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Analysis of factors affecting adoption of big data in the automotive assembly industry in Kenya.

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ANALYSIS OF FACTORS AFFECTING ADOPTION OF BIG DATA IN THE AUTOMOTIVE ASSEMBLY INDUSTRY IN KENYA

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Declaration

I declare this proposal is my original work and has not been presented any other institution for the award of diploma or degree

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Approval

This research dissertation has been reviewed and approved by me as the university appointed supervisor

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Date **……17th August 2023……**

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Dedication

I dedicate my work to my family, Sharon who stood with me during the entire academic journey. Their encouragement helped me to complete my academic journey. Special gratitude goes to parents Mr. and Mrs. Macharia, for giving me the foundation in education, may God bless them abundantly. To my sister and the entire MBA 2022 classmates, I salute you for being there to cheer me up to the finishing line.

ABSTRACT

The study seeks to assess factors that influence the big data acceptance in the automotive sector in Kenya. The application of big data in companies has been linked to increased customer satisfaction, improved quality, better decision-making, and robust financial performance. Furthermore, in the automotive industry, the big data is applied with the aim of improving safety and providing timely data vital in enhancing customer experience. Despite the benefits associated with big data, the Kenya's automotive industry has not fully integrated the technology within its operation, hence, missing out on the advantages. The goal of the present study was to establish how the independent variables (innovative culture, perceived ease-of-use, and perceived usefulness) influence the adoption of big data. TAM theory applied. To determine the factors affecting the adoption of big data in the automotive industry, a correlational research design was used. The quantitative study is grounded on the positivist research philosophy. A sample of 235 respondents was obtained from Kenya Vehicles Manufacturers, Associated Vehicles Assemble, Isuzu East Africa, Mobius Motors, and Trans Africa Ltd using a correlational research design and simple random sampling technique. Both the descriptive and inferential statistics were provided. Results indicated a strong and significant relationship between the perceived ease-of-use, perceived usefulness, and innovative culture and the adoption of big data in the automotive industry. Recommendations included improved leadership to enhance big data adoption in automotive sector, improve technology safety, and foster simplification of big data. Future researchers should consider exploring the big data use in other industries and apply mixed research methodology.

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Definition of Terms

Ease-of-use: The extent to which a given technology or innovation can be used without much effort (Sayem et al., 2022)

Innovative Culture: Workplace environment that fosters imagination, creativity, and positive attitudes towards new ideas, and that everyone can use these ideas to improve their operations (Oyewo, 2022).

Perceived usefulness: The degree to which users of an innovation believe it has benefits that will help improve performance of the organization (Lufti et al., 2021)

CHAPTER ONE: INTRODUCTION

1.1 Background Information

The automotive industry is a key player in Kenya's economy, which is currently undergoing a transformation that promises to reshape its landscape and drive innovation. One of the transformative forces at the forefront of the change in question is the analytics integration of the big data (Raj et al., 2017). Big data, which is characterized by its vast volume, velocity, variety, and value (Graf-Vlachy et al., 2018; Chauhan et al., 2021; Oyewo, 2022) have become one of the powerful tools, with a potential to revolutionize the automotive sector in Kenya. Consequently, the application of big data analytics within this industry offers a multitude of benefits, making it a topic of great interest and significance. For instance, enhanced vehicle safety is one of the benefits of big data in the automotive industry as it can collect and analyze real-time data from multiple sensors within vehicles. Consequently, the obtained data can be used to detect anomalies and potentially prevent accidents. It also helps in developing advanced driver assistance systems (ADAS) and autonomous vehicles, which have the potential to significantly reduce road accidents (Deloitte, 2020). Optimized maintenance is another crucial benefit of big data in the automotive industry. Unquestionably, monitoring the condition of vehicle components and predicting maintenance needs based on data analysis, big data can lead to proactive maintenance schedules (Sayem et al., 2022). This not only increases vehicle reliability but also reduces downtime, lowering operational costs for fleet owners and individual consumers.

Big data has been defined as the high-volume, high-velocity, and high-variety information (Raj et al., 2017; Dremel, 2017) that continues to grow exponentially, requiring sophisticated method of analysis and storage (Oyewo et al., 2021; Chauhan et al., 2021), and whose insights are applied to make informed decisions in various sectors (Raj et al., 2019; Lufti et al., 2021; Oyewo, 2022). According to a report by Deloitte (2020), factors such need to enhance customer satisfaction, demand for quality and safety, and the demand for self-driving vehicles, have created the increased application of big data and analytics in the automotive industry. Similar observations were made by Singh and Bhardwaj (2019)

who indicated that the need to enhance customer experience, increase efficiency, and address safety issues were driving manufacturers in the automotive industry towards the application of the big data. Big data analytics have been linked to increase in income, improved quality of decisions (Oyewo et al., 2022), customer satisfaction, increase in sales and efficiency (Lufti et al., 2021; Nguyen & Liaw, 2020; Chauhan et al., 2021). Thus, benefits of big data to different sectors cannot be ignored.

1.1.1. Factors Affecting Adoption of Big Data

Many studies demonstrate that perceived use of a major factor influencing the adoption of technology. According to Li et al. (2019), the ease-of-use, which relates to the complexity of big data technologies, is a major big data adoption barrier in organizations. The application of big data requires a higher level of knowledge and skills leading to high training costs and may discourage employees from adopting big data technologies. The study notes that the solution to this issue lies in providing employees with appropriate training and support to use big data effectively. In another similar study, Chauhan et al. (2021) established that technology skills, knowledge, and relevant support were strong predictors of adoption of technology. From these studies, if the technology is perceived complex and requiring much effort to apply, it is more likely to be rejected.

Other studies have established the organizational culture has a significant influence to the adoption of big data in the automobile sector is the organizational culture (Graf-Vlachy et al., 2018; Kshetri, 2014). Graf-Vlachy et al. (2018) states that organizational culture is the shared values, beliefs, attitudes, behaviors, and practices that define how an organization operates. It is the organizational glue that brings members of the organization together and guides their actions. A lack of culture of technology in many companies and on the part of government, particularly on data protection and financial support (Graf-Vlachy et al., 2018). On the contrary, Kshetri (2014), observed that the automobile industry has a hierarchical culture that is not conducive to the big data adoption. The automobile industry is characterized by a top-down decision-making structure, making it almost impossible for middle and lower-level staff to contribute significantly to the decision-making process.

From the findings, Muriithi et al. (2016) determined that culture of technology was lacking in many organizations hampering the adoption of innovation. Culture has been found to influence attitudes and beliefs, which can act as enablers or barriers to technology adoption. Sayem et al. (2022), established that companies who were convinced of the benefits of big data were more likely to invest in it than those who did not. For instance, many company managers linked big data to mass production, more informed decision-making, and improved quality leading to the adoption. From these studies, barriers to adoption of big data include the perceived usefulness of the technology, the ease of use, and the organizational culture.

1.1.2 Extent of Adoption of Big Data

Ancient forms of big data can be traced back to 18,000 BCE when Paleolithic tribespeople marked notches on sticks to keep information on daily sales and supplies. The stored information was useful in making prediction about future sales, expected profits, and the trading activities (Firican, 2016). In 300 BC Egyptians attempted to create a system that would help them summarize data from the Alexandria library (Firican, 2016). Similarly, the Roman Empire, in an effort to increase the efficiency of the distribution of resources to their military, applied statistics to analyze the previous supplies. Thus, the concept of big data is not new to humanity.

In 1880, the U.S. Census Bureau determined analysis of data was cumbersome and would take years to obtain actionable information (Foote, 2017). This saw the development of technologies such as punch cards by IBM to help the government analyze population data for decision-making (Firican, 2016). Similarly, during the World War II, British experienced challenges of deciphering Nazi's code due to information overload. The development of Colossus device reduces the time required to analyze Nazi's information from days to hours, hence, enabling the British military to make quick and more accurate decisions (Firican, 2016). The age of internet began in the early 1980s and has played a significant role in the growth and development of the big data (Foote, 2017; Raj et al., 2019; Lutfi et al., 2022). Thus, from history, it is apparent that big data was commonly

applied by governments. Today, however, big data is now applied in businesses to make informed decisions.

With the current global technological advancement, the automotive industry is shifting towards the Fourth Industrial Revolution (Industry 4.0), which is characterized by adoption of latest technologies to foster smart, quick, and evidence-based decision-making (Deloitte, 2020; Raj et al., 2019; Lutfi et al., 2022). Industry 4.0 technologies, including sensors, cloud technologies, artificial intelligence, and big data analytics, are fundamental in understanding customer behavior, particularly, their tastes and preferences (Raj et al., 2019). In the 21st century, data becomes the most valued asset for companies. Big data refers to the structured or unstructured data mined from various sources, including as social media posts, marketing firms, and smartphone location data, which is later analyzed and information used in major decision-making. According to ReportLinker, a reputable technology company based in France, the value of big data market in automotive industry was about $4.21 billion in 2022 and expected to rise to $9.92 billion in 2027 (ReportLinker, 2022), indicating the perceived importance of big data. In the field of automotive, big data analytics is applied in supply chain management, automobile financing, and predictive analysis.

Despite the benefits associated with big data, including enhanced vehicle safety, optimized maintenance, understanding customer behavior, enhancing efficiency in manufacturing sector, and minimizing supply chain risks (Deloitte, 2020; Sayem et al., 2022), the adoption of big data, especially in the developing countries, is a big challenge (Raj et al., 2019; Lutfi et al., 2022). Some studies show a link between internal digital culture, data security issues, and awareness on technological benefits and adoption of big data technology (Moktadir et al., 2018; Alalawneh & Alkhatib, 2020; Nguyen & Liaw, 2020). However, the major gap is that most of these studies used small sample sizes, mainly focused on barriers to big data adoption in developed countries, and were mainly qualitative.

In the United States and China, the lack of an innovative culture was cited as one of the main barriers to the adoption of big data (Graf-Vlachy et al., 2018). In the same study, it

was apparent that managers and leaders play a fundamental role in establishing perceptions, beliefs, and attitudes that can act as enablers or barriers to technology adoption. Another study by Moktadir et al. (2018) also established that in Bangladesh, negative attitudes and beliefs about technology hampered adoption of big data in various sectors. In Jordan, Lufti et al. (2022), indicated that while culture was a predictor of big data adoption, it was not the only factor as many users of technology made adoption decisions based on the perceived usefulness of the said technology. The finding of this study has been corroborated by others (Alalawneh & Alkhatib; Graf-Vlachy et al., 2018), showing the importance of perceived usefulness of technology, including whether the technology increases sales, helps to improve quality, increases revenue, or rises market shares. Other studies, however, indicate that even with the supportive culture and positive perception of technology, adoption of technology can be hampered by the perceived ease of use (Nguyen & Liaw, 2020; Chauhan et al., 2021; Oyewo et al., 2021). For instance, Moktadir et al. (2018), established that the perceived ease of use of technology became a barrier to adoption of technology in Bangladesh since many staff felt that they did not have the right skills and knowledge.

