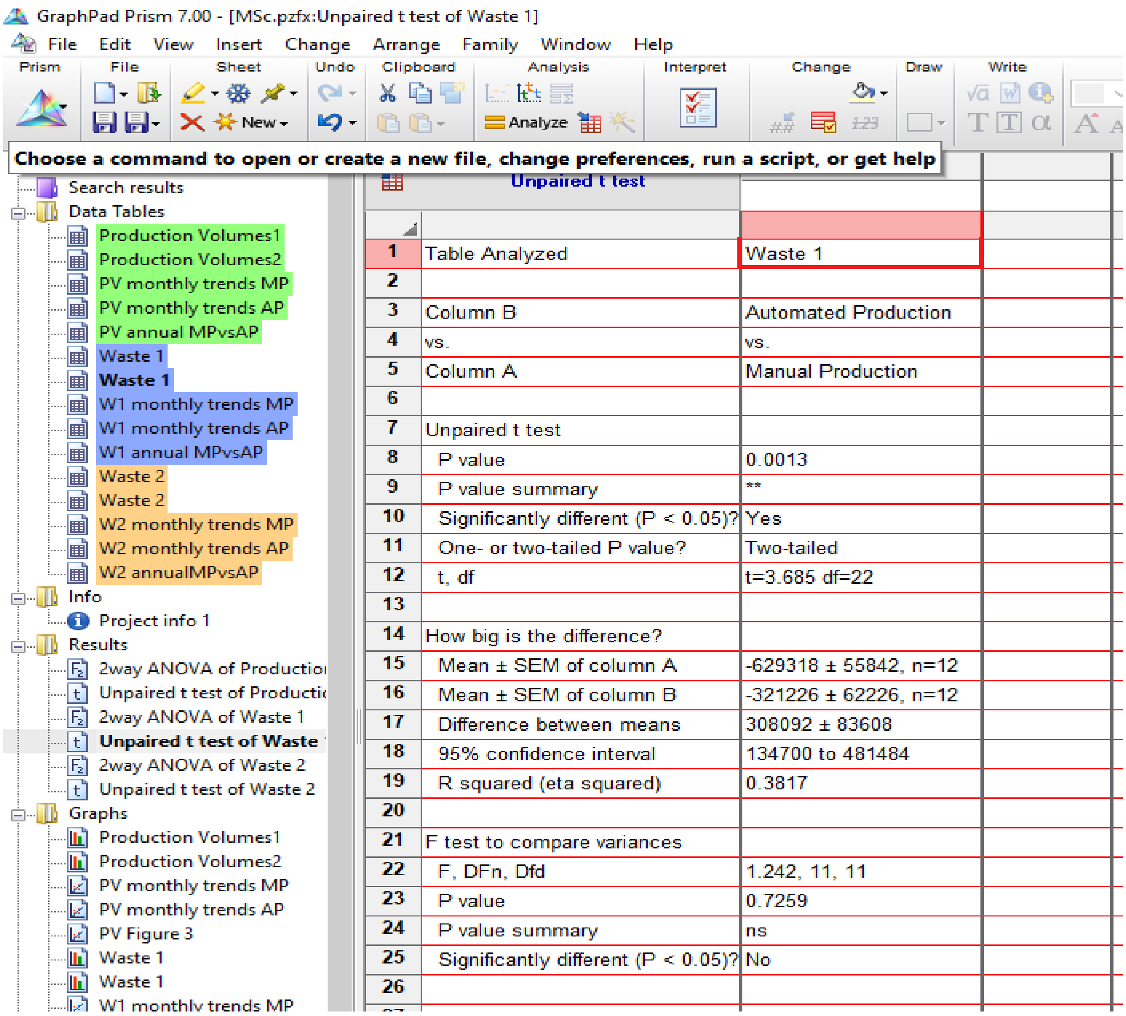
1	Table Analyzed	Production Volumes2
2		
3	Column B	Automated Production
4	vs.	vs.
5	Column A	Manual Production
6		
7	Unpaired t test	
8	P value	<0.0001
9	P value summary	****
10	Significantly different (P < 0.05)?	Yes
11	One- or two-tailed P value?	Two-tailed
12	t, df	t=11.47 df=22
13		
14	How big is the difference?	
15	Mean ± SEM of column A	4307559 ± 411289, n=12
16	Mean ± SEM of column B	9132171 ± 88399, n=12
17	Difference between means	4824612 ± 420681
18	95% confidence interval	3952172 to 5697052
19	R squared (eta squared)	0.8567
20		
21	F test to compare variances	
22	F, DFn, Dfd	21.65, 11, 11
23	P value	<0.0001
24	P value summary	****
25	Significantly different (P < 0.05)?	Yes

Table 7: Two-way ANOVA of Waste 1.



