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Influence of data literacy on managerial decision making in medium sized textile manufacturing companies in Kenya.

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INFLUENCE OF DATA LITERACY ON MANAGERIAL DECISION MAKING IN MEDIUM SIZED TEXTILE MANUFACTURING COMPANIES IN KENYA

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DECLARATION

I wish to declare here that this study is my original work and has not any way been submitted and approved for the award of a degree by this or any other University. To the best of my understanding and conviction, the dissertation does not contain any material produced for publishing or written by another person except where reference is made appropriately in the dissertation itself.

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Signature. Date **06.09.2022**

Approval

This research dissertation has been assessed and commended for examination by the University Supervisor.

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Signature. Date **06.09.2022**

ABSTRACT

Data literacy is important to any organization as it propels forward momentum and success. It is essential for employees and other stakeholders in an organization to understand the value of improving their data literacy. Organizations should be able to use data to influence their operations as well as make strategic decisions. On the other hand, poor data literacy is one of the main roadblocks to an organization's success and a company's ability to grow. Data-based decision making is therefore increasingly becoming popular in both private and public policy discourses and texts. Policy makers and top managers in organizations have placed tremendous faith in the power of data to transform practice. However, the fate of their efforts depends on the great measure of the very practice they hope to move. The relationship between data and practice, however, have been under conceptualized. There exists a gap regarding studies on the use and effect of data in decision making in the Kenyan Textile Industry. The purpose of this study therefore was to evaluate how data literacy of managers influence their decision making in the Kenyan textile industry. To fulfill this purpose, the study employed a positivism research philosophy as well as a descriptive research design to describe the situation in the Kenyan textile industry as it is. Quantitative method was used to collect data. The target population was 52 medium and large textile manufacturing companies operating outside the EPZ in Kenya. Probability sampling technique (simple random sampling) was employed to include the entire medium and large sized companies outside the Export Processing Zone. Data collection was done using a structured questionnaire with both closed and open-ended questions. Data analysis was done using STATA and MS excel, to provide descriptive statistics such as means, standard deviations and correlations and regression. The findings are presented using graphs and tables. The study findings from the descriptive data and simple linear regression models indicated that there was high data accessibility and availability in the Kenyan textile manufacturing industry. The findings also indicate that there was a high level of data skills possessed by the managers of the selected Kenyan textile manufacturing companies. However, the findings revealed a mixed level of data usage among the managers. A positive correlation with managerial decision making as well as from the multiple regression the study established that data literacy by managers significantly contribute to managerial decision making. In conclusion, the study offers appropriate recommendations for managers, policy makers as well contribution to knowledge based on the study.

Key Words: *Data Literacy, Data Accessibility, Data Skills, Data Use, Data-based Decision-Making*

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DEDICATION

To my Dad, the late Engineer Vincent Kagwera, who gave me all I needed and much more, continue to rest in perfect peace. And to my beloved daughters Keza and Kera, who have thought me what matters and never let me get away with mediocrity.

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ABBREVIATIONS AND ACRONYMNS

EHRs -Electronic Health Records

ENACTS – Enhancing National Climate Services

EPZ – Export Processing Zone

SME – Small and Medium Enterprise

DEFINITIONS OF KEY TERMS

Data - That which is collected, observed, or created for purposes of analysis to produce original research results (Briney, 2015)

Data Accessibility- Refers to the degree to which individuals in an organization can use data. Where data is not just available, but usable (Stobierski, 2019).

Data Availability – Can be defined as the timeliness and reliability of access to and use of data (Stobierski, 2019).

Data literacy - refers to the strategies, skills and knowledge needed to define information needs, and to locate, evaluate, synthesize, organize, present and/or communicate information as needed (Vanhoof et al., 2011).

Data skills level - a set of capabilities that surrounds the support of application of data for critical thoughtful insight in decision-making and problem-solving initiatives (Wolff & Zdraha, 2018).

Data Use – Refers to instances where data is reviewed to inform a decision for action in strategic planning, policymaking, program planning and management, advocacy, or delivering services (Wolff & Zdraha, 2018).

Data-driven decision making - the practice of basing decisions on the analysis of data rather than purely on intuition (Provost and Fawcett, 2013).

Decision making - the process of making choices by identifying a decision, gathering information, and assessing alternative resolutions (Mandinach, 2021).

CHAPTER ONE

INTRODUCTION TO THE STUDY

1.0 Introduction

This chapter provides a discussion of the background of the study, introduces the concepts, and describes the problem under study. It also presents the research objectives and questions that this study seeks to answer, as well as the scope and significance. There are many factors that influence decision making. However, in this research, we shall focus on data access and use and its influence on market availability and access.

1.1 Background Information

Data can be defined more contextually in the scope of research to mean that which is collected, observed, or created for purposes of analysis to produce original research results (Briney, 2015). According to Schildkamp et al., (2013), data are any "information that is collected and organized to represent a phenomenon and include input data, process data, outcome data and context data. Data are the primary base of information that describes real world objects in a format that can be stored, retrieved, and processed by a software procedure, and communicated through a network (Batini et al., 2009).

Raw or unprocessed data refers to a collection of numbers or characters before it has been cleaned and corrected (Oliver, 2015). Data processing commonly occurs by stages, and the processed data from one stage may still be considered the raw data of the next stage. Once raw data has been collected, it is measured, analyzed, reported, and used to create data visualizations such as graphs, tables, or images. The existing information or knowledge is represented or coded in some form suitable for better usage or processing (Oliver, 2015). The terms data and information are often used interchangeably, even though they have distinct meanings. According to Frazao and Weeks (2016) data is said to be transformed into information when viewed in context or in post-analysis. In academic treatment, data is simply units of information and is used in scientific research, businesses management, finance, governance, marketing and in virtually every other form of human organizational activity (Frazao and Weeks, 2016).

1.1.1 Data Literacy

Data literacy, according to Vanhoof et al. (2011) refers to the strategies, skills and knowledge needed to define information needs, and to locate, evaluate, synthesize, organize, present and/or communicate information as needed. Data literacy is composed of a specific skill set and knowledge base that enables organizations to transform data into information and ultimately into actionable knowledge (Mandinach and Gummer, 2013). It is the ability to read, work with, analyze and communicate with data. It's a skill that empowers all levels of workers to ask the right questions of data and machines, build knowledge, make decisions, and communicate meaning to others.

Wolff and Zdraha (2018) assert that data literacy implies a set of capabilities that surrounds the support of application of data for critical thoughtful insight in decision-making and problem-solving initiatives. Morrow (2018) notes that data literacy emphasizes on ability to understand through careful reading, analyze and handle data irrespective of key function and your level of skill and tools used for the analysis. The roles played coupled with tools and technique applied is believed to strengthen decision made based on the result of data before the person handling it. Calzada, Prado and Marzal (2013), according to whom data literacy enables individuals to access, interpret, critically assess, manage, handle and ethically use data. Data literacy is the ability to ask and answer real-world questions from large and small data sets through an inquiry process, with consideration of ethical use of data. It is based on core practical and creative skills, with the ability to extend knowledge of specialist data handling skills according to goals. These include the abilities to select, clean, analyze, visualize, critique and interpret data, as well as to communicate stories from data and to use data as part of a design process. (Wolff et al. 2016, 23; Ridsdale et al., 2015; Gupta and Cannon, 2020).

According to Marr (2020), poor data literacy is one of the main roadblocks to an organization's success and a company's ability to grow. Data literacy is important to any organization as it propels forward momentum and success. It is essential for employees and other stakeholders in an organization to understand the value of improving their data literacy. Organizations should be able to use data to influence their operations as well as make strategic decisions. If used the right way, data literacy can help the business achieve its objectives, reach their goals and contribute to overall company performance (Marr, 2020).

While organizations claim to possess good and quality data, the real challenge is defining the characteristics that determine the quality of data (Stobierski, 2019). What some consider good quality data, others might view as poor quality data. Determining the quality of data therefore requires an examination of some universal characteristics, then weighing them according to what is most important to the organization and its applications to the business. There are many characteristics that determine data quality, and each can be prioritized differently by different organizations. Prioritization also changes depending on the current business stage of growth of an organization or its current business cycle. Organizations must therefore define what is most important when evaluating data and use these characteristics to define the criteria for high-quality, accurate data (Toonders, 2014).

According to Ortega (2017) there are seven characteristics that define data quality: accuracy and precision, legitimacy and validity, reliability and consistency, timeliness and relevance, completeness and comprehensiveness, availability and accessibility, granularity and uniqueness. Accuracy and precision refer to the exactness of the data, without erroneous elements and conveys the correct message that is not misleading. Without understanding how the data will be consumed, ensuring accuracy and precision could be off-target or more costly than necessary. Legitimacy and validity are characteristics dealing with whether the data is well grounded or justifiable, while also being in accordance with the law or established legal forms and requirements. Organization need to understand what data is valid or not to them, so the requirements must be leveraged when evaluating data quality. Reliability and Consistency refer to the degree to which the result of a measurement, calculation, or specification can be depended on to be accurate while being in harmony with parts or features to one another. Regardless of the data source data or where it is stored, it cannot contradict a value residing in a different source or collected by a different system (Ortega, 2017).

Ortega (2017) continues by explaining that timeliness and relevance is another important characteristic of data that refer to the collection of data at the right moment in time and should be relevant for the purpose it is intended. Data collected too soon or too late or for a different purpose could misrepresent a situation and drive inaccurate decisions. Completeness and Comprehensiveness refers to the state or condition of data having all the necessary or appropriate parts available. Gaps in data collection lead to a partial view of the overall picture to be displayed and could lead to uninformed actions. Availability and Accessibility refer to the characteristic of data being able to be used or obtained at the time it is required. Organizations need the right level of access to the data to fulfill their objectives and presumes that the data exists and is available for access to be granted. Granularity and Uniqueness refer to the characteristic of the scale or level of detail in a set of data as well as being particularly remarkable and special for its intended purpose. An appropriate level of granularity must be defined to provide sufficient uniqueness and distinctive properties to become visible and to function effectively (Ortega, 2017).

Shearer and Schmidt (2016) identify the skills to include knowledge of repositories, data manipulation, data discovery mechanisms, funders' policies and requirements, data centres, data publication requirements of journals, sharing and access, data citation and referencing, metadata standard and schemas amongst others. According to Fary and Owen (2013) as well as Creamer et al. (2012) data skills include storage, data migration, networking, legal, financial, security, metadata creation and assignment, scholarly data communications and preservation. Kennan (2016) focused on data professionals and identified essential data skills to include interpersonal skills, data specific knowledge and skills and metadata. According to Plotkin (2014), essential data skills include ability to identify and analyse data. Earley and Henderson (2017) identify that researcher should understand manipulation of data, intellectual property rights, metadata standards and schemas, data formats, domain ontologies, identifiers, data citation, data licensing discovery tools, database design types and structures, data linking and data integration techniques, data repository and storage platforms.

1.1.2 Decision making

Decision making is defined as the process of making choices by identifying a decision, gathering information, and assessing alternative resolutions (Mandinach, 2021). It is regarded as the cognitive process resulting in the selection of a belief or a course of action among several possible alternative options. It could be either rational or irrational. Decision-making process is a reasoning process based on assumptions of values, preferences, and beliefs of the decision-maker. Every decision-making process produces a final choice, which may or may not prompt action (Ning and You, 2017). Decision making can be classified into three categories based on the level at which they occur. Strategic decisions set the course of organization. Tactical decisions are decisions about how things will get done. Finally, operational decisions are decisions that employees make each day to run the organization (Mandinach, 2021).

According to Licidchart (2017), decision-making process involves a step-by-step process where managers solve problems by weighing evidence, examining alternatives, and choosing a path from there. This defined process also provides an opportunity, at the end, to review whether the decision was the right one. The most common process identified and used by scholars and businesses is a seven-step decision process. Though there are other variations of the decision-making process, professionals most commonly use these seven steps that include Identification of the decision, gathering information, identifying alternatives, weighing the evidence, choosing among alternatives, taking action and review of the decision (Licidchart, 2017).

Provost and Fawcett (2013) define data-driven decision making as the practice of basing decisions on the analysis of data rather than purely on intuition. It refers to individuals or organizations using facts, metrics, and data to guide strategic business decisions that align with goals, objectives, and initiatives. Data driven decision making empowers organizations to make better decisions with data. Better decision making however, is not achieved by simply choosing the appropriate analytics technology to identify the next strategic opportunity. Organizations needs to create a culture of making data driven decision the norm, while encouraging a practice that encourages critical thinking and curiosity (Mandinach, 2021). This requires empowering employees at every level to have conversations that start with data as they develop their data literacy and skills levels through practice and application. Establishing these core capabilities will help encourage data-driven decision-making across all job levels so business groups will regularly question and investigate information to discover powerful insights that drive action (Ning and You, 2017).

According to Brynjolfsson and McElheran (2016), data Driven decision making approach can be of great benefit to any organization. One of the main benefits is that it leads to improved transparency and accountability to every organization which works to improve teamwork and staff engagement. Another advantage is that it leads to constant improvement which enhances the overall performance and efficiency of a business organization. Third, data driven decision making ties Business Decisions to Analytics Insights which helps the entrepreneurs to mine data, saving time to end up with useful insights. Fourth advantage of data-driven decision-making approach is that it helps to get feedback and helps the organization to be able to formulate new products, reliable services, and come up with new workplace initiatives. Fifth, is that it enhances Consistency to help people within the organization to know how decisions are made (McElheran, 2016).

Lai & Schildkamp (2012) reviewed an overview of data-based decision making for school leaders and teachers. In their review, they sought to answer the questions: what does using data for decision-making mean? And What counts as “data”? In their review, the authors address what is meant by the word “data” and what kinds of data are available and needed. The latter should overlap, but sometimes the available data are not needed and sometimes needed data are not available. They also discussed why teachers and school leaders should use data, the process of using data and the different ways data can and should be used.

Van Geel et al. (2016) assessed the effects of a school wide data-based decision-making intervention on student achievement growth in Primary schools. In the study, the effects of a two-year data-based decision-making intervention on student achievement growth were investigated. Fifty-three primary schools participated in the project, and student achievement data were collected over the two years before and two years during the intervention. Linear mixed models were used to analyze the differential effect of data use on student achievement. A positive mean intervention effect was estimated, with an average effect of approximately one extra month of schooling. Furthermore, the results suggest that the intervention especially significantly improved the performances of students in low socioeconomic status schools.

In the agricultural sector, Gandhi & Armstrong (2016) provided a review of research on the application of data mining techniques for decision making in agriculture. The study reported the application of several data mining techniques including artificial neural networks, Bayesian networks and support vector machines. The review outlined several promising techniques that have been used to understand the relationships of various climate and other factors on crop production. This review proposed that further investigations are needed to understand how these techniques can be used with complex agricultural datasets for crop yield prediction integrating seasonal and spatial factors by using GIS technologies.

With regards to the textile industry, there have been few and far in between studies. Banica and Hagiu (2016), studied using big data analytics to improve decision making in apparel supply chains, with a focus to provide several ways to increase the competitiveness in Romanian apparel and fashion on the international market, focusing on originality, quality, online commerce, and marketing. Polay, Rahman, Billah and Al-Sabbahy (2020) discussed issues associated with the application of big data analytics for decision-making about the introduction of new technologies in the textile industry in the developing world. The findings indicate that the limited use of technological resource was linked to several factors, mainly cultural, generational, and educational factors.

The decision-making process involves a step-by-step process where managers solve problems by weighing evidence, examining alternatives, and choosing a path from there. This process involves seven steps that include Identification of the problem, gathering information, identifying alternatives, weighing the evidence, choosing among alternatives, taking action and review of the decision (Licidchart, 2017). To make a decision, the manager must first identify the problem that needs to be solved or the question that needs an answer. The decision should be clearly defined. If the problem is misidentified or is too broad, the purpose of the decision-making process would have been compromised before it has even begun. Specific goals from the decision, must be measurable and timely. Once a decision is identified, it leads to the second step, to gather the information relevant to that choice. This can be done through an internal assessment, seeing where the organization has succeeded and failed in areas related to the decision. Information can also be sought from external sources, including studies, market research, and, in some cases, evaluation from paid consultants. The decision maker should be weary not to become bogged down by too much information and that might only complicate the process. The third step is to identify the alternatives available. With relevant information available, possible solutions to the problem should be identified. There could be more than one option to consider when trying to meet a goal. Once the multiple alternatives have been identified, weighing the evidence for or against each of the alternatives is done. Study what other organizations have done in the past to succeed in these areas and take a good look at the organization's own wins and losses. Potential pitfalls for each of the alternatives are identified (Licidchart, 2017).