1.1.3 Automobile Industry in Kenya

In Africa, including Kenya, the main limitation is the lack of sufficient empirical studies on big data application in various sectors. As a result, it is difficult to determine what barriers or enablers influence the adoption of technology. From the analysis above, a major limitation is small data size applied by researchers to warrant generalizability of some results. While barriers such as perceived usefulness, perceived ease of use, and innovative culture have been mentioned, it was not clear which among them is the greatest barrier, to what extent, and whether they can also be considered as the main barriers in Kenya. Thus, this study will seek to address some of these barriers.

While studies show a link between big data and benefits such as customer satisfaction, quality of decisions, increased safety and quality, and high revenue and rise in market share, barriers to adoption means low big data adoption, especially in the automotive sector. The limited number of studies in Africa, including Kenya, makes it difficult to

understand the state of adoption of big data. In other countries, such as the United States, General Motors have adopted big data and analytics obtained from sensors in the connected vehicles, are being used to improve safety standards, quality, and efficiency (Graf-Vlachy et al., 2018). The use of big data analytics to improve quality and safety standards in vehicles assembled in Kenya is fundamental. Besides, the background information highlights a lack of sufficient empirical studies on big data application in various sectors in Africa, including Kenya. This research aims to address this gap by providing empirical evidence specific to the Kenyan automotive industry. This empirical approach distinguishes this study from past research that may have relied more on qualitative or theoretical analyses. Additionally, in the past studies, there is a limitation in many past studies, which used small sample sizes, potentially limiting the generalizability of their results. Consequently, this study aims to collect a more extensive and diverse dataset to enhance the generalizability of your findings and contribute valuable insights that can be applied to the broader automotive industry in Kenya.

In the modern society, there are various barriers and factors that affect adoption in the automotive industry. For instance, the automotive industry may face challenges in terms of the existing IT infrastructure and technological capabilities necessary for handling and processing big data. Inadequate data storage, processing power, and network connectivity could hinder adoption. Privacy and security issues are paramount, especially when dealing with sensitive customer and vehicle data. Concerns about data breaches and misuse can impede adoption efforts. Implementing big data solutions in the automotive industry can be costly. This includes investments in hardware, software, personnel training, and ongoing maintenance. Cost-related barriers may discourage adoption, especially for smaller companies.

Unquestionably, in Kenya, the automotive provides a significant contribution to the country's economy and holds immense potential for growth and innovation. Currently, the adoption of big data in this sector is in its nascent stages, with notable opportunities and accompanying challenges. Kenya's automotive industry, which encompasses vehicle

assembly, distribution, sales, and servicing, is gradually recognizing the potential of big data technologies. Several key developments indicate a growing interest in incorporating big data analytics. For instance, most automotive companies have started exploring connected vehicles technologies, where data generated by vehicles can be collected, analyzed, and utilized for various purposes, including safety monitoring and predictive maintenance. The industry in question is also beginning to appreciate the benefits of data-driven supply chain management, which can help in optimizing inventory levels, reducing costs, and improving overall efficiency. Additionally, automotive businesses are becoming more interested in collecting and analyzing customer data to enhance the overall customer experience and tailor their products and services accordingly. Also, there is recognition that big data can be employed to enhance vehicle safety and compliance with regulatory standards, a crucial factor given the increasing focus on road safety.

Challenges of big data application in Kenya are evidenced by a survey conducted by Fuso, a multinational automotive company (Figure 1.1 below). In this particular survey, Fuso wanted to test various parameters such as fuel consumption, cargo transported, efficiency, kilometers covered, and general customer experience. One of the main limitations in the survey was the application of manual methodology, including use of excel sheet to collect and analyze data, leading to biased findings. As a result, it was difficult for Fuso to achieve its objectives since the data obtained was considered inaccurate and inadequate. Additionally, use of manual technique required more human resources and time making the whole process expensive. This example demonstrates why the adoption of big data is vital.

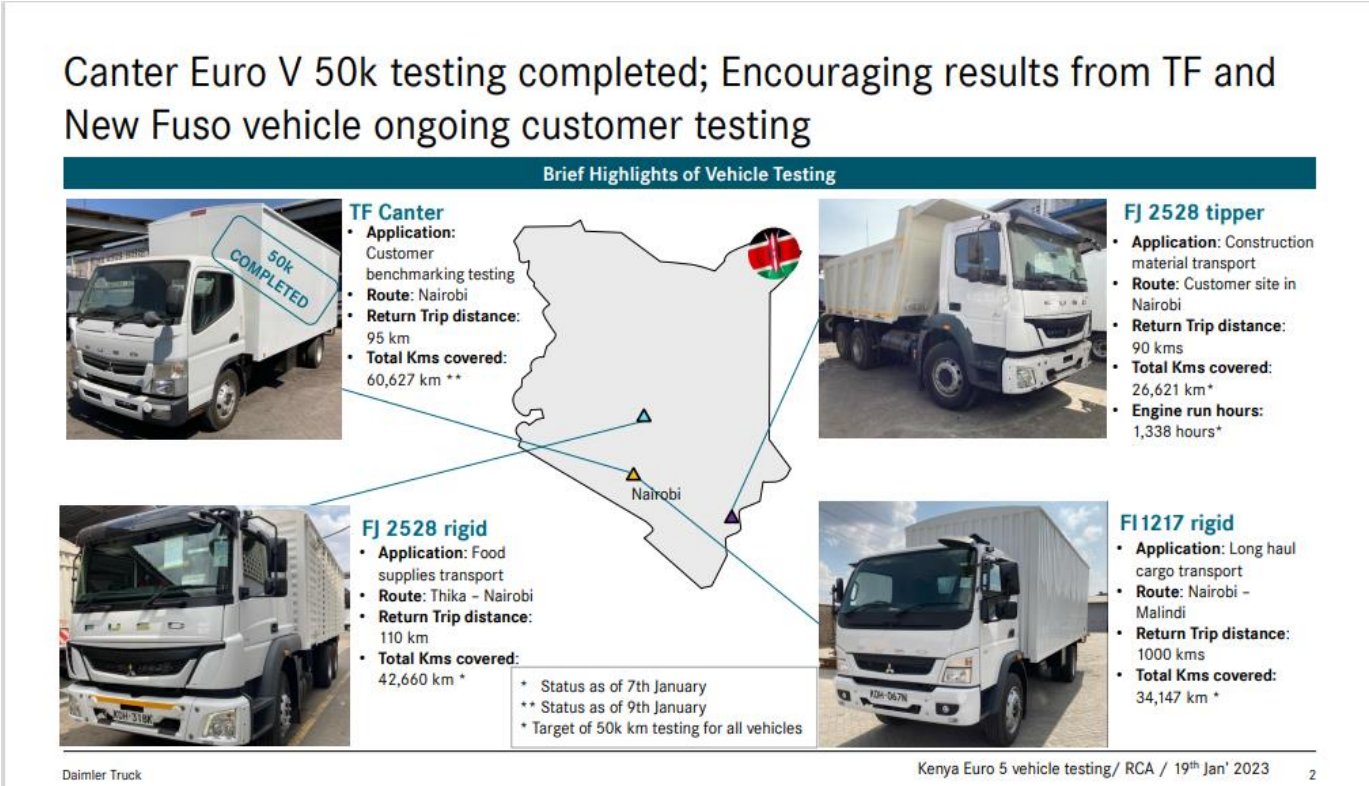

Figure 1.1 Customer Testing Technology

Despite these positive developments, the extent of big data adoption in Kenya's automotive industry is still limited compared to more developed automotive markets globally. Challenges and barriers persist, which impact the full-scale integration of big data technologies.

For example, insufficient IT infrastructure and technology can hinder the effective implementation of big data solutions. These limitations may include inadequate data storage, slow network connectivity, and outdated systems. Also, protecting sensitive customer and vehicle data is a top priority in the adoption of big data technologies. The high cost of implementing big data solutions, including hardware, software, staff training, and maintenance, is also a substantial barrier for smaller automotive businesses.

1.2 Statement of the Problem

Ideally, big data can contribute significantly to the development and growth in the automobile industry. Consequently, that helps in creating more employment opportunities and increased for the government as demonstrated from the background information (Kshetri, 2014; Graf-Vlachy et al., 2018). Big data can help in better and informed decision-making, enhancing efficiency, reducing costs of operation, and fostering a business competitiveness (Lufti et al., 2022). Thus, benefits of big data to the automotive industry cannot be underestimated. However, organizations cannot leverage big data benefits if they fail to identify the impediments to big data adoption (Graf-Vlachy et al., 2018). By understanding the barriers, organizations can take necessary measures aimed at fostering the big data adoption.

In Kenya, there is limited information regarding the factors that influence the adoption of big data in the automotive industry, explaining the need for the present study. From the KAM report (2020), factors such as the lack of adequate information about big data, limited technological skills and competency, and a general lack of technology culture influence adoption of technology in companies. However, there is a lack of empirical studies that should demonstrate objectively whether such factors (mentioned by KAM) are indeed barriers and to what extent they influence the adoption of big data in the automotive industry in Kenya. This is a significant gap which this study seeks to address.

In addition to the mentioned gaps, there are other issues that justify this study. For example, existing studies on big data adoption in the automotive industry have primarily focused on developed countries (Lufti et al., 2022; Graf-Vlachy et al., 2018), leaving a significant research gap in understanding the dynamics and barriers to adoption in developing regions like Kenya. Besides, many previous research efforts have been largely theoretical or qualitative in nature (Kshetri, 2014; Sayen et al., 2022), lacking sufficient empirical studies specific to the Kenyan context. There is a gap in the availability of comprehensive, data-driven research. Additionally, past research has often explored individual barriers to big data adoption in isolation. A research gap exists in terms of conducting a comparative

analysis to understand which barriers are most significant, to what extent, and whether they interact with one another in the Kenyan automotive industry.

The proposal, therefore, is to encourage a culture of technology adoption within the automotive industry. This will include supportive government policies, effective leadership, and steps aimed at improving technology-related safety and privacy. Enhancing technology skills and competency will motivate adoption of big data. Furthermore, creating knowledge on the benefits associated with the big data can foster its adoption within the Kenya's automotive industry.

1.3 Research Objectives

1.3.1 General Objective

The main objective of the study demonstrate how various factors influence the adoption of big data in the automotive sector in Kenya.

1.3.2 Specific Objectives

i. To assess how the lack innovative culture influences the big data adoption in the automobile sector in Kenya.
ii. To evaluate the link between staff's negative perception on ease-of-use influences big data adoption in the automotive industry in Kenya
iii. To examine how the perceived lack of usefulness influences the adoption of big data in the automotive industry in Kenya.

1.4 Research Questions

i. How does the lack of innovative cultures influence the acceptance of big data in the automotive industry in Kenya?
ii. What is the link between staffs' perceived ease-of-use and adoption of big data in the automotive industry in Kenya?
iii. How does the perceived lack of usefulness influence the adoption of big data in the automotive industry in Kenya?

1.5 Scope of the Study

The study is conducted in the automotive industry in Kenya, targeting employees in the Kenya Vehicle Manufacturers (KVM), Associated Vehicle Assemblers (AVA) & Isuzu East Africa. Specifically, the study is only focused on understanding how barriers (perceived usefulness, perceived ease-of-use, and innovative culture) influence adoption of big data.

