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Assessing the Effects of Data Analytics on Operational Efficiency among Small Scale Manufacturing Enterprises in Lusaka

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Abstract

Small and Medium scale Enterprises (SMEs) play an important role in promoting inclusive growth in the contemporary economy of Lusaka. The aim of the study was to investigate the factors influencing the growth of Small and Medium Enterprises via use of Data Analytics. The study employed a descriptive research design to achieve the objectives. The following were the research objectives:

i) To identify the types of data analytics tools and practices used among small-scale manufacturing enterprises in Lusaka.
ii) To examine how data analytics are integrated into decision-making processes among small-scale manufacturing enterprises in Lusaka.
iii) To explore the perceptions and experiences of small-scale manufacturing enterprises with data analytics on operational efficiency in Lusaka
iv) To establish challenges faced by small-scale manufacturing enterprises in implementing data analytics on improving efficiency in Lusaka. The study used a questionnaire to collect the required data. The data collected was coded, quantified and analysed quantitatively and qualitatively. Quantitative data was analysed by the use of STATA, Excel. The study recommended the following ways:

The study concludes that data analytics adoption among SMEs remains very low, and this significantly limits their ability to operate efficiently and make timely, informed decisions. The dominance of manual record-keeping systems and experience-based decision-making suggests that SMEs are missing opportunities to reduce downtime, enhance productivity and streamline operations. Where basic analytics tools such as Excel are used, evidence shows improved production planning and reduction in operational delays, indicating that even simple tools can produce measurable benefits

i) SMEs should begin by incorporating low-cost tools such as Excel, Google Sheets or free statistical packages.
ii) Training programs should be introduced to equip SME managers and staff with basic data management and analysis skills.
iii) SME owners and leaders should be sensitized on the value of data in enhancing decision-making and reducing inefficiencies.
iv) SMEs can adopt a phased approach to technology adoption, beginning with spreadsheets and gradually moving toward dashboards, automated reporting tools and business intelligence software such as Power BI.
v) SMEs should institutionalize periodic review of production, sales and inventory data

Keywords: Data Analytics, Small and Medium Enterprise, SME, Systematic Review

Introduction

1.0 Overview

This study assesses the impact of data analytics on operational efficiency among small-scale manufacturing enterprises in Lusaka, Zambia. The study aims to explore how data analytics can improve decision-making, optimize production processes, and enhance quality control in small-scale manufacturing enterprises.

1.1 Background

Global Perspective

Data analytics has become a crucial tool for businesses worldwide, enabling them to make informed decisions, optimize operations, and gain a competitive edge (Davenport & Harris, 2020). However, small-scale manufacturing enterprises (SMEs) face significant challenges in adopting data analytics, including limited resources, lack of expertise, and inadequate infrastructure (Wamba *et al*., 2020). According to a recent study, only 22% of SMEs in the manufacturing sector have adopted data analytics, compared to 45% of large enterprises (OECD, 2022). In today's interconnected world, data analytics has become a crucial tool for businesses to stay ahead of the competition, identify new opportunities, and drive growth. According to a recent report by McKinsey, companies that use data analytics to inform their decision-making processes are 23 times more likely to acquire new customers, 6 times more likely to retain existing customers, and 19 times more likely to be profitable (McKinsey, 2020). The adoption of data analytics is widespread across industries and geographies. A recent survey by Gartner found that 70% of organizations have already invested in big data and analytics, and 80% of organizations plan to increase their investment in data analytics in the next two years (Gartner, 2022). This trend is driven by the increasing availability of data, advances in analytics technologies, and the growing recognition of the value of data-driven decision-making. Data analytics provides businesses with insights into customer behavior, market trends, and operational efficiency, enabling them to make informed decisions that drive business growth and profitability. It can also help businesses streamline their operations, reduce waste, and improve productivity, leading to cost savings and improved profitability. Furthermore, data analytics can help businesses identify new opportunities, anticipate customer needs, and develop targeted marketing campaigns. Acting as the backbone of both established and developing economies, small and medium-sized enterprises (SMEs) are absolutely vital for employment creation and global economic progress (Ojeleye *et al*., 2023). By encouraging innovation, therefore increasing competition, and so improving market variety, they greatly help to propel economic progress (Akujor & Eyisi, 2020). By creating jobs, helping nearby suppliers, and boosting regional businesses, SMEs frequently become rather important in local communities. Their agility and flexibility help them to address particular customer demands, react quickly to changes in the market, and provide individualised services which bigger corporations could not do (George & Mwikya, 2021). Moreover, very important in producing fresh ideas and encouraging entrepreneurship are SMEs, which also help to diversify sectors by promoting technical development (Abdilahi *et al*., 2017). The dynamism and resilience of SMEs highlight their significance in maintaining economic vitality and advancing equitable development in many different spheres.

Despite the benefits of data analytics, businesses face several challenges in adopting data analytics, including data quality issues, lack of expertise, data security concerns, and integration with existing systems. Data quality issues can arise from a variety of sources, and businesses need to invest in data quality management to ensure that their data is accurate, complete, and consistent. Lack of expertise is another challenge that businesses face in adopting data analytics, and businesses need to invest in training and development programs to build the skills needed for data analytics. Data security concerns are also a major challenge for businesses that adopt data analytics. Businesses need to ensure that their data is secure and protected from unauthorized access, and they need to comply with relevant data protection regulations. Integration with existing systems is another challenge that businesses face in adopting data analytics, and businesses need to invest in integration technologies to ensure that their data analytics systems are integrated with their existing systems and processes. Small-scale manufacturing enterprises (SMEs) face unique challenges in adopting data analytics, including limited resources, lack of expertise, and inadequate infrastructure. According to a recent study, only 22% of SMEs in the manufacturing sector have adopted data analytics, compared to 45% of large enterprises (OECD, 2022). SMEs need to invest in data analytics to stay competitive and drive business growth. Data analytics can help SMEs gain insights into customer behavior, market trends, and operational efficiency, enabling them to make informed decisions that drive business growth and profitability.

Regional Perspective

Data analytics is a crucial tool for businesses to stay ahead of the competition, identify new opportunities, and drive growth. Despite the benefits of data analytics, businesses face several challenges in adopting data analytics, including data quality issues, lack of expertise, data security concerns, and integration with existing systems. SMEs face unique challenges in adopting data analytics, including limited resources, lack of expertise, and inadequate infrastructure. Businesses need to invest in data analytics to stay competitive and drive business growth.

The benefits of data analytics are well-documented, including improved operational efficiency, enhanced decision-making, and increased competitiveness (Kiron *et al*., 2020). However, SMEs face several challenges in adopting data analytics, including: Limited resources: SMEs often lack the financial resources, infrastructure, and expertise needed to invest in data analytics (Wamba *et al*., 2020). Data quality issues: SMEs may struggle with data quality issues, including incomplete, inaccurate, or inconsistent data (Kiron *et al*., 2020). Lack of expertise: SMEs may lack the expertise needed to analyze and interpret data, making it difficult to make informed decisions (OECD, 2022).

Sadly, many SMEs particularly in Sub-Saharan Africa fail beyond their fifth year mostly because of their difficulty in adapting to fast-changing market circumstances and properly predicting future trends (Esiebugie *et al*., 2018). Usually resulting from poor resource management and insufficient strategic planning, this difficulty may cause major problems like inventory mismanagement, financial instability, and lost development prospects (Ndayako, 2021). SMEs find themselves unable to make intelligent judgements without the capacity to predict and react to changing customer tastes and competitive pressures, therefore compromising their operational efficiency and market position (Alotaibi & Khan, 2023). The high failure rate of SMEs emphasises how urgently strong analytical tools and improved forecasting methods should be used. Investing in data-driven strategies and strategic planning tools can help SMEs maximise their operations, control uncertainty, and improve their prospects of long-term success and sustainability (Asad *et al*., 2020). Hence, SMEs that want to survive in a competitive environment and attain steady expansion must be able to predict and adjust. A plethora studies have thoroughly reported predictive analytics as a major improvement in organisational performance (e.g., Alotaibi & Khan, 2023; Vachkova *et al*., 2023; Seddaoui *et al*., 2023; Asad *et al*., 2020). Defined is an advanced analytical field that uses historical data, statistical methods, and machine learning to estimate future occurrences and trends (Wolniak & Grebski, 2023). Predictive analytics helps organisations forecast future trends, expect market shifts, and make data-driven choices by using historical data and sophisticated statistical techniques (Seddaoui *et al*., 2023). This capacity enhances operational effectiveness, strategic planning, and financial management among other facets of organisational success (Mafini & Muposhi, 2017). Organisation which use predictive analytics well will maximise resource allocation, save expenses, and improve their capacity to meet consumer requirements and competitive constraints (Wolniak & Grebski, 2023; Vachkova *et al*., 2023). Better decision-making and more profitability follow from this, as well as general company agility and resilience. Thus, in the data-driven corporate world of today, the extensive use of predictive analytics has become a crucial determinant of performance and the acquisition of a competitive advantage. Despite the considerable research on predictive analytics and its effects on organisational performance globally, to the best of our knowledge, no study particularly focused on the impact of predictive analytics on SMEs' operational efficiency and revenue growth in Sub-Saharan Africa, especially in Ghana and Nigeria. This disparity in the literature underscores the need of this research, which seeks to investigate how predictive analytics could improve SMEs' competitiveness in these areas. Through an analysis of predictive analytics algorithm usage, the research aims to find if these technologies may raise operational efficiency for African SMEs, increase customer happiness, and stimulate revenue growth. This study is essential to show the worth of predictive analytics in enabling Ghanaian and Nigerian SMEs to better their general performance and meet customer requirements SMEs face unique challenges in adopting data analytics, including limited access to technology, inadequate infrastructure, and lack of expertise (Kshetri, 2020). According to a recent study, only 15% of SMEs in Kenya have adopted data analytics, compared to 30% of SMEs in developed economies (UNCTAD, 2022). The adoption of data analytics is gaining momentum, driven by the increasing availability of data, advances in analytics technologies, and the growing recognition of the value of data-driven decision-making. According to a recent report by the African Development Bank, data analytics has the potential to unlock significant economic value in Africa, including improved business efficiency, enhanced customer experience, and increased competitiveness (African Development Bank, 2020). African businesses face several challenges in adopting data analytics, including limited infrastructure, limited expertise, data quality issues, and limited access to funding. Many African countries lack the infrastructure needed to support data analytics, including reliable internet connectivity, data storage facilities, and analytics software. There is also a shortage of skilled data analysts and scientists in Africa, which can make it difficult for businesses to adopt data analytics. Despite these challenges, there are significant opportunities for businesses to leverage data analytics to drive growth and competitiveness. Data analytics can provide businesses with insights into customer behavior, market trends, and operational efficiency, enabling them to make informed decisions that drive business growth and profitability. It can also help businesses streamline their operations, reduce waste, and improve productivity, leading to cost savings and improved profitability.

Mobile money services, such as M-Pesa, have used data analytics to improve customer experience, reduce fraud, and increase revenue. Retailers, such as Shopryt, have used data analytics to understand customer behavior, optimize supply chains, and improve operational efficiency. Governments, such as the government of South Africa, have used data analytics to improve public services, reduce corruption, and enhance transparency. Data analytics has the potential to drive significant economic value in Africa, including improved business efficiency, enhanced customer experience, and increased competitiveness. However, these businesses face several challenges in adopting data analytics, including limited infrastructure, limited expertise, data quality issues, and limited access to funding. Despite these challenges, there are significant opportunities for African businesses to leverage data analytics to drive growth and competitiveness.