	2way ANOVA					
1	Table Analyzed	Waste 1				
2						
3	Two-way ANOVA	Ordinary				
4	Alpha	0.05				
5						
6	Source of Variation	% of total variation	P value	P value summary	Significant?	
7	Interaction	22.93	<0.0001	****	Yes	
8	Row Factor	0.317	0.8328	ns	No	
9	Column Factor	19.73	<0.0001	****	Yes	
10						
11	ANOVA table	SS	DF	MS	F (DFn, DFd)	P value
12	Interaction	13789721872	2	6894860936	F (2, 66) = 13.27	P<0.0001
13	Row Factor	190629328	2	95314664	F (2, 66) = 0.1834	P=0.8328
14	Column Factor	11865085058	1	11865085058	F (1, 66) = 22.83	P<0.0001
15	Residual	34297438439	66	519658158		
16						
17	Number of missing values	0				
18						

Table 8: Unpaired t test of Waste 1.



	Unpaired t test	
1	Table Analyzed	Waste 1
2		
3	Column B	Automated Production
4	vs.	vs.
5	Column A	Manual Production
6		
7	Unpaired t test	
8	P value	0.0013
9	P value summary	**
10	Significantly different (P < 0.05)?	Yes
11	One- or two-tailed P value?	Two-tailed
12	t, df	t=3.685 df=22
13		
14	How big is the difference?	
15	Mean ± SEM of column A	-629318 ± 55842, n=12
16	Mean ± SEM of column B	-321226 ± 62226, n=12
17	Difference between means	308092 ± 83608
18	95% confidence interval	134700 to 481484
19	R squared (eta squared)	0.3817
20		
21	F test to compare variances	
22	F, DFn, Dfd	1.242, 11, 11
23	P value	0.7259
24	P value summary	ns
25	Significantly different (P < 0.05)?	No
26		

Appendix 1.1: Data collection instrument(s)

No data collection instrument used since the data already exist.

Appendix 2.1: One-page bio of the researcher including declaration of interest in the research and funders, if any

Nobert Zvoushe is an experienced and qualified engineer with a Bachelor of Science (Hons) degree in Electrical Engineering from the University of Zimbabwe. I have extensive experience managing maintenance, capital projects and leading teams in various national and international manufacturing organisations such as Delta Beverages, Unilever Zimbabwe, and PepsiCo. I have an in-depth understanding of production management and technologies used in various manufacturing processes. I am passionate about developing talent, teams and delivering exceptional results. I am a part-time MBA student at Wits Business School, motivated by the desire to learn and develop as a leader. I am married with 3 children, a boy aged 14 and two girls aged 10 and 8 years, respectively. I enjoy travelling and meeting new people.

The researcher declares that there was no interest in the research other than for purposes of fulfilling the requirements of Wits Business School, Master of Business Administration studies. Hence, the researcher had no known financial and competing interests in the case company which could have influenced the work reported in this study. In addition, there are no personal relationships that could also have influenced the work carried out by the researcher. The researcher did not receive any funding either directly or indirectly for purposes of completing this study. The researcher made use of own resources and university facilities for carrying out the study.

Appendix 2.2: Ethic documentation

Graduate School of Business Administration
University of the Witwatersrand, Johannesburg

Wits Business School

Wits Business School Ethics Committee
Constituted under the University Human Research Ethics Committee (Non-Medical)

Ethics Clearance Certificate

Ethics protocol number: WBS/BA2275033/579

This certificate is only valid with a legitimate ethics protocol number and signed by the Researcher (below).

Project title	Efficacy of automation in a South African manufacturing company
Investigator / Researcher	Mr Nobert Zvoushe
Nature of Project	MBA (Research Article)
Decision of the Committee	Approved, provided stakeholders and participants are guaranteed anonymity and confidentiality.
Issue Date of Certificate	2021-04-12
Expiry date	Date of submission of the project report
Chairperson	Prof Anthony Stacey +27 11 717 3587 +27 82 880 4531 Anthony.Stacey@wits.ac.za

Declaration by Researcher

One copy must be signed by the Researcher and returned to the Chairperson of the Wits Business School Ethics Committee.

I fully understand the conditions under which I am authorized to carry out the abovementioned research and I guarantee to ensure compliance with these conditions. Should any departure to be contemplated from the research procedure as approved I undertake to resubmit the protocol to the Committee.

Signature

12 | 04 | 2021
Date:

Appendix 2.2: Ethic documentation

Note: This was a desktop study. Company authorisation letter (presented for clearance) shows the company letterhead/name hence can not be presented here as the company has chosen to remain anonymous.

Appendix 3.1: Dully filled in data collection instrument(s)

No data collection instrument used since the data already exist.