1.6 Significance of the Study

In Kenya, the research barriers to the big data adoption in the automotive sector holds paramount significance in multiple stakeholders, including policymakers, practitioners, and scholars. For policymakers, the study in question provides crucial insights into the challenges and opportunities associated with the big data adoption in the automotive sector. As a result, understanding the specific barriers faced by the industry allows policymakers to develop targeted initiatives and policies that support technology adoption, stimulate economic growth, and improve safety and regulatory compliance. Therefore, by addressing these barriers, policymakers can create an environment conducive to innovation and technological advancement, fostering Industry principles in line with Kenya's economic development goals.

Similarly, automotive industry practitioners, including manufacturers, dealers, and service providers, will benefit from this research by gaining a comprehensive understanding of the hurdles they face in embracing big data analytics. Unquestionably, by identifying the most significant barriers, management can strategize and invest wisely in mitigating these challenges. This research enables industry players to make informed decisions regarding technology adoption, data security, infrastructure development, and talent acquisition. Ultimately, it empowers them to enhance safety, streamline supply chains, and deliver a superior customer experience, promoting competitiveness and growth.

Lastly, academic scholars and researchers will find value in this study as it contributes to the existing body of knowledge on big data adoption, particularly in the context of a developing country's automotive industry. The research provides a deeper understanding

of the dynamics, challenges, and opportunities specific to Kenya, enabling scholars to expand their research horizons. Additionally, the comparative analysis of barriers and the empirical evidence generated offer insights that can inform further studies and enhance the quality of research in the field of big data adoption, not only in Kenya but also in similar contexts.

CHAPTER TWO: LITERATURE REVIEW

2.0 Introduction

The chapter outlines and critically analyzes the theoretical framework. Furthermore, a critical analysis of empirical information from previous studies is provided. Additionally, the limitation of literature on the barriers of big data adoption in the automotive sector is also discussed. Thus, the literature review is divided into theoretical review, empirical review, literature review gaps, and summary.

2.1 Theoretical Literature Review

As a source of competitive advantages, big data analytics is pivoting the automotive sector. Globally the automotive sector is experiencing significant transformation driven by the increasing availability and potential of big data. Big data analytics provide an understanding of vehicle performance, safety, customer behavior, and empirically. However, the application of big data analysis in the automotive sector in Kenya has met several barriers. This theoretical literature review aims to analyze and identify the obstacles to adopting enormous data in the automotive sector. The use of big data in the automotive industry faces various challenges. Various theoretical literature perspectives can provide insights into these challenges and experiences. The theoretical perspectives include; technology acceptance model and Institution theory. Applying these theories' perspectives to the study objectives helps in understanding how employees' perceptions of big data technology are likely to influence its adoption, more so in Kenya's automotive industry context, thus helping identify the role of culture and perceptions in adoption process.

2.1.1 Adoption of Big Data from Technology Acceptance Model Perspective

Fred Davis is the main proponent of Technology Acceptance Model (TAM), which has become one of the most widely applied theories to explain why and what motivates people to adopt a given technology. Davis developed this theory in 1989 being a modification of Theory of Reasoned Action by Ajzen and Fishbein. The theory posits that the adoption of technology is explained by two main factors: The perceived usefulness and the perceived ease-of-use (Davis, 1989). A technology aims to address certain challenges, including

improving quality, fast-tracking processes, and minimizing wastages. These benefits, if met, would then mean that the technology is helping an organization or people to overcome their main challenges. Thus, perceived usefulness is defined as the extent to which a given technology is perceived by its users to help in overcoming certain shortcomings or in enhancing job performance. A technology is likely to be adopted if it adds significant value to an organization in terms of efficiency, effectiveness, and performance.

Davis argued that perceived usefulness is not sufficient to warrant the technology adoption. The perceived ease-of-use is equally fundamental. The users of technology must not struggle to use the technology. Perceived ease-of-use refers to the perception of the people that the technology is free from effort (Davis, 1989). A complex technology would increase barrier to its adoption because of the strain it causes on its users. In this regard, it is imperative that users of technology have the necessary technical knowledge and skills to use the technology with minimal assistance.

Later developments of TAM theory have seen other factors such social influence included as a factor affecting adoption of technology. The social influence refers to the culture of technology adoption within the society (Graf-Vlachy, et al., 2018). The same authors argued that if a society values and creates a favorable environment for technology, there is increased positive attitudes towards innovation and possible adoption. While the theory in question is widely applied to explain the adoption technology, it has attracted criticism for being subjective and simplistic (Graf-Vlachy et al., 2018). Nonetheless, this theory remains fundamental in achieving the aim of this study and will be utilized together with the findings from empirical studies. The theory in question is relevant to this study because it relates to the research topic that seeks to establish barriers to adoption of big data.

The model focuses on factors that impact individual adoption and reception of innovative technologies. The context of extensive data adoption in the automotive industry in Kenya can help identify barriers related to intentions, attitudes, and perceptions toward big data technologies. The focus can be on perceived ease of use and resistance to change.

Businesses operate under a legal framework that impacts their activities (Arpaci, 2019). In Kenya, the automotive industry operates under a regulatory framework that needs to adequately address the various challenges posed by the adoption of big data. There are concerns about unclear regulations concerning data collection, ownership, sharing, and privacy creating uncertainty and hindering the application of big data analytical initiatives in the automotive field. In addition, the ownership and management of enormous data in the automotive sector can be complex, involving various stakeholders such as service providers, dealers, and manufacturers. The uncertainty of appropriate data management and ownership measures involving data sharing, ownership, and access among the stakeholders impede the application of big data initiatives in the automotive industry.

Perceived ease of use denotes to the level at which people are confident about applying a specific technological skill. In the data adoption context, focus on the perception of the stakeholders to utilize and understand big data techniques and analytics. In accordance with the technology acceptance model, perceived ease of use is a significant determinant that impacts an individual's intentions and attitude toward adopting new technologies. A negatively perceived ease of use can significantly hinder the implementation of big data analytical initiatives in the automotive industry. The perception can involve having a viewpoint that adopting big data is complex and challenging, deterring its adoption and employee resistance. In addition, adequate training and knowledge about big data analytics can lead to a positive perception of the benefits of extensive data adoption.

TAM directly aligns with the first objective, which aims to assess the influence of innovative culture on the big data acceptance in the automobile industry in Kenya. For instance, the theory suggests that people's perceptions of a technology's ease of use and usefulness influence their adoption behavior. Therefore, the theory is essential in examining how the innovative culture within automotive companies impacts employees' perceptions of big data technology, usefulness, and ease of use. The second objective, to evaluate the connection between staff's perceived ease-of-use and adoption of big data in the automotive industry in Kenya, is one of the core elements of TAM. Consequently, this theory aligns with the objective, making it essential in exploring how employees' perceived

ease of use of big data tools and systems influences their willingness to adopt these technologies. Similarly, the third objective, to examine how the perceived usefulness influences the implementation of big data in the automotive industry in Kenya, corresponds with this theory directly. As a result, the theory is essential to this study as it helps in investigating how the perceived usefulness of big data technology affects its adoption within the context of the automotive industry in Kenya.

According to Davis (1989), one of this theory's strengths its focus on its key factors, perceived ease of use and perceived usefulness, which are crucial for understanding technology adoption. Besides, multiple studies have validated the theory's predictions and have demonstrated that perceived ease of use and perceived usefulness do influence technology adoption (Smith, 2018; Jones & Brown, 2019). Conversely, Jones & Brown (2019), also states that the model in question tends to overlook contextual factors that are likely to impact technology adoption. Furthermore, they argue that real-world adoption decisions are often influenced by external factors such as organizational policies, social norms, and economic conditions, and TAM does not explicitly consider these factors, which can limit its explanatory power. Likewise, Lee & Park (2020), argues that TAM places a heavy emphasis on individual perceptions, assuming that individuals make adoption decisions primarily based on their personal beliefs about ease of use and usefulness. In reality, social and organizational factors can exert a strong influence on technology adoption, and TAM does not fully address these influences.

2.1.2 Institution Theory Perspective on Adoption of Big Data

The institutional theory that was established by John Meyer and Brian Rowan in the late 1970s, help in exploring the way firms fit with, are connected to, and were shaped by their societal, state, national, and global environments (Peters, 2019). The theory in question is essential in understanding organizations and management practices as the product of social rather than economic pressures. In modern society, it has become a popular perspective within management theory due to its ability to explain organizational behaviors that defy economic rationality. In the context of enormous data adoption in the automotive industry in Kenya, a lack of established policies, standards, and regulations to guide the collection,

storage, and use of data can hinder the adoption of big data analytical initiatives. In an effort to avoid conflicts and uncertainty in the regulations and policies, automotive industries shy away from adopting big data analytics. Data analytics initiatives raise ethical concerns regarding data collection, potential bias, and usage. In adopting big data analytics, companies need to uphold ethical considerations such as anonymization, informed consent, and fairness in data analysis to enhance public trust and promote sharing of crucial information by customers, which is essential in making informed decisions. Concerns about clarity guidelines regarding data collection, ownership, distribution, and discretion create hesitation and delay the application of big data analytical initiatives in the automotive sector. In addition, the ownership and management of big data in the automotive industry can be complex, involving various stakeholders such as service providers, dealers, and manufacturers (Ebrahimi & Koh, 2021). The uncertainty of appropriate data management and ownership measures involving data sharing, ownership, and access among the stakeholders impede the application of big data analytical strategies in the automotive industry.

Institutional theory is a valuable framework theory to consider when conducting research on the big data adoption in the automotive sector in Kenya, as it explores how industries and organizations are shaped by external values, pressure, and norms. However, various scholars have several critiques for this theory. For instance, Scott (1995), argues that the theory in question often emphasizes the role of external pressures and norms in shaping organizational behaviors, which can sometimes downplay the role of individual agency and internal organizational dynamics. Additionally, DiMaggio and Powell (1983), states that institutional theory assumes that organizations within the same industry tend to conform to similar institutional norms. The authors further states that it would be essential for the theory to acknowledge that industries can vary significantly, even within the same country.

Institutional theory can be applied to understand the broader context and the influence of institutional factors on the implementation of big data in the Kenyan automotive field. One of the objectives in this research, to assess the influence of innovative culture on the adoption of big data in the automobile industry in Kenya, aligns with the perspective

theory. According to the institutional theory, organizations tend to adopt practices and technologies that align with prevailing institutional norms and expectations. In the Kenyan automotive industry, innovation culture can be seen as an institutional norm or pressure that may either hinder or facilitate the adoption of big data.

Arguably, perceived ease-of-use, which is one of the objectives for this study, is often influenced by organizational practices and norms. According to the institutional theory, employees' perceptions and behaviors are shaped by the institutional environment.

The other objective of this study is to examine how the perceived usefulness influences the adoption of big data in the automotive industry. Since the perceived usefulness of big data can be influenced by industry norms and pressures, the objective in question aligns the perspective theory. Institutional environment, including industry practices and standards, has significant impacts on the organizations' perceptions of the usefulness of big data.