The fifth step is choosing among the alternative. This is the step where the decision is made. Once the decision has been made, it is now time to act on it. The decision makers should develop a plan to make the decision tangible and achievable and a project plan related to the decision, and then assign tasks to the team. The final step in the decision-making process is a review of the decision made. After a predetermined amount of time that is defined in step one of the decision-making processes, the organization needs to take an honest look back at the decision. Did it solve the problem? Did it answer the question? Did it meet the goals set? If so, the organization should take note of what worked for future reference. If not, learn from the mistakes and begin the decision-making process again (Licidchart, 2017).

According to Brynjolfsson and McElheran (2016), data Driven decision making approach can be of great benefit to any organization. One of the main benefits is that it leads to improved transparency and accountability to every organization which works to improve teamwork and staff engagement. Another advantage is that it leads to constant improvement which enhances the overall performance and efficiency of a business organization. Third, data driven decision making ties Business Decisions to Analytics Insights which helps the entrepreneurs to mine data, saving time to end up with useful insights. Fourth advantage of data-driven decision-making approach is that it helps to get feedback and helps the organization to be able to formulate new products, reliable services, and come up with new workplace initiatives. Fifth, is that it enhances Consistency to help people within the organization to know how decisions are made (McElheran, 2016).

During the decision-making process, there are intervening factors apart from data literacy that can affect the type of decisions made. These include political, environmental, and sociocultural factors. Political factors relate to how the government intervenes in the economy through tax, labor, trade, and other macro factors. Environmental factors include climate change, natural disasters, and pollution among others. Sociocultural factors include population size, demographics, and cultural trends and practices. In order to determine the specific effect of data literacy on managerial decision making, these intervening factors are assumed to be held constant and therefore not considered as objectives of the study.

1.2 Problem Statement

According to Bourassa et, al. (2021), data-based decision making is increasingly becoming popular in both private and public policy discourses and texts. Policy makers and top managers in organizations place tremendous faith in the power of data to transform practice. However, the fate of their efforts depends on the great measure of the very practice they hope to move. In most conversations about data use, however, relationship between data and practice have been under conceptualized (Splillane, 2021). This can be said to be the case in the textile industry.

Under the Manufacturing Pillar of the Government of Kenya's Big 4 Agenda, the textile, apparel, and cotton subsector has been identified as a key priority with the potential for high growth and economic impact. By 2022, cumulative investments in the subsector are targeted to increase to $2 billion, with 500,000 new cotton jobs and 100,000 new apparel jobs. This is expected to be achieved, in part, through policy and incentive reviews, the construction of 5 million square feet of industrial sheds, the planting of 200,000 hectares of cotton and the training of 50,000 youth and women in the sector. (Kenya Association of Manufacturers, 2018). On the other part, this can be achieved by individual companies through data driven decision making especially on market availability and access.

There are numerous studies and empirical reviews on data-based decision making in different sectors and industries (Palmer et, al. 2019, Dinku 2019, Ramani et, al. 2018, Bourassa et, al. 2021). However, there have been few and far in between within the textile industry. Banica and Hagiu (2016), studied using big data analytics to improve decision making in apparel supply chains, with a focus to provide several ways to increase the competitiveness in Romanian apparel and fashion on the international market, focusing on originality, quality, online commerce, and marketing. Polay, Rahman, Billah and Al-Sabbahy (2020) discussed issues associated with the application of big data analytics for decision-making about the introduction of new technologies in the textile industry in the developing world. The findings indicate that the limited use of technological resource was linked to several factors, mainly cultural, generational, and educational factors. However, there exists a gap regarding studies on the use and effect of data in decision making in the Kenyan Textile Industry. This is the gap that this study sought to fill.

1.3 Study Objectives

The purpose of this study was to evaluate how data literacy of managers influence their decision making in the Kenyan textile industry. To achieve the purpose of this study, the study addressed the following specific objectives:

i. To assess the effect of data accessibility to managers and managerial decision making in the Kenyan textile manufacturing industry.

ii. To assess the effect data skills levels of managers and managerial decision making in Kenyan textile manufacturing industry.

iii. To assess the effect of data use by managers and managerial decision making in Kenyan textile manufacturing industry for decision-making.

iv. To determine the correlation between data literacy levels and managerial decision making in the Kenyan textile manufacturing industry.

1.4 Research questions

i. What is the effect of data access to managers and managerial decision making in the Kenyan textile manufacturing industry?

ii. What is the effect of data skills levels of managers and managerial decision making in Kenyan textile manufacturing industry?
iii. What is the effect of data use by managers and managerial decision making in Kenyan textile manufacturing industry?
iv. What is the correlation between data literacy and managerial decision making in the Kenyan textile manufacturing industry?

1.5 Significance of study

Data is relevant now than ever in governments, businesses, and policy makers as a means to make well informed decisions. To policy makers: the study helps to fill gaps on policy formations that affect startups in the textile manufacturing sector in Kenya. It also helps policy makers understand whether textile manufacturing businesses use data to make decisions are more likely to succeed than those that don't use data in their decision making. More so, this study helps policy makers ascertain whether arming executives with data management skills would increase their chance of succeeding in growing the businesses. To businesses in the textile manufacturing industry in Kenya: The study enlightens them on how data plays an important role in facilitating well informed decision making which impacts on the success of their businesses. To the academia, this study is also important for students and scholars as it provides a basis for future research areas.

1.6 Scope of study

This study focused on how data influences decision making in textile manufacturing businesses in Kenya. The theoretical scope was based on the rational decision-making theory and the Skill based theory to form the foundation and basis of the argument that data literacy in the management of the textile industry in Kenya is a critical knowledge and skill when making strategic decisions. The empirical scope focused on studies across the world on data literacy and decision making as major variable. The study also focused on the large and medium textile manufacturing companies in Kenya as the target population and sample. The study was conducted for a period of three months (May to July 2022).

CHAPTER TWO

REVIEW OF RELATED LITERATURE

2.0 Introduction

This chapter discusses literature on data literacy and decision making that anchors the study. It also reviews the work of other scholars in relation to data literacy and decision making. It concludes with a conceptual Framework consisting of the relationship between the independent and dependent variables of the study that was tested in data collection and analysis.

2.1 Theoretical Review

The rational decision-making theory and the Skill based theory have been extensively used in literature as foundational models anchoring studies on decision making. This section looks at the two theories that will form the foundation and basis of the argument that Data literacy in the management of any organization is a critical knowledge and skill when making strategic decisions that will determine the success or failure of an organization

2.1.1 Rational Decision Theory

Uzonwanne (2016) defines the Rational model of decision making as a model where parties use facts and information, analysis, and a step-by-step procedure to come to a decision. Almost always, decision making involves a world full of choices where an individual is constantly arraigned with options which can be as basic or complex in nature. Rational decision-making theory origins date back centuries, with Philosopher Adam Smith considered the instigator of rational decision theory from his essay titled "An Inquiry into the Nature and Causes of the Wealth of Nations," in 1776. Smith based his work on fellow philosopher Thomas Hobbes' "Leviathan" (1651) In "Leviathan," Hobbes explained that political institution functioning was a result of individual choices. Philosopher Niccolò Machiavelli also introduced ideas related to rational decision theory in his treatise. In the 1950s and 1960s, sociologists George C. Homans, Peter Blau and James Coleman promoted rational decision theory in relation to social exchange. These social theorists stated that a rational calculation of an exchange of costs and rewards drives social behavior.

Building on these theorists, Scott and Bruce (1995) proposed four different types of decision-making models: (a) rational decision-making model, where they lay particular emphasis on the characteristics of thorough research and logical evaluation as it concerns rational decision making. ; (b) intuitive decision-making model, characterized by a reliance on personal Intuition; (c) dependent decision-making model, characterized by individuals seeking advice and direction from others; and (d) avoidant decision-making model, characterized by avoidance of making decisions altogether (Scott and Bruce 1995). For this study, we will focus on the rational decision theory which involves the process of gathering data and utilizing logic to organize and analyze these data in such a way that they aid accurate or near accurate decision making.

In a behavioral science study, Oliveira (2017) defined rationality as the compatibility between choice and value. Rational behavior therefore seeks to enhance the importance of the consequences focusing on the process of choosing rather than emphasizing the selected alternative. Rational decision making is therefore the model of decision making that is most likely to apply to higher-level decision making of a more serious nature. These are the sort of decisions that managers and higher-level leaders are faced with in their leadership roles.

In a rational decision-making process, a manager often employs a series of analytical steps to review relevant facts, observations, and possible outcomes before choosing a particular course of action. Decision makers assess several possible replacements from different possible situations before selecting the best choice (Oliveira 2017). The alternatives are weighed by probabilities, and managers can determine the expected result for each choice (Oliveira 2007). The final choice that the decision maker chooses would be the one offering the best-predictable consequence and with the highest prospects of consequence (Oliveira 2007).

This theory is relevant to the study because it sought to evaluate the effect of data literacy on decision making within the textile manufacturing industry in Kenya. Application of data literacy by managers to make decisions can be considered a rational decision-making process. The study therefore sought to assess the extent to which rational decisions are applied in the textile manufacturing industry. Scott and Bruce (1995) lay particular emphasis on the characteristics of thorough research and logical evaluation as it concerns rational decision making.

2.1.2 The Skill Based Theory of Leadership

Skills-based theory is based on the idea that there are skills anyone can learn that can enhance their decision-making process. The idea that skills can be taught and learned is the foundation for management training and and learning activities (Johnston, 2020). The skills-based theory emerged as a leading theory in 1955 when Robert Katz published his paper "Skills of an Effective Administrator" in the "Harvard Business Review." Katz studied executives and identified skill areas that the executives had in common and used on a regular basis. Researcher M.D. Mumford and his team expanded on Katz approach with their paper "Leadership Skills for a Changing World: Solving Complex Problems, " published in "The Leadership Quarterly" in 2000. They proposed a capabilities model of research that outlined five major components, most of them skill-based, that affect a leader's performance.

The Skills Based Theory identifies what assets make up a good leader in addition to how we can identify a leader that is a best fit for the role in an organization, (Guerrer and Rowe, 2013). Katz posited that managers must have a set of skills within an organization, which includes intellectual, technical, human, and conceptual skills in order to make effective and efficient decision. Guerrer and Rowe (2013) further allude to the fact that with these set of skills, senior level managers need to have stronger literacy and conceptual skills as opposed to Operational managers and employees who need to have stronger technical skills. While many leaders advocate for leaders' intuition as a major asset in decision making process, the skills-based leadership theory maintains that leaders can learn other skills to be more effective (Mumford, 2000). An effective manager must balance the use of them to maintain company proficiency.

The theory suggests that an effective leader must be proficient in the technical essential tasks necessary to a company's core business. They should understand the work processes and advise individuals and departments on how to solve specific problems (Bass, 2010). They must also possess conceptual skills which involves working with ideas and concepts, strategizing, planning, visualizing, and setting goals. Conceptual skills can be improved through managers-in-training, goal-setting seminars, and training sessions. Baas (2010) continues by stating that an effective leader also needs to have appropriate human skills which include the ability to empathize, the willingness to listen to conflicting points of view, and expertise at resolving seemingly incompatible perspectives.

This theory is relevant to the study as a focus on acquisition data literacy as a managerial skill, is considered important in decision making in the organization. The skill-based theory suggests that managers must develop such technical and conceptualization skills that allows them to take in the big picture of the entire organization, collect as much data as possible and use abstract ideas to set strategic initiatives and decisions in motion (Johnston, 2020). This study will seek to assess the technical and conceptualization skills of managers in the textile manufacturing industry in Kenya that allows them to make decisions. A major benefit of the data literacy skill is that managers can make informed decisions in all stages of an organization. The study therefore indicates that a strong belief in skills-based theory often demands that considerable effort and resources be devoted to acquiring information and skills to add knowledge to the innate skills that the managers possess.

2.2 Empirical Review

There are numerous studies and empirical reviews available on data-based decision making in different sectors and industries. Most common studies available have been focused on the Information technology, education, and health sector while there are limited studies available in the manufacturing sector. This section discusses the research available that are relevant to the objectives of the study and identifies the gaps that the study sought to fill.

2.2.1 Data Accessibility and Managerial Decision Making

Data must be readily available and accessible when it is needed. Not only is this essential to the efficient running of a business but is also critical to achieving the organizations goals. Maintaining a high level of high data availability and accessibility is vital to any business's sustainable success and any compromise can have serious consequences, on many levels (Lysecki, 2019).

Dowling et, al. (2016) reviewed the role and implications of data availability and quality in a multilevel tier system in the Australian fisheries sector. The systems assessment and management were widely used but defined differently by jurisdiction. The study applied a principal component analysis to the expanded Australian Commonwealth 8-tier system for fishery assessment and management to determine whether it adequately delineates across stocks according to data availability and quality. The study sought to score information availability and quality for each of the main Australian Commonwealth species of fisheries. The findings indicate that a multivariate analysis of the eight tiers delineated between the extreme tier levels on the first principal component, although there was overlap for intermediate tiers. More generally, it was important to note that the aim of tier systems and the basis for tier delineations are explicitly defined given the increasing association of tiers with trade-offs between overfishing risk, management cost and catch. According to Schonfel, et al. (2020) depending on the organization, the services that it provides, the type of data that it relies on to function and how the data is used to service the organization as well as its customers and the wider community, the magnitude of the impact from unavailable data can vary greatly. Inconsistent fluctuations in data availability could potentially have catastrophic implications for some organizations (Schonfel, et al. 2020)

Palmer et, al. (2019) assessed data availability and quality within an electronic health record system through external validation against an external clinical data source. The study sought to understand the availability and quality of data regarding smoking as a health risk in electronic health records (EHRs). The problem under study was that current practices in the recording of this health risk in have not led to discernable changes in health outcomes. The authors developed an informatics pipeline that extracted data on smoking using 1,504 clinical notes matched to an external questionnaire. The findings indicated that most of the on-smoking behavior information was not available, and the quality was low to extract relevant information. The study demonstrated that the methodology applied however, was able to extract smoking behaviors from unannotated EHR notes when the information was present. This data quality therefore became reliable enough to identify patients most likely to be eligible for smoking related services. This study findings were in line with Stobierski (2019) who asserted that while organizations claim to have access to available data, the real challenge is defining the characteristics that determine the quality of data. What some consider good quality data, others might view as poor quality data. Determining the availability and quality of data therefore requires an examination of some universal characteristics, then weighing them according to what is most important to the organization and its applications to the business. According to Ortega (2017) there are seven characteristics that define data quality: accuracy and precision, legitimacy and validity, reliability and consistency, timeliness and relevance, completeness and comprehensiveness, availability and accessibility, granularity, and uniqueness. Reliable data should therefore have these characteristics.

Dinku (2019) performed a study on the challenges with the availability and quality of climate data in Africa. The problem of the study was that even though climate data are essential in an array of climate research and applications that include analyses of climate variability, the impact of climate variability and change on different socioeconomic activities, the use of climate data for research and applications in Africa has been scanty because availability of and access to climate data is very limited. The findings indicated that in many parts of Africa, weather stations are sparse, and their number has been declining. The distribution of existing stations is uneven, with most located along major roads. Where data exist, they are often of poor quality with many gaps. However, there have been different efforts underway to overcome these challenges including the Enhancing National Climate Services (ENACTS) initiative that works with National Meteorological Services in Africa to improve the availability and quality of climate data by combining quality-controlled station observation with satellite and reanalysis proxies.

Ramani et, al. (2018) studied secure and efficient data accessibility in blockchain based health care systems. The problem under study was that as the healthcare industry is constantly changing in technological evolutions and transitions, the crucial requirements in the current smart healthcare systems is the protection of patients' sensitive data against the potential adversaries. It is therefore critical to have secure data access mechanisms that can ensure only authorized entities can access the patients' medical information. The study considered the blockchain technology as a distributed approach protect the unauthorized access to data in healthcare systems. The findings indicated that a blockchain based secure and efficient data accessibility mechanism for the patient and the doctor in each healthcare system was appropriate and effective. The proposed system was able to protect the privacy of the patients as well and can resist to well-known attacks along with maintaining the integrity of the system. This study asserted that the measures employed to safeguard data accessibility need to permit, manage, and sustain the accessibility of the data only to authorized users. This is critical because if the data accessible is not secure, it would be compromised, failures will arise, often leading to accumulative damage, both directly to the business as well as to those that the business services (Mesly, 2015).

Capocasa et, al. (2016) performed an exploratory survey of samples and data accessibility in research biobanks. The authors stated that even as biobanks provide a crucial contribution to the progress of biomedical research, the effective and efficient use of biobank resources depends on their accessibility. The authors conducted a questionnaire-based survey in order to investigate sample and data accessibility in 46 research biobanks operating all over the world. Most of bio banks gave access to their samples and data, but free and unconditioned accessibility seemed not to be common practice. The analysis of the guidelines regarding data accessibility highlighted three issues: (i) the request to explain what they would like to do with the resources requested; (ii) the role of funding, public or private, in the establishment of fruitful collaborations between biobanks and research labs; (iii) the request of co-authorship to give access to their data. The findings suggest that economic and academic aspects are involved in determining the extent of sample and data sharing stored in biobanks. The analysis of informative answers suggested that the different modalities of resource accessibility seem to be largely influenced by both social context and legislation of the countries where the biobanks operate.