Zambian Perspective

SMEs play a vital role in the economy, contributing to employment, innovation, and economic growth (Zambia Development Agency, 2022). However, SMEs in Zambia face significant challenges in adopting data analytics, including limited resources, lack of expertise, and inadequate infrastructure (Mwenya *et al*., 2020). According to a recent study, only 10% of SMEs in Zambia have adopted data analytics, compared to 20% of SMEs in other developing economies (World Bank, 2022). The adoption of data analytics is still in its infancy, but there is growing recognition of its potential to drive economic growth and competitiveness. According to a recent report by the Zambia Development Agency, data analytics can help Zambian businesses improve their operational efficiency, enhance customer experience, and increase competitiveness (Zambia Development Agency, 2022). Zambian businesses face several challenges in adopting data analytics, including limited infrastructure, limited expertise, and limited access to funding. Many businesses lack the infrastructure needed to support data analytics, including reliable internet connectivity, data storage facilities, and analytics software. There is also a shortage of skilled data analysts and scientists in Zambia, which can make it difficult for businesses to adopt data analytics. A plethora studies have thoroughly reported predictive analytics as a major improvement in organisational performance (e.g., Alotaibi & Khan, 2023; Vachkova *et al*., 2023; Seddaoui *et al*., 2023; Asad *et al*., 2020). Defined is an advanced analytical field that uses historical data, statistical methods, and machine learning to estimate future occurrences and trends (Wolniak & Grebski, 2023). Predictive analytics helps organisations forecast future trends, expect market shifts, and make data-driven choices by using historical data and sophisticated statistical techniques (Seddaoui *et al*., 2023). This capacity enhances operational effectiveness, strategic planning, and financial management among other facets of organisational success (Mafini & Muposhi, 2017). Organisation which use predictive analytics well will maximise resource allocation, save expenses, and improve their capacity to meet consumer requirements and competitive constraints (Wolniak & Grebski, 2023; Vachkova *et al*., 2023). Unemployment, coupled with the rising of population are among the economic problems that most less developing countries are faced with, and not only less developed countries but as well as developed countries experience the same phenomena. The situation in less developed countries has been worsened by white collar jobs that have declined tremendously (World Bank IMF (2017). As a result of such a situation, many SMEs have continued to mushroom and will continue as no one would doubt or question the contributions of Small and Medium Enterprises (SMEs) in driving forward the economies of many countries. However, it is important to note that SMEs are hailed for their pivotal role in promoting grassroots economic growth and equitable sustainable development (Pelham 2000). The other way for SMEs to grow is through access to finance, however, 70 percent of SMEs fail because of poor capital funding as finance is the backbone of SMEs and any other business enterprise (Mckernan and Chen, 2005). As such governments are expected to boost the role of such private sector initiatives, however, the situation is different in most countries and that SMEs have struggled to have access to finance and grow their businesses (Evboumwan *et al*. 2012 and Deressa (2014). Small and medium-sized enterprises (SMEs) are crucial economic actors within the economies of nations (Wolff and Pett, 2006). They are a major source of job creation and they represent the seeds for future large companies and corporations. The small and micro enterprises (SMEs) play an important role in the Zambian economy. According to the Economic Survey (2012), the sector contributed over 50 percent of new jobs created in the year 2011. Despite their significance, past statistics indicate that three out of five businesses fail within the first few months of operation (Zambia Statistics Office, 2011). 1 Starting and operating a small business includes a possibility of success as well as failure. Because of their small size, a simple management mistake is likely to lead to sure death of a small enterprise hence no opportunity to learn from its past mistakes. Lack of credit has also been identified as one of the most serious constraints facing SMEs and hindering their development (Oketch, 2000). According to Amyx (2005) one of the most significant challenges in the performance of SMEs is lack of technological innovations. Potential clients perceive small businesses as lacking the ability to provide quality services and are unable to satisfy more than one critical project simultaneously. Often larger companies are selected and given business for their clout in the industry and name recognition alone. Timmons (2008) argued that SMEs primarily owe their business success and growth to the development of innovations, which gradually effect their transformation into large enterprises. Innovations can include new products, services and ideas, as well as new enterprise processes (production process, procurement process), new organizational structures and administrative processes (Amyx, 2005). SMEs are more innovative than larger firms, due to their flexibility and their ability to quickly and efficiently integrate inventions created by the firms' development activities (Acs, 2009). The personal characteristics of the SME owners have also been touted to play a significant role in the growth of SMEs particularly in rural areas. Personal characteristics like level of education, level of training, their adoption of technology among others have influenced SME growth. In fact, one of the key characters of an entrepreneur circling around development of economy in many countries is entrepreneurial education. The significance of entrepreneurship and entrepreneurial education and training ranges from commencing a small scale unit to build up big business concerns (Alama, 2008). It should be noted that financial and capitation as a factor is important but its study is now saturated and will thus not form part of this study as a variable. As a country, Zambia has been struggling on how it could best address the issues that constrain the SMEs from performing at the frontier and a number of Micro Financial Institutions (MFIs) were established. According to Bank of Zambia (2017) there were currently 28 MFIs with 42 branches all engaged in micro financing and their main purpose is financing of SMEs. Even though the MFIs have been established to assist SMEs, Deressa (2014) revealed and acknowledged the low percentage of the SMEs obtaining loans from MFIs. The low percentage 2 showed the extent to which microfinance was unattractive to SMEs in Zambia. He further acknowledged the extremely high interest rates charged by Zambian microfinance for Micro and Small enterprises. According to Zambia Manufacturing Sector Survey (2003) found that the SMEs sector in Zambia had stagnated due to a number of barriers hindering its growth. World Bank (2015) in its past and latest analysis of Zambia's business environment had acknowledged and shown that there was little support in access to finance by SMEs as financial institutions usually focused on largely formal sector enterprises. According to the CSO (2015) despite the establishment of many lending banks from independence, Parliamentary Acts, MFIs, SMEs have continued with challenges of accessing finance and many empirical researches have looked at many countries visa vie developing and underdeveloped and have obtained almost the same scenario. It was for this reason that this research attempted to add more voice of the voiceless by looking at this scenario in Lusaka District Urban with a different environment visa vie socio-economic, characteristics of the entrepreneurs, internal factors and enabling environmental factors of SMES with an attempt to further understanding factors affecting growth in SMEs, hence the study. Better decision-making and more profitability follow from this, as well as general company agility and resilience. Thus, in the data-driven corporate world of today, the extensive use of predictive analytics has become a crucial determinant of performance and the acquisition of a competitive advantage. Despite the considerable research on predictive analytics and its effects on organisational performance globally, to the best of our knowledge, no study particularly focused on the impact of predictive analytics on SMEs' operational efficiency and revenue growth in Sub-Saharan Africa, especially in Ghana and Nigeria. This disparity in the literature underscores the need of this research, which seeks to investigate how predictive analytics could improve SMEs' competitiveness in these areas. Through an analysis of predictive analytics algorithm usage, the research aims to find if these technologies may raise operational efficiency for African SMEs, increase customer happiness, and stimulate revenue growth. This study is essential to show the worth of predictive analytics in enabling Ghanaian and Nigerian SMEs to better their general performance and meet customer requirements. 1.1. Concept of Operational Efficiency Recent scholarly definitions of operational efficiency highlight its purpose in raising production while lowering resource use and waste. Barth *et al*. (2023), for instance, define operational efficiency as the ability of an entity to provide products or services with as minimal resources as possible whilst maintaining high quality. Dildhani *et al*. (2019), defined it as the degree to which a corporation maximises its activities to save money, time, and effort, therefore improving general performance. Abd-Elmageed *et al*. (2020), claimed that this is the degree of efficiency with which a company manages its operations to generate the maximum output with the minimum of input. To Kahraman and Rigopoulos (2023), is the capacity of a company to maximise processes and eliminate duplicates, therefore producing faster delivery and reduced prices. Lee and Johnson (2013), described it as the ongoing development of business operations aimed at raising output while controlling expenses and resource allocation by means of continuing improvement of corporate procedures. Therefore, operational efficiency may be described as the ability of a company to maximise its resources and procedures thereby generating the highest potential output while reducing input, cost, and waste. To stay competitive and raise efficiency, it underlines the need of streamlining procedures, cutting duplicates, and always raising performance. Attaining long-term growth and success so depends on operational efficiency. 1.2. Concept of Revenue Growth Recent scholarly definitions of revenue growth stress its significance as an indicator of the financial situation and market success of an organisation. For instance, Phillips (2021) characterised revenue growth as an indication of a company's potential to expand its market share and customer base that is, as a gain in sales income during a certain period. Revenue growth, according to Johnson *et al*. (2021), is the speed at which a company's income from main operations increases, therefore indicating its possible expansion and increase of profitability. Olaoye and Olaoye (2022), described it as the acceleration of income from products and services, driven by both strategic efforts like market expansion and natural development. Mwombeki (2023), viewed revenue growth as a company's success in rising revenues from present and 2282 World Journal of Advanced Research and Reviews, 2024, 23(03), 2281–2291 new markets, therefore supporting general business sustainability. Okerekeoti (2021), underlined its importance in generating long-term financial stability and shareholder value by characterising it as the consistent increase of the general revenues of a firm. Revenue growth may therefore be described as the slow increase in a company's sales income brought about by its capability to build market share, increase operational scalability, and effectively implement strategic goals. It is a good gauge of the financial situation of a business as it shows its capacity to keep competitiveness, adapt to changes in the market, and guarantee long-term profitability. 1.3. Concept of Predictive Analytics Predictive analytics is not a new phenomenon, and many organisations have successfully used it, notably in the financial services and supermarket retail industries (Ogunleye, 2014; Brown *et al*., 2015). However, its larger benefits and potential have only lately been realised, owing primarily to the emergence of big data. Predictive analytics is an advanced analytical field that uses historical data, statistical methods, and machine learning to estimate future occurrences and trends (Wolniak & Grebski, 2023). It is a subset of advanced analytics, analyses current and historical data using methods from statistics, data mining, machine learning, and artificial intelligence to forecast future occurrences (Kumar & Garg, 2018). Predictive analytics is a type of analytics undergone on big data that deal with extracting information from data and predict the trends and behaviour patterns (Poornima & Pushpalatha, 2018). It enables organisations to identify risks in the past, opportunities, and trends, as well as develop plans for suitable actions and this is only feasible when accurate forecasts are made using organised and unorganised information (Rustagi & Goel, 2022). Despite these challenges, there are significant opportunities for businesses to leverage data analytics to drive growth and competitiveness. Data analytics can provide Zambian businesses with insights into customer behaviour, market trends, and operational efficiency, enabling them to make informed decisions that drive business growth and profitability. It can also help Zambian businesses streamline their operations, reduce waste, and improve productivity, leading to cost savings and improved profitability. The Zambian government has launched many initiatives to promote the use of data analytics in the country. For example, the government formed the Zambia Information and Communications Technology Authority (ZICTA) to support ICT growth in the country, including data analytics. The government has also undertaken measures to help people gain data analytics skills, including as training programs for data analysts and scientists. Data analytics has the potential to generate enormous economic benefit in Zambia, such as increased corporate efficiency, better customer experience, and more competitiveness.

Study Context

However, Zambian businesses confront a number of hurdles when it comes to implementing data analytics, including insufficient infrastructure, experience, and finance. Despite these limitations, Zambian businesses have great opportunity to use data analytics to drive growth. For SMEs to increase operational effectiveness, obtain a competitive edge, and make wise decisions, data analytics is crucial. Poor decision-making, ineffective operations, and decreased competitiveness might result from a failure to use data analytics. To solve the problem of data analytics in SMEs, several initiatives have been implemented, such as: Policies: Tax incentives and funding programs are among the measures that governments have put in place to encourage SMEs to use data analytics (OECD, 2022). Training programs: Organizations have launched training programs to develop the skills needed for data analytics, including data analysis, interpretation, and visualization (Kiron *et al*., 2020). Despite these measures, SMEs still face significant challenges in adopting data analytics, and there is a need for further research to understand the impact of data analytics on operational efficiency in SMEs.

1.2 Statement of the Problem

The ideal situation for Small-Scale Manufacturing Enterprises (SMEs) in Zambia would be to leverage data analytics to drive business growth, improve operational efficiency, and enhance customer experience. In an ideal world, SMEs in Zambia would have access to the necessary infrastructure, expertise, and resources to adopt data analytics, enabling them to make informed decisions, optimize operations, and stay competitive in the global market. However, the reality is that many SMEs in Zambia face significant challenges in adopting data analytics. According to a recent study by the Zambia Development Agency (2022), only 10% of SMEs in Zambia have adopted data analytics, citing limited infrastructure, lack of expertise, and limited access to funding as major barriers. Another study by Mwenya *et al*. (2020) found that SMEs in Zambia struggle with data quality issues, inadequate data analysis skills, and limited resources, which hinder their ability to adopt data analytics. The prevailing situation in Zambia is that many SMEs are not leveraging data analytics to drive business growth and competitiveness. Instead, they rely on intuition and experience to make decisions, which can lead to suboptimal outcomes. The lack of adoption of data analytics in SMEs in Zambia can have significant consequences, including reduced competitiveness, decreased productivity, and poor decision-making. This study aims to investigate the challenges that SMEs in Zambia face in adopting data analytics and to identify potential solutions that can help them overcome these challenges. By exploring the current state of data analytics adoption in SMEs in Zambia, this study will provide insights into the opportunities and challenges of data analytics adoption in the Zambian context.