Therefore, institutional theory provides a lens through which you can analyze how external institutional factors, including industry culture and norms, influence the adoption of big data in the Kenyan automotive industry. Considering such institutional pressures gives a deeper understanding of the barriers and facilitators to the adoption of big data in this specific context, aligning with the study's research objectives and variables.

The application of these theoretical frameworks can help stakeholders in the automotive industry in Kenya to identify barriers to the adoption of big data and develop practical strategies to address these challenges. The implementation of big data analysis in the automotive sector holds immense benefits revolutionizing various elements of the industry. The theoretical literature review has identified critical barriers such as skill gap, organizational resistance, infrastructure limitations, security concerns, and data privacy using the institutional theory.

2.2 Empirical Literature Review

2.2.1 Big data Adoption in Automotive Industry

The adoption of big data has become increasingly significant in different industries, such as the automotive industry. With the advancement of the automotive industry in Kenya, there is a surging curiosity in exploiting big data to enhance functionalities, make well-informed decisions and acquire a competitive advantage. Nevertheless, although big data holds the potential for remarkable advantages, significant obstacles challenge its acceptance in the Kenyan automotive sector. This manuscript endeavors to recognize and scrutinize such obstacles, illuminating the factors obstructing the victorious execution of big data undertakings. This chapter will examine the theoretical review, empirical review, research gaps and the conceptual framework.

2.2.2 Influence of Perceived Usefulness on Technology Adoption

The automotive industry is rapidly transitioning into the era of big data analytics, with the potential to improve various aspects of the industry, such as supply chain management, customer relationship management, and vehicle design. Despite its potential, the acceptance of big data in the automotive industry has been slow. One of the reasons behind this is the perceived usefulness of big data. Davis (1986) introduced the perceived usefulness concept, which he defined as "the degree to which a person believes that using a particular system would enhance his or her job performance". Perceived usefulness has been proposed as a potential predictor of acceptance and adoption of a technology or innovation (Sayem et al., 2022). Thus, perceived usefulness, particularly, the belief about the value of the big data will influence the adoption.

To determine the influence of perceived usefulness and adoption of big data, Sayem et al. (2022) conducted a qualitative study involving comprehensive review of literature and expert opinions. From the findings, Sayem et al. (2022), established that companies who were convinced of the benefits of big data were more likely to invest in it than those who did not. For instance, many company managers linked big data to mass production, better decision-making, and improved quality leading to the adoption (Sayen et al., 2022). Companies that did not utilize big data technology were unconvinced of its significant

benefits. The findings by Sayen were similar to that of Kshetri (2014), who observed that the lack of understanding of the potential benefits of the big data was a major impediment to its adoption. While big data analytics can offer numerous opportunities for improvement, these benefits may not be immediately apparent to those working in the industry. The complexities of big data, as well as the wide range of potential applications, may make it difficult for those unfamiliar with the technology to identify its potential usefulness. The main limitations of Sayem et al. (2022) study is selective and attrition bias that could have affected the findings. In addition, being a qualitative study, the generalizability of the findings is limited.

Other similar studies also demonstrate that perceived benefits such as higher product quality, better understanding of customers' preferences, and increasing market share were major technology adoption enablers. To determine how the perceived usefulness influence adoption of big data, Lufti et al. (2022) conducted a quantitative study using a sample of 2210 small and medium enterprises (SMEs) in Jordan. From the findings, many SMEs were motivated to adopt big data by the benefits of improved performance and gaining better understanding of customer behavior. However, the value and usefulness of the big data is contingent on effectiveness of the data collection process and the reliability of data (Carswell, 2015). For effective decision-making, big data must be clean, organized, and accessible. This process presents significant challenges, including significant investments in technology and infrastructure, and a significant change to current data collection and management practices (Carswell, 2015). These challenges can deter companies from investing in big data analytics. The study's main limitation is that the sample is not representative of the larger population as it focused mainly on sample from Jordan. In other settings, the findings could be different based on cultural differences and perceptions of the technology.

A qualitative study by Raj et al. (2019) established the lack of resources and national policies technology as the primary barriers to implementation of big data. This study focused on the acceptance of big data in the developing nations based on the systematic review of literature. From the findings, it is apparent for governments from the developing

nations to create a favorable environment that fosters adoption of technology. This includes providing clear guidance or policies on data security and privacy. However, in another qualitative study, Kshetri (2014), observed that big data analytics is still in its early stages in the industry, successful case studies are limited. Thus, there is a lack of empirical evidence about the usefulness of big data which may contribute to a lack of faith in the technology, resulting in a reluctance to invest in its implementation. As indicated before, qualitative studies such as this one has a limitation of generalizability.

2.2.3 Influence of Innovative Culture on the Adoption of Technology

The use of big data in industries has been on the rise in recent times. However, despite the numerous benefits associated with big data, its adoption has not been smooth sailing in various organizations, especially in the automobile industry. One of the significant barriers to the acceptance of big data in the automobile sector is the organizational culture. Organizational culture, according to Graf-Vlachy et al. (2018), refers to the shared values, beliefs, attitudes, behaviors, and practices that define how an organization operates. It is the organizational glue that brings members of the organization together and guides their actions. The automobile industry, like any other industry, has its distinctive culture, which has evolved over time, and this culture influences how the industry operates. The industry's culture presents itself as an important barrier to the implementation of big data in various ways.

In TAM model, Davis (1989), illustrated how social influences, especially culture can influence adoption of technology. Modern studies have tested TAM model and established a relationship between culture and technology adoption. In one of such studies, Graf-Vlachy et al. (2018) steered a survey of companies in China and the United States to establish the role of social influence (culture) on the adoption of technology. The findings demonstrated that culture significantly influenced the adoption of technology. In countries such as China and the United States where the government created innovative environment and encouraged firms to use technology through policies, organizations were more willing to adoption technology (Graf-Vlachy et al., 2018). The main limitation of this study is that

it only focused on survey from two countries. The validity of the findings could be challenged because the lack of a representative sample.

Another similar study by Moktadir et al. (2018) applied a qualitative method (Delphi technique) to determine how culture influenced adoption in Bangladesh. Findings indicated a lack of culture of technology in many companies and on the part of government, particularly on data protection and financial support. As a result, the adoption of big data in Bangladesh is minimal compared to developed countries such as the United States and the emerging economies such as China where government have invested heavily in supporting use of technology in companies. On the contrary, Kshetri (2014), observed that the automobile industry has a hierarchical culture that is not conducive to the adoption of big data. The automobile industry is characterized by a top-down decision-making structure, making it almost impossible for middle and lower-level staff to contribute significantly to the decision-making process. As a result of such culture, important decisions are made by top management who may not have adequate knowledge or understanding of the complexities involved in big data analytics. Thus, the study shows how the organizational structure and how decisions are made can become an impediment to adoption of technology. Again, the main limitation from the mentioned studies, is the methodology, where small sample size and there is a risk of subjectivity makes it difficult to generalize the findings.

In Kenya, Muriithi, Horner, and Pemberton (2016) applied a mixed method in their attempt to establish the influence of various factors, including the social influences (culture) on the adoption of information technology. From the findings, Muriithi et al. (2016) determined that culture of technology was lacking in many organizations hampering the adoption of innovation. Culture has been found to influence attitudes and beliefs, which can act as enablers or barriers to technology adoption (Muriithi et al., 2016). Privacy is a major barrier to the adoption of big data (Jain et al., 2016). Organizational culture can impact the adoption of big data analytics by affecting the organization's view of data privacy, security, and ethics. In particular, the automobile industry has been sensitive to data privacy and security (Kumar et al., 2021). The industry has been reluctant to share data with external

parties, including third-party vendors, out of fear that confidential information may be leaked to competitors or hackers. As a result, the industry has adopted a culture of information hoarding, which is contrary to the open, collaborative nature of big data analytics (Yu et al., 2022). Additionally, the industry has been wary of ethical issues arising from the use of big data analytics, such as discrimination, biases, and manipulation. This caution has made it difficult for organizations to invest in big data analytics that may leave them exposed to ethical violations. From the observation, it is apparent that anxiety concerning the privacy of information is a major challenge that affect adoption of the big data. Despite many empirical studies showing the influence of culture on adoption of technology, some limitations noted included the small sample sizes and the methodology. Small sample sizes could affect the validity of the findings and qualitative approaches to studies hamper the generalizability of the results.

2.2.4 Influence of Staff's Perceived Ease-of-Use and Adoption of Technology

In recent years, the automobile industry has been adopting big data technologies to improve their performance in various aspects such as manufacturing, supply chain, customer service and safety. However, the use of big data in the automobile industry is still hindered by some barriers, with ease of use being one of the biggest concerns. According to a qualitative study conducted by Li et al. (2019), the ease-of-use barrier relates to the complexity of big data technologies, which requires a higher level of knowledge and skills to use effectively. This complexity can lead to high training costs and may discourage employees from adopting big data technologies. The study notes that the solution to this issue lies in providing employees with appropriate training and support to use big data effectively.

Many studies demonstrate that perceived use of a major enabler or barrier to adoption of technology. For instance, Li et al. (2019) conducted a qualitative study to determine how ease-of-use influenced adoption of big data in smart factories in China. From the findings, the staff was more likely to view technology positively and support it if they considered it easy to use. Main limitation of this study is use of small sample size, which affects the validity of the findings. Another similar study by Chauhan, Singh, and Luthra (2021) sought to determine how technical skills and competency influenced adoption of

technology using 142 manufacturing companies in India. Using mixed method, Chauhan et al. (2021) established that technology skills, knowledge, and relevant support were strong predictors of adoption of technology. Like in the above scenario, the major challenges with the studies reviewed include small sample sizes and inability to generalize the findings because of methodology applied. Thus, it becomes difficult to show a correlation between the independent and dependent variables, including if the existing relationship is statistically significant.

Urbinati, Franzò, and Chiaroni (2021) is an Empirical study in the Italian Automotive Industry. The study investigates various factors that support or hinder the implementation of circular business models in the Italian automotive sector. The research employs an empirical analysis methodology to obtain information and make inferences. The approach involves a questionnaire administered to professionals in the Italian automotive industry, which yielded responses from various companies. Further, the article examines the enablers and barriers of circular business models, illuminating aspects like financial advantages, client requisites, legal structure, cooperative supply chain, and technological progress. The discoveries offer valuable perspectives into the obstacles and possibilities the Italian automobile sector encounters in embracing circular commercial models, adding to the wider comprehension of sustainable manufacturing and consumption.

2.3 Literature Review Gaps

From the reviewed literature, some gaps related to methodology and scarcity of similar studies in developing countries, especially in Kenya, emerged. While a qualitative study is vital in providing deeper analysis of a phenomenon, its major weakness is the generalizability of the findings and determining if existing relationship between variables is statistically significant. This study seeks to address these gaps by using a quantitative study. Another challenge is that most of the studies focused on technology in general but this study is specific on big data adoption. Such studies also focused on other industries, but this study is interested on the automobile industry. There were also limited empirical studies in Kenya focusing on barriers to adoption of big data in automotive industry. Thus,

this study seeks to contribute to the existing body of knowledge by addressing the existing gaps from the previous empirical studies.