Bourassa et, al. (2021) studied big data, accessibility, and urban house prices. The purpose of the study was to explore whether the inclusion of big data accessibility indices improves the accuracy of hedonic price models used for residential property valuation. The study compared a big data index with an index derived from a regional travel demand model developed by a local transportation planning agencies and traditional measures of accessibility defined as distances to employment centers. The study assessed control for submarkets and a combined special autoregressive and spatial error model for capturing the value of location. The study concluded that big data accessibility measures does not add meaningful explanatory or predictive power. In contrast, the special autoregressive and error model outperformed the other options considered.

In most of these empirical studies on data availability and accessibility, not being able to access critical data when needed will cause business operations to come to a standstill. The ability to maintain high data availability and accessibility should be a top priority for any business. Not only can low levels of data availability and accessibility impact the organization financially but the inability to function and provide services to customers, clients, patients, the community and so on will result in the loss of trust in the business or service and could have long-lasting damaging effects on the business's reputation (Schonfel, et al. 2020).

2.2.2 Data Skills Level and Managerial Decision Making

Wolff & Zdraha (2018) assert that data skills level implies a set of capabilities that surrounds the support of application of data for critical thoughtful insight in decision-making and problem-solving initiatives. Morrow (2018) notes that data skills level refers to the ability to understand through careful reading, analyze and handle data irrespective of key function and your level of skill and tools used for the analysis. The roles played coupled with tools and technique applied is believed to strengthen decision made based on the result of data before the person handling it. Calzada, Prado and Marzal (2013), according to whom, data skills level enables individuals to access, interpret, critically assess, manage, handle and ethically use data.

Wolff et, al. (2016), in an article on creating understanding of data literacy for a data driven society argued that the foundations for a data literate society begin by acquiring key data skill competences in school though there is no clear definition of what these should be. This article explored the different perspectives currently offered on both data and statistical skills and then critically examined which of these variables address the data literacy needs of citizens today. The authors surveyed existing approaches to teaching data literacy in schools, to identify how data skills were interpreted in practice. Based on these analyses, they proposed a definition of data literacy that is focused on using data to understand real world phenomena. This proposal echoes Marr (2020), who states that poor data skills is one of the main roadblocks to an organization's success and the ability to grow. Organizations should therefore be able to use data to influence their operations as well as make strategic decisions. If used the right way, data literacy can help the business achieve its objectives, reach their goals, and contribute to overall performance (Marr, 2020).

In a study on a systematic view of Implementing data literacy in educator preparation, Mandinach & Gummer (2013) sought to determine whether policymakers require educators to use data to inform practice. The findings indicated that although the policy emphasis is growing, attention to building human capacity and skills around data use is lacking. They recommended that educators need to gain data skills to inform practice. The study also found that although some professional development opportunities exist for current educators, fewer formal courses, and opportunities for data skill development in schools of education have been developed and implemented. The study finally explored issues around the growing need for data-driven decision making in programs in schools of education with a systems perspective to explore course and programmatic implementation being presented.

Mandinach & Gummer (2015) further built a conceptual framework for data literacy. The purpose of the exploration was to develop a conceptual framework to undergird research, development, and capacity building around data skills levels for teaching. The conceptual framework is based on a sequence of qualitative studies that sought to determine the nature of knowledge and skills that are required for teachers to be considered data literate. A first study examined the ways that the knowledge and skills around the use of data were characterized in practical guides, books, and manuals on data use, formative assessment, and related topics. These characteristics were integrated with definitions of data skill level elicited from experts. A second study examined the licensure and certification documents required by states for teacher candidates for their treatment of data- and assessment-related knowledge and skills. The synthesis of these studies and their components yielded an evolving conceptual framework for a new construct: data literacy for teachers.

When it moves from the conceptual framework to application the organizational context, managers are struggling with successfully implementing solutions in their day-to-day business. This is because there exists a gap between data experts or analytical specialists, and the business users that need to understand the analysis and turn it into business insights, actions and ultimately value (Johnson, 2018). This gap can be filled by educating managers in the organization on the concept of data as fuel for the analytics that give the insights to improve the work, and by educating the data experts on the business implications of analytics. This requires an organization to elevate on the four cornerstones of data skills – understand, engage, analyze, and reason with data.

To start working with data, managers need to understand the data. To engage with the data, managers need to use data and know what is available within the dataset (Paton, 2017). The next skill set required to analyze a dataset is an important step in becoming more data-literate. Being able to use statistical and analytical methodologies to create valuable insights will become a skill that is necessary for more and more business roles within an organization. The most important, and complex, aspects of data literacy are the ability to reason with data. If a manager cannot talk the language of data or reason with data in a proper way, misalignment or misunderstanding will take place (Plotkin, 2014).

Bhargava & Dignazio (2017), researched on designing tools and activities for data skills learners. The study proposed a set of pedagogical design principles to guide the development of tools and activities that help learners build data literacy. They outlined a rationale for these tools to be strongly focused, well guided, very inviting, and highly expandable. Based on these principles, Bhargava & Dignazio (2017) offered an example of a tool and accompanying activity created. Reviewing the tool as a case study, they outlined design decisions that align it with our pedagogy. Based on these results, they suggested that to better support the growing number of people learning to read and speak with data, tool designers and educators must design from the start with these strong pedagogical principles in mind.

Becoming data literate is important, but the required knowledge levels depend on the data role of the business user. According to Patron (2017), there are five levels of proficiency in data skills level: conversational, literacy, competency, fluency and multilingual as described in Figure 2.1.

Level	Definition	Example
Conversational	Basic understanding of the concepts of data, analytics and use cases; one who "gets it" but cannot explain it to others	A professional who has a basic understanding of an analytics value proposition and the ingredients involved
Literacy	Ability to speak, write and engage in data and analytics programs and use cases	A professional who can explain all aspects of an analytics use case, including the industry problem, business process moment/decision affected, data sources leveraged and analytical methods applied
Competency	Competent of designing, developing and applying data and analytics programs	Experienced data and analytics program managers who have designed and delivered analytical projects from concept through outcome
Fluency	Fluent in all three elements of information language across most business domains within an industry vertical	A smart meter registers kW demand. Over time it creates kWh averages and peak demand. That is interpreted by billing far differently than generation or distribution planning. Fluent speakers can explain all of these use cases
Multilingual	Fluency across all three elements of the information language across multiple business domains, industries and ecosystems	An experienced data analytics strategy consultant who has designed and delivered analytical solutions across multiple industries and business domains, and can explain them to non-native speakers

Figure 2.1: Data skills levels of proficiency

2.2.3 Data Use and Managerial Decision Making

Data use depends on the different data personalities that exist within the organization. The personnel in organizations consists of different individuals with different backgrounds, interests, intrinsic motivation, and organizational focus areas. To become proficient in the use of data therefore, the organization needs to focus more on data and create a culture where data literacy is embraced. The culture is a key to ensure championship, stewardship, and change (Bass, 2010).

Schildkamp & Ehren (2012) studied the move from intuition to data-based decision making in Dutch schools. Previous research had shown that most teachers do not use data properly, or do not use data at all in the Netherlands. A data team intervention consisting of 4–6 teachers, a data expert, an (assistant) school leader, and a researcher was therefore developed and piloted to support schools in the use of data. The findings show the data team intervention led to an increase in effective data use, changes in classroom instruction, and to school improvement. According to KPMG (2016), there are four data roles for the data business users, with different data skills, capabilities and learning requirements. These are the data believer, the data user, data scientist, and data leader. These data use levels are closely associated with the data knowledge and skills level of the individuals in the organization.

The data believers are individuals with limited to no analytical knowledge but need to understand and engage with data to use data to make business decisions. These are typically people that have extensive business knowledge, but little analytical capabilities. The mindset of a data believer needs to change from making decisions based on intuition to using data to make decisions (KPMG, 2016). Data users incorporate data and analyses in their daily work. They can understand and engage with the data, like business controllers of process owners. Important for them is that they know what's in the dataset, understand where the data is coming from and the insights that can be derived from it. However, their analytical capabilities are basic and there is need to be developed to a proper level. Although the data user doesn't need to be as technical as a data scientist, understanding analyses and more complex methodologies is important (KPMG, 2016).

Data scientists are individuals who have profound analytical and statistical skills, such as data analysts. No further development is required in analytical and statistical methodologies. The focus areas for a data scientist would be to improve on communicating, explaining, and reasoning with data regarding business users to reach a level of data fluency or even multilingualism. Implementations of their analytical methodologies strongly depends on the capabilities of a data scientist to explain and show their analysis results to the organization and give useful insights (KPMG, 2016). Data leaders have a good understanding of the data, can interpret results or analyses, and have a good level of understanding analytical methodologies. They are the front runners of data literacy within the organization. They see the added value of using analytics in day-to-day business and understand the impact of an analysis. A data leader does not need to have the same level of analytical skills as a data scientist but is required to be able to apply some analytical methodologies on his own. Furthermore, the data leader needs to be able to communicate, discuss and reason with the data. Data leaders need to understand the complexity of the analysis and follow the steps and then translate them to business users with more limited analytical knowledge (KPMG, 2016).

2.3 Overview of the Textile Industry in Kenya

The global textile industry is primarily concerned with the design, production and distribution of yarn, cloth, and clothing (Global Industry Analyst, 2011). The global textile industry value chain consists of five levels: Raw materials networks, component networks, production networks, the export networks, and the marketing networks (Deloitte, 2015). The raw material networks consist of natural fibers (cotton, wool, silk etc.), or synthetic fibers (oil, chemical and natural gas). The component networks consist of textile companies who yarn the natural fibers to create the natural fabric or use the petrochemicals to produce the synthetic fabrics. The production networks consist of global apparel manufacturers across the continent depending on the type of fibers they produce and process to fabric. The export networks consist of wholesale outlets that distribute the apparel through brand named apparel companies, overcut buying offices and trading companies. Finally, the marketing networks consist of retail outlets that include department stores, specialty stores, mass merchandise chains and discount chains (Deloitte, 2015).

According to World Bank (2014), this level of relationship between consumers and manufacturers, however, has been changing. Consumers are no longer restricted to buying from retailers who in turn access their produce from wholesalers, as each level purchase from one level up the chain. Improvements in logistics and information flows globally has led to the possibility of retailers increasingly bypassing wholesalers to procure apparel directly from manufacturers (World Bank, 2014). This has opened a range of possibilities for the future as manufacturers can market not only to wholesalers and retailers, but also directly to consumers.

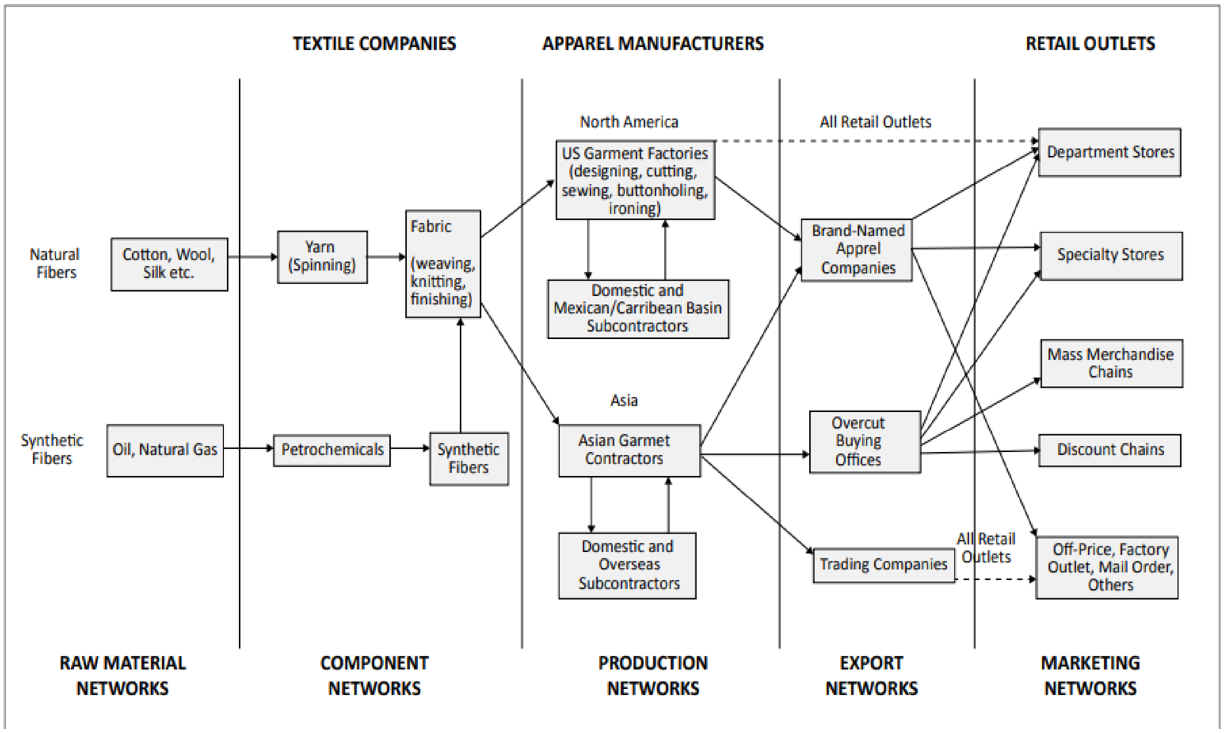
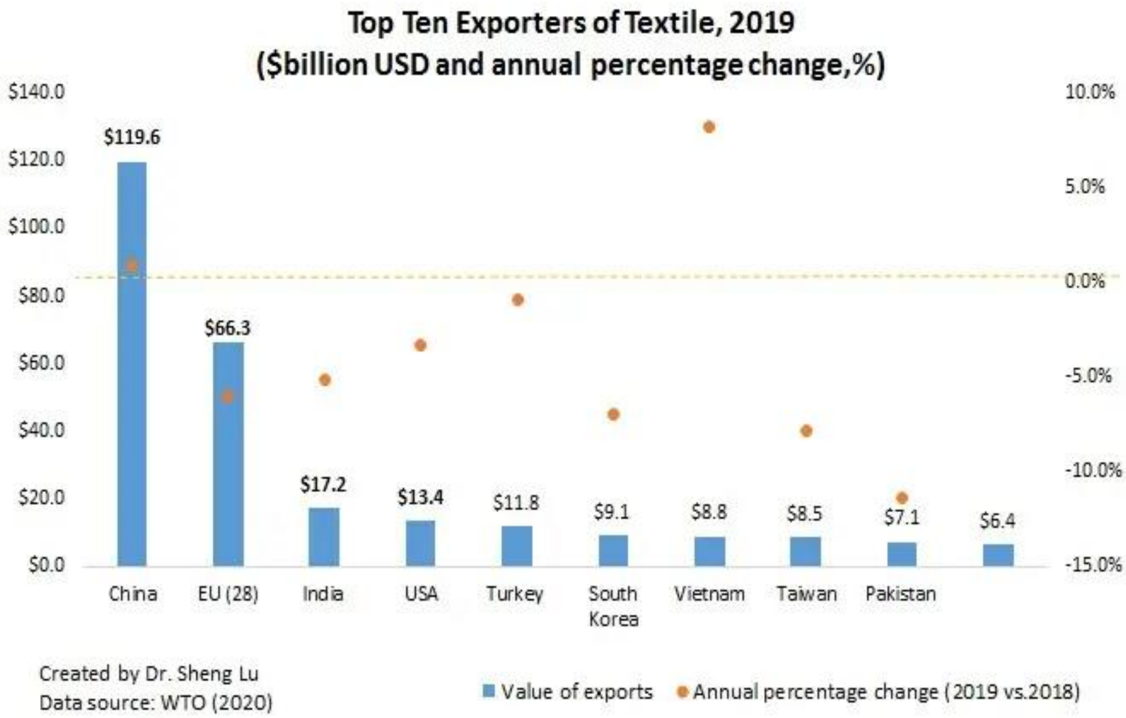


Figure 1.1: Textile Manufacturing Industry Value chain (Source: Global Industry Analyst (2011)

According to Kohan (2021), the global textile industry was estimated to be around USD 920 billion in 2018, and it is projected to witness a growth of approximately 4.4% to reach approximately USD 1,230 billion by 2024 with key competitors being China, the European Union, the United States, and India.



Regionally, as key competitors in Asia move towards farm-to fashion models, countries such as Ethiopia and Uganda are trying to follow suit. While the latter have expanded their efforts to increase the availability of locally produced fabrics, similar efforts at integration in other regional economies have not yielded positive results (World Bank Group and Global Development Solutions, 2016). The regional textile industry continues to rely on high cost of imported raw material. This practice is leading to value attrition, further lowering the revenue generating potential for regional firms and postponing needed efforts to source locally available material to help reduce the cost and time of apparel production (Deloitte, 2015).