1.3.1 General Objective

Assessing the effects of data analytics on operational efficiency among small scale manufacturing enterprises in Lusaka.

1.3.2 Specific Objectives

i) To identify the types of data analytics tools and practices used among small-scale manufacturing enterprises in Lusaka.
ii) To examine how data analytics are integrated into decision-making processes among small-scale manufacturing enterprises in Lusaka.
iii) To explore the perceptions and experiences of small-scale manufacturing enterprises with data analytics on operational efficiency in Lusaka
iv) To establish challenges faced by small-scale manufacturing enterprises in implementing data analytics on improving efficiency in Lusaka

1.4 Research Questions

i) What types of data analytics tools and practices are used among small-scale manufacturing enterprises in Lusaka?
ii) How are data analytics integrated into decision-making processes among small-scale manufacturing enterprises in Lusaka?
iii) What are the perceptions and experiences of small-scale manufacturing enterprises with data analytics on operational efficiency in Lusaka?
iv) What challenges do small-scale manufacturing enterprises face in implementing data analytics to improve efficiency in Lusaka?

1.5 Theoretical Framework

This study is guided by two theoretical frameworks: the Technology-Organization-Environment (TOE) framework and the Resource-Based View (RBV) theory. These frameworks provide a comprehensive understanding of the factors that influence the adoption and use of data analytics in small-scale manufacturing enterprises, and how these enterprises can leverage data analytics to achieve operational efficiency.

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1.5.1 Technology-Organization-Environment (TOE) Framework

The TOE framework, developed by Tornatzky, Fleischer, and Chakrabarti (1990), provides a framework for understanding the factors that influence the adoption and implementation of technological innovations, such as data analytics, within organizations. The TOE framework considers three contexts: Technological context: This refers to the characteristics of the technology itself, such as its compatibility, complexity, and relative advantage. Organizational context: This refers to the internal characteristics of the organization, such as its size, structure, and culture. Environmental context: This refers to the external environment in which the organization operates, including factors such as competition, regulation, and market demand. The TOE framework suggests that the adoption and use of data analytics in small-scale manufacturing enterprises is influenced by these three contexts. For example, the technological context may influence the ease of use and compatibility of data analytics tools, while the organizational context may influence the availability of resources and support for data analytics adoption.

1.5.2 Resource-Based View (RBV) Theory

The RBV theory, developed by Barney (1991) and Werner felt (1984), provides a framework for understanding how organizations can achieve competitive advantage through the development and deployment of valuable, rare, and inimitable resources. In the context of this study, the RBV theory suggests that data analytics can be a valuable resource for small-scale manufacturing enterprises, enabling them to improve operational efficiency and achieve competitive advantage.

By combining the TOE framework and the RBV theory, this study provides a comprehensive understanding of the factors that influence the adoption and use of data analytics in small-scale manufacturing enterprises, and how these enterprises can leverage data analytics to achieve operational efficiency and competitive advantage.

Scholars: (Tornatzky, Fleischer, & Chakrabarti (1990); Barney (1991); Werner felt (1984).

1.6 Significance of the Study

This study on the assessment of the effectiveness of data analytics on operational efficiency among small-scale manufacturing enterprises in Lusaka, Zambia, is significant for several reasons: The study will contribute to the existing body of knowledge on data analytics and operational efficiency in small-scale manufacturing enterprises. By exploring the impact of data analytics on operational efficiency, this study will provide valuable insights into the benefits and challenges of adopting data analytics in small-scale manufacturing enterprises. The study will also provide insights into the challenges and opportunities associated with data analytics adoption in small-scale manufacturing enterprises. By identifying the key factors that facilitate or hinder the adoption of data analytics, this study will inform policymakers and practitioners about the potential benefits and challenges of data analytics adoption in small-scale manufacturing enterprises. Furthermore, the study will inform policymakers and practitioners about the potential benefits of data analytics adoption in small-scale manufacturing enterprises. By highlighting the impact of data analytics on operational efficiency, this study will provide evidence-based insights to support the development of policies and programs that promote the adoption of data analytics in small-scale manufacturing enterprises.

In addition, the study will contribute to the development of strategies and interventions that can support small-scale manufacturing enterprises in adopting and implementing data analytics. By identifying best practices and challenges, this study will provide valuable insights for small-scale manufacturing enterprises, policymakers, and practitioners seeking to improve operational efficiency through data analytics. This study will provide valuable insights into the effectiveness of data analytics on operational efficiency among small-scale manufacturing enterprises in Lusaka, Zambia. The findings of this study will contribute to the development of evidence-based policies and programs that support the growth and development of small-scale manufacturing enterprises in Zambia.

1.7 Scope of the Study

This study focused on assessing the effectiveness of data analytics on operational efficiency among small-scale manufacturing enterprises in Lusaka, Zambia. The findings of the study will be relevant to policymakers, practitioners, and researchers interested in promoting the growth and development of small-scale manufacturing enterprises in Zambia and similar contexts.

Literature Review

2.0 Overview

This literature review provides an in-depth examination of the existing research on data analytics and operational efficiency in small-scale manufacturing enterprises. The review is structured around the study's objectives, identifying the types of data analytics tools and practices used, examination of how data analytics are integrated into decision-making processes, exploring the perceptions and experiences of small-scale manufacturing enterprises with data analytics on operational efficiency and Establishment challenges faced by small-scale manufacturing enterprises in implementing data analytics on improving efficiency.

Global Perspective

In Bangladesh, Chowdhury and Alam (2017) studied factors affecting access to Finance of Small and Medium Enterprises (SMEs). Data was collected data from a sample of 86 SMEs from various types of businesses to investigate the problems and suggest policy recommendations. Instruments used to collect data were depth interviews with structured questionnaire for self-guidance. A five-point Likert type scale statements were used to measure the variables. Convenience sampling was used reason being that the SMEs located in the region of the study were too many that it was impossible to include every SME within a short duration of time Secondary data was also collected for the same purpose.

Regional Perspective

A sampled review of literature that was relevant and similar from Africa was taken into consideration. The African sample of SMEs was done because they could have a different result on the growth of SMEs as compared to outside Africa. By doing so, it helped the researcher to have first-hand information on factors that affect growth in Africa as Africa has its share of problems and successes. Though Zambia is in Africa, there are still some differences in social, cultural and economic development. In order to identify academic gaps from the reviewed empirical researches, methodologies and results were studied because from methods results are obtained. The empirical researches are provided in the next paragraphs from Ghana, Kenya, Libya, Nigeria and South Africa. Mmieh and Mordi (2017) carried out a study on factors influencing the growth of SMEs in Ghana. It was a case study using entrepreneurs (or owner/managers) of SMEs as the unit of analysis.. It was discovered that due to stringent conditions that were set up by industry to access credits to SMEs, the credits granted to SMEs had little impact on their growth. This was more compounded by other factors such as lack of viable entrepreneurial skills, high lending rate and high loan requirement had been impacting negatively on the SMEs in Nigeria's economic development.

Zambian Perspective

It was important for the researcher to sample and review some of the literature in Zambia to have a feel of what was happening before the current study. The literature that was relevant and similar from Zambia was taken into consideration. The Zambian sample of SMEs was done because they could have been near to reality as compared to Africa and outside Africa. This enlightened the researcher on how commercial banks operate SMEs in accessing finance in Zambia. Some gaps were identified from the review. In that review, the study did not address factors affecting SMEs in accessing finance but, assessed the real demand for financial services in selected cities of Kabwe and Lusaka in Zambia by MSMEs.

2.1 Identification of the Types of data Analytics Tools and Practices Used among Small-Scale Manufacturing

A study conducted by Liave (2017) Systematic review of B1 in SMEs, the finding from the study show shows SMEs typically begin with descriptive analytics using spreadsheets and self-service BI dashboards (Power BI, Tableau), fed by data integrated from transactional systems. Progression to diagnostic/predictive tools depends on improving data quality, modest ETL capacity, and analytics skills. Reported practices include KPI scorecards, sales and cost dashboards, and lightweight data integration; comparatively fewer SMEs operationalize predictive modelling because of skills and governance constraints.

Maroufkhani, Wagner & Wan Ismail (2020) conducted a study on Cross-country SME BDA adoption/performance. The findings from the study shows that top-management support, IT infrastructure, data quality, and skills to adoption of big-data analytics. Performance gains are concentrated in firms that move beyond static reporting to predictive analytics and real-time data pipelines; firms that remain at dashboarding see more modest effects.

Božič & Dimovski (2019) conducted a study on BI&A use, innovation ambidexterity, and performance. the study finds that BI&A use supports exploratory and exploitative innovation and, through these, firm performance. In practical terms, SMEs that embed BI dashboards and data-informed routines realise gains when analytics is linked to innovation processes rather than only to weekly reporting.

A study conducted by Kasiri (2024), the aim of the study was Qualitative study of 50 US SMEs. Interviews show a patterned ladder of adoption: most SMEs use cloud BI/ETL and CRM-embedded analytics; a smaller subset experiments with ML-based demand forecasting. Common practices include KPI scorecards, cohort analysis, A/B testing, and unit cost dashboards; constraints are talent, data engineering, and change management.

A study conducted by Wessels, Zide & Jokonya (2022) on Big Data as s Service adoption in South African. The examining of Big Data as a Service through the TOE lens, the study shows SMMEs adopt cloud analytics where security, cost, regulatory alignment, and integration with ERP/CRM are satisfactorily addressed. BDaaS is positioned as a pragmatic pathway to analytics without heavy onpremise investments. Additionally, Zide, Jokonya & Wessels (2022) conducted a study on titled Data Management as a Service adoption in SMEs, the study finding highlights security and cost as dominant determinants. The practical takeaway is that managed cloud data platforms can lower barriers to analytics by externalising storage, backup, and basic governance preconditions for BI/ML use.

2.2 Examination of How Data Analytics are Integrated into Decision-Making Processes among Small-Scale Manufacturing Enterprises

Chatterjee *et al*. (2023) conducted a study that focused on real-time decisions, and performance using a multi-industry firm sample, this study shows that big-data analytics (BDA) influences performance through decision integration: firms that embed analytics into real-time or near-real-time choices (inventory, scheduling, customer responses) report stronger agility and outcomes than firms that confine analytics to monthly reports. Integration is enabled by data quality, IT infrastructure, and top management support; it is constrained by weak governance and skills. For small manufacturers, the practical lever is moving from descriptive dashboards to event-driven decision points (alerts, triggers, exception rules).

Furthermore Tawil *et al*. (2024) carried out a Three-year analysis of 85 UK SMEs on DDDM Drawing on three years of evidence across 85 SMEs, the paper maps how organizations transition from spreadsheet reporting to data-driven decision making (DDDM). It finds that decision integration advances when firms create repeatable decision routines (S&OP, weekly ops huddles, quality "stop the line" reviews) that are fed by single-source-of-truth dashboards. Barriers are predictable skills, fragmented data, and funding but the study demonstrates practical pathways: cloud tooling, minimal ETL, and progressive upskilling tied to specific decisions (e.g., reorder points, yield interventions).

Ragazou *et al*. (2023) wrote an open article on BI model for SME decision quality, this open-access article proposes and empirically grounds a business intelligence model that links information quality, analytics capabilities, and organizational processes to decision quality and competitive advantage in SMEs. The core argument is that tools alone are insufficient; governance and process design determine whether analytics outputs are actually used in day-to-day and strategic decisions. It provides a useful conceptual scaffold for designing your thesis framework around capabilities, routines, decisions and performance.

Alsibhawi *et al*. (2023) carried out a study on BI adoption factors and decision use Focusing on SMEs this study proposes a conceptual framework of BI adoption drivers' management support, data governance, skills, and fit with business processes and explains how these factors enable integration of analytics into operational and managerial decisions. Its value for your work is the explicit mapping of adoption antecedents to decision-making outcomes, which you can adapt to small-scale manufacturing in Lusaka. Additionally, Wessels, Zide & Jokonya (2022) conducted a study om Big Data as a Service adoption in South African SMMEs. The study shows SMMEs adopted Big Data as a Service where security, cost, and regulatory concerns were addressed and where BDaaS integrates with ERP/CRM. Integration into decisions is pragmatic: cloud dashboards and alerts feed procurement, inventory, and production meetings without heavy on-premise IT.