2.3.1 Literature Review Gap Summary

Authors	Major Findings	Literature Gap
Oyewo et al. (2021), Chauhan et al. (2021), Singh and Bhardwaj (2019), Lufti et al.(2021), Nguyen & Liaw, (2020), Chauhan et al. (2021)	Big data analytics have been linked to increase in income, improved quality of decisions, customer satisfaction, increase in sales and efficiency	▪ Many studies in other industries as opposed to automotive industry ▪ Small sample sizes
Lufti et al. (2022), Graf-Vlachy et al. (2018), Kshetri (2014), Sayen et al. (2022),	Perceived benefits such as higher product quality, better understanding of customers' preferences, and increasing market share were major technology adoption enablers.	▪ Mainly qualitative studies ▪ Small samples ▪ Focus on developed countries
Raj et al. (2019), Moktadir et al. (2018), Muriithi et al. (2016), Yu et al. (2022), Li et al. (2019), Chauhan, Singh, and Luthra (2021)	The staff was more likely to view technology positively and support it if they considered it easy to use. determined that culture of technology was lacking in many organizations hampering the adoption of innovation.	▪ Many applied systematic review of literature (qualitative) ▪ Lack of representative sample ▪ Limited generalizability

Table 2.1: Literature gap

2.4 Conceptual Framework

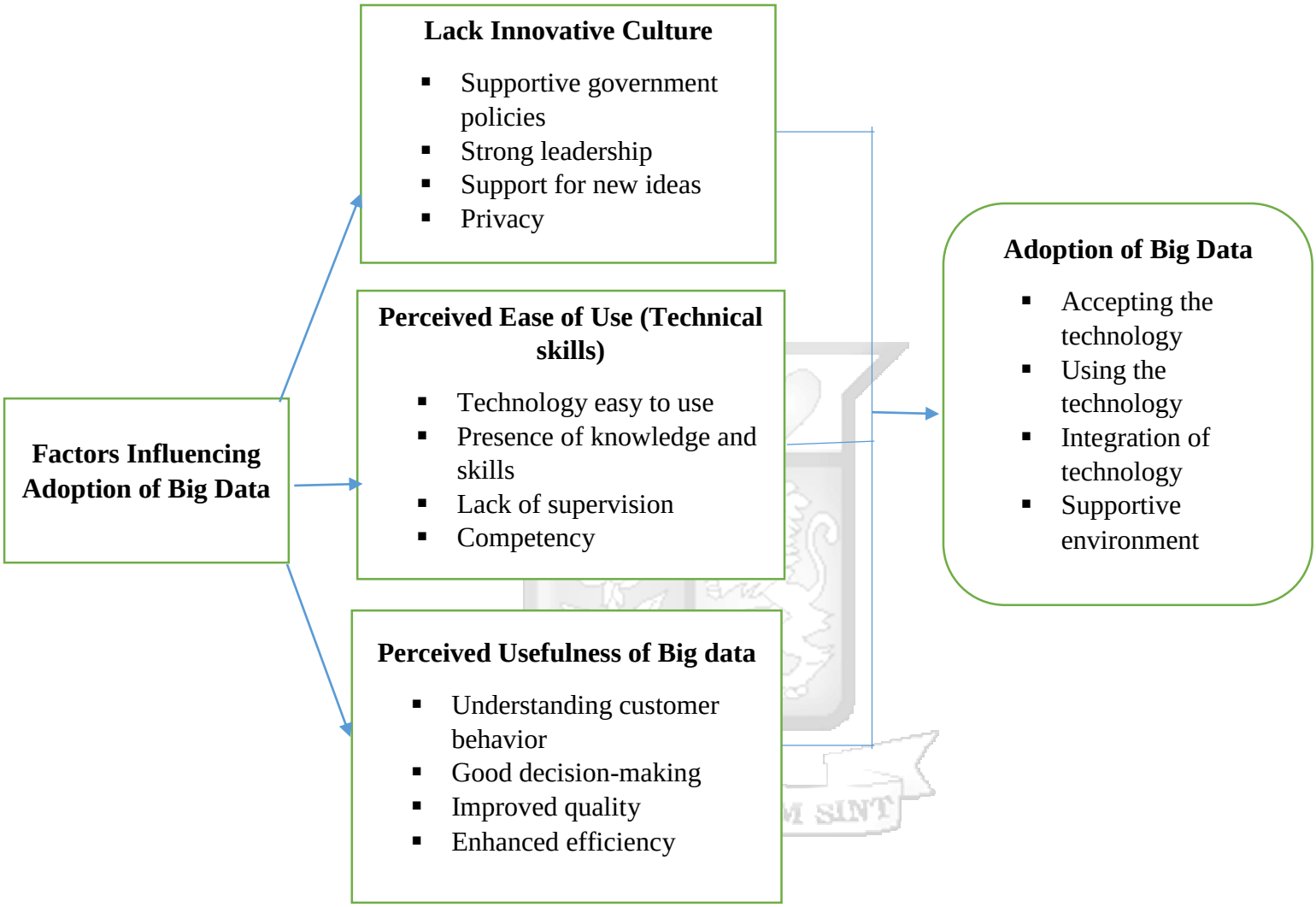

Figure 2.1: Conceptual Framework

Source: (Author, 2022)

The above conceptual framework demonstrates the proposed relationship between the independent variables (innovative culture, ease of use, decision-making and perceived usefulness) and the dependent variable (adoption of big data). The researcher will analyze data to test whether the relationship between the independent variables and the dependent variable exists.

2.4.1 Innovative Culture

Unquestionably, organizations that have strong support from government policies for innovation are likely to have a higher innovative culture score, this making it a crucial indicator. Similarly, companies that have innovative and visionary leadership are expected to promote innovative culture more. Support for new ideas is crucial for promoting the culture in question. Also, the extent to which organizations prioritize data privacy is likely to affect their innovative culture. Unquestionably, higher privacy measures are likely to result in higher innovative culture score.

2.4.2 Staff's Perceived Ease of Use

The ease of use for a certain technology is crucial to the organization. Employees that find the technology ease to use are likely to utilize it more comfortably, thus enhancing their productivity. Additionally, organizations should invest in training and development programs for their employees to improve their knowledge and skills. Arguably, if workers require minimal supervision to use big data tools effectively, their perceived ease of use score will be high. High levels of perceived competency are likely to be associated with employees who feel confidence in using big data technology.

2.4.3 Perceived Usefulness of Big Data

Unquestionably, understanding customer behaviors is crucial for organizations' prosperity. Therefore, organizations that utilize big data effectively for understanding customer behavior are likely to have higher perceived usefulness scores. Besides, big data tools contribute to better decision-making, which is likely to result in high scores in perceived usefulness. Companies that experience quality improvements as a result of big data are expected to score higher in perceived usefulness. Also, firms that attribute increased operational efficiency to big data are likely to report higher perceived usefulness score.

2.4.4 Adoption of Big Data

Adoption of a greater number of big data tools indicates a higher level of adoption. Similarly, when a company has a higher percentage of its employees using the tools in question, it suggests broader adoption. Also, frequent use usage of bid data tools indicates

a high adoption level and integration into daily operations. Shorter time for full adoption suggests a rapid uptake of big data technologies in the organization.

2.5 Operationalization of Variables

To determine how various barriers, influence the big data acceptance in the automotive sector in Kenya, various variables and measures will be considered. The independent variables (barriers) are innovative culture, staffs' perceived ease of use, and perceived usefulness. On the other hand, the dependent variable is the big data adoption. The table below demonstrates the variables operationalization.

Table 2.1 Operationalization of Variables

Variables	Measures	Likert Scale	Theory	Authors
Innovative culture	• Supportive government policies • Strong leadership • Privacy • Support for new ideas	5-Point Likert Scale	Institutinal Theory	Graf-Vlachy et al. (2018), Moktadir et al. (2018), Kumar et al., (2021), Muriithi et al. (2016), Yu et al. (2022)
Staffs' Perceived Ease of Use	• Technology easy to use • Presence of knowledge and skills • Little supervision • Competency	5-Point Likert Scale	Acceptance Model Perspective	Li et al. (2019), Li et al. (2019), Chauhan et al. (2021), Chauhan et al.(2021), Raj et al. (2019), Kshetri (2014), Carswell, 2015
Perceived Usefulness of Big data	• Understanding customer behavior • Good decision-making • Improved quality • Enhanced efficiency	5-Point Likert Scale	Acceptance Model Perspective	Kshetri (2014), Lufti et al. (2022), Sayem et al. (2022), Li et al. (2019)
Adoption of Big Data	• Accepting the technology • Using the technology	5-Point Likert Scale	Acceptance Model Perspective	Yu et al. (2022), Sayem et al. (2022), Moktadir et al. (2018), Raj et al. (2019), Li et al. (2019

	• Integration of technology • Supportive environment			

Table 2.1: Operationalization of variables

CHAPTER THREE: METHODOLOGY

3.0 Introduction

Chapter three highlights the methodology to be applied in this study. The section addresses philosophy of the research, research design, research method, population, sample, and sampling technique, data collection method, pilot study, reliability and validity, and data analysis method.

3.1 Research Philosophy

The methodology is based upon the positivism research philosophy. From the positivist perspective, only knowledge gained through empirical evidence is considered trustworthy (Mesly, 2015). Furthermore, the knowledge should be factual and attained through observation as opposed to feelings or intuition (Goertzen 2017). A quantitative research method is also proposed since it is aligned with the research philosophy. The quantitative study helps to analyze numerical data, test causal relationships, and make predictions based on the established relationship between the variables (Goertzen, 2017). Results from quantitative studies can be generalized to wider population, which shows the importance of quantitative approaches in providing information that could be used to make policies or vital decisions. However, the validity or the result from quantitative studies could be affected by the sample size and how accurate the researcher constructs objectives of the study (Bryman, 2012). Nonetheless, quantitative study is relevant for this study, as it will help to achieve the aims and objectives of the study.

3.2 Research Design

A correlational research design is arguably the most ideal for this study. The rationale is that the correlational research design helps to demonstrate relationship between variables, which is the main objective of this study. Specifically, the study will demonstrate how the independent variables (perceived usefulness, perceived ease of use, and innovative culture) are linked to the adoption of big data (dependent variable). A Correlation also helps to determine the direction and the strength of the relationship. For instance, if the relationship

exists, the correlation will illustrate whether it is positive or negative and whether it is strong or weak.

3.3 Population and Sampling

The population of study will be employees from automotive industry in Kenya. The sample size will be obtained from the approximately 570 employees in five major motor companies in Kenya: Kenya Vehicles Manufacturers, Associated Vehicles Assemble, Isuzu East Africa, Mobius Motors, and Trans Africa Ltd. All the three companies have been targeted to obtain a representative sample, which is likely to increase the validity of the findings. A simple indiscriminate sampling technique was used to obtain the sample. Specifically, the researcher informed the leadership and HR managers in each of the companies about the research and requested the assistance in obtaining the sample. The HR helped and gave the permission to access employees' data where a random sampling technique was applied to obtain the sample. The rationale is to minimize sample bias by giving each employee an equal chance to participate in the study. Even after applying the formula, the recommended formula for sample size is less than or equal to 10% of the population (Kadam & Bhalerao, 2010).