In Kenya, the textile industry has played an important role in the industrialization of today's developed countries. This is because Kenya has unique characteristics of being labor intensive and its links with other sectors of the economy such as agriculture. As Kenya looks to boost its local textile industry, stakeholders have highlighted the impediments such as second-hand clothing donations that are creating a dilemma for the Kenyan economy and the growing trend of imported second-hand clothing (World Bank Group and Global Development Solutions, 2016). The Textile sector in Kenya is three-tiered: The Export Processing Zone (EPZ), consisting of 21 large companies, 170 medium and large companies outside the EPZ, and more than 70,000 micro and small ones. The industry currently contributes to 7 percent of the country's export earnings, employs about 30 percent of the labor force from the national Cotton Farming Ginning Weaving and Knitting, Dyeing and Finishing Garment Making manufacturing sector. The industry also supports the livelihoods of over 200,000 small-scale farmers by providing markets for cotton (Kenya National Bureau of Statistics, 2019).

Some of the Key challenges experienced in the industry according to Kohan (2021), include lack of policy coherence and institutional alignment, low level of value addition and a disconnect between the apparel sector and the rest of the value chain segments, supply-side constraints with regards to quality and price of fabrics, with focus on afro-centric cloth and garments, weak business environment, high cost of production and built-in systemic inefficiencies, lack of market readiness, high cost and difficulties to access credit and finance, predominance of SMEs operating in the informal sector, lack of visibility of Kenya's design capabilities and absence on the formal retail platform, illicit imports and negative impact of second-hand clothing, and the lack of a clear national policy on textile and apparel.

Market availability and access however is a great concern to members of the local textile industry. For firms that are not within the EPZ, access to the international and domestic market is problematic due to export competition from firms within the EPZ who enjoy tax breaks as well as the influx of second-hand clothing in the local market. Public agencies, which could be very large customers, opt to import from Asian markets like India and China to fulfill their needs. High-end Kenyan fashion designers sell items to a niche local customer base and have ad hoc agreements with international buyers. To maximize on the available opportunities and implement mitigation measures to improve access to markets, members of the textile industry require quality data that will enable them to make informed decisions. This study sought to explore data and decision making to improve market availability and access of firms in the textile industry (Kohan, 2021).

2.4 Research Gaps

From the empirical review, there are numerous studies and empirical reviews on data literacy and data-based decision making in different sectors and industries. Most common studies available are focused on the health and education sector. There exists a gap therefore as a review of the literature and studies shows that there had not been any research carried out in Kenya on the use and effect of data in decision making in the Kenyan Textile Industry at the time of the study. Similarly, there was no study available to the researcher combining the variables of data availability and accessibility, data and knowledge levels, data use and data-based decision making.

Table 2.1: Summary of Research Gap

Variable/Author/References	Deficiencies in Research	Research Gap
Data Accessibility Dowling et, al. (2016), Palmer et, al. (2019), Dinku (2019), Ramani et, al. (2018), Capocasa et, al. (2016), Bourassa et, al. (2021).	- The studies outlined several promising techniques for data accessibility However, practical applications of these techniques were not conclusively studied.	- The studies available were conducted in the education, housing, environmental, and agricultural industry. - There was no research available carried out in Kenya on data accessibility and managerial decision making in the Kenyan Textile Industry.
Data Literacy Level Wolff et, al. (2016), Mandinach & Gummer (2013), Bhargava & Dignazio (2017).	- The arguments are centered on definitions of data literacy as well as sources of literacy - There was more focus on the sources if data literacy as opposed to the literacy levels of managers -	- The studies available were mostly conducted in the education, industry. - There was no research available carried out on data skills levels of manager in the textile industry and especially in Kenya
Data Use Schildkamp & Ehren (2012), (KPMG, 2016),	- The studies described the move from intuition-based decision making to data-based decision making - The studies also centered on definitions of data use as well as terms and related levels of expertise and use	- The studies available were mostly conducted in the education, industry. - There was no research available carried out on data use of manager for decision making in the textile industry and especially in Kenya

Source: Researcher (2022)

2.5 Conceptual Framework

The conceptual framework of this study shows a visual representation of the variables under study relate to one another through the aid of a diagram. The conceptual framework is a depiction of the correlation between the variables of the study in a diagrammatic form to provide and create a conceptual form that can be easily understood. The conceptual framework is based on the Figure 2.2 below.

Independent Variable (*Data Literacy*) **Dependent Variables (*Managerial Decision Making)***

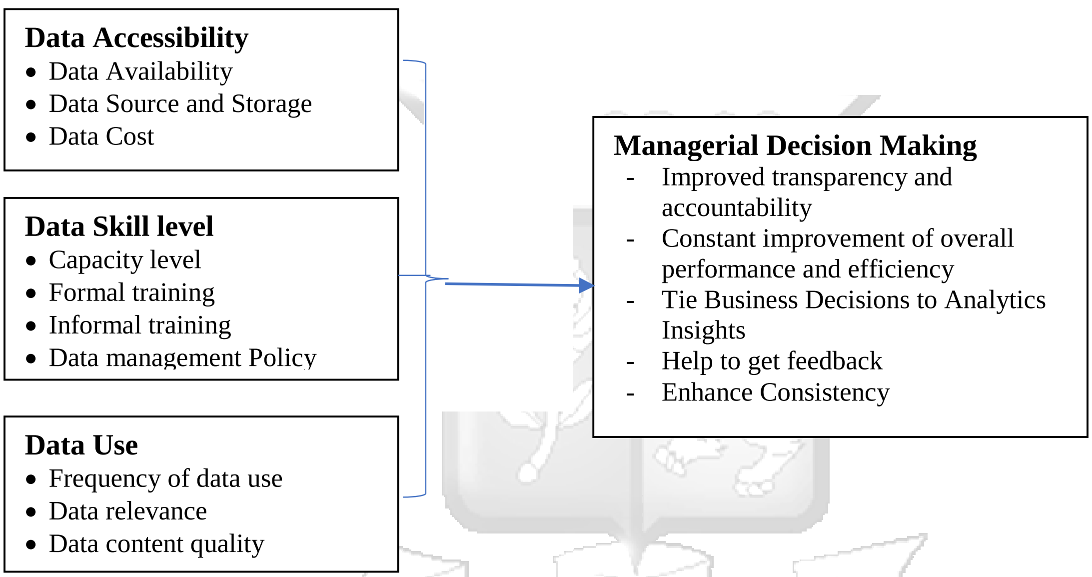


Figure 2.2: Conceptual Framework

Source: Researcher (2022)

2.6 Operationalization of Variables

Table 2.2: Operationalization and Measurement of Research Variables

Variable	**Indicator**	**Measurement**	**Data Analysis Method**
Data Availability and Accessibility	• Data Source and Storage • Data availabilty • Data Cost	Likert Scale Questionnaire	Descriptive
Data skill and Knowledge Levels	• Capacity level (skills level) • Data management Policy	Likert Scale Questionnaire	Descriptive
Data Use	• Frequency of data use, • Data relevance • Data content quality	Likert Scale Questionnaire	Descriptive
Data driven Decision Making	• Improved transparency and accountability • Constant improvement of overall performance and efficiency • Tie Business Decisions to Analytics Insights • Help to get feedback • Enhance Consistency	Likert Scale Questionnaire	Descriptive Correlation

Source: Researcher (2022)

2.7 Chapter Summary

This chapter has discussed the relevant literature underpinning the study. The rational decision theory and the skill-based theory of leadership were selected as the most appropriate models that anchor the study. The chapter then outlines the empirical review that consists of studies relevant to the objectives of the study. The chapter summarizes the studies outlined and identifies the gaps to be filled. The chapter concludes with a conceptual framework and operationalization of the variables.

CHAPTER THREE

RESEARCH METHODOLOGY

3.0 Introduction

This chapter includes details of the design adopted in this study, the population to be studied as well as the various methods to be applied during this research to identify the appropriate sampling technique and size. The chapter presents the data collection tool selected, methods for data collection and the methods for data analysis. The chapter also provides a brief discussion on the validity and reliability of the instruments to be used as well as a succinct account of various ethical considerations.

3.1 Research Philosophy

Research philosophy refers to the source, nature, and development of knowledge. It is the belief about ways in which data should be collected, analyzed, and used (Tsung, 2016). Saunders, et, al. (2012) explains that within the scope of business studies there are four main research philosophies: Pragmatism, Positivism, Realism, and Interpretivism. Pragmatism accepts that there are many ways of interpretations while undertaking research while positivism contends that only factual knowledge gained through observation is trustworthy. Interpretivism integrates human interest into a study while realism relies on the idea of independence of reality from the human mind (Saunders, et, al., 2012). This study proposed the positivism philosophy to inform source, nature, and development of knowledge in the research process. The choice for positivism was selected because it allows for a quantitative methodology approach.

3.2 Research Design

Research design is an important element of research as it brings together the different components being studied. Kombo and Tromp (2014) explain that it is the glue that holds all the elements in a research project together, and that it can be regarded as an arrangement of conditions for collecting and analyzing of data in a manner that aims to combine relevance with the research purpose. Punch (2014) alludes that research design means all the issues that are involved in the planning and execution of a research project, which begins with the identification of the problem through to reporting and publishing the results.

The research design process that was suitable for this study was the descriptive design. The purpose of descriptive design is the description of the situation as it exists, as well as reporting of the finding of the study (Kombo & Tromp, 2014). The descriptive process enabled collection of data that was current from the potential respondents as the problem under study was current and ongoing. By using the descriptive design method, the study linked the research questions to the conceptual framework. The descriptive design has four major areas of focus, that is the formulating of the objective of the study, designing the methods of data collection, selecting samples, as well as collection of data that the researcher will undertake to achieve successful results for this process, (Kothari & Garg, 2016).

Research designs can be classified into two major categories, – qualitative and quantitative research design. Qualitative research seeks to collect and works with non-numerical data, and also seeks to interpret meaning from these data that help us understand social life through the study of targeted populations or places while quantitative seeks to collect numerical data for a more objective analysis (Crossman, 2018). This study used the quantitative design to collect the numerical data to examine the phenomenon under study. Quantitative research design was used to quantify data and generalize results, to measure the incidence of various views and opinions in a chosen sample. Semi structured techniques such as questionnaires were used. Statistical data is in the form of tabulations and the findings is conclusive and descriptive in nature.

3.3 Population and Sampling

3.3.1 Target Population

Within the context of this research study, the target population is primarily the textile Manufacturing industry in Kenya. According to the Kenya National Bureau of Statistics (2019) the textile sector in Kenya is three-tiered: the Export Processing Zone (EPZ), consisting of 21 large companies, 52 medium and large companies outside the EPZ, and more than 70,000 micro and small ones. The researcher selected the 52 medium and large textile manufacturing companies as the population.

3.3.2 Sampling Design

The process of sampling considers various issues and depends on the organization type, purpose, complexity, time constraints and previous research in the area. This granted the researcher the privileged to focus on aspects of the population that are of interest, and that assist in answering the research questions. It also provided clarity in the choice of locality and proximity to the possible respondents, a view that is held by Acharya, Prakash, and Saxena (2013). In this view, the researcher identified the entire group of 52 medium and large textile companies outside the EPZ to form sample of the study. The purpose of the study was to evaluate the effect of data literacy on managerial decision making. It was therefore critical to select a sample of organizations that have the resources and capacity to acquire and use data in their decision-making process.

Based on the total number of 52 medium and large companies outside the EPZ, the study used the survey methodology and include the entire sample size for data collection. Saunders, Lewis, & Thornhill (2019), contend that where the target sample is small, a researcher should collect data from the whole target population as the influence of one extreme case on statistical analysis that may be done later is more distinct than for a bigger sample. The study collected data from all the 52 medium and large textile manufacturing companies (List is provided in Appendix I)

The study adopted probability sampling technique in identifying the respondents to the study who shall be three managers from each of the 52 large and medium companies outside the EPZ. The items for the sample were also selected by the researcher, since the small units selected represent the whole, (Kothari and Garg, 2016).

3.4 Data Collection Procedure

The data collection procedure involves administering questionnaires to the respondents. The researcher clarified to the respondents in writing on the questionnaires concerning the overall purpose of the study. This was done with a view to enhance the understanding of the respondents on the content of the study to extract relevant information for the study. The questionnaires were administered by trained research assistants to be completed by the selected respondents. The questionnaires were distributed to the selected respondents who were given a time frame within which they were required to respond.

3.4.1 Data Type

The type of data that was collected was all quantitative. Quantitative data are any quantifiable information that can be used for mathematical calculations and statistical analysis. This data can be verified and can also be conveniently evaluated using mathematical techniques. Quantitative data makes measuring various parameters controllable due to the ease of mathematical derivations they come with. The retrieved results can be established across a population (Miles, Huberman, Saldana, 2014).

3.4.2 Data Collection Instruments

The study used a questionnaire as primary data collection instrument. According to Punch (2014), a self-administered questionnaire is the only way to elicit self-report on people's opinion, attitudes, beliefs, and values. The questionnaire (Appendix I) was designed to give a brief introduction of respondents. The questionnaire was designed and divided into sections representing the variables for the study. The questionnaire includes closed structured and open-ended questions that sought the attitude, opinions and views from the respondent. The questions were designed to collect quantitative data. The open-ended questionnaires gave unrestricted freedom of answer to respondents.

3.5 Research Quality

3.5.1 Reliability

Reliability refers to issues of consistency, and is also a central concept of measurement, (Punch, 2014). The consistency of measurement is expressed in the questions; that is if the same instruments were administered to the same people, but in a different environment, would the scores be the same? It is also worth noting that when reliability is high, the error variance is low, whereas when reliability is low, the error variance is high. Reliability test enabled the study to identify the ambiguities and inadequate items in the research instrument; where the instrument reliability is the dependability, consistency, or trustworthiness of a test. The test-retest technique is the measure, where questionnaires were administered to a group of individuals (according to the tested number) with similar characteristics as the actual sample. Tests were repeated at intervals of one week. The scores obtained from each test were then correlated to get the coefficient of reliability.

The Spearman's Rank Correlation Coefficient 0.796 and confirmed that the instrument is 79.6% reliable and therefore consistent to answer the research questions of the study. The study pre-tested the questionnaire using a sample of respondents not included in the main sample, so as to evaluate the relevance of the questions and the ease with which participants could respond to them.

3.5.2 Validity

Validity is the extent to which differences found with a measuring instrument reflect true differences among those being tested, (Kothari and Garg, 2016). Research instruments can be understood to include questionnaires', interviews schedules, observation, and focus groups, (Kombo and Tromp, 2014). As one formulates the collection instrument, it should ensure suitability of the instrument, proper geographical distribution, as well as having proper questions. On the same breath Punch (2014) indicates that validity means the extent to which an instrument measures what it claims to measure. Validity is also one of the strengths of qualitative research, as it is based on determining whether the findings are accurate from the standpoint of the researcher, the participant, or the readers account, (Creswell, 2014).

To ensure content validity, the usual procedure according to Creswell (2014), is to use a professional or expert in a particular field which helps in discovering question content, correction in the wording and the sequencing problems before the actual study as well as exploring ways of improving overall quality of study. For the sake of this study, the researcher sought opinions of experts in the field of study especially university research instructors to establish the validity of the research instrument. This facilitated the necessary revision and modification of the research instrument thereby enhancing validity.

3.5.3 Pilot study

Piloting refers to the preliminary testing of a portion of the sample size (Crossman, 2019). It is intended to improve reliability of the data collection tool through revising them based on the results of the pilot study. The pilot study was done on a representative sample of 10 respondents, which is 10% of the sample size as recommended by Mugenda and Mugenda (2011). The pilot was done to 5 medium and large textile companies in Nairobi. Any mistakes and ambiguity in the questions were corrected before the actual data collection took place.

3.6 Data Analysis

According to Creswell (2014,) data analysis consists of the examining, categorizing, tabulating, or otherwise recombining the evidence to address the initial propositions of the study. Once the respondents return the questionnaires, they were checked for completeness and consistency where poorly filled in questionnaires were not be used for the study. Data was coded by assigning of a numerical or alphanumeric value to represent the responses. Most of the questions in the questionnaire were close ended and coded upon the completion of the survey. Data capturing involved the initial summation of data using frequency distribution that helped to establish the out of range, missing and extreme values for each variable. STATA and excel were the selected software that the study employed to manipulate the data.

In analyzing quantitative data, the study used descriptive statistics. Measures of central tendency (mean), measures of dispersion (standard deviation), frequencies and percentage were the descriptive statistics that were applied on the quantitative data (Kothari, 2012). Tables and other graphical representation were used as appropriate to present the data findings while explanations presented in prose. Regression analysis was used to examine the relationship between the dependent and independent variables.