Rautenbach, de Kock & Grobler (2022) carried a study that focused on structured review on data science in SMEs in developing countries. Across African/developing country contexts, the study's finding show that SMEs integrate analytics mostly via Excel models and descriptive dashboards into operational routine decisions (ordering, production run sizing). Moves toward predictive models are constrained by skills and data quality, limiting integration into more advanced decisions such as predictive maintenance or optimization.

Mandizha (2025) in South Africa conducted a study that focused on decision-making improvement via analytics. Using a mixed-methods design with ML modelling (random forest, SVM), the study finds showed that SMEs that integrate analytics into real-time decision points (e.g., inventory reorder, routing, and pricing adjustments) report faster decision cycles and better resilience. The paper underscored that data trustworthiness and analytics literacy are prerequisites for successful integration.

Butala & Nasilele (2024) conducted a survey in Lusaka that focused on SMEs' analytics in supplychain decision-making the survey focused on SMEs in manufacturing, agribusiness, retail/wholesale shows growing use of inventory dashboards, demand-forecasting spreadsheets, and basic BI tools. Integration into decision-making occurs in procurement and replenishment meetings, but is hindered by skills gaps, infrastructure limits, and data integration challenges. The paper documents concrete decision points where analytics is used (reorder thresholds, supplier selection shortlists).

A study conducted by Bwalya (2025) in Lusaka district a case study on BI & analytics and firm performance. The case study reports showed that data grounded decision making via BI dashboards and periodic analytics reviews improves firm performance. Integration mechanisms include monthly KPI reviews and exception reporting that trigger managerial action. The study distinguished capabilities (people/process) from mere tool possession, highlighting the importance of decision routines.

2.3 Explore the Perceptions and Experiences of Small-Scale Manufacturing Enterprises with Data Analytics on Operational Efficiency

Kasiri (2024) carried out a study that focused on the US SMEs lived experiences with analytics. A qualitative study of 50 SMEs in the United States found that most firms perceived data analytics as a practical tool to "tighten operations," especially around inventory management, process timing, and cost tracking. Managers reported that dashboards, CRM analytics, and basic ETL-fed performance scorecards helped them detect inefficiencies earlier and make faster day-to-day decisions. They described analytics not as something "advanced/AI" but as something "operational," for example: knowing which machine is slowing output, which client segment is causing rework, or where margin is eroding. At the same time, several SMEs expressed anxiety about internal capacity. Owners said they struggled to interpret advanced analytics (for example, ML-based demand forecasting) without hiring specialised analysts, which they often could not afford. This created a perception that analytics is valuable but also "fragile," because it depends on a few key people.

Bozic & Dimovski (2019) carried a study tilted Decision quality and innovation culture. This study linked business intelligence and analytics (BI&A) use to what it called "innovation ambidexterity," meaning the firm's ability to both improve current operations and explore new ways of working. SME managers in the sample reported that analytics supported more disciplined decision-making on production planning, quality control, and cost efficiency. They felt better equipped to justify process changes using evidence, instead of intuition. Importantly, the perceived benefit was not only efficiency ("we cut downtime") but governance ("we can defend our decisions internally"). This speaks to an experience many SMEs share: analytics gives legitimacy to operational decisions, which can reduce internal conflict and speed adoption of process improvements.

Chatterjee *et al*. (2023) focused a study on big data analytics (BDA) and agility. In a multi-industry global sample, managers described big data analytics as improving their "operational responsiveness," especially under uncertainty. They reported that access to near real-time data on throughput, supplier delays, and customer demand helped them reallocate resources more quickly and avoid production bottlenecks. Perception here is strongly tied to competitiveness: managers believed analytics is no longer "nice to have," but a survival factor. However, they also warned that analytics can overwhelm decision-makers with information if internal processes are not adapted. In other words, data improved efficiency when it was embedded in clear decision routines (like daily production huddles), but it created confusion when pushed to staff without training. Research Gate

Synthesis of global perception globally, small firms and small manufacturers tend to see analytics as operational, immediate and practical: "show me where we are losing time or money." They experience direct efficiency benefits (less downtime, better inventory turns), but they also experience stress around skills, interpretation, workflow disruption, and organisational buy-in. There is an emerging narrative that analytics is not only a tool but a cultural shift toward evidence-based decision-making, which not all team's welcome.

Rautenbach, de Kock & Grobler (2022) conducted a study that aimed to Perceptions of analytics maturity in SMEs in development countries in this structured review of data science use in SMEs in developing settings (including African contexts), owners and managers consistently described analytics as "Excel first." Their experience is that spreadsheet-based dashboards already help with line efficiency, demand planning, basic scrap/rework analysis, and cash visibility. Many did not perceive advanced machine learning as realistic yet; instead, their belief was that getting "clean, consistent numbers every week" is already a major operational win. They also reported frustration that donors, investors, or corporate clients talk about predictive analytics and AI, while local SMEs are still battling basic data capture and staff capacity. So, expectations projected onto them (be "data-driven") sometimes feel disconnected from their daily operational reality.

Mandizha conducted a study in 2025 South Africa the aim of the study was SMEs resilience through analytics In a mixed-methods study using both qualitative interviews and machine learning modelling, South African SMEs in manufacturing and logistics sectors described analytics as a resilience tool. They reported that monitoring operations in near real-time helped them re-route supply, adjust labour allocation, and manage shocks. Owners said analytics gave them "confidence to act quickly," which they linked directly to surviving volatile input costs and disruptions. But they also said analytics increased pressure: once managers could see inefficiency clearly, they were expected to "fix it now," even without new capital. In other words, transparency improved efficiency but also created new performance expectations, and some staff experienced that as stress.

Across African SMEs, the perception is very pragmatic. Owners see analytics as something that can immediately reduce waste and improve operational control, particularly in stock, procurement, downtime, and routing. They do not romanticise "AI"; they frame analytics as "finally knowing what's happening in my business." At the same time, they express strong concerns around:

a) Data security and vendor lock-in when analytics is cloud-based,
b) Dependence on external technical partners, and
c) Pressure to perform once inefficiencies become visible. They also resent being judged against "global digital maturity" standards when their real bottleneck is still basic data capture and analysis capacity.

Butala & Mwanza (2025)-SMEs in Lusaka (manufacturing, agribusiness, retail/wholesale). A survey of 220 SMEs in Lusaka found that many firms, including small-scale manufacturers, recognise that data analytics could improve operational efficiency in areas like inventory control, stock movement, and supplier management. Respondents reported positive attitudes toward analytics in principle, especially for avoiding stock-outs and reducing waste. However, they also admitted very limited actual use of advanced analytics. Many described a skills gap inside the firm, difficulty integrating data from different sources, and weak infrastructure. The perception was "we know data can help us work smarter, but we don't yet have the people or systems to do it." The authors concluded that SMEs themselves are aware of the efficiency upside, but feel practically under-equipped to capture it without training, tools, and policy incentives such as tax relief or subsidised systems.

Bank of Zambia (2020) Manufacturing SME efficiency and utilisation capacity. The Bank of Zambia's working paper on technical efficiency and capacity utilisation among manufacturing SMEs highlights how owners and plant managers interpret data and performance metrics. Respondents reported that they often rely on informal judgement rather than systematic production data when deciding shift patterns, machine use, and input purchasing. The paper argues that to close Zambia's efficiency gap, SMEs must routinely measure indicators like capacity utilisation, downtime, reject rates, and unit cost. Implicit in these findings is a perception among SME operators that "data exists but is not structured," leading to reactive rather than proactive operational management. The report frames basic production analytics (even Excel-level tracking) as a missing discipline that could immediately improve throughput and cost control.

IEOM Society (2023) Industry case evidence from Zambian manufacturing.

Case material presented at IEOM on Zambian manufacturing firms shows that where analytics is used, it is typically tied to ERP reports, Excel/Power BI summaries, and basic sensor readings. Production supervisors said these tools help them see machine downtime, plan maintenance, and monitor quality deviations. They ass ociated this visibility with improved efficiency (less scrap, less rework) and quicker corrective action. However, the same supervisors described major barriers: high cost of digital systems, cybersecurity fears, complexity of integrating legacy equipment, and the lack of internal technical staff to maintain dashboards. The emotional tone is cautious optimism: "This helps us run better, but it is expensive and fragile."

Bwalya (2025) Business intelligence (BI) and SME performance in Lusaka District.

In a Lusaka District study with 377 SMEs, respondents described BI systems as giving them "visibility and control," particularly around revenue patterns, cost drivers, and customer trends. Owners linked that visibility to growth and competitiveness. Importantly, the study found that SMEs perceived BI not just as a reporting tool, but as something that supports strategic decisions (market positioning, pricing, customer segmentation) and operational ones (where to allocate limited labour and working capital). At the same time, participants identified barriers: lack of staff who can interpret dashboards, fear of exposing weaknesses internally, and high dependency on specific individuals who "understand the numbers." This shows a perception that analytics can strengthen both day-to-day and strategic efficiency, but also introduces internal vulnerability if knowledge is concentrated in one person.

Zambian SMEs, including small-scale manufacturers, generally "believe in" analytics for efficiency they talk about reducing waste, avoiding stock-outs, planning production, understanding cost leakages but they experience analytics as something still out of reach. They report three repeating issues: capacity and skills shortages inside the firm, fragmented or unreliable data, and cost and sustainability concerns around adopting and maintaining tools. Managers recognise that operational efficiency is directly linked to better use of data, yet they feel structurally constrained from realising that benefit. There is also anxiety about transparency: once analytics exposes inefficiency, the owner or supervisor is expected to fix it with limited capital.

2.4 Establishment Challenges Faced by Small-Scale Manufacturing Enterprises in Implementing Data Analytics on Improving Efficiency

Justy (2023) analysed the Internal (endogenous) vs external (exogenous) barriers to analytics in SMEs. The research made a key distinction between internal (endogenous) and external (exogenous) barriers. Internal barriers included lack of strategy, lack of analytics culture, and shortage of in-house skills, while external barriers included competitive pressure, vendor availability, and regulatory expectations. The striking finding was that internal barriers had a stronger negative effect than external ones. In other words, global SMEs are not primarily blocked by the market or by technology supply. They are blocked by their own organisational readiness: no clear data strategy, no budget line for analytics, no staff who can interpret outputs, and no governance to make analytics "stick" in routine decisions. These internal constraints reduce the degree to which analytics can actually drive efficiency improvements on the production floor (for example, cutting scrap, reducing downtime, optimising batch sizes).

Willetts (2020) Cost, skills, and underutilisation of Big Data Analytics by SMEs. Willetts (2020) examined the cost, skills and underutilization of Big Data Analytics by SMEs despite evidence that analytics can shorten product development cycles and drastically reduce production costs.

The study found persistent concerns in three areas: cost of analytics infrastructure and tools; lack of in house expertise to clean, manage, and interpret data; and fear of complexity. SMEs perceived analytics as "expensive, specialised and risky," and many felt they could not afford to experiment because wrong decisions could be operationally disruptive. As a result, firms stayed with manual or spreadsheet-based monitoring even when they knew that more advanced analytics could improve efficiency, reduce lead time, and inform continuous improvement initiatives in manufacturing.

Koppmann (2021) explored barriers faced by smaller advanced manufacturing firms attempting to adopt data-driven methods. Reported challenges included integration of analytics tools with legacy machines, data quality problems from inconsistent sensors, and limited cyber security capacity. Managers also expressed that even when analytics dashboards existed, they struggled to translate them into action because frontline supervisors were not trained in interpretation. The study concluded that analytics does not automatically become an "efficiency engine." Without change management and capacity-building, analytics can generate more data but not necessarily better operational decisions.

Michalkova/OECD SME & Entrepreneurship Paper on Data Analytics in SMEs (OECD, 2024). OECD work on SME data analytics adoption highlights recurring global constraints: cost of digital infrastructure, shortage of analytical talent, and the organisational effort required to redesign processes around data-driven decision-making. Owners of small firms repeatedly raised concern about business disruption: introducing analytics means more monitoring, more transparency, and sometimes uncomfortable accountability. The OECD notes that many SMEs are aware of the theoretical productivity benefits of data analytics but hesitate to fully implement because they anticipate internal resistance and do not have support for incremental, low-risk rollout.