To achieve the sample size, the researcher applied Cochran's formula, which is n = N/ [1 + N (e) 2, where 'n' is the sample size, 'N' is the population, and 'e' is the level of significance. Cochran considers level of significance of 5% to be acceptable. Thus, the following shows how the sample size was obtained:

n = N/ [1 + N (e) 2]

= 570/ [1+570(0.05)2]

= 570/2.425

= 235.05

Thus, the sample size for this study will be 235

Sample Distribution

Table 3.1: Population and Sample in Each Company

Company	Population	Sample	Proportion %
Kenya Vehicles Manufacturers	80	33	14.0
Associated Vehicles Assemble	180	74	31.6
Isuzu East Africa	110	45	19.3
Mobius Motors	35	14	6.1
Trans Africa Ltd	165	68	28.9
Total Number of Employees	570	235	100

3.4 Data Collection

Data collection shall be through self-administered online Liker scale questionnaires as indicated in appendix C. Questionnaire will reflect statements representing each of the variables. A questionnaire is proposed because it is aligned with the research design, it is easier to administer, enhances data accuracy, and be rapidly be used to collect data from a large population (Singh & Bhardwaj, 2019). The main limitation, however, is that a questionnaire has predetermined responses (ReportLinker, 2022). This limits the amount of information that can be gathered. However, this is not going to be a limitation for this study.

3.5 Pilot Study

A pilot study will be conducted using a sample of 50 employees. The aim of the pilot study will be to assess the validity of the research instrument (questionnaire). Results will be used to make any necessary adjustments to the research instrument. Enhancing the validity of the questionnaire would help to increase the credibility of the results.

3.6 Reliability and Validity

One way to promote the reliability and validity of the study was by enhancing the sample validity. As demonstrated above, the researcher has used a reliable method of determining

the sample size. The pilot study results will also be used to test the reliability. Greater consistency of the findings demonstrates a high reliability. Major deviance from the results of similar reviewed literature could raise reliability questions (Kumar et al., 2021). However, provided that the research instrument is valid, the researcher will explain the reasons for the differences in the findings.

3.6.1 Pilot Test Results

This section presents the findings of the questionnaires' validity and reliability.

3.6.1.1 Reliability Test Results

For internal consistency, the researcher applied a reliability test. Additionally, Cronbach's Alpha helped to ascertain the presence of internal consistency. Table 4.2 below provides the results.

Table 3.2: Reliability Test Results

Variable	No. of items	Cronbach's Alpha Results	Recommendation
Innovation Culture	7	.725	Reliable
Perceived Ease-of-Use	7	.828	Reliable
Perceived Usefulness of Big Data	7	.774	Reliable
Adoption of Big Data	7	.847	Reliable

Source: Research Data (2023)

According to Table 4.2, the adoption of big data had the highest reliability coefficient of 0.847, Perceived Ease-of-Use 0.828, Perceived Usefulness of Big Data with a reliability coefficient of 0.774 and lastly Innovation Culture of 0.725. According to Creswell (2008), a scale's internal consistency can be inferred with a Cronbach's alpha of 0.6 or higher. Therefore, all variables' alpha reliability coefficients were found to be greater than 0.7, indicating that the 0.7 threshold had been met and the questionnaire was reliable.

A pilot test was used to verify the veracity of the data. A sample size of 23 respondents was established for the study. Throughout one day and face-to-face encounters at the various outlets, this response count was reached. The results from the pilot study

determined that the different scales and the questionnaire as a whole were designed to measure the objectives of Tavakol & Dennick, (2017) every item was understandable and matched the dimension that it was meant to evaluate, therefore, valid.

3.7 Data Analysis

Data analysis will be done using statistical package of social science (SPSS) version 20. Both inferential and descriptive statistics will be provided. Descriptive information summarizes basic information while the inferential statistics will help to show the relationship between independent and dependent variables. Specifically, both correlation and regression analyses will be performed. The correlation will demonstrate the strength and direction of the relationship while regression analysis will, in addition to confirming the relationship, demonstrate whether the relationship between the variables is statistically significant. Below is the multiple regression analysis equation that will be used to determine how the dependent variable (adoption of big data) is prejudiced by the independent variables (perceived usefulness, perceived ease of use, and innovative culture):

$Y = a + b_1X_1 + b_2X_2 + b_3X_3$, where,

Y= Dependent Variable ((adoption of big data)

X_1 = Independent variable one (usefulness)

X_2 = Independent variable two (ease of use)

X_3= Independent variable three (innovative culture)

a = the intercept

b_1, b_2, b_3 = The slope

3.8 Chapter Summary

Positivist research philosophy informs the application of a correlation research design and a quantitative research method. A sample size of 235 employees will be used. Data collection will be done through online questionnaires. For data analysis, correlation and regression analysis will be used.

CHAPTER FOUR: DATA ANALYSIS, PRESENTATION AND INTERPRETATIONS

4.1 Introduction

The aim of the chapter was to provide a summary of the results. The researcher used the SPSS software to provide both the descriptive and inferential statistics. Correlation and regression results helped to demonstrate whether perceived ease-of-use, perceived usefulness, and innovative culture influenced the adoption of big data in the automotive industry in Kenya.

4.2 Response Rate

The researcher distributed 235 questionnaires to respondents in selected motor vehicle companies in Kenya. Table 4.1 displays the study's response rate.

Table 4.1: Response Rate

Questionnaires	Frequency	Percentage
Response	197	83.8
Non-response	38	16.2
Total	**235**	**100**

Source: Research Data (2023)

From Table 4.1 of the 235 questionnaires that were distributed, 197 of them were accurately completed and returned, accounting for 83.8% of the total. 38 questionnaires were not returned constituting 16.2% of the total questionnaires. As per Mugenda & Mugenda (2008), a response rate of about 50% is enough for reporting and analysis, arounf 60% is remarkable, and 70% or above rate is exceptional. The study's results showed that the response rate was extremely high.

4.3 Demographic Analysis

The subsection provides a summary of the participant’s demographic information. Outcomes of the questionnaire's first section. The age group, gender, degree of education, and length of service are the demographic characteristics.

4.3.1 Gender of the Respondents

Genders of the participants were the researcher's main focus. The results are displayed in Figure 4.2.

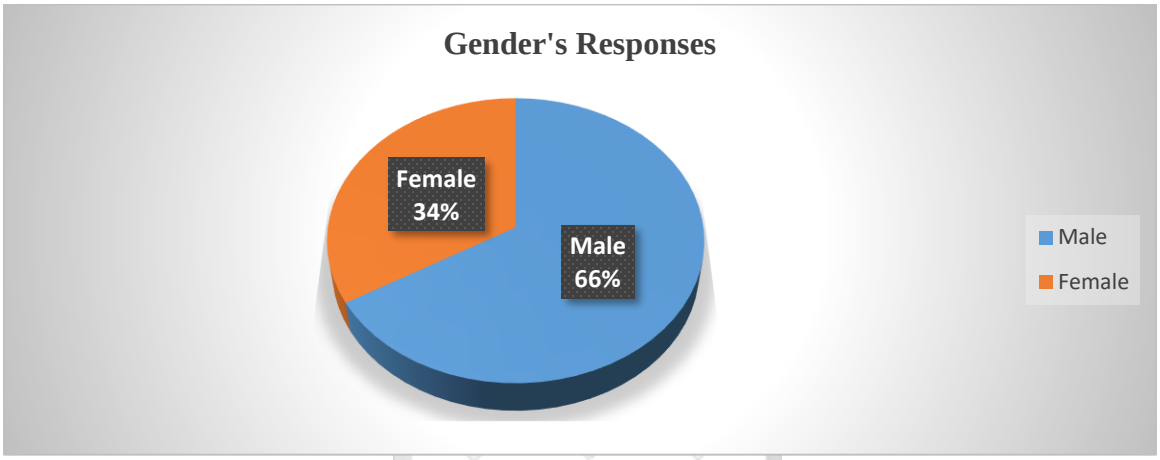

Figure 4.2: Gender of Responders

Source: Research Data (2023)

Men were the majority as per Figure 4.1 above. 34% of those surveyed were women, and 66% of respondents were male. The 2010 Kenyan Constitution mandates gender equality in all organizations. This demonstrated that the automotive industry in Kenya has a 1/3 information equity ratio and a gender balance.

4.3.2 Age Bracket of the Respondents

Results in Table 4.3 below illustrates the age of the participants.

Table 4.3: Age of Respondents

Bracket	Frequency	Percentage
25-35 Years	25	12.7
35-45 Years	97	49.2
45-55 Years	54	27.4
55-65 Years	15	7.6
Above 65 Years	6	3.0
Total	**197**	**100**

Source: Research Data (2023)

Table 4.3 indicated that 49.2% of participants were aged between 35 and 45, while 27.4% fell between 45 and 55 years old. 12.7 percent fell between 25 and 35 years of age 7.6 percent fell between 55 and 65 years old and lastly 3.0% of the population is over the age of 65, People of various ages took part in the study as a result, and the outcomes were clear-cut. The age range of the bulk of responders was between 35 and 45. There was a good representation of people in this age group (45–55). This shows that participants in the organization's operations and activities are drawn from the various groups. This supports the claim stated by Jan and Stoeldraijer (2018) that an individual's age and experience level have a significant impact on their value in the workplace. As a result, the investigator was satisfied with the data supplied to support the investigation's goals.

4.3.3 Level of Education

Goal was to determine the education attainment of the participants. Results shown in Figure 4.2.

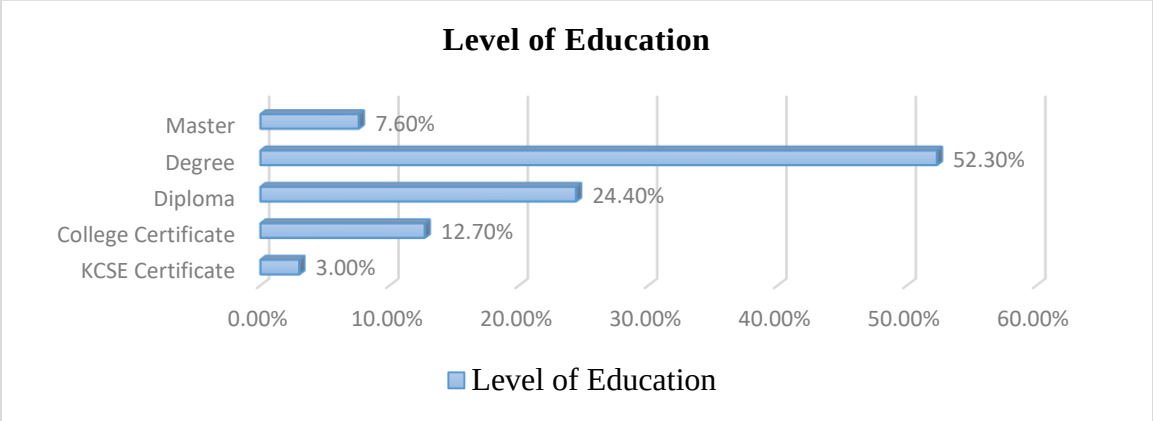

Figure 4.2 Level of Education

Source: Research Data (2023)

Figure 4.2 revealed that most responders (52.3%) held a bachelor's degree, followed by diploma (24.4%), masters 7.6% and 3.0 percent had a KCSE certificate. Consequently, the great majority of respondents were educated, making them perfect sources of reliable information and data, ensuring the study's objectivity. The majority of survey respondents were those with degrees and diplomas. This indicates their appreciation of the study's goal

and their capacity to supply accurate data, as well as their understanding of the automotive industry's operations and procedures.