This study was conducted primarily for academic purposes and therefore the dissemination of the findings are based on strict academic processes and procedures. This means that the findings is first made available to both internal and examiners for examination in fulfilment of the academic requirements. Secondly, the findings were made available to participants of the study who requested for the same.

3.7 Ethical Considerations

The study observes several universal ethical principles in research which include justice, respect for participants, beneficence, and non-maleficence. In this regard, all participants gave their consent, their role and the fact that their participation was voluntary. First was seeking clearance from the relevant authorities including the University, the selected sample, as well as any other legal requirements stipulated by graduate school including the National Council for Science and Technology (NACOSTI) where an authority letter was obtained from them.

Second, the study ensured the confidentiality of all respondents that participated in the study while ensuring their anonymity. The researcher sought to encourage voluntary and informed consent, where all the participants in the study participated freely after understanding the purpose of the study. The participants were also informed about their right to withdraw consent of participation at any time without a penalty. In addition, participants were assured that all information they provided was kept private and confidential. This study guards against the potential possibility of infringing on the privacy and security of the research participants. Anonymity was observed by ensuring that the respondents do not write their names on the questionnaire, but instead special codes used. Lastly, the study ensured that all findings to the study are disclosed in a factual manner that will not compromise on the accuracy of the study.

CHAPTER FOUR

DATA ANALYSIS AND INTERPRETATION

4.0 Introduction

This chapter entails the data analysis, the presentation and interpretation of the results. The purpose of this study is to evaluate how data literacy of managers influence their decision making in the Kenyan textile industry. The study also purposed to get from respondents what are the main sources of data at their organizations, the main barriers for data use in their organization as well as the biggest determinant to decision making by managers in the organizations. The present data were collected by means of questionnaires and examined to answer the question communicated in the problem statement. This chapter starts by giving the response rate and demographic profile of the subjects under study.

4.1 Response rate

The study targeted 156 respondents but managed to get the views of 109 respondents as shown in Figure 4.1. This translated to a study response rate of 69.87%. This was deemed adequate for statistical analysis based on the criteria advanced by Kothari and Garg (2016), that a response of above 50% is adequate for statistical analysis.

4.2 Demographic information of the respondents

4.2.1 Years of existence

From the findings in Table 4.1, most of the companies 64% have been in existence for 5-10years, 32.41% less than 5years and 8.34% above 10 years

Table 4.1: Years of existence of the company

Duration	Frequency	Percentage
Less than 5 years	35	32.41%
5-10 years	64	59.26%
10 to 15 years	8	7.41%
15-20 years	1	0.93%
Sample Size	108	

Source: Researcher (2022)

4.2.2 Gender and age of the respondents

From Table 4.2, out of the total respondents to the study, the highest frequency 74 (68.52%) were female and the rest 34 (31.48%) were male. In terms of age, the majority were the youth age bracket of 25-35years (53.7%) and 35-45 years (27.78%), then 14.8% below 20 years and least respondents were 3.7% were 45-55 years. This means that managerial positions in the Kenyan textile industry are dominated by female who are less than 35 years in age. This is in line with the current trend in the country where female professionals are getting more opportunities.

Table 4.2: The distribution of respondents by gender and age

Age Group	Frequency	Percentage
Below 25 years	16	14.81%
25-35 years	58	53.70%
35-45 years	30	27.78%
45-55 years	4	3.70%
Sample Size	108	
Gender		
Male	34	31.48%
Female	74	68.52%
Sample Size	108	

Source: Researcher (2022)

From table 4.3, For education level, at least everyone had attained a diploma at 48.15% with the majority being undergraduates at 50.93% and only 1 respondent (0.93%) attaining a Masters degree.

Table 4.3: The distribution of respondents by education level and years worked

Education	Frequency	Percentage
Diploma	52	48.15%
Undergraduate	55	50.93%
Masters	1	0.93%
Sample Size	108	
Years Worked		
Less than 1 year	43	39.81%

2-5 years	61	56.48%
6-9 years	4	3.70%
Sample Size	108	

Source: Researcher (2022)

In this study, most respondents were at middle level management at 59.26% followed by low level management at 39.81% and less than 1% at top level management. And majority of the respondents (56.48%) had worked for 2-5 years followed by less than 1 year (39.81%).

Table 4.4: The distribution of respondents by leadership level

Leadership	Frequency	Percentage
Lower-Level Management	43	39.81%
Middle-Level Management	64	59.26%
Top-Level Management	1	0.93%
Sample Size	108	

Source: Researcher (2022)

4.3 Data accessibility to managers and managerial decision making in the Kenyan textile manufacturing industry

In this section, descriptive analysis is based on the objectives of the study which include: To assess the extent of data accessibility to managers, to assess the extent of data skills levels of managers, to assess extent of data use by managers, to determine the correlation between data literacy levels and managerial decision making in the Kenyan textile manufacturing industry.

4.3.1 To assess the extent of data accessibility to managers descriptive

The first objective sought to assess the extent of data accessibility in Kenyan textile manufacturing industry. This was done on a Likert scale of 1-5, where 5= strongly agree, 4= Agree, 3= Moderately Agreed, 2= Disagree and 1= Strongly Disagree. The mean and standard deviations (std) are as illustrated in Table 4.5.

Table 4.5: Frequencies and percentages of data accessibility

Statement	Strongly disagree	Disagree	Uncertain	Agree	Strongly Agree
The Company seeks to constantly identify and collect the relevant data required for managerial decision making.	0 **(0%)**	0 **(0%)**	0 **(0%)**	38 **(35%)**	70 **(65%)**
The Company has consistent and readily available sources of data required for managerial decision making.	0 **(0%)**	0 **(0%)**	0 **(0%)**	55 **(51%)**	53 **(49%)**
The data required for managerial decision making is stored securely with accessibility checks and restrictions where necessary.	0 **(0%)**	0 **(0%)**	3 **(3%)**	49 **(45%)**	56 **(52%)**
The data required for managerial decision making is easily and conveniently accessible to managers in the company.	0 **(0%)**	0 **(0%)**	0 **(0%)**	62 **(57%)**	46 **(43%)**
The data that is available and accessible to the company is current, accurate and relevant to the current decision-making needs.	0 **(0%)**	0 **(0%)**	0 **(0%)**	64 **(59%)**	44 **(41%)**
The data that is available and accessible to the company is comprehensive and complete to the current decision-making needs.	0 **(0%)**	0 **(0%)**	0 **(0%)**	74 **(69%)**	34 **(31%)**
The data that is available and accessible to the company is unique and detailed to provide sufficient distinctive properties for better decision-making.	0 **(0%)**	0 **(0%)**	0 **(0%)**	61 **(56%)**	47 **(44%)**
The cost of accessing data required for decision making is manageable to the organization	0 **(0%)**	0 **(0%)**	0 **(0%)**	66 **(61%)**	42 **(39%)**
The company can maintain high data availability and accessibility to all managers.	0 **(0%)**	0 **(0%)**	0 **(0%)**	65 **(60%)**	43 **(40%)**

Source: Researcher (2022)

From the study findings in Table 4.5, most of the respondents indicated that there is a high extent of data accessibility to managers in the Kenyan textile manufacturing industry. Most of the respondents strongly agree (65%) that the Company seeks to constantly identify and collect the relevant data required for managerial decision making with a mean of 4.648 and standard deviation of 0.4798**.** More so, on the consistency and readily available sources of data required for managerial decision making, most respondents agree 51% and strongly agree with 49%, a mean of 4.491 and standard deviation of 0.5022.

Most respondents 52% strongly agreed that data required for managerial decision making is stored securely with accessibility checks and restrictions where necessary, 45% agreed and only 3% of the respondents were uncertain with a mean of 4.491 and standard deviation of 0.5553. On data required for managerial decision-making being easily and conveniently accessible to managers in the company, 57% agreed and 43% strongly agreed with a mean of 4.426 and standard deviation of 0.4968. 59% and 41% agreed and strongly agreed respectively (mean of 4.407 and standard deviation of 0.4964) that the data that is available and accessible to the company is current, accurate and relevant to the current decision-making needs.

In addition, 69% agree and 31% strongly agree that the data that is available and accessible to the company is comprehensive and complete to the current decision-making needs with mean of 4.315 and standard deviation of 0.4666. 56% agree and 44% strongly agree that the data that is available and accessible to the company is unique and detailed to provide sufficient distinctive properties for better decision-making with a mean of 4.315 and standard deviation of 0.4981. Lastly, 61% agree and 39% strongly agree that the data that is available and accessible to the company is comprehensive and complete to the current decision-making needs with mean of 4.389 and standard deviation of 0.4897. While 60% agree and 40% strongly agree that the company can maintain high data availability and accessibility to all managers with mean of 4.398 and standard deviation of 0.4918.

Table 4.6: Data accessibility Means and Standard Deviation

Statement	Mean	Standard Deviation

The Company seeks to constantly identify and collect the relevant data required for managerial decision making.	4.648	0.4798
The Company has consistent and readily available sources of data required for managerial decision making.	4.491	0.5022
The data required for managerial decision making is stored securely with accessibility checks and restrictions where necessary.	4.491	0.5553
The data required for managerial decision making is easily and conveniently accessible to managers in the company.	4.426	0.4968
The data that is available and accessible to the company is current, accurate and relevant to the current decision-making needs.	4.407	0.4964
The data that is available and accessible to the company is comprehensive and complete to the current decision-making needs.	4.315	0.4666
The data that is available and accessible to the company is unique and detailed to provide sufficient distinctive properties for better decision-making.	4.315	0.4981
The cost of accessing data required for decision making is manageable to the organization	4.389	0.4897
The company can maintain high data availability and accessibility to all managers.	4.398	0.4918

Source: Researcher 2022

The study also sought to find out what the main sources of data were at the organization. The respondents were asked to give their opinions through an open-ended item and their varied responses and similarities were summarized and analyzed as shown in table **4.7** The findings are shown below indicating that the majority of the respondents 37.05% believe that the main source of data is market research followed by 30.55% from sales personnel and the smallest number of respondents 9.25% felt that the organizations main source of data is ICT department.

Table 4.7: Main sources of data in Textile industries

Response	Frequency	Percentage
ICT department	10	9.25%
Retail displays	25	23.15%
Salespeople	33	30.55%
Market research	40	37.05%
Total	**108**	**100%**

Source: Researcher (2022)

4.3.2: Relationship between data accessibility to managers and managerial decision making in the Kenyan textile manufacturing industry

The study further sought to determine the relationship between data accessibility to managers and managerial decision making in the Kenyan textile manufacturing industry using regression analysis tests. The results of the correlation between data accessibility and managerial decision making in the Kenyan textile manufacturing industry are presented in table 4.8

Table 4.8: Relationship between data accessibility to managers and managerial decision making in the Kenyan textile manufacturing industry

```
Residuals:
      Min        1Q    Median        3Q       Max
-0.266814 -0.007358 -0.007358 -0.007358  0.287778

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.86090    0.14494   12.84   <2e-16 ***
X1           0.38918    0.03257   11.95   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.08204 on 106 degrees of freedom
Multiple R-squared:  0.5739,    Adjusted R-squared:  0.5698
F-statistic: 142.7 on 1 and 106 DF,  p-value: < 2.2e-16
```

Source:Researcher(2022)

From the findings in Table 4.8, the analysis represents the managerial decision making in the Kenyan textile manufacturing industry (dependent variable) and data accessibility to managers (independent variable). It indicates that there exists a high degree of correlation between employee data accessibility to managers and managerial decision making in the Kenyan textile manufacturing industry. The value of R square = 0.5739 indicates how much of the total variation in the managerial decision making in the Kenyan textile manufacturing industry (dependent variable) are data accessibility to managers (independent variable). In this case, 57.39% of the variation in the managerial decision making in the Kenyan textile manufacturing industry (dependent variable) are accounted for by data accessibility to managers (independent variables). The value of adjusted R square =0.5698 (56.98%) represents the total variation in managerial decision making in the Kenyan textile manufacturing industry (dependent variable) as explained by data accessibility to managers (independent variable) if population data were to be used.

Furthermore, the study findings indicate that the regression model predicts the dependent variable (managerial decision making in the Kenyan textile manufacturing industry) significantly well given that p-value (sig) = 0.0000<0.05 (95% significance level). This indicates that the regression model is a good fit for the data, that is, it significantly predicts the outcome variable (managerial decision making in the Kenyan textile manufacturing industry). The coefficients of the regression model provide the necessary information to determine the relationship between data accessibility to managers and managerial decision making in the Kenyan textile manufacturing industry. More so, the results also provide information showing whether data accessibility to managers is statistically significant to the model.

Accessibility of data to managers contributes statistically significantly to the model given the p-values = 0.0000 that 0.05 (95% significance level).

4.4 Extent of data skills levels of managers in Kenyan textile manufacturing industry

4.4.1 To assess the extent of data skills levels of managers in Kenyan textile manufacturing industry.

The study sought to assess the extent of data skills levels of managers in Kenyan textile manufacturing industry. In order determine Extent of data skills levels of managers in Kenyan textile manufacturing industry descriptive responses from respondents were recorded on a Likert scale of 1-5, where 5= strongly agree, 4= Agree, 3= Moderately Agreed, 2= Disagree and 1= Strongly Disagree. The mean and standard deviations (std) are as illustrated in Table 4.10

The study found that the majority of respondents 85% strongly agree, only 7% agree and only 8% are uncertain on hierarchical layers within the company have a basic understanding of the concept of data and can engage with data data fitting their role with a mean of 4.759 and standard deviation of 0.5939. 52% strongly agree that the company has in place a data management policy that indicates required data skills level for managers in different positions with mean 4.398 and standard deviation of 0.6963, 36% agree and 12% are uncertain. More so, 58% agreed that managers can identify the producers of data available and understand who the targeted data consumers are, 26% strongly agree and 15% are uncertain with mean 4.12 and standard deviation of 0.6371. Additionally, 57% of the respondents agree that managers have the skills to access, write and engage in data analytics programs, 28% strongly agree and 15% are uncertain at a mean of 4.13 and standard deviation of 0.6426.

The study also found that 39% agree that the managers have the general knowledge and capabilities of retrieving and use of data for decision making, 33% strongly agree and 28% were uncertain with mean 4.056 and standard deviation 0.7834. Further more,57% were uncertain of whether managers have the skills to select, clean and analyze data for decision making, 24% strongly agree and 19% agree with mean 3.667 and standard deviation of 0.8428. 55% are uncertain on whether the managers can critically assess, visualize and interpret data available for decision making,30% strongly agree and 15% agree with mean 3.741 and standard deviation 0.8899. And lastly, 54% of the respondents are uncertain that managers have the skills to effectively reason and communicate the right stories from data and use it for decision making, 33% strongly agree and 13% agree with mean 3.976 and standard deviation 0.9147.

Table 4.9: Descriptive statistics of extent of data skills levels of managers in Kenyan textile manufacturing industry

Statement	**Strongly disagree**	**Disagree**	**Uncertain**	**Agree**	**Strongly Agree**
All hierarchical layers within the company have a basic understanding of the concept of data and can engage with data fitting their role.	0 **(0%)**	0 **(0%)**	9 **(8%)**	8 **(7%)**	91 **(85%)**
The company has in place a data management policy that indicates required data skills level for managers in different positions.	0 **(0%)**	0 **(0%)**	13 **(12%)**	39 **(36%)**	56 **(52%)**

Managers can identify the producers of data available and understand who the targeted data consumers are.	0 **(0%)**	**0** **(0%)**	16 **(15%)**	63 **(58%)**	29 **(26%)**
The managers have the skills to access, write and engage in data analytics programs	0 **(0%)**	0 **(0%)**	16 **(15%)**	62 **(57%)**	30 **(28%)**
The managers have the general knowledge and capabilities of retrieving and use of data for decision making	0 **(0%)**	0 **(0%)**	30 **(28%)**	42 **(39%)**	36 **(33%)**
The managers have the skills to select, clean and analyse data for decision making.	0 **(0%)**	0 **(0%)**	62 **(57%)**	20 **(19%)**	26 **(24%)**
The managers can critically assess, visualize and interpret data available for decision making	0 **(0%)**	0 **(0%)**	60 **(56%)**	16 **(15%)**	32 **(30%)**
The managers have the skills to effectively reason and communicate the right stories from data and use it for decision making.	0 **(0%)**	0 **(0%)**	58 **(54%)**	14 **(13%)**	36 **(33%)**

Source: Researcher (2022)

Table 4.10 Extent of data skills levels means and standard deviation

Statement	**Mean**	**Standard Deviation**
All hierarchical layers within the company have a basic understanding of the concept of data and can engage with data fitting their role.	4.759	0.5939
The company has in place a data management policy that indicates required data skills level for managers in different positions.	4.398	0.6963
Managers can identify the producers of data available and understand who the targeted data consumers are.	4.120	0.6371
The managers have the skills to access, write and engage in data analytics programs	4.130	0.6426
The managers have the general knowledge and capabilities of retrieving and use of data for decision making	4.056	0.7834

The managers have the skills to select, clean and analyse data for decision making.	3.667	0.8428
The managers can critically assess, visualize and interpret data available for decision making	3.741	0.8899
The managers have the skills to effectively reason and communicate the right stories from data and use it for decision making.	3.976	0.9147

Source: Researcher (2022)

4.4.2 Relationship between data skills level of managers and managerial decision making in the Kenyan textile manufacturing industry

The study also sought to determine the relationship between relationship between data accessibility and managerial decision making in the Kenyan textile manufacturing industry using regression analysis tests. The results of the correlation between employee involvements in the planning of change management on organizational operations are presented in table 4.11.