Wessels, Zide & Jokonya (2022) conducted a study that focused on Cloud-based analytics services in South Africa although this work focused on Big-Data-as-a-Service (BDaaS) and related cloud analytics models in South African SMMEs, the findings speak directly to perceive implementation challenges at firm level. Managers cited data security, compliance, and vendor lock-in as critical worries. Many small firms felt that putting operational and cost data into an external cloud platform made them vulnerable. They also noted regulatory uncertainty and whether outsourced analytics providers would respect data privacy. At the same time, they acknowledged they could not afford on premise infrastructure. So, analytics was seen as "necessary for efficiency" but also "risky to rely on outsiders for."

Kgakatsi (2024) carried out a study titled Systematic review on big data and SME performance in African and developing synthesised evidence on how big data analytics affects SMEs' operational efficiency and performance. The review reports that SMEs repeatedly cite resource scarcity, fragmented data, and limited human capacity as core barriers to using analytics to streamline operations. It also finds that even where analytics tools are available, SMEs often lack basic data governance processes, which leads to mistrust of the data and low uptake in decision-making. In other words, owners do not act on analytics if they do not believe the data quality, so the efficiency benefit is lost.

Jama (2024) conducted a study on Barriers to digital procurement tool in South Sudan the research studied barriers to e-procurement adoption among SMEs in South Sudan and found recurrent issues with infrastructure, cost of digital systems, unstable internet, and low digital literacy in procurement staff. Although this study is about e-procurement, the challenges mirror analytics uptake in operations: firms cannot exploit data-driven purchasing, supplier evaluation, or stock monitoring because they lack reliable connectivity, their staff are not trained in digital tools, and they cannot absorb recurring software costs. Respondents also noted fear of transparency and traceability, especially where procurement processes are politically or relationally sensitive. These same fears apply to production analytics (fear that data will expose inefficiencies or internal leakage).

For Zambia, we are focusing on studies that speak to barriers to digital/analytics use, efficiency management, and operational decision support in SMEs, including manufacturing. Because Zambian manufacturing analytics literature is still thin, we also draw on closely related Zambian work on SME digitalisation, operational control, and growth constraints, which reflect the same structural obstacles that small manufacturers face. Butala and Mwanza (2025) conducted a Study on Data analytics utilisation in Lusaka SMEs a quantitative study of 220 SMEs in Lusaka (including manufacturing, agribusiness, and retail/wholesale) found that most firms recognise the value of analytics for supply chain control and efficiency, but are not using it consistently. Respondents cited four main constraints: limited internal data skills, weak integration between different data sources (procurement, stock, production), inadequate digital infrastructure, and cost. The study concluded that there is a structural "analytics readiness gap": SMEs in Lusaka want to apply analytics to improve efficiency, but face capability and resourcing constraints that prevent consistent implementation. It recommends targeted training, infrastructure support, and policy incentives such as tax relief on digital systems to close this gap.

Muchoka (2020) carried a study on constraints to SME growth in Lusaka although focused on SME growth in Lusaka District, this study identified barriers that map directly to analytics implementation challenges: chronic financial constraints, limited access to new technology, and skills shortages. SMEs reported difficulty acquiring modern systems that support data tracking, citing capital costs and limited access to finance. They also highlighted the absence of managerial and technical training to interpret performance data. These constraints slow digital adoption, keep operations manual, and therefore limit the use of analytics for efficiency improvements in production and procurement.

Chilembo (2021) examined access to finance for Lusaka-based SMEs and showed that firms struggle to secure affordable capital for technology upgrades. Owners reported that high interest rates, collateral requirements, and lender risk perceptions prevented them from investing in digital systems. This creates a direct barrier to analytics-enabled efficiency: without affordable finance, SMEs cannot implement data capture tools (for example, basic production monitoring, inventory tracking solutions) that would later feed analytics. In other words, the financial system itself becomes a blocker to analytics adoption and therefore to efficiency gains.

Methodology

3.0 Overview

This chapter outlines the research methodology used to assess the effectiveness of data analytics on operational efficiency among small-scale manufacturing enterprises in Lusaka, Zambia. The chapter covers the research design, target population, sampling design, sample size determination, data collection methods, data analysis, triangulation, limitations of the study, and ethical considerations.

Epistemological Assumption

This study adopts a positivist epistemological assumption, which emphasizes the use of scientific methods to uncover objective knowledge. The study aims to test hypotheses and identify causal relationships between data analytics adoption and operational efficiency using empirical data. The researcher will employ a systematic and structured approach to collect and analyze data, with the goal of generating objective and generalizable findings (Sabelo J, 2022).

3.1 Research Design

A qualitative approach is appropriate because it allows the researcher to explore participants' perspectives, experiences, and practices in their natural settings, providing rich and nuanced insights that cannot be captured through numerical measures alone. The analysis will follow a thematic approach, allowing patterns, themes, and categories to emerge from the data. By employing a qualitative research design, the study aims to provide a deep and contextualised understanding of data analytics adoption in Zambia's small-scale manufacturing sector. The findings will offer evidence-based insights that can inform capacity-building initiatives, policy formulation, and strategies to enhance operational efficiency.

3.2 Target Population

A research population is a group of individuals, objects or items from which samples are taken for analysis. The target population for this study will be small manufacturing businesses in Lusaka, Zambia, that have adopted big data analytics or have plans to adopt it soon. Targeting businesses that have adopted or plan to adopt big data analytics ensures that the study is relevant and timely. By exploring the experiences and challenges of these businesses, the study can provide actionable insights that can inform the development of effective big data analytics strategies and support systems for small manufacturing businesses in Zambia.

3.3 Sampling Methods

Sampling is the procedure a researcher uses to gather people, places or things to study. It is the process of selecting a number of individuals or objects from a population such that the selected group contains elements representative of the characteristics found in the entire group (Orodho and Kombo, 2002). The study will employ Snowball sampling. Snowball sampling is a non-probability sampling technique that involves recruiting participants through referrals from existing participants. Snowball sampling is a useful technique for recruiting participants in qualitative research, particularly when the population is hard to reach or identify. By using this method, the study aims to gather valuable insights into the challenges, benefits, and best practices associated with big data analytics adoption in small manufacturing businesses in Zambia.

3.4 Sample Size

From the 100 small manufacturing businesses in Lusaka, Zambia, the sample size of 30 was adopted

3.5 Data Analysis

This study employed thematic analysis to analyse the qualitative data collected from the participants. Thematic analysis is a widely used method in qualitative research that involves identifying, coding, and categorizing themes and patterns in the data (Braun & Clarke, 2006). Given the large sample size of 30, the researcher may also consider using qualitative data analysis software, such as NVivo or Atlas. ti, to facilitate the coding and theme development process. The themes and patterns that emerge from the data will be interpreted in the context of the research questions and objectives, and will inform the development of conclusions and recommendations.

3.6 Data Collection Method

This study will employ a combination of primary and secondary data collection methods to gather relevant data. A questionnaire will be designed and administered to SME owners and managers to collect data on digital transformation and competitive strategy. The questionnaire will include both closed-ended and open-ended questions to capture quantitative and qualitative data (Saunders *et al*., 2019). In-depth interviews will also be conducted with SME owners and managers to gather more detailed and qualitative data on digital transformation and competitive strategy. The interviews will be semi-structured, allowing for flexibility and probing to gather rich and insightful data (Creswell & Creswell, 2018).

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3.7 Ethical Considerations

The study will be conducted in accordance with the principles of ethical research, as outlined in the Declaration of Helsinki and the American Psychological Association's Ethical Principles of Psychologists and Code of Conduct (APA, 2017; World Medical Association, 2013). Participants will be fully informed about the purpose, procedures, and risks of the study before providing their consent to participate. The informed consent form was provided to participants before the survey or interview.

Presentation of Research Findings

4.0 Overview

The aim of this chapter is to present the findings of the study according to the research objectives. It will also make an analysis and interpretation of the research findings.

Section A: Background Information

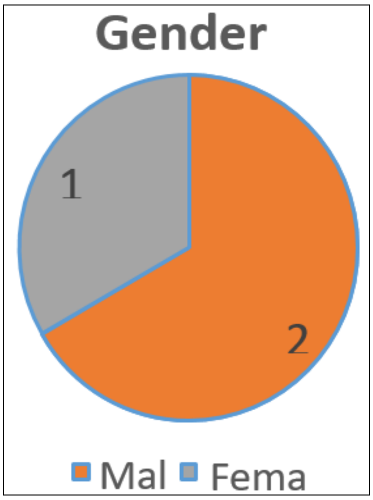


Fig 1: Gender Distribution

Figure 1 results show that two-thirds of the respondents (n = 20; 66.7 percent) were male, while one third (n = 10; 33.3 percent) were female. This indicates that participation in the survey was predominantly male. The gender imbalance may reflect the general composition of staff working in small and medium manufacturing enterprises, where operational and supervisory roles are often male dominated. However, the presence of female respondents also demonstrates growing involvement of women in key enterprise functions. Overall, the distribution suggests that male perspectives are more strongly represented in the study sample, which may influence how digital tools and data analytics adoption are perceived within the sector.

. tabulate TypeEnterprise

Type Enterprise	Freq.	Percent	Cum.
Food and beverages	3	10.00	10.00
Furniture	8	26.67	36.67
Other	7	23.33	60.00
Textile/clothing	4	13.33	73.33
Transport logistics	8	26.67	100.00
Total	30	100.00	

Fig 2: Types of Enterprise

The results in the table above show that the surveyed SMEs operate across diverse sectors, with the largest proportions coming from Furniture and Transport Logistics, each representing 26.67 percent of all firms (8 out of 30). This is followed by enterprises categorized as other at 23.33 percent, and Textile/Clothing at 13.33 percent. The smallest group was Food and Beverages, contributing 10 percent of the sample. These findings indicate that although the sample includes a variety of industries, manufacturing-related and logistics sectors form the bulk of the SMEs assessed. This diversity strengthens the generalizability of the study by providing insights from different operational contexts within Lusaka's SME landscape.

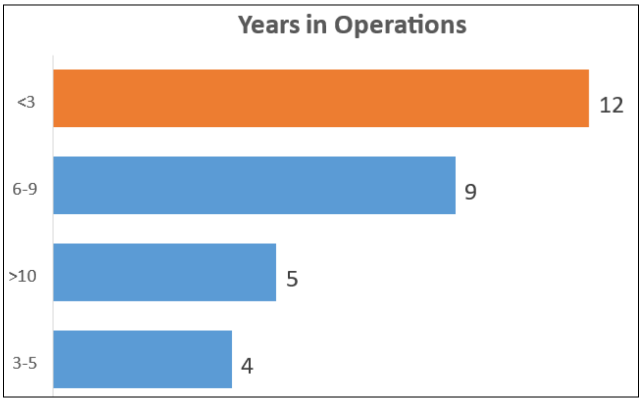


Fig 3: Years in operation

Figure 3 presents the distribution of years in operation among the 30 sampled small-scale manufacturing enterprises in Lusaka. The findings indicate that 40 percent (n=12) of the enterprises have been in operation for less than three years, making this the dominant category. This is followed by 30 percent (n=9) of enterprises that have operated for six to nine years, while 17 percent (n=5) have been in existence for more than ten years. The smallest category consists of firms operating for three to five years (13 percent; n=4).

The results suggest that the small-scale manufacturing landscape in Lusaka is characterised by a relatively young and emerging enterprise base, with the majority having less than three years of operational experience. This aligns with regional entrepreneurship trends reported in Sub-Saharan Africa, where most SMEs are newly established and still in the early stages of growth.

Enterprises operating between six and nine years form the second-largest group, suggesting that a considerable proportion of SMEs survive past the early stages of the business lifecycle. By this point, firms often begin to stabilise operations and may start considering structured tools for operational efficiency, although resource constraints may persist Firms operating beyond ten years represent a smaller portion of the dataset. These more established enterprises are likely to have greater organisational maturity, more stable cash flows, and clearer processes

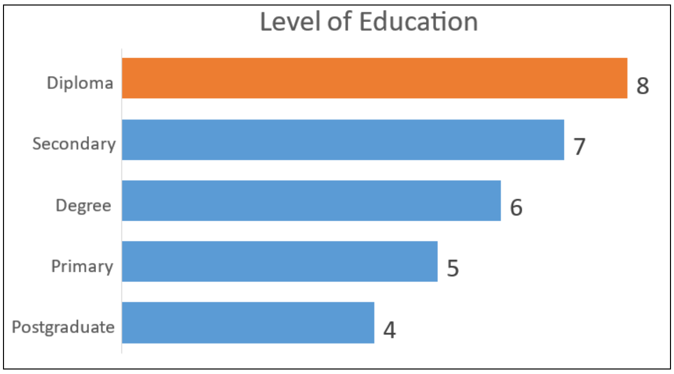


Fig 4: Shows the level of Education

Figure 5 presents the distribution of respondents according to their highest level of education. The results show that a significant proportion of respondents hold a Diploma qualification (n=8), representing the largest single group in the sample. This is followed closely by those with Secondary education (n=7) and Bachelor's Degrees (n=6). Smaller proportions reported Primary education (n=5) and Postgraduate qualifications (n=4).