4.3.4 Level in the organization

The investigator aimed to ascertain the level in the motor companies. Findings are summarized in Figure 4.3.

Figure 4.2 Level in the Organization

Source: Research Data (2023)

Majority of respondents, or 50.3%, were shown in Figure 4.2, had been employed at the lower managerial level, 27.4% had been employed on middle managerial level, 18.8% had been employed in a non-managerial level, and 3.6% had been employed in senior managerial level. This implied that majority of the employee are lower level of management followed by middle level management.

4.4 Analysis of Study Variables

The descriptive statistics for the independent variables of perceived adoption of big data is the dependent variable were provided in this section. The variables analyses are presented hereafter.

4.4.1 Adoption of Big Data

The researcher aimed to establish effect of adoption of big data at the automotive industry in Kenya. Table 4.4. summarizes the findings.

Table 4.4: Results of Descriptive Statistics for Adoption of Big Data

Statement	Mean	Std. D
The organization provides supportive environment for big data adoption	4.523	.7184
The organization accepts big data use	3.518	1.5406
The organization uses big data for various activities	3.584	1.4067
The organization has integrated technology to its various functions	3.599	1.5208
Big data is actively used to improve their products and services	3.939	1.5637
Big data is employed to gain insights into customer behavior and preferences.	3.990	1.3170
The organization has invested in the necessary infrastructure to support big data processing.	3.640	1.2277
Overall Mean	**3.828**	

Source: Research Data (2023)

Survey findings in Table 4.4 suggest the organization provides a supportive environment for technology acceptance, with a high mean score of 4.523 (M = 4.523, SD = 0.7184). This indicates a positive organizational climate that encourages the integration of big data technologies. However, the mean score of 3.518 (M = 3.518, SD = 1.5406) for the statement regarding the organization's acceptance of big data use implies a less definitive stance, suggesting there may be opportunities for fostering greater acceptance within the organizational culture. Additionally, the mean scores ranging from 3.584 to 3.990 (M =

3.584 to 3.990, SD = 1.3170 to 1.5637) for various statements on using big data for different activities and gaining insights into customer behavior indicate a moderate level of engagement in these areas. The overall mean of 3.828 suggests a generally positive organizational attitude towards big data adoption, with room for improvement in certain aspects, such as enhancing acceptance and expanding the scope of big data applications across various functions.

This implied that acceptance of technology has a major effect at automotive industry. Adoption of big data fosters a shift towards data-driven decision-making processes. This can empower industry leaders to make more informed strategic decisions, backed by insights derived from comprehensive data analysis. Overall, the incorporation of big data in the automotive industry in Kenya holds the potential to revolutionize various aspects of operations, from production efficiency to product quality and customer satisfaction.

4.4.2. Perceived Usefulness of Big Data

The researcher aimed to establish the effect of perceived usefulness of big data as a factor affecting adoption of big data. Table 4.5 below illustrates the findings.

Table 4.5 Descriptive Statistics for Perceived Usefulness of Big Data

Statement	Mean	Std. D
Adoption of big data is influenced by how easy it is to use	4.365	.8562
Knowledge and skills will influence use of big data in our organization	3.695	1.3660
Adoption of big data can be influence by competency of its users	3.863	1.3652
Big data use requires little supervision	4.188	1.4322
Employees can complete tasks with technology without feeling frustrated.	4.325	1.5669
Using big data is straightforward and uncomplicated	4.127	1.4809
Big data technologies are user-friendly.	3.970	1.3206
Overall Mean	**4.076**	

Source: Research Data (2023)

Survey results in Table 4.5 above indicate that acceptance of big data in organization is positively influenced by perceived ease of use, with a mean score of 4.365 (M = 4.365, SD = 0.8562). This underscores the importance of user-friendly interfaces and accessible tools in facilitating the integration of big data technologies. The mean score of 3.695 (M = 3.695, SD = 1.3660) for the statement regarding the influence of knowledge and skills suggests a moderate impact on big data utilization within the organization. Additionally, the mean score of 3.863 (M = 3.863, SD = 1.3652) for the statement on the influence of user competency further emphasizes the significance of employee skills in shaping the effective use of big data. The acknowledgment that big data use requires little supervision is evident with a mean score of 4.188 (M = 4.188, SD = 1.4322), indicating a perception of the accessibility and manageability of these tools. The overall mean of 4.076 suggests a generally positive attitude towards big data adoption within the organization, with a strong reliance on ease of use and employee competencies as key factors influencing successful integration.

This implied that perceived usefulness of big data has a significant effect of adoption the big data. The finding suggests a direct relationship between the perceived usefulness of big data and its integration. In essence, when individuals or organizations perceive big data as valuable and advantageous for their goals, they are more likely to embrace and integrate it into their operations. This underscores the importance of recognizing the practical benefits and utility that big data can bring in order to drive successful adoption in various contexts

4.4.3 Innovative Culture

The aim was to examine the effect of innovative culture on the adoption of big data. Findings are reported in Table 4.6.

Table 4.6: Descriptive Statistics Results for Innovative Culture

Statement	Mean	Std. D
Employees have supportive government policies to help in the adoption of big data	3.680	.9606

The organization has strong leadership that fosters the adoption of big data	4.508	.8608
Issues of privacy influence the adoption of big data in the organization	3.863	1.0910
The organization supports new ideas and innovations	4.381	1.2340
Technological innovation is seen as a top priority for the organization's success.	3.919	.8592
The organization actively encourages employees to propose new technological ideas and solutions.	4.452	1.2138
Technological innovation is integrated into the organization's long-term strategic planning.	4.396	.9560
Overall Mean	**4.171**	

Source: Research Data (2023)

Survey results from Table 4.6 suggest that employees within the organization perceive a strong foundation for acceptance and integration of big data, particularly emphasizing crucial benefit of leadership support (M = 4.508, SD = 0.8608). This underscores the significance of strong leadership in fostering technological advancements. Additionally, the organization is seen as supportive of new ideas and innovations (M = 4.381, SD = 1.2340), actively encouraging employees to propose technological solutions (M = 4.452, SD = 1.2138). Technological innovation is recognized as a top priority for the organization's success, as reflected in the mean score of 3.919 (SD = 0.8592). However, there are indications that the influence of government policies on big data adoption (M = 3.680, SD = 0.9606) and the impact of privacy issues (M = 3.863, SD = 1.0910) are areas that may benefit from further attention. Nevertheless, the organization demonstrates a commitment to long-term success through the integration of technological innovation into strategic planning (M = 4.396, SD = 0.9560). Overall, these findings highlight a positive organizational environment that values leadership support, encourages innovation, and recognizes the importance of technology in strategic planning.

This implied that innovation culture influences integration as well as technology use. Finding underscores that the presence of an innovation culture significantly influences the

adoption of big data. An organizational culture that fosters innovation encourages openness to new technologies and approaches, making it more likely for the industry to embrace and successfully integrate big data solutions into its operations. This highlights the crucial interplay between cultural aspects and technological adoption in driving advancements within the automotive assembly sector in Kenya.

4.4.4 Perceived Ease-Of-Use

The study sought to determine the influence of perceived ease-of-use on adoption big data. Table 4.7 presents the findings.

Table 4.7: Results of Descriptive Statistics for Perceived Ease-Of-Use

Statement	Mean	Std. D
Adoption of big data is influenced by how easy it is to use	4.315	.9161
Knowledge and skills will influence use of big data in the organization	4.025	1.2390
Adoption of big data can be influence by competency of its users	3.914	1.1551
Big data use requires little supervision	3.655	1.3064
Employees can complete tasks with technology without feeling frustrated.	3.827	.9952
Using big data is straightforward and uncomplicated	3.964	1.3301
Big data technologies are user-friendly.	3.645	1.1587
Overall Mean	**3.906**	

Source: Research Data (2023)

Survey results in Table 4.7 suggest that the adoption of big data within the organization is positively influenced by the perceived ease of use, as reflected by a mean score of 4.315 (M = 4.315, SD = 0.9161). This underscores the significance of user-friendly interfaces and straightforward tools in facilitating the integration of big data technologies. The mean score of 4.025 (M = 4.025, SD = 1.2390) for the statement concerning the influence of knowledge and skills emphasizes the importance of employee competencies in shaping the effective use of big data within the organization. Additionally, the mean score of 3.914 (M = 3.914, SD = 1.1551) for the statement on the influence of user competency further

underscores the role of skilled users in driving successful integration of data analytics. While the acknowledgment that big data use requires little supervision is evident with a mean score of 3.655 (M = 3.655, SD = 1.3064), indicating a perception of the accessibility and manageability of these tools. The overall mean of 3.906 suggests a generally positive attitude towards big data adoption within the organization, with a strong emphasis on ease of use and employee competencies as crucial factors contributing to effective integration.

This implied that the perceived ease of use has a significant on the integration and acceptance of technology. This finding suggests that the perceived ease of use plays a crucial role in influencing the adoption of data analytics. When individuals within the organization perceive big data technologies as user-friendly and accessible, it is more likely that they will embrace and incorporate these tools into their workflow. This emphasizes the importance of user-friendly interfaces and intuitive design in facilitating the successful integration of big data solutions within the automotive assembly industry in Kenya.

4.5 Inferential Analysis

This section presents the inferential analysis of the study. This includes the analysis of correlation, regression coefficient and analysis of variance between the factors affecting adoption of big data**.**

4.5.1 Correlation Analysis of Perceived Usefulness of Big Data

The study's objective was to determine whether there was a relationship between perceived usefulness of big data and adoption of big data. The results are shown in Table 4.8.

Table 4.8: Correlation of Perceived Usefulness of Big Data

		Perceived Usefulness of Big Data	Adoption of Big Data
PU	Pearson Correlation	1	.849**
	Sig. (1-tailed)		.000
	N	197	197
BDA	Pearson Correlation	.849**	1
	Sig. (1-tailed)	.000	

N	197	197

Source: Research Data (2023 ** Correlation is significant at the 0.01 level (1-tailed).