Table 4.11: Relationship between data skills level of managers and managerial decision making in the Kenyan textile manufacturing industry

```
Residuals:
   Min     1Q Median     3Q    Max
 -0.27   0.00   0.00   0.00   0.09

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  2.61000    0.06123   42.63   <2e-16 ***
X2           0.24000    0.01491   16.10   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.06771 on 106 degrees of freedom
Multiple R-squared:  0.7097,    Adjusted R-squared:  0.7069
F-statistic: 259.1 on 1 and 106 DF,  p-value: < 2.2e-16
```

Source:Researcher(2022)

From the findings in Table 4.11, the value of R=0.8424 represents the simple correlation between dependent variable managerial decision making and independent variable data skills It indicates that there exists a high degree of correlation between data skills and managerial decision making. The value of R square = 0.7097 indicates how much of the total variation in the managerial decision making (dependent variable) are explained by data skills (independent variable). In this case, 71% of the variation in managerial decision making (dependent variable) are accounted for by data skills (independent variables). The value of adjusted R square =0.7069 represent the total variation in managerial decision making (dependent variable) as explained by data skills (independent variable) if population data were to be used. Furthermore, the study findings indicate that the regression model predicts the dependent variable (managerial decision making) significantly well given that p-value (sig) = 0.0000<0.05 (5% significance level). This indicates that the regression model is a good fit for the data, that is, it significantly predicts the outcome variable (data skills). The coefficients of the regression model provide the necessary information to predict managerial decision making from data skills. Moreover, the results also provide information showing whether data skills contribute statistically significantly to the model. It can be seen that accessibility of data to managers contributes statistically significantly to the model given the p-values = 0.0000 is less than 0.05 (95% significance level).

4.5 Data use by managers in Kenyan textile manufacturing industry for decision-making.

4.5.1 To assess extent of data use by managers in Kenyan textile manufacturing industry for decision-making

The third objective of the study was to assess extent of data use by managers in Kenyan textile manufacturing industry for decision-making. The objective of the study was achieved by use of a Likert scale of 1-5, where 5= strongly agree, 4= Agree, 3= Moderately Agreed, 2= Disagree and 1= Strongly Disagree. The mean and standard deviations (std) are as illustrated in Table 4.12.

Table 4.12: Descriptive statistics of extend of data use by managers in Kenyan textile manufacturing industry for decision-making.

Statement	Strongly disagree	Disagree	Uncertain	Agree	Strongly Agree
The company has created a culture where data use is encouraged and embraced.	0 **(0%)**	0 **(0%)**	35 **(33%)**	38 **(35%)**	35 **(32%)**
The company encourages managers to use data available in making decisions	0 **(0%)**	0 **(0%)**	28 **(26%)**	43 **(40%)**	37 **(34%)**
The company has engaged data sources that provide relevant data for decision making	0 **(0%)**	0 **(0%)**	30 **(28%)**	37 **(34%)**	41 **(38%)**
The higher the hierarchical management levels, the more data is used in managerial decision making	0 **(0%)**	0 **(0%)**	18 **(17%)**	46 **(43%)**	44 **(41%)**
Managers have extensive operational and business knowledge but limited to no data analytical knowledge	0 **(0%)**	0 **(0%)**	34 **(32%)**	36 **(33%)**	38 **(35%)**
Managers understand and engage with data but have little analytical capabilities.	0 **(0%)**	0 **(0%)**	28 **(26%)**	35 **(32%)**	45 **(42%)**
In addition to understanding and engaging data, Managers in the company have profound data analytical and statistical skills.	0 **(0%)**	0 **(0%)**	39 **(36%)**	23 **(21%)**	46 **(43%)**
Managers can effectively interpret and communicate results and reason with data for decision making	0 **(0%)**	0 **(0%)**	36 **(33%)**	27 **(25%)**	45 **(42%)**
The managers have the skills to effectively reason and communicate the right stories from data and use it efficiently for decision making.	0 **(0%)**	0 **(0%)**	50 **(46%)**	11 **(10%)**	47 **(44%)**

Source: Researcher (2022)

The study sought to obtain the respondents views on extent to which managers use data in decision making in the Kenyan manufacturing industry. The findings obtained indicate that 35% of the respondents agree that the company has created a culture where data use is encouraged and embraced, 33% are uncertain and 32% strongly agree with mean of 4 and standard deviation of

0.8088. 40 % of the respondents agree that the company encourages managers to use data available for decision making, 34% strongly agree and 26% are uncertain with mean of 4.102 and standard deviation of 0.8081. More so, with the mean of 4.241and standard deviation of 0.7218, the findings show 38% strongly agree that the company has engaged data sources that provide relevant data for decision making, 34% agree and 28% are uncertain.

In addition, 43% of the respondents agree that the higher the hierarchical management levels, the more data is used in managerial decision making, 41% strongly agree and 17% are uncertain with a mean of 4.037 and standard deviation of 0.8195. With a mean of 4.157 and standard deviation of 0.8107, 35% of the respondents strongly agree that managers have extensive operational and business knowledge but limited to no data analytical knowledge, 33% agree and 32% are uncertain. Further, 42% of the respondents strongly agree that managers understand and engage with data but have little analytical capabilities, 32% agree and 26% are uncertain with a mean of 4.065 and standard deviation of 0.8889.

Lastly, with a mean of 4.083 and standard deviation of 0.866, 43% of the respondents strongly agree that in addition to understanding and engaging data, Managers in the company have profound data analytical and statistical skills, 36% are uncertain and 21% of the respondents agree. 42% of the respondents strongly agree that Managers can effectively interpret and communicate results and reason with data for decision making, 33% are uncertain and 25% agree with a mean of 3.972 and standard deviation of 0.9517. And finally, 46%of the respondents are uncertain that the managers have the skills to effectively reason and communicate the right stories from data and use it efficiently for decision making, 44% strongly agree and 10% of the respondents agree with mean of 4.426 and standard deviation 0.6295.

Table 4.13: Extent of data use means and standard deviation

Statement	**Mean**	**Standard Deviation**
The company has created a culture where data use is encouraged and embraced.	4.000	0.8088

The company encourages managers to use data available in making decisions	4.102	0.8081
The company has engaged data sources that provide relevant data for decision making	4.241	0.7218
The higher the hierarchical management levels, the more data is used in managerial decision making	4.037	0.8195
Managers have extensive operational and business knowledge but limited to no data analytical knowledge	4.157	0.8107
Managers understand and engage with data but have little analytical capabilities.	4.065	0.8889
In addition to understanding and engaging data, Managers in the company have profound data analytical and statistical skills.	4.083	0.8660
Managers can effectively interpret and communicate results and reason with data for decision making	3.972	0.9517
The managers have the skills to effectively reason and communicate the right stories from data and use it efficiently for decision making.	4.426	0.6295

Source: Researcher (2022)

The study also sought to find out what the main barriers of data use were at the organizations. The respondents were asked to give their opinions through an open ended item and their varied responses and similarities were summarized and analyzed as shown in table 4.14 The findings indicate that, the biggest barrier is unavailability & variability of manufacturing data at 51.85% , followed by lack of management commitment at 19.45%, lack of understanding & planning 18.51% and least barrier being resistance to change at 10.19%

Table 4.14: Main barriers of data use

Response	Frequency	Percentage
Unavailability & Variability of manufacturing data	**56**	**51.85%**
Lack of top management commitment	**21**	**19.45%**
Resistance to change	**11**	**10.19%**
Lack of understanding & planning	**20**	**18.51%**
Total	**108**	**100%**

Source: Researcher (2022)

The study further sought to determine the relationship between data use by managers and Managerial decision making in the Kenyan textile manufacturing industry using regression analysis tests. The results of the correlation are presented in table 4.15.

4.5.2 Relationship between data use by managers and Managerial decision making

Table 4.15: Relationship between data use by managers and Managerial decision making in the Kenyan textile manufacturing industry

```
Residuals:
    Min      1Q  Median      3Q     Max
-0.0241 -0.0241 -0.0241 -0.0241  0.3709

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  2.30533    0.11188   20.61   <2e-16 ***
X3           0.31469    0.02734   11.51   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.08377 on 106 degrees of freedom
Multiple R-squared:  0.5556,	Adjusted R-squared:  0.5514
F-statistic: 132.5 on 1 and 106 DF,  p-value: < 2.2e-16
```

Source:Researcher (2022)

From the findings in Table 4.15 The value of R= 0.745 represents the simple correlation between managerial decision making (dependant variable) and data use (independent variable). It shows that there’s a high degree of correlation between the dependant variable and the independent variable. The R square value = 0.5556 shows how much of the total variation in managerial decision making are explained by data use. In this case, 55.6% of the variation in managerial decision making are accounted for by data use. The adjusted R squared = 0.5514 indicates how much total variation in managerial decision making are explained by data use if population data was to be used. In addition, the findings indicate that the regression model predicts the dependent variable (managerial decision making in the Kenyan textile manufacturing industry) significantly well given that p-value (sig) = 0.0000<0.05 (95% significance level). This indicates that the regression model is a good fit for the data, that is, it significantly predicts the outcome variable (managerial decision making in the Kenyan textile manufacturing industry). The coefficients of the regression model provide the necessary information to determine the relationship between data accessibility to managers and managerial decision making in the Kenyan textile manufacturing industry. More so, the results also provide information showing whether data use by managers is statistically significant to the model. Data use by managers contributes statistically significantly to the model given the p-values = 0.0000 less that 0.05 (95% significance level).

4.6 Managerial decision making

The research further sought to examine the managerial decision-making activities in the companies. This was done on a Likert scale of 1-5, where 5= strongly agree, 4= Agree, 3= Moderately Agreed, 2= Disagree and 1= Strongly Disagree. The results are shown in Table 4.16.

Table 4.16: Descriptive statistics of managerial decision making

Statement	Strongly disagree	Disagree	Uncertain	Agree	Strongly Agree
Managerial decisions in the company are made heavily backed by data.	0 **(0%)**	0 **(0%)**	8 **(7%)**	46 **(43%)**	54 **(50%)**
Managerial decisions in the company are made mainly through the managers intuition and experience	0 **(0%)**	24 **(22%)**	23 **(21%)**	16 **(15%)**	45 **(42%)**
Managerial decisions in the company are made using both the managers intuition and experience and backed by data.	0 **(0%)**	6 **(6%)**	77 **(71%)**	8 **(7%)**	17 **(16%)**
Data based decision making in the company has helped improve transparency and accountability in managerial decision making	0 **(0%)**	12 **(11%)**	72 **(66%)**	6 **(6%)**	18 **(16%)**
There is constant improvement and overall performance and operational efficiency due to data-based decision making in the company.	0 **(0%)**	36 **(33%)**	55 **(51%)**	7 **(7%)**	10 **(9%)**
Critical managerial business decisions made are tied to data analytics insights	0 **(0%)**	49 **(46%)**	14 **(13%)**	7 **(6%)**	38 **(35%)**
Data based decision making in the company helps in getting relevant and timely feedback on decisions made and implemented	0 **(0%)**	6 **(6%)**	79 **(73%)**	6 **(6%)**	17 **(16%)**
Data based decision making at the company has enhanced consistency in operations and strategic direction.	5 **(5%)**	0 **(0%)**	23 **(21%)**	22 **(20%)**	58 **(54%)**

Source: Researcher (2022)

From the study findings, respondents indicate that 50% strongly agree with managerial decisions in the company are made heavily backed by data, 43% agree and only 8% are uncertain. More so, 42% of the respondents strongly agree that managerial decisions in the company are made mainly through the mangers intuition and experience, 22% disagree, 21% are uncertain and 15% agree. The findings also indicate that 71% of the respondents were uncertain on whether managerial decisions in the company are made are made using both the managers' intuition & experience and backed by data, 16% strongly agree that mangers do, & 7% agree and 6% disagree.

In addition, 66%of the respondents are uncertain on whether data-based decision making in the company has helped improve transparency and accountability in managerial decision making, 16%

strongly agree, 11% disagree and 6% agree. Reference to whether there's constants improvement and overall performance & operational efficiency due to data-based decision making in the company, 9% strongly agree, 7% agree,51% are uncertain and 33% disagree.

The findings also show that 46% of the respondents disagree that critical managerial business decisions made are tied to data analytics insights, 13% are uncertain,6% agree and 35% strongly agree.16% of the respondents strongly agree that data-based decision making in the company helps in getting relevant and timely feedback on decisions made and implemented, 6% agree, 73% are uncertain and 6 % disagree. And lastly, 54% of the respondents strongly agree that data-based decision making in the company had enhanced consistency in operations and strategic direction,20% agree, 21% uncertain and 5% strongly disagree.

The study also sought to find out the biggest determinant to decision making by managers at the organization. The respondents were asked to give their opinions through an open-ended item and their varied responses and similarities were summarized and analyzed as shown in table 4.17. From the findings, 27.8% of the respondents believe that the biggest determinant of decision making by managers is informed by company resources, 25% say objectives of the company, 23.15% believe its competition and 24.07% believe its vision of the organization**.**

Table 4.17 Determinant of managerial Decision making

Response	**Frequency**	**Percentage**
Company resources	30	27.78%
The objective of the company	27	25%
Competition	25	23.15%
The vision of the organization	26	24.07%
Total	**108**	**100%**

Source: Researcher (2022)

4.7 Overall correlation between data literacy levels and managerial decision making in the Kenyan textile manufacturing industry

The regression analysis sought to determine the correlation between data literacy levels and Managerial decision making in the Kenyan textile manufacturing industry. The results of the test are shown in table 4.18.

Table 4.18: Model summary showing the relationship between data accessibility (X1), data skills (X2), data use (X3) and managerial decision making (Y)

Variable	Correlation Coefficient (R)	P-value
Data accessibility to managers	0.7575329	0.0000
Data skills levels of managers	0.8424235	0.0000
Data use by managers	0.7453935	0.0000

Source: Researcher (2022)

From the findings, it was established that there is a significant positive association between the dependent variable (managerial decision making) and the independent variables (data literacy levels). The study findings show that there is a high positive association between data accessibility to managers and managerial decision making (r=0.7575329, p-value = 0.0000<0.05), data skills levels of managers and managerial decision making (r=0.8424235, p-value = 0.0000<0.05), data use by managers and managerial decision making (r=0.7453935, p-value = 0.0000<0.05). In determination of the relationship between data literacy levels and Managerial decision making in the Kenyan textile manufacturing industry multiple regression model was used where X1, X2 and X3 represents the independent variables and Y as the dependent variable. The results are presented in Table 4.18.

Table 4.19: Multiple regression model

```
Residuals:
    Min      1Q  Median      3Q     Max 
-0.1029  0.0000  0.0000  0.0000  0.2571 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  3.21905    0.12754  25.239  < 2e-16 ***
X1          -0.51429    0.05823  -8.832 2.71e-14 ***
X2           0.41905    0.02981  14.057  < 2e-16 ***
X3           0.23143    0.01871  12.367  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.04219 on 104 degrees of freedom
Multiple R-squared:  0.8894,	Adjusted R-squared:  0.8862 
F-statistic: 278.8 on 3 and 104 DF,  p-value: < 2.2e-16
```

Source: Researcher (2022)

The value of R square = 0.8894 indicates how much of the total managerial decision making (dependent variable) are explained by data literacy level X1, X2, X3 (independent variables). In this case, 88.94% of the variation in the managerial decision making (dependent variable) are accounted for by data literacy levels (independent variables). This is a high variation in managerial decision making. On the other hand, Adjusted R square =0.8862 represent the total variation in managerial decision making (dependent variable) as explained by data literacy levels (independent variables) if population data were used.