These results indicate that the small-scale manufacturing sector in Lusaka is largely staffed and managed by individuals with mid-level professional or technical education. The relatively high number of Diploma and Secondary school graduates suggests that many enterprises rely on practical, skills based competencies rather than advanced academic qualifications.

The presence of six respondents with university degrees and four with postgraduate qualifications demonstrates that a subset of enterprises is investing in more specialised managerial or analytical capabilities. In contrast, the five respondents with only primary education may reflect segments of the sector that still operate with traditional methods and limited exposure to digital systems.

Overall, the distribution suggests that while Lusaka's small-scale manufacturing enterprises possess a generally educated workforce, the capacity for adopting advanced data analytics varies depending on the educational profile of the decision-makers. Enterprises with diploma and degree-level staff are more likely to possess the foundational skills required to interpret and apply data insights, whereas those with lower qualifications may face challenges without targeted skills training or simplified analytics tools.

4.1 Objective one: Types of data analytics tools and practices used among small-scale manufacturing' Figure 6 Show Data Analytics Tool Used

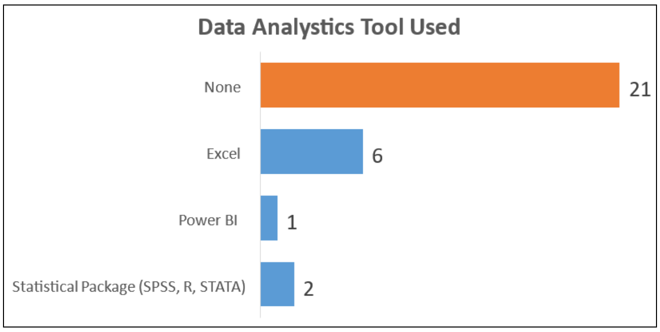


Fig 5: Show Data Analytics Tool Used

Figure 6 presents the distribution of data analytics tools used among the 30 small-scale manufacturing enterprises surveyed in Lusaka. The results show a dominant reliance on non-digital methods, with 21 out of 30 enterprises (70 percent) reporting that they do not use any form of data analytics tool. This indicates that the majority of small enterprises continue to operate using manual systems such as paper based records, basic tallies, and informal decision-making approaches.

Among the minority (30 percent) who reported using data analytics, Excel was the most frequently used tool, accounting for 6 enterprises (20 percent). This suggests that spreadsheet-based analysis is the entry point for digital data usage within the sector, likely due to its accessibility, low cost, and limited technical requirements.

A very small proportion of enterprises have adopted more advanced tools. Only one enterprise (3.3 percent) reported using Power BI, and two enterprises (6.7 percent) indicated the use of statistical software packages such as SPSS, R, or STATA. The low uptake of advanced analytics tools implies limited digital capability and low integration of data-driven processes across most manufacturing enterprises.

Overall, the findings show that data analytics adoption is still at an early stage, with a large gap between basic and advanced tool usage. The results highlight that while a small segment of enterprises is beginning to digitize their operations, the broader sector operates with minimal use of structured data analytics tools, which may affect operational efficiency, planning, and performance monitoring.

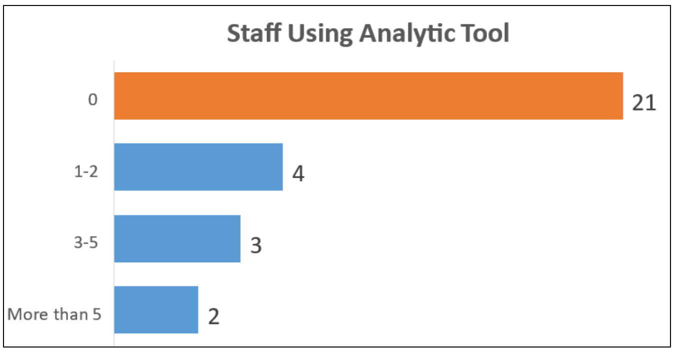


Fig 6: Shows staff using analytic tools

The results in Figure 7 show the distribution of staff members involved in the use of data analytics tools across the surveyed small-scale manufacturing enterprises in Lusaka. The findings indicate that a large proportion of enterprises (n = 21) reported having zero staff using any analytical tool. This aligns with the earlier findings that the majority of SMEs in the sample do not use analytics tools in their operations. The absence of personnel dedicated to data analytics may reflect limited digital capacity, low awareness, or a lack of investment in analytical skills.

Among enterprises that use analytics, the results show that four enterprises have 1–2 staff members trained or able to use analytical tools. This suggests that where analytics is adopted, it is typically handled by a small segment of the workforce, likely supervisors, managers, or ICT-related staff. Another three enterprises indicated having 3–5 staff members using analytical tools, which may represent slightly more formalized or structured adoption of analytics within the organization. Only two enterprises reported having more than five staff involved in analytics use. This category represents the most analytics-mature enterprises in the dataset.

Overall, the distribution shows a strong concentration at the lower end of staff involvement in analytics. This reflects minimal analytics capacity within most small-scale manufacturing firms. The fact that only a few enterprises have more than three trained users suggests that analytics adoption is still emerging, mostly informal, and driven by a small number of individuals rather than being fully embedded across operational departments.

Figure 8 shows frequency of analytics monitoring

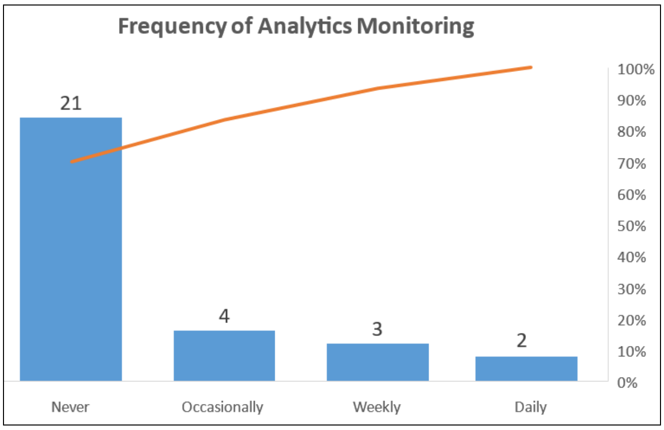


Fig 7: Analytics Monitoring

The results presented in Figure 8 show the frequency with which small-scale manufacturing enterprises in Lusaka monitor or review data analytics within their operations. The findings reveal a strong concentration of enterprises that never conduct analytics monitoring, with 21 out of 30 SMEs (70 percent) reporting that they never review or monitor analytics output. This aligns with earlier descriptive results showing that the majority of SMEs do not currently use digital analytics tools and instead rely on manual or informal processes.

A smaller proportion of enterprises reported some level of analytics monitoring. Specifically, 4 SMEs (13 percent) indicated that they review analytics *occasionally*, while 3 SMEs (10 percent) reported weekly monitoring. Only 2 SMEs (7 percent) conducted daily monitoring of analytics. These low levels of engagement with frequent analytics review suggest that only a small minority of firms have integrated analytics into routine operational oversight.

Overall, the distribution indicates that data analytics monitoring practices remain largely undeveloped among small manufacturing enterprises, with only a limited number engaging in structured or frequent analytical review. This low monitoring frequency has implications for operational decision-making, responsiveness to production problems, and opportunities for efficiency improvements. Figure 9 shows the purpose of data analytics

. tabulate B4Purpose

B4 Purpose	Freq.	Percent	Cum.
Financial tracking	1	3.33	3.33
Inventory management	4	13.33	16.67
Monitoring production output	4	13.33	30.00
None	21	70.00	100.00
Total	30	100.00	

Fig 8: Data Analytics Purpose

Figure 9 presents the distribution of responses on the purpose for which small-scale manufacturing enterprises in Lusaka use data analytics. The results show that a substantial majority of enterprises (n=21) do not use any form of analytics for operational decision-making. This aligns with earlier findings in your dataset indicating that most SMEs operate manually and rely on traditional recordkeeping systems rather than digital tools.

Among enterprises that do apply analytics, the most common purposes include monitoring production output (n=4) and inventory management (n=4). This suggests that the few firms using analytics tend to focus on functions that directly affect day-to-day production efficiency and material flow. Only a single enterprise (n=1) reported using analytics for financial tracking, indicating minimal adoption of data driven approaches for financial planning or cost management.

Overall, the distribution indicates that analytics adoption is still at a very early stage among small-scale manufacturing enterprises, with limited use restricted to basic operational tasks. The dominance of the "None" category highlights a gap in digital utilisation and signals potential opportunities for capacity building in data-driven production, inventory optimisation and financial management.

Figure 10 shows report frequency

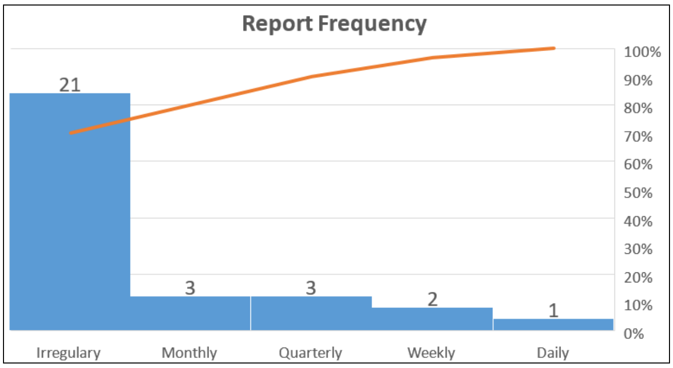


Fig 9: Data Analytics frequency

The results reveal that a significant proportion of small-scale manufacturing enterprises in Lusaka do not follow a structured reporting routine when working with production, inventory, or operational data. As shown in Figure X, 21 out of 30 enterprises (70 percent) indicated that they produce reports irregular*y*. This dominance of irregular reporting suggests limited institutionalisation of data-driven processes within most enterprises. Only a small number reported structured intervals: 3 enterprises (10 percent) produce monthly reports, while another 3 enterprises (10 percent) generate quarterly reports. Furthermore, 2 enterprises (7 percent) indicated producing reports weekly, and only 1 enterprise (3 percent) prepares reports on a daily basis.

The pattern suggests that a substantial majority of enterprises lack established data workflows or automated reporting systems, which may contribute to inconsistent monitoring of production trends, inefficiencies in decision-making, and delays in identifying operational challenges. The small proportion of businesses reporting monthly, weekly, or daily suggests that only a minority have adopted basic analytic routines or structured documentation practices. These findings highlight a considerable gap in the adoption of regular and systematic reporting practices, pointing toward the need for interventions that encourage routine data use, standardised documentation, and integration of digital record-keeping tools. Figure 11 shows useful data analytics tool or practice

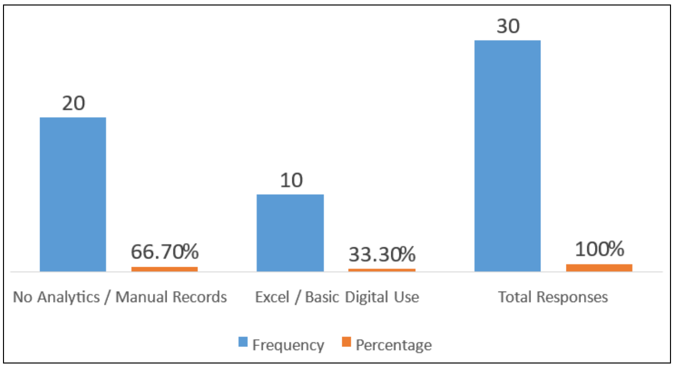


Fig 10: Data Analytics Tool practice

The responses in the highlight a clear divide in data practices among SMEs. Approximately two-thirds (66.7 percent) of enterprises do not use any form of analytics tools, instead relying exclusively on manual paper-based ledgers. These SMEs report keeping daily stock, production tallies, and operational information entirely by hand, a process that limits real-time insights and makes information retrieval slow.

Conversely, only one-third (33.3 percent) of SMEs reported using basic digital tools, primarily Excel. These SMEs explained that Excel supports improved visibility of stock and production tallies, suggesting that even minimal digital adoption begins to enhance operational clarity. However, no enterprise reported use of advanced analytics tools such as Power BI, R, SPSS, ERP dashboards, or automated reporting systems. Figure 12 show frequency of reports use

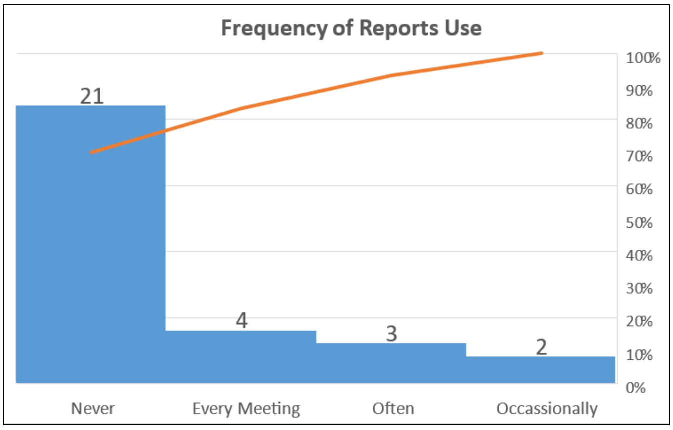


Fig 11: Data Analytics Report frequency use

The results presented in Figure 12 show how frequently small-scale manufacturing enterprises in Lusaka use analytical or operational reports to support decision-making. The distribution reveals a high reliance on non-data-based decision-making, with 21 out of 30 respondents (70%) indicating that they never use reports in their routine managerial or operational processes. This finding is consistent with the earlier pattern observed in the dataset, where the majority of firms reported not using any formal data analytics tools.

A smaller proportion of enterprises reported some level of report utilisation. Specifically, 4 respondents (13.3%) indicated that they use reports in every meeting, suggesting a structured, data driven culture within a few firms. Additionally, 3 respondents (10%) reported using reports *often*, while 2 respondents (6.7%) said they use them occasionally. This indicates that only a minority of enterprises integrate reporting into management practices with any regularity.

Overall, the graph highlights a clear pattern: report-driven decision-making is limited among small-scale manufacturing enterprises in Lusaka, with the vast majority relying on informal, experience-based judgement rather than structured documentation or analytical outputs. This has significant implications for operational efficiency, monitoring, and long-term planning, suggesting potential gaps in recordkeeping, internal data processing capacity, and awareness of the value of structured reporting.

Figure 13 shows management level using analytics

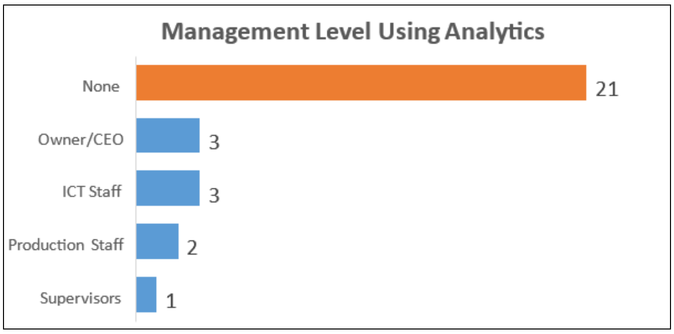


Fig 12: Data Analytics Management usage

Figure 13 presents the distribution of management levels within small-scale manufacturing enterprises who reported using data analytics tools. The results show that a significant majority of enterprises (21 out of 30) indicated that no management-level staff are currently using analytics in their decision-making processes. This reinforces the earlier findings suggesting that most SMEs in Lusaka have not yet institutionalised analytics practices.

Among the enterprises that reported some level of analytics use, 3 respondents each identified Owners/CEOs and ICT staff as the primary users of analytics tools. This indicates that in the minority of firms where analytics is present, usage tends to be concentrated at the top leadership level or within technically skilled roles. Only 2 respondents noted that production staff engaged with analytics, while supervisors accounted for the lowest usage with 1 respondent.

Overall, these results show that analytics use within SMEs remains highly centralised and limited to a few individuals, with minimal engagement across middle management or operational teams. This suggests a lack of internal diffusion of analytics capabilities and highlights potential gaps in organisational readiness, staff skills, and digital adoption. Such patterns may constrain the ability of SMEs to leverage

analytics for operational efficiency, process optimisation, and real-time decision support.
Figure 14 shows number of dashboards produced monthly

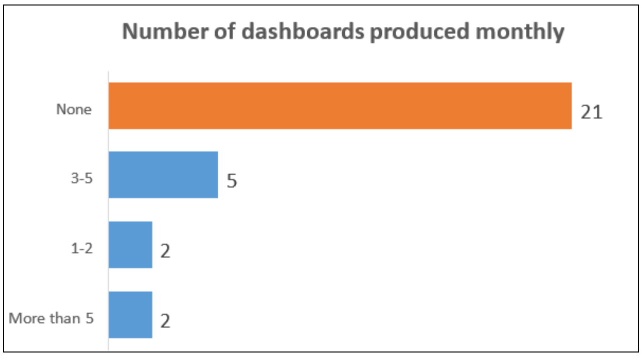


Fig 13: Data Analytics Dashboard usage

The results indicate that the majority of small-scale manufacturing enterprises (70 percent; n = 21) do not produce any dashboards on a monthly basis. This shows that most firms are not generating structured analytical outputs for operational monitoring.
Only a minority of enterprises report producing dashboards: five firms produce 3–5 dashboards per month, while two firms produce 1–2 dashboards, and another two firms generate more than five dashboards monthly. This pattern suggests that dashboard production is highly concentrated among a small proportion of relatively more advanced enterprises.
Overall, these findings demonstrate low adoption of dash boarding and business intelligence practices, reinforcing earlier results showing that most SMEs rely on manual processes and lack formalized data analytics systems. Limited production of dashboards also implies minimal real-time visibility into production, inventory, or operational performance, which may constrain decision-making efficiency

4.2 Objective two: Integration of Data Analytics in Decision-Making

Figure 15 shows decision influenced by analytics

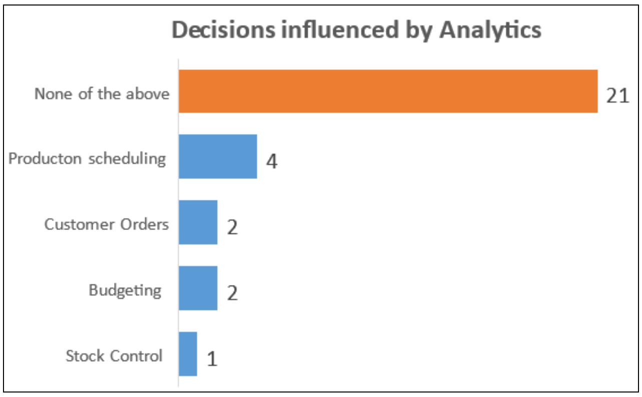


Fig 14: Data Analytics and Decision Making

The results in Figure 14 show that the majority of small-scale manufacturing enterprises in Lusaka do not use data analytics to support decision-making, with 21 out of 30 respondents (70 percent) indicating that analytics do not influence any managerial or operational decisions within their firms. This finding reinforces earlier results showing limited adoption and integration of analytics tools across most enterprises in the sample.

Among the minority of firms that do use analytics, the areas influenced are primarily production scheduling, reported by 4 enterprises. This suggests that the small subset of analytics users tends to apply data insights to optimise workflows, align production with demand, and reduce inefficiencies. Additionally, customer order management and budgeting were each identified by 2 enterprises, indicating limited yet emerging use of analytics for operational planning and financial oversight.
Only 1 enterprise reported using analytics for stock control, demonstrating that inventory-related analytics capabilities remain largely underutilised. This is notable given that inventory management is typically one of the most common entry points for data-driven decision-making in manufacturing SMEs globally.
Overall, the distribution reveals that data analytics has minimal influence on decision-making among most small manufacturing firms surveyed. Where analytics is used, it is applied selectively in areas directly linked to productivity and workflow optimisation. This pattern points to a broader challenge of integrating data analytics into organisational decision structures, potentially influenced by resource limitations, skills gaps, or lack of digital systems.
Figure 16 shows decisions to be made after data reports are generated

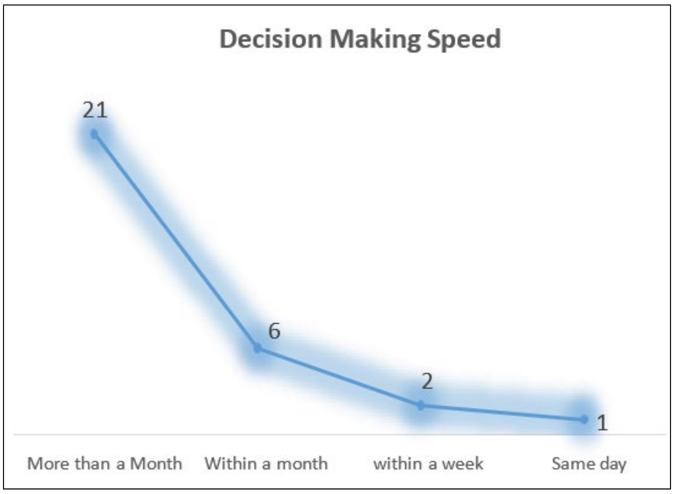
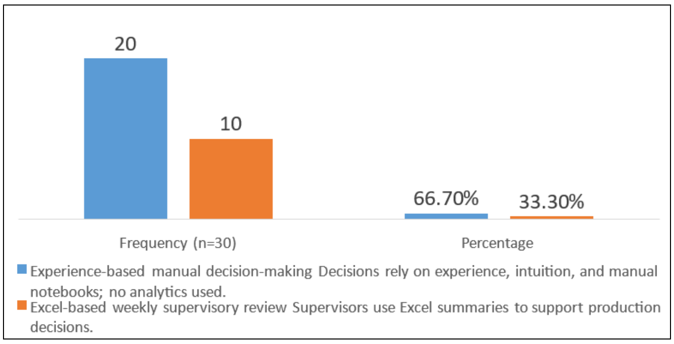


Fig 15: Data Analytics Speed

The results show that most small-scale manufacturing enterprises take long periods to make operational decisions, with 21 out of 30 enterprises indicating that decisions are made after more than one month. This represents the largest proportion and suggests that decision-making processes are slow and largely reactive rather than data-driven.
A smaller group of firms (6 enterprises) reported making decisions within a month, showing some improvement in turnaround time but still indicating limited agility. Only 2 enterprises make decisions within a week, while just 1 enterprise reported making decisions on the same day, reflecting very low levels of real-time or near-real-time decision-making.
Overall, the pattern shows a sharp decline in decision-making speed across categories, confirming that fast, data-supported decisions are rare among the surveyed SMEs. The predominance of delayed decision-making aligns with low analytics adoption across enterprises and reliance on manual processes, which limits responsiveness to operational challenges Figure 17 shows how data analytics information is used during your enterprise's decision-making process



The figure 17 findings show that decision-making across the surveyed SMEs remains predominantly manual and experience-driven. Out of 30 responses, 20 enterprises (66.7%) reported relying on experience, judgement, and handwritten notebooks, with no form of data reporting or digital support. This suggests that most SMEs lack structured decision-support systems and are yet to adopt analytics oriented practices.

Conversely, 10 enterprises (33.3%) indicated that supervisors use basic Excel summaries to review weekly production tallies and determine reorder levels. These findings demonstrate an emerging but limited uptake of rudimentary analytical tools. However, the use of Excel is primarily operational rather than strategic, and does not extend to deeper analytical functions such as forecasting, optimization, or trend analysis.

Overall, the responses indicate that analytics-driven decision-making is still at an early stage, with the majority of enterprises not yet benefiting from digital reporting systems or analytic insights. This aligns with earlier quantitative results showing low adoption of analytics tools within SMEs.