The study findings in Table 4.18 indicates that the regression model predicts the dependent variable (managerial decision making) significantly well given that p-value = 0.0000<0.05 (95% significance level). This indicates that the regression model is a good fit for the data, that is, it significantly predicts the outcome variable (managerial decision making). These results provide the necessary information to determine the correlation between data literacy levels and managerial decision making in the Kenyan textile manufacturing industry. Furthermore, the results also provide information showing whether X1, X2 and X3 contribute statistically significantly to the model. Thus, the model can be precisely written as follows:

Managerial decision making = **3.21905 – 0.51429** Data accessibility **+ 0.41905** Data skills level **+ 0.23143** Data use

From this model, it can be seen that data skills level of managers and data use by managers contribute positively towards managerial decision making. Conversely, data accessibility to managers, contributes negatively towards managerial decision making. The independent variables contribute statistically significantly to the model given the p-value 0.0000 which is less that 0.05 (95% significance level).

4.8 Chapter summary

In this Chapter, the extend of data accessibility to managers, data skills level of managers and data use by managers were assessed. The study findings from the simple linear regression models indicated that data skills levels of mangers, has the highest correlation with managerial decision making. From the multiple regression the study established that data accessibility to managers, data skills level of managers and data use by managers significantly contribute to managerial decision making.

CHAPTER FIVE

DISCUSSIONS, CONCLUSIONS AND RECOMMENDATIONS

5.0 Introduction

Chapter five begins with a presentation of the summary of the findings, and discussion of the specific objective findings. The chapter further presents the conclusions and derives specific implications from the objectives and ends with the recommendations and possible areas of research that have emerged from the study.

5.1 Summary of Study

The purpose of this study was to evaluate how data literacy of managers influence their decision making in the Kenyan textile industry. Based of this main objective, the following specific objectives were: To assess the extent of data accessibility to managers in the Kenyan textile manufacturing industry; To assess the extent of data skills levels of managers in Kenyan textile manufacturing industry; To assess extent of data use by managers in Kenyan textile manufacturing industry for decision-making; To determine the correlation between data literacy levels and managerial decision making in the Kenyan textile manufacturing industry.

To demonstrate the relationship between data literacy and managerial decision making, the study was anchored on the Rational decision theory posited by Adam Smith. The study sought to fill the contextual, conceptual, empirical, and theoretical gaps. Contextually, the study was conducted in Kenya, a developing economy whereas similar previous studies have been performed majorly in developed European economies as well as Asian economies. Conceptually, the study adopted the skill-based theory of leadership by Robert Katz in 1955 where he studied executives and identified skill areas that the executives had in common and used on a regular basis for decision making. A relationship was conceptualized between data literacy as a resource-based skill and effective managerial decision-making. Empirically, the research identified and presented various studies in different economies with similar and contrasting findings, revealing the existence of controversy between different scholars. This is the gap that the study sought to fill within the

Kenyan economy and specifically the Kenyan Textile industry. Data literacy was operationalized by data accessibility, data skill level and data use while managerial decision making was operationalized Improved transparency and accountability, Constant improvement of overall performance and efficiency, tie business decisions to analytics Insights, help to get feedback and enhance Consistency

The study adopted pragmatic research philosophy because it allows for a mixed or multiple methods therefore allowing for both quantitative and qualitative method using the descriptive cross-sectional survey as the research design. The study focused on 52 large and midsized textile companies operating outside the Export Processing Zone (EPZ) according to the Kenya National Bureau of Statistics (2019). The sample size that was targeted was 156 respondents that included three respondents in every company. Data was collected using structured questionnaires. The study's response rate was 70% which was considered sufficient allowing the data collected to be analyzed. Descriptive statistics and correlation analysis were used in data analysis. The researcher's proposal was reviewed and approved by the Ethics Review Board of Strathmore University as well as obtaining a research permit from NACOSTI.

The study also purposed to get from respondents what the main sources of data at their organizations, the main barriers for data use in their organization as well as the biggest determinant to decision making by managers in the organizations. The present data were collected by means of questionnaires and examined to answer the question communicated in the problem statement.

5.2 Discussion of the Findings

This section provides a summary of the findings and discussions thereafter.

5.2.1 Demographic Information of Respondents

The study sought to understand the demographic characteristics of the respondents and the companies under study. Majority of the organization had been in existence for more that 5 years and therefore possessed the information sought to fulfil the objectives of the study. Majority of the respondents were female and above the age of 25 years and middle level managers and majority having worked at the organization for more than 2 years. These demographic characteristics are critical to the study because the absence of it according to Hammer (2011), would risk the researcher assuming the stance of absolutism; that assumes a similarity in response without the influence of these important characteristics. We can therefore conclude that the majority of the respondents from the selected sample possessed relevant characteristics to be able to provide the required information for the study without assuming absolutism.

5.2.2 Data accessibility and managerial decision making

The first objective of the study was to assess the extent of data accessibility to managers in the Kenyan textile manufacturing industry. The findings showed that there is a high extent of data accessibility to managers in the Kenyan textile manufacturing industry. Though more than half of the respondents strongly agreed that their company seeks to constantly identify and collect the relevant data required for managerial decision making the availability, consistency and readily available sources of data as well required for managerial decision making, the average response was agreed. Similarly, the respondents agreed that data required for managerial decision making in the textile companies is stored securely with accessibility checks and restrictions where necessary, and that the data required for managerial decision-making is easily and conveniently accessible to managers in their company. The respondents also agreed that the data that is available and accessible to the company is current, accurate and relevant to the current decision-making needs.

The respondents also agreed that the data that is available and accessible to the company is comprehensive and complete to the current decision-making needs, that the data that is available and accessible to the company is unique and detailed to provide sufficient distinctive properties for better decision-making. Finally, the respondents agreed that the data that is available and accessible to the company is comprehensive and complete to the current decision-making needs and that that the company can maintain high data availability and accessibility to all managers. With regards to the main source of data available in the companies, the respondents believed it was mostly from market research either conducted by company or bought from already existing research of the industry. With regards to the relationship between data accessibility and decision making, the correlation showed that there exists a high degree of correlation between employee data accessibility to managers and managerial decision making in the Kenyan textile manufacturing industry. The regression model finding was significant in testing the relationship between data accessibility and managerial decision making in the Kenyan textile manufacturing industry.

This finding reveals that the textile manufacturing industry in Kenya agree with the assertions by Lyeski (2019) that maintaining a high level of high data availability and accessibility is vital to any business's sustainable success and any compromise can have serious consequences, on many levels. Similarly, Schonfel, et al. (2020) indicates that inconsistent fluctuations in data availability could potentially have negative implications for some organizations in decision making. In the case of the subject of this study, the high level of data accessibility was shown in the high levels of positive correlation between data accessibility and managerial decision making thus enabling the companies to avoid the serious negative implications.

5.2.3 Data Skills level of Managers in the Kenyan Textile Manufacturing Industry

The second objective was to assess the extent of data skills levels of managers in Kenyan textile manufacturing industry. Majority of respondents strongly agreed that all hierarchical layers within the company have a basic understanding of the concept of data and can engage with data fitting their role. The respondents further agreed that their respective companies had in place a data management policy that indicates required data skills level for managers in different positions. The respondents also agreed that managers can identify the producers of data available and understand who the targeted data consumers are. Additionally, the respondents agreed that managers have the skills to access, write and engage in data analytics programs. Although findings from studies in Africa on managerial data skills in Africa like Wolff et, al. (2016) reveal acquiring key data skill competences in school though there is no clear definition of what these should be, and Marr (2020), who states that poor data skills is one of the main roadblocks to an organization's success and the ability to grow in Africa, this study shows that the Kenyan textile manufacturing industry has been able to overcome this data skills challenge.

The findings also reveal that the respondents agree that the managers have the general knowledge and capabilities of retrieving and use of data for decision making. Furthermore, the respondents were uncertain of whether managers have the skills to select, clean and analyze data for decision making, as well as whether the managers can critically assess, visualize, and interpret data available for decision making, and those managers have the skills to effectively reason and communicate the right stories from data and use it for decision making. These findings agree with those of Mandinach & Gummer (2013) whose findings indicated that although the data skills policy emphasis is growing, attention to building human capacity and skills around data use is lacking. They further indicated that although some professional development opportunities exist in the studies respondents, fewer formal courses, and opportunities for data skill development in schools of education have been developed and implemented, which is similar to the case of Kenyan textile manufacturing companies.

With the regards to the relationship between data skills level and managerial decision making, the findings showed a high degree of positive correlation. The regression model further indicates a good fit for the data skills and to predict managerial decision making from data skills. The findings agree with Guerrer and Rowe, 2013 who assert that the Skills Based Theory identifies what assets make up a good leader in addition to how we can identify a leader that is a best fit for the role in an organization based on the skills they possess and helps in effective managerial decision-making.

5.2.4 Data use by managers in Kenyan textile manufacturing industry for decision-making

The third objective sought determine the extent to which managers use data in decision making in the Kenyan manufacturing industry. The findings indicate that the respondents agree that the Kenyan textile manufacturing industry has created a culture where data use is encouraged and embraced as well as agree that the company encourages managers to use data available for decision making, Furthermore the respondents agree that the Kenyan textile manufacturing industry has engaged data sources that provide relevant data for managerial decision making.

In addition, the respondents agree that the higher the hierarchical management levels, the more data is used in managerial decision making, that managers have extensive operational and business knowledge but limited to no data analytical knowledge and that those managers understand and engage with data but have little analytical capabilities in the Kenyan textile manufacturing industry. This finding agrees with that of Johnson (2018) who found that when it moves from the conceptual framework to use and application of data in the organizational context, managers are struggling with successfully using and implementing solutions in their day-to-day business because there exists a gap between data experts or analytical specialists, and the business users that need to understand the analysis and turn it into business insights, actions and ultimately value. Lastly, the respondents agree that in addition to understanding and engaging data, Managers in the company have profound data analytical and statistical skills, that Managers can effectively interpret and communicate results and reason with data for decision making, that the managers have the skills to effectively reason and communicate the right stories from data and use it efficiently for decision making the Kenyan textile manufacturing industry. These findings agree with those of Plotkin (2014) who states that the most important, and complex, aspects of data literacy are the ability to reason with data and effective use it and that a manager cannot talk the language of data or reason with data in a proper way, misalignment or misunderstanding will take place (Plotkin, 2014).

With the regards to the relationship between data use and managerial decision making, the findings show a high degree of positive correlation while the regression model further indicates a good fit for the data use and to predict managerial decision making from data use by managers in the Kenyan textile manufacturing industry. Schildkamp & Ehren (2012) findings are similar to this in the context of the educational sector and show that the data team intervention in the effective use of data lend to a positive correlation between data use and decision making and led to an increase in effective data use, changes in classroom instruction, and to school improvement.

5.2.5 Correlation between data literacy and managerial decision-making in the Kenyan textile manufacturing industry.

The final objective was to determine the correlation between data literacy levels and managerial decision making in the Kenyan textile manufacturing industry. The findings show that respondents agree that managerial decisions in the Kenyan textile manufacturing industry heavily backed by data. However, managerial decisions in the Kenyan textile manufacturing industry are also made through the manger’s intuition and experience, therefore agreeing that managerial decisions in the Kenyan textile manufacturing industry are made using both the managers’ intuition & experience and backed by data. This finding goes against the Rational decision theory which according to Uzonwanne (2016) defines it as a model where parties use facts and information, analysis, and a step-by-step procedure to come to a decision offering the best-predictable consequence and with the highest prospects of consequence.

Further, the respondents are uncertain on whether data-based decision making in the Kenyan textile manufacturing industry has helped improve transparency and accountability in managerial decision making, that there’s constants improvement and overall performance & operational efficiency due to data-based decision making in the company, that critical managerial business decisions made are tied to data analytics insights in Kenyan textile manufacturing industry. The respondents are further uncertain that data-based decision making in the Kenyan textile manufacturing industry helps in getting relevant and timely feedback on decisions made and implemented. This finding disagrees with those of Brynjolfsson and McElheran (2016), who states that data Driven decision making approach can be of great benefit to any organization as it leads to improved transparency and accountability to every organization which works to improve teamwork and staff engagement. This brings out the issue of the mixed effects of data-based decision making where Licidchart, 2017 posits that if the wrong data is used or applied, then the effects on decision making can be negative. This is brought out in the next finding where the respondents strongly agree that data-based decision making in the Kenyan textile manufacturing industry had enhanced consistency in operations and strategic direction.

The study also sought to find out the biggest determinant to decision making by managers at the organization. The respondents believe that the biggest determinant of decision making by managers is informed by company resources, objectives of the company, its competition, and the vision of the organization**.** From the findings, it was established that there is a significant positive association between managerial decision-making data literacy levels while the multiple regression model predicts the managerial decision making significantly well. This indicates that the regression model is a good fit for the data, that is, it significantly predicts the outcome of managerial decision making.

5.3 Conclusions

With regards to the first objective, to assess the extent of data accessibility to managers in the Kenyan textile manufacturing industry, we can conclude that there is high data accessibility and availability to managers that positively affects decision making in the Kenyan textile industry. Similarly, with the second objective, to assess the extent of data skills levels of managers in Kenyan textile manufacturing industry, we can conclude from the findings that managers in the Kenyan textile industry, have high levels of data skills that also positively affects decision making.

Regarding the third objective, to assess extent of data use by managers in Kenyan textile manufacturing industry for decision-making, we can conclude from the findings that there are high levels of data use among the managers which also translated to better decision making. Lastly, with regard to the fourth objective, to determine the correlation between data literacy levels and managerial decision making in the Kenyan textile manufacturing industry, we can conclude that there was positive correlation between the two variables though there were uncertainties on whether data-based decision making has helped improve transparency and accountability, that there's constants improvement and overall performance & operational efficiency, that critical managerial business decisions made are tied to data analytics insights and that data-based decision making helps in getting relevant and timely feedback on decisions made and implemented.

The study findings from the descriptive data and simple linear regression models indicated that the general objective of the study, has high positive correlation with managerial decision making. From the multiple regression the study established that data accessibility to managers, data skills level of managers and data use by managers significantly contribute to managerial decision making.

5.4 Recommendations

The findings and conclusions of the study has elicited the following recommendations:

i) **Managerial recommendations:** The findings have important managerial implications that form the basis for managerial recommendations. First, the study recommends to the management of the Kenyan textile manufacturing industry, especially the large and medium sized ones operating outside the EPZ to keenly consider improvement in their data literacy levels. Special attention should be paid to increasing their data use and continue to monitor their level of data skills and periodic reviews of the likely changes in data quality and management. Due to the positive correlation between data literacy and better decision making, increasing managerial data skills and use will enable them to improve on their decision-making process thereby likely to improve personal and organizational performance. Additionally, the management of the Kenyan textile manufacturing should consistently improve their employees and subordinate staff data literacy so as to improve on their general organizational performance and stay ahead of their competition. This could be implemented by frequent trainings and capacity building for their personnel.

ii) **Recommendations for Policy Makers:** The Kenyan textile manufacturing industry faces numerous challenges especially from cheap and counterfeit imports. Policy makers in the industry therefore need to be proactive in supporting the industry to thrive. The findings of this study have revealed a strong positive relationship between data literacy and managerial decision making and the Government and the institutions responsible for formulating policies on trade beyond the borders of the country should develop policies based on data and research that will enable the industry to generate, access, disseminate data at low and manageable costs. This will enhance decision making of managers and therefore improve performance in the industry. Furthermore, the government through it regulating agencies should be able to avail data literacy support to the industry players so that they can have adequate data resources to effectively compete with other global organizations in the textile manufacturing industry. The government should further invest in data literacy training and capacity building of the Kenyan textile manufacturing companies on aspects of technology and data use where limitations of this vital information may limit their growth in these countries. The government could also seek to offer incentives to companies that have invested heavily on data literacy of their staff and employees like tax reliefs so as to encourage the textile manufacturing companies to continuously expand their data literacy levels for better decision making. The government could as well form data exchange agreements with foreign nations where possible so as to support Kenyan textile manufacturing companies access valuable data from the developed economies.

iii) **Contribution to Knowledge:** The purpose of this study was to evaluate how data literacy of managers influence their decision making in the Kenyan textile industry. To demonstrate the relationship between data literacy and managerial decision making, the study was anchored on the Rational decision theory posited by Adam Smith. The study sought to fill the contextual, conceptual, empirical, and theoretical gaps. This provides a basis for scholars to further explore these concepts and theoretical foundations. Conceptually, the study adopted the skill-based theory of leadership by Robert Katz in 1955 where a relationship was conceptualized between data literacy as a resource-based skill and effective managerial decision-making. This study therefore contributed to application of this theory into practical applications. Empirically, the research identified and presented various studies in different economies with similar and contrasting findings, revealing the existence of controversy between different scholars. Contextually, the study was conducted in Kenya, a developing economy whereas similar previous studies have been performed majorly in developed European economies as well as Asian economies. This study has therefore provided valuable empirical research in an area that had not been previously studied.

5.5 Limitations of the Study

The study focused on the large and medium sized textile manufacturing companies in Kenya and operating outside the EPZ only. This therefore does not include the other large companies operating within the EPZ zone as well as the SMEs in the textile manufacturing industry in Kenya. The findings and views presented in this study therefore do not represent the entirety of the textile manufacturing companies in Kenya. Hence, the findings of this study could not be generalized for all the textile manufacturing industry. Secondly, data collection was conducted in the midst of the Covid-19 pandemic and most of the businesses were affected due to the closing of borders that had been affected in many countries including Kenya. This affected data collection process greatly and it took longer than expected.

5.6 Suggestions for Future Research

This study covered data literacy and a major contributor to effective managerial decision making. Scholars interested in further research could focus on data literacy policies in developing economies and how they affect data literacy levels of managers. The findings showed that there was limited data literacy policies and the subject of the study; large and medium Textile manufacturing companies in Kenya, used their own internal policies to access and used useful data. This study also focused on the Kenyan large and medium sized companies operating outside the EPZ. Future research could therefore be conducted on other sectors of the economy, for example, service delivery companies, the hospitality industry, or the tertiary educational organizations. Scholars also interested in studying data literacy in the textile manufacturing industry could study its relationship to other variables like organizational performance, change management among others.

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APPENDICES

APPENDIX I: INTRODUCTION LETTER

PERSONAL ADDRESS........................

Dear Respondent,

RE: Data Collection for Academic Research

I am Clara Kenyana currently undertaking a research project in partial fulfilment for award of Master Degree in Business Administration at Strathmore University.

I am currently undertaking a study on the topic *"Influence of Data Literacy on Managerial Decisions Making in Medium Sized Textile Manufacturing Companies in Kenya*". You company has been selected as one of the respondents. The information sought here is purely for academic purposes and will be treated with high level of confidentiality. You are hereby, humbly requested to cooperate with us voluntarily and honestly in providing the data sought. Remember that you have the freedom to withdraw any time from participating in the study.

Thank you in advance for understanding.

Yours sincerely
Clara Kenyana
Signed ....

Date..............................

APPENDIX II: PARTICIPANT INFORMATION AND CONSENT FORM

SECTION 1: INFORMATION SHEET

Investigator: Clara Kenyana

Institutional Affiliation: Strathmore Business School (SBS)

Research Topic: INFLUENCE OF DATA LITERACY ON MANAGERIAL DECISION MAKING IN MEDIUM SIZED TEXTILE MANUFACTURING COMPANIES IN KENYA

Initials of Participant: ....

Gender: ....

Place of Residence: ....

Contact Address: ....

Interview Location: ……………………………………………..

SECTION 2: INFORMATION SHEET–THE STUDY

2.1: Why is this study being carried out?

To evaluate how data literacy levels of managers influence their decision making in the Kenyan textile industry.

2.2: Do I have to take part?

No. Taking part in this study is entirely optional and the decision rests only with you. If you decide to take part, you will be asked to complete a questionnaire to get information on data literacy levels of managers and how they influence their decision making in the Kenyan textile industry. If you are not able to answer all the questions successfully the first time, you may be asked to sit through another informational session after which you may be asked to answer the questions a second time. You are free to decline to take part in the study from this study at any time without giving any reasons.

2.3: Who is eligible to take part in this study?

Primarily managers from the textile Manufacturing industry in Kenya. Specifically, managers from medium and large textile companies located outside the Export Processing Zone

2.4: Who is not eligible to take part in this study?

Anyone below the age of 18 years'

2.5: What will taking part in this study involve for me?

You will be approached by the researcher and requested to take part in the study. If you are satisfied that you fully understand the goals behind this study, you will be asked to sign the informed consent form (this form) and then taken through a questionnaire to complete.

2.6: Are there any risks or dangers in taking part in this study?

There are no risks in taking part in this study. All the information you provide will be treated as confidential and will not be used in any way without your express permission.

2.7: Are there any benefits of taking part in this study?

The information will be used to improve research study of data literacy and managerial decision making and inform policy makers, academicians and other stakeholders in the area of study. Therefore, as a manager in the textile industry in Kenya, your input in this study will have benefits for the common cause of improving and enhancing data literacy for decision making.

2.8: What will happen to me if I refuse to take part in this study?

Participation in this study is entirely voluntary. Even if you decide to take part at first but later change your mind, you are free to withdraw at any time without explanation.

2.9: Who will have access to my information during this research?

All research records will be stored in securely locked cabinets. That information may be transcribed into our database, but this will be sufficiently encrypted, and password protected. Only the people who are closely concerned with this study will have access to your information. All your information will be kept confidential.

2.10: Who can I contact in case I have further questions?

You can contact me, Clara Kenyana, at SBS, or by e-mail ckenyana@gmail.com, or by phone. 0771870552. You can also contact my supervisor, Everlyne makhanu at the Strathmore Business School, Nairobi, or by e-mail emakhanu@strathmore.edu

I, ______________________________, have had the study explained to me. I have understood all that I have read and have had explained to me and had my questions answered satisfactorily. I understand that I can change my mind at any stage.

Please tick the boxes that apply to you.

Participation in the research study

- ☐ I AGREE to take part in this research
- ☐ I DO DON'T AGREE to take part in this research

Storage of information on the completed questionnaire

- ☐ I AGREE to have my completed questionnaire stored for future data analysis
- ☐ I DO NDON'T AGREE to have my completed questionnaire stored for future data a

Participant's Signature:

Date:

______/_______/_________

____

DD / MM / YEAR

Participant's Name:

Time: ______ /_______

____

(Please print name) HR / MN

I, Clara Kenyana certify that I have followed the SOP for this study and have explained the study information to the study participant named above, and that s/he has understood the nature and the purpose of the study and consents to the participation in the study. S/he has been given opportunity to ask questions which have been answered satisfactorily.

Investigator's Signature:

Date:

______/_______/_________

____

Strathmore
UNIVERSITY

8th July 2022

Ms Kenyana Clara,
clara.kenyana@strathmore.edu

Dear Ms Kenyana,

<u>RE: Influence of data literacy on managerial decision making in medium sized textile manufacturing companies in Kenya</u>

This is to inform you that SU-ISERC has reviewed and **approved** your above **SU Masters'** research proposal. Your application reference number is **SU-IERC1333/22.** The approval period is **8th July 2022 to 7th July 2023.**

This approval is subject to compliance with the following requirements:

i. Only approved documents including (informed consents, study instruments, MTA) will be used
ii. All changes including (amendments, deviations, and violations) are submitted for review and approval by SU-ISERC.
iii. Death and life-threatening problems and serious adverse events or unexpected adverse events whether related or unrelated to the study must be reported to SU-ISERC within 48 hours of notification
iv. Any changes, anticipated or otherwise that may increase the risks or affected safety or welfare of study participants and others or affect the integrity of the research must be reported to SU-ISERC within 48 hours
v. Clearance for export of biological specimens must be obtained from relevant institutions.
vi. Submission of a request for renewal of approval at least 60 days prior to expiry of the approval period. Attach a comprehensive progress report to support the renewal.
vii. Submission of an executive summary report within 90 days upon completion of the study to SU-ISERC.

Prior to commencing your study, you will be expected to obtain a research license from National Commission for Science, Technology, and Innovation (NACOSTI) https://research-portal.nacosti.go.ke/ and obtain other clearances needed.

Yours sincerely,

for: **Dr Ben Ngoye,**
Secretary; SU-ISERC

Cc: Prof Fred Were,
Chairperson; SU-ISERC

STRATHMORE UNIVERSITY INSTITUTIONAL ETHICS REVIEW COMMITTEE
(SU-IERC)
08-Jul-2022
Email:ethicsreview@strathmore.edu
P.O BOX 59857-00200
NAIROBI-KENYA

REPUBLIC OF KENYA

NATIONAL COMMISSION FOR
SCIENCE,TECHNOLOGY & INNOVATION

Ref No: **843593**

Date of Issue: **06/May/2022**

RESEARCH LICENSE

This is to Certify that Ms.. Clara - Kenyana of Strathmore University, has been licensed to conduct research in Nairobi on the topic: INFLUENCE OF DATA LITERACY ON MANAGERIAL DECISION MAKING IN MEDIUM SIZED TEXTILE MANUFACTURING COMPANIES IN KENYA for the period ending : 06/May/2023.

License No: **NACOSTI/P/22/17333**

843593
Applicant Identification Number

Director General
NATIONAL COMMISSION FOR
SCIENCE,TECHNOLOGY &
INNOVATION

Verification QR Code

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Scan the QR Code using QR scanner application.

APPENDIX III: QUESTIONNAIRES TO MANAGERS FOR MEDIUM AND LARGE TEXTILE MANUFACTURING COMPANIES IN KENYA

INSTRUCTIONS:

Dear Respondent,

The aim of this questionnaire is to gather information relating to the "Influence of Data Literacy on Managerial Decision Making in Medium sized Textile Manufacturing Companies in Kenya." You have been chosen as one of the participants and humbly requested to participate by filling in your responses to the questions below with utmost honesty. Kindly note that this data will be treated with the utmost confidentiality and will not be used for any other purpose apart from the purpose of research.

Part A: Demographic Information

1. Number of Years the Company has been in operation

    - o Less than 5 years o 5 to 10 years
    - o 10 to 15years o 15 to 20 years
    - o Over 20 years

2. What is your Gender?

    - o Male o Female

3. What Age Bracket do you belong to?

    - o Below 25 years o 25 to 35 years
    - o 35 to 45 years o 45 to 55 years
    - o Over 55 years

4. What is your Highest Educational Level achieved?

    - o Diploma o Undergraduate Degree
    - o Masters Degree o PhD

5. For how long have you worked for the Company?

    - o Less than 1 year o 2 to 5 years
    - o 6 to 9 years o 10 years and above

6. What is your Leadership Level? *

    - o Lower-Level Management o Middle Level Management
    - o Top Level Management o Owner/Director

PART B: DATA ACCESSIBILITY

The researcher aims to assess the accessibility in the Kenyan textile manufacturing industry. Please use the Likert scales 1-5, where 1- Strongly Agree, 2- Agree, 3-Uncertain, 4- Disagree, 5- Strongly disagree, to indicate your degree of agreement or disagreement with the statement on the left.

Statement	**1**	**2**	**3**	**4**	**5**
7. The Company seeks to constantly identify and collect the relevant data required for managerial decision making.					
8. The Company has consistent and readily available sources of data required for managerial decision making.					
9. The data required for managerial decision making is stored securely with accessibility checks and restrictions where necessary.					
10. The data required for managerial decision making is easily and conveniently accessible to managers in the company.					
11. The data that is available and accessible to the company is current, accurate and relevant to the current decision-making needs.					
12. The data that is available and accessible to the company is comprehensive and complete to the current decision-making needs.					
13. The data that is available and accessible to the company is unique and detailed to provide sufficient distinctive properties for better decision-making.					
14. The cost of accessing data required for decision making is manageable to the organization					
15. The company can maintain high data availability and accessibility to all managers.					

16. In your opinion, what are the main sources of data at your organization?

____

____

____

____

PART C: DATA SKILLS LEVEL

The researcher aims to evaluate the data skills levels of Managers in Kenyan textile manufacturing industry. Please use the Likert scales 1-5, where 1- Strongly Agree, 2- Agree, 3-Uncertain, 4-Disagree, 5- Strongly disagree, to indicate your degree of agreement or disagreement with the statement on the left.

Statement	1	2	3	4	5
17. All hierarchical layers within the company have a basic understanding of the concept of data and can engage with data fitting their role.					
18. The company has in place a data management policy that indicates required data skills level for managers in different positions.					
19. Managers can identify the producers of data available and understand who the targeted data consumers are.					
20. The managers have the skills to access, write and engage in data analytics programs					
21. The managers have the general knowledge and capabilities of retrieving and use of data for decision making					
22. The managers have the skills to select, clean and analyse data for decision making.					
23. The managers can critically assess, visualize and interpret data available for decision making					
24. The managers have the skills to effectively reason and communicate the right stories from data and use it for decision making.					

PART D: DATA USE

The researcher aims to evaluate the extent of data use and how it relates to managerial decision making in Kenyan textile manufacturing industry in decision-making. Please use the Likert scales 1-5, where 1- Strongly Agree, 2- Agree, 3-Uncertain, 4- Disagree, 5- Strongly disagree, to indicate your degree of agreement or disagreement with the statement on the left.

Statement	**1**	**2**	**3**	**4**	**5**
25. The company has created a culture where data literacy and use are encouraged and embraced.					
26. The company encourages managers to use data available in making decisions					
27. The company has engaged data sources that provide relevant data for decision making					
28. The higher the hierarchical management levels, the more data is used in managerial decision making					
29. Managers have extensive operational and business knowledge but limited to no data analytical knowledge					
30. Managers understand and engage with data but have little analytical capabilities.					
31. In addition to understanding and engaging data, Managers in the company have profound data analytical and statistical skills.					
32. Managers can effectively interpret and communicate results and reason with data for decision making					
33. The managers have the skills to effectively reason and communicate the right stories from data and use it efficiently for decision making.					

34. In your opinion, what is are the main barriers for data use in your organization?

____
____
____
____

PART E: MANAGERIAL DECISION MAKING

The researcher aims to assess the decision making in the Kenyan textile manufacturing industry. Please use the Likert scales 1-5, where 1- Strongly Agree, 2- Agree, 3-Uncertain, 4- Disagree, 5- Strongly disagree, to indicate your degree of agreement or disagreement with the statement on the left.

Statement	**1**	**2**	**3**	**4**	**5**
35. Managerial decisions in the company are made heavily backed by data.					
36. Managerial decisions in the company are made mainly through the managers intuition and experience					
37. Managerial decisions in the company are made using both the managers intuition and experience and backed by data.					
38. Data based decision making in the company has helped improve transparency and accountability in managerial decision making					
39. There is constant improvement and overall performance and operational efficiency due to data-based decision making in the company.					
40. Critical managerial business decisions made are tied to data analytics insights					
41. Data based decision making in the company helps in getting relevant and timely feedback on decisions made and implemented					
42. Data based decision making at the company has enhanced consistency in operations and strategic direction.					

43. In your opinion, what is the biggest determinant to decision making by managers in your organization?

____
____
____
____
____

APPENDIX IV: LARGE AND MEDIUM SIZED TEXTILE MANUFACTURING COMPANIES OUTSIDE EPZ IN KENYA

1. Spin Knit Limited, Location: Eldoret/Nairobi

2. Rivatex East Africa Limited, Location: Nairobi/Eldoret

3. Thika Cloth Mills, Location: Thika

4. Sunflag Textile & Knitwear Mills, Location: Nairobi

5.Spinners & Spinners Ltd, Location: Nairobi

6. Fine Spinners Ltd, Location: Nairobi

7. Alliance Garment Industries Ltd, Location: Nairobi

8. KEMA East Africa Ltd, Location: Nairobi

9. Supra Textiles Ltd, Location: Nairobi

10. Specialised Towel Manufacturers Ltd, Location: Nairobi

11. United Footwear Ltd

12.AfricanLeatherIndustriesLtd

13. C&P Industries Limited, Location: Nairobi

14. Bantu Shoes, Location: Nairobi

15. Peponi Footwear Industries, Location: Mombasa

16. Macquin Shoes Ltd, Location: Mombasa

17. Supra Textile Ltd, Location: Nairobi

18. Adix Ltd, Location: Nairobi

19.United Aryan EPZ ltd , Location: Nairobi

20.Brother Knitwear factory Ltd , Location: Nairobi

21.Kenyamasken Garments Ltd , Location: Nairobi

22.Specialised Towel Manufacturers Limited , Location: Nairobi

23.Ken Knit (Kenya) Ltd , Location: Eldoret

24.Oriental mills ltd , Location: Nairobi

25.Zig-Zag furnishings , Location: Nairobi

26.Ashton Apparel EPZ Mombasa

27.Sai sport wear & uniforms ltd Nairobi

28.Association of Fashion designers Nairobi

29.United textile industry Ltd Nairobi

30.Riera-Tex ltd – Nairobi

18Kiboko Leisure wear Ltd Nairobi

31.IKOROMEO (Kiro Ltd) Nairobi

32.Kimili Africa Nairobi

33.Kitui Ginneries Ltd Kitui

34.LOULOU CREATIONS Nairobi

35.Makueni Ginnery Makueni

36.MEFA Creations Nairobi

37.Silver star manufacturers Nairobi

38.Midco Textiles (EA) Ltd Nairobi

39.New wide Garments Kenya EPZ Ltd Athi River

40.Rupa Mills (EPZ)td Athi River

41. Sandstorm Nairobi

42. Bhupco textile mills Ltd

43. Tosheka Textiles Makueni

44. TSS spinning & weaving mills Nairobi

45. Ultra Kenya Ltd Nairobi

46. Africa of Women Entrepreneur Program Athi River

47. Alltex EPZ Ltd Ruiru

48. Alpha Knits Limited Nairobi

49. Equator Apparels Nairobi

50. Smartex garmets Nairobi

51. Fair Trade Africa

52. Global Apparels