4.3 Objective three: Perceptions and Experiences of Small-scale Manufacturing Enterprises with Data Analytics on Operational Efficiency

Figure 18 Shows since adopting analytics, have production delays reduced

. tabulate UsesAnalytics D1DelaysReduced, chi2

Uses Analytics	D1 DelaysReduced No	Not sure	Yes	Total
0	21	0	0	21
1	3	3	3	9
Total	24	3	3	30

Pearson chi2(2) = 17.5000 Pr = 0.000

Fig 16: Data Analytics Perceptions and Operations

The chi-square analysis examined the association between the use of data analytics and whether enterprises experienced reduced production delays ("D1 Delays Reduced"). The results in the table indicate a strong and statistically significant relationship between the two variables, $\chi^2(2) = 17.50$, $p = 0.000$. Among enterprises that do not use data analytics (n=21), none reported reduced delays, with all 21 respondents indicating that delays had not reduced. In contrast, among the 9 enterprises using data analytics, one-third (n=3) reported reduced delays, another one-third were not sure (n=3), and the remaining reported no improvement (n=3). The statistically significant p-value suggests that the observed differences are unlikely to have occurred by chance, indicating that the use of data analytics is strongly associated with improvements in production delays among small-scale manufacturing enterprises.

Overall, the results demonstrate that enterprises adopting data analytics are more likely to report perceived improvements in operational efficiency, particularly in reducing delays, compared to those relying on traditional, non-analytic processes. This aligns with the broader pattern observed in the dataset, where analytic-using firms show incremental efficiency advantages relative to non-users.

. oneway UsesAnalytics D2DowntimeSaved

Analysis of Variance

Source	SS	df	MS	F	Prob > F
Between groups	3.675	3	1.225	12.13	0.0000
Within groups	2.625	26	.100961538		
Total	6.3	29	.217241379		

Presents the one-way ANOVA results examining whether the amount of downtime saved (D2) differs significantly between enterprises that use data analytics and those that do not. The results show a statistically significant difference between the groups, $F(3, 26) = 12.13$, $p < 0.001$. This p-value indicates that the likelihood of observing such differences by chance is extremely low.

These results suggest that data analytics adoption plays a significant role in improving operational efficiency, particularly by reducing unproductive time during production processes. The statistical evidence confirms that enterprises that have integrated analytics tools though few in the sample experience greater benefits in downtime reduction compared to those relying solely on manual or traditional methods

4.4 Objective Four: Challenges in Implementing Data Analytics

Figure 21 Shows analytics reports lead to production adjustments

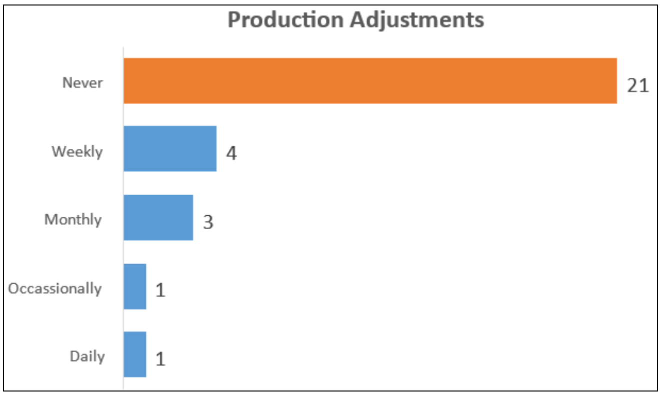


Fig 18: Data Analytics and Production Adjustments

The results presented in Figure 21 show the frequency with which small-scale manufacturing enterprises in Lusaka adjust their production based on available data or operational insights. The findings indicate that the majority of SMEs (21 out of 30; 70 percent) reported that they never adjust production, suggesting limited use of data-driven or responsive production management practices. Only a small proportion reported making periodic adjustments: 4 enterprises (13 percent) adjust production weekly, while 3 enterprises (10 percent) reported doing so monthly. Minimal adjustments were observed at the lower frequencies, with 1 enterprise (3 percent) adjusting production occasionally and another 1 enterprise (3 percent) adjusting daily.

These results show that production changes are largely reactive rather than strategic, reflecting limited integration of analytics into real-time operational control. The high number of enterprises that never adjust production aligns with earlier findings indicating low uptake of data analytics tools, where most firms rely on manual processes and do not generate regular reports. Consequently, they lack the insights required to inform timely production changes.

Overall, the pattern demonstrates that data analytics has not yet become a central driver of production decisions among most small-scale manufacturing enterprises in Lusaka. This strengthens the argument that the absence of analytics limits operational agility, efficiency improvements, and the ability to respond to fluctuating demand or raw material availability.

In contrast, the majority of SMEs (66.7 percent) stated that they experienced no meaningful efficiency gains, primarily due to the absence of any form of data analytics. These respondents relied heavily on manual notebooks, personal experience, and ad-hoc judgment to manage operational processes. As a result, improvements in efficiency could not be attributed to data-driven insights, reinforcing the earlier quantitative findings showing very low levels of analytics adoption.

Overall, the qualitative data strongly aligns with the quantitative results by demonstrating that SMEs that use even simple analytics tools experience some operational benefits, while those that rely solely on manual approaches do not observe significant efficiency improvements. This highlights a clear gap in digital readiness and further underscores the potential value of strengthening data analytics capabilities among SMEs. Figure 24 shows the main barriers to adopting analytics tools

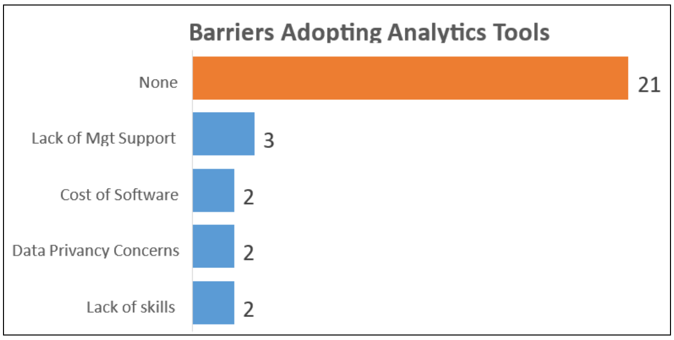


Fig 21: Data Analytics barriers

The findings reveal that most SMEs (n = 21) reported no barriers to adopting analytics tools. This aligns with the earlier results showing that 70 percent do not use analytics at all, suggesting that the absence of perceived barriers is primarily due to limited exposure rather than readiness for adoption. Among the SMEs that reported challenges, the most common barrier was lack of management support (n = 3). This suggests that in some enterprises, decision makers may not prioritise data-driven processes, which limits investments in analytical tools.

Other barriers were reported at low but equal frequencies, including software cost, data privacy concerns, and lack of skills (each n = 2). These challenges indicate that for SMEs attempting to transition into data-driven operations, both financial and technical constraints remain relevant.

Overall, these results demonstrate that while barriers do exist, they are concentrated among the minority of SMEs attempting to adopt analytics, reinforcing that the key issue in this sector is not resistance but low levels of uptake and awareness of the value of data analytics.

Figure 25 shows how often the respondents experience system or network downtime affecting analytics use

The results presented in the table assess whether the frequency of operational downtime differs significantly between SMEs that use data analytics tools and those that do not. The table shows a distribution of 30 respondents across downtime categories (Daily, Never, Occasionally, Rarely, Weekly).

Overall, the majority of respondents (21 out of 30) reported never experiencing downtime, while a very small number reported daily downtime (n=2), occasional downtime (n=2), rarely (n=2), or weekly downtime (n=3). This distribution is highly skewed, with most SMEs falling into the "Never" category irrespective of whether they use analytics.

The Pearson Chi-square test produced a value of χ^2 (116) = 120.000, p = 0.381. Since the p-value is greater than 0.05, the result is not statistically significant. This indicates that there is no meaningful association between the use of data analytics tools and the frequency of operational downtime among the SMEs sampled.

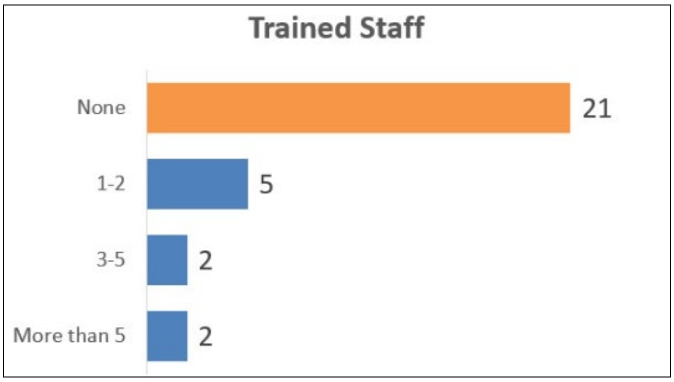


Fig 22: Data Analytics Trained staff

The results show that a large majority of SMEs do not have any staff trained in data analytics, with 21 out of 30 enterprises (70 percent) reporting zero trained personnel. Only a small proportion indicated having some level of trained staff, with 5 enterprises (17 percent) having between one and two trained employees, while 3–5 trained staff and more than five trained staff were each reported by 2 enterprises (7 percent) respectively.

This pattern indicates that most SMEs operate without internal analytical capacity, which directly limits their ability to adopt, utilise, and benefit from data-driven decision-making. The very low number of trained personnel aligns with earlier findings showing limited use of analytic tools and minimal integration of analytics into operational processes. The distribution suggests that data analytics skills remain concentrated in only a few enterprises, and that capacity-building gaps persist across the sector.

Majority of SMEs report low management support for the adoption and use of data analytics tools. Out of the 30 enterprises surveyed, 24 indicated low support, making it the dominant response category. Only a small proportion of firms rated their management support as very high (n=3), high (n=1), moderate (n=1), or very low (n=1).

This distribution suggests that although management may generally acknowledge the importance of business operations, there is limited active encouragement, investment, or strategic focus directed toward data analytics. Low support likely affects the availability of resources such as training, software, and dedicated personnel, which ultimately constrains SMEs' capacity to integrate analytics into routine decision-making. The small number of firms reporting high or very high support indicates that only a minority of enterprises have leadership that prioritizes evidence-driven practices.

Overall, these findings highlight management support as a key barrier to analytics adoption within SMEs, reinforcing the need for leadership buy-in, resource allocation, and change management initiatives if data-driven systems are to be sustained

Summary, Conclusions and Recommendations

Overview

This study examined the adoption and use of data analytics among Small and Medium Enterprises (SMEs) and assessed its influence on operational efficiency, decision making, and overall business performance. The research focused on four key areas: the tools and practices currently used by SMEs, the extent to which data analytics is integrated into decision-making processes, the perceived efficiency outcomes resulting from analytics use, and the barriers preventing wider adoption of analytical tools. Data were collected from 30 SMEs using a structured questionnaire consisting of quantitative and qualitative items. The findings showed that most SMEs continue to rely on manual systems, with only a minority using basic tools such as Excel. Statistical tests including chi-square, ANOVA and descriptive analysis provided evidence of significant relationships between analytics use and certain aspects of operational efficiency. This chapter presents a summary of the major findings, conclusions drawn from the analysis, and practical recommendations tailored to the context of SMEs.

Conclusions

The study concludes that data analytics adoption among SMEs remains very low, and this significantly limits their ability to operate efficiently and make timely, informed decisions. The dominance of manual record-keeping systems and experience-based decision-making suggests that SMEs are missing opportunities to reduce downtime, enhance productivity and streamline operations. Where basic analytics tools such as Excel are used, evidence shows improved production planning and reduction in operational delays, indicating that even simple tools can produce measurable benefits. The statistical tests performed support the conclusion that analytics use has a positive and significant effect on some dimensions of operational efficiency, such as reducing delays and saving downtime. However, more complex outcomes such as waste reduction may require more advanced analytical tools and structured systems. The barriers identified also highlight that analytics adoption is not purely a technical issue but is influenced by leadership attitudes, digital skills, financial constraints and the absence of clear data policies. Overall, the findings show that SMEs have the potential to leverage analytics for efficiency gains, but this requires deliberate investment and capacity development.

Recommendations

Based on the findings, several recommendations are proposed to strengthen analytics adoption and improve operational efficiency among SMEs:

1. SMEs should begin by incorporating low-cost tools such as Excel, Google Sheets or free statistical packages. These tools can provide immediate operational benefits without requiring major financial investments.
2. Training programs should be introduced to equip SME managers and staff with basic data management and analysis skills. Partnerships with training institutions, ICT hubs and business support organizations can enhance capacity-building efforts.
3. SME owners and leaders should be sensitized on the value of data in enhancing decision-making and reducing inefficiencies. Improved leadership buy-in is essential to move from manual practices to data-driven operations.

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