The study in the automobile industry in Kenya reveals a highly significant positive correlation between the perceived usefulness of big data and the adoption of big data with a Pearson correlation coefficient of .849 ($p < .01$, one-tailed). This indicates a strong association between the perceived usefulness of big data technologies and the extent to which they are adopted within the organization. The findings suggest that individuals who perceive big data as more useful are more likely to endorse and embrace its adoption. This correlation underscores the importance of stakeholders' perceptions regarding the utility of big data in influencing the organizational decision to adopt and integrate these technologies. The study's robust statistical significance at the 0.01 level emphasizes the reliability and validity of the relationship between perceived usefulness and adoption, providing valuable insights for organizations seeking to enhance their big data utilization strategies.

4.5.2 Correlation Analysis of Innovative Culture

The study's objective was to determine whether there was a relationship between innovative culture and adoption of big data. The results are shown in Table 4.9.

Table 4.9: Correlation of Innovative Culture

		Innovative Culture	**Adoption of Big Data**
Innovative Culture	Pearson Correlation	1	.574**
	Sig. (1-tailed)		.000
	N	197	197
Adoption of Big Data	Pearson Correlation	.574**	1
	Sig. (1-tailed)	.000	
	N	197	197

Source: Research Data (2023) **. Correlation is significant at the 0.01 level (1-tailed).

The results presented in Table 4.9 from the study conducted in the automobile companies in Kenya reveal a highly significant positive correlation between innovative culture and the adoption of big data. The Pearson correlation coefficient of .574 (one-tailed) indicates a strong and positive relationship between the presence of an innovative culture within the organization and the level of adoption of big data technologies. This finding suggests that organizations fostering an environment characterized by innovation and a willingness to explore new ideas and approaches are more likely to embrace and implement big data solutions. The robust statistical significance at the 0.01 level underscores the importance of cultivating an innovative culture as a key factor influencing the successful adoption of big data technologies in the automobile industry. This insight is valuable for organizations seeking to enhance their big data adoption strategies by recognizing and promoting an innovative work culture.

4.5.3 Correlation Analysis of Perceived Ease of Use

The study's objective was to determine whether there was a relationship between perceived ease of use and adoption of big data. The results are shown in Table 4.10.

Table 4.10: Correlation of Perceived Ease of Use

		Perceived Ease of Use	Adoption of Big Data
Perceived Ease of Use	Pearson Correlation	1	.650**
	Sig. (1-tailed)		.000
	N	197	197
Adoption of Big Data	Pearson Correlation	.650**	1
	Sig. (1-tailed)	.000	
	N	197	197

Source: Research Data (2023) **. Correlation is significant at the 0.01 level (1-tailed).

The findings in Table 4.10 from the study conducted reveal a highly significant positive correlation between perceived ease of use and the adoption of big data. The Pearson correlation coefficient of .650 ($p < .01$, one-tailed) indicates a strong and positive relationship between how users perceive the ease of use of big data technologies and the extent to which these technologies are adopted within the organization. This implies that individuals who find big data tools more user-friendly are more likely to endorse and adopt them. The robust statistical significance at the 0.01 level underscores the importance of user experience and ease of use as influential factors in the successful adoption of big data technologies within the automotive industry. These findings highlight the significance of ensuring user-friendly interfaces and accessible tools to facilitate the integration of big data solutions, providing valuable insights for organizations aiming to enhance their adoption strategies.

4.6 Regression Analysis

The researchers employed a multivariate regression analysis to ascertain factors affects adoption of big data in the automotive industry.

4.7.1 Regression Analysis of Perceived Usefulness of Big Data

The researchers employed a multivariate regression analysis to ascertain how perceived usefulness affect adoption of big data in the automotive industry.

Table 4.11: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.849[a]	.721	.719	.57234

Source: Research Data, (2023*)*

The results presented in Table 4.11 from the study conducted in the automotive companies in Kenya indicate the statistical performance of a regression model examining the relationship between the variables. The model demonstrates a significant overall fit, with an R-squared value of .721, suggesting that approximately 72.1% of the variance in the Adoption of Big Data can be explained by the predictor variables included in the model.

The adjusted R-squared value of .719 accounts for the influence of the number of predictors, providing a more accurate reflection of the model's explanatory power. The standard error of the estimate is .57234, representing the average distance between the observed and predicted values, indicating a reasonably precise fit. Overall, the model, as denoted by the R value of .849, exhibits a strong correlation between the predictor variables and the Adoption of Big Data, emphasizing the effectiveness of the chosen variables in explaining the variance in big data adoption within the automotive industry. These statistical indicators collectively underscore the model's robustness in capturing and explaining the relationships between the specified variables.

Table 4.12 ANOVA of Perceived Usefulness of the Big Data

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	164.705	1	164.705	502.806	.000[b]
	Residual	63.876	195	.328		
	Total	228.581	196			

a. Dependent Variable: Adoption of Big Data

b. Predictors: (Constant), Perceived Usefulness of Big Data

Source: Research Data (2023)

The results presented in Table 4.12 from the study showcase the analysis of variance (ANOVA) for the regression model. The ANOVA table indicates that the regression model, with Perceived Usefulness of Big Data as the predictor variable, is highly significant ($F = 502.806$, $p < .000$). This suggests that the variation in the Adoption of Big Data is not due to random chance but is significantly influenced by the inclusion of the predictor variable in the model. The sum of squares for the regression (164.705) is notably larger than the sum of squares for the residual (63.876), indicating that a substantial portion of the total variance in the adoption of big data is explained by the regression model. The findings underscore the effectiveness of perceived usefulness of big data as a predictor,

providing valuable insights into the factors influencing the adoption of big data technologies within the automotive industry.

4.6.1 Regression Coefficients of Perceived Usefulness of Big Data

The study's goal was to determine how the dependent variable, adoption big data, related to the factors (perceived usefulness). The results are summarized in Table 4.13.

From the Table 4.10's data was used to produce the regression equation that follows:

Table 4.13: Regression Coefficient of Perceived Usefulness of Big Data

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.695	.146		4.773	.000
	Perceived Usefulness	.769	.034	.849	22.423	.000

Source: Research Data (2023)

$$\mathbf{Y = 0.695+0.769X_1}$$

The coefficients presented in Table 4.13 from the study conducted in the automotive companies in Kenya reveal essential information about the regression equation predicting the adoption of big data. The constant term (B = 0.695) represents the estimated value of adoption of big data when the predictor variable, perceived usefulness of big data (X_1), is zero. The coefficient for Perceived Usefulness (B = 0.769) indicates the change in the adoption of big data for each one-unit change in perceived usefulness. The standardized coefficient (Beta = 0.849) provides insight into the relative importance of the predictor variable in explaining the variance in the dependent variable. The t-statistic (t = 22.423) is highly significant ($p < .000$), indicating that the coefficient for perceived usefulness is significantly different from zero. The regression equation $Y = 0.695 + 0.769X_1$ can be interpreted as follows: for every one-unit increase in Perceived Usefulness, the Adoption of Big Data is expected to increase by 0.769 units, and the constant term represents the estimated baseline level of adoption when perceived usefulness is zero. These coefficients collectively contribute to a comprehensive understanding of the predictive relationship

between perceived usefulness and the adoption of big data within the automotive industry in Kenya.

4.6.2 Regression Analysis of Innovative Culture

The researchers employed a multivariate regression analysis to ascertain how innovative culture affect adoption of big data in the automotive industry.

Table 4.14: Model Summary of Innovative Culture

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.574[a]	.329	.326	.88668

Source: Research Data, (2023*)*

The model summary in Table 4.14 from the study conducted at the automotive companies in Kenya provides key statistical indicators of the regression model's performance. The R-squared value of .329 suggests that approximately 32.9% of the variance in the Adoption of Big Data is explained by the predictor variable. The adjusted R-squared value of .326 considers the model's complexity, offering a more conservative estimate of its explanatory power. The standard error of the estimate is .88668, representing the average deviation between observed and predicted values. Overall, the model demonstrates a moderate fit, capturing a significant portion of the variability in big data adoption within automotive companies in Kenya.

Table 4.15 ANOVA of Innovative Culture

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	75.271	1	75.271	95.740	.000[b]
	Residual	153.310	195	.786		
	Total	228.581	196			

a. Dependent Variable: Adoption of Big Data

b. Predictors: (Constant), Innovative Culture

Source: Research Data (2023)

The ANOVA results in Table 4.15 for the study conducted in the automotive companies in Kenya illustrate the analysis of variance for the regression model with innovative culture as the predictor variable. The highly significant F-statistic of 95.740 ($p < .000$) indicates that the regression model is effective in explaining the variance in the adoption of big data. The sum of squares for the regression (75.271) is substantially larger than the sum of squares for the residual (153.310), emphasizing the model's ability to account for a significant proportion of the variability in big data adoption. These findings underscore the importance of Innovative Culture as a predictor, providing valuable insights into the factors influencing the adoption of big data technologies within the automotive companies in Kenya.

4.6.3 Regression Coefficients of Innovative Culture

The study's goal was to determine how the dependent variable, adoption big data, related to the factors (Innovative Culture). The results are summarized in Table 4.16.

From the Table 4.16's data was used to produce the regression equation that follows:

Table 4.16: Regression Coefficient of Innovative Culture

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.655	.330		1.982	.049
	Innovative Culture	.761	.078	.574	9.785	.000

Source: Research Data (2023)

$$Y = 0.655+0.761X_2$$

The coefficients presented in Table 4.16 from the study conducted at the automotive companies in Kenya provide insights into the regression equation predicting the adoption of big data, with innovative culture as the predictor variable. The constant term ($B = 0.655$) represents the estimated value of adoption of big data when the predictor variable is zero.

The coefficient for innovative culture (B = 0.761) indicates the change in the adoption of big data for each one-unit change in innovative culture. The standardized coefficient (Beta = 0.574) reflects the relative importance of the predictor variable in explaining the variance. The t-statistic (t = 9.785) is highly significant (p < .000), suggesting that the coefficient for Innovative Culture is significantly different from zero. The regression equation $Y = 0.655 + 0.761X_2$ implies that for every one-unit increase in innovative culture, the adoption of big data is expected to increase by 0.761 units, providing valuable insights into the influence of innovative culture on big data adoption within the automotive companies in Kenya.

4.6.4 Regression Analysis of Perceived Ease of Use

The researchers employed a multivariate regression analysis to ascertain how perceived ease of use affect adoption of big data at automotive companies in Kenya.

Table 4.17: Model Summary of PEU

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.650[a]	.423	.420	.82263

Source: Research Data, (2023*)*

The model summary in Table 4.17 from the study conducted at the automotive companies in Kenya provides key statistical indicators for the regression model. The R-squared value of .423 suggests that approximately 42.3% of the variance in the adoption of big data is explained by the predictor variable. The adjusted R-squared value of .420 considers the model's complexity, providing a more conservative estimate of its explanatory power. The standard error of the estimate is .82263, representing the average deviation between observed and predicted values. Overall, the model demonstrates a substantial fit, capturing a significant portion of the variability in big data adoption within automotive companies in Kenya.

Table 4.18 ANOVA of Perceived Ease of Use

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	96.620	1	96.620	142.777	.000[b]
	Residual	131.961	195	.677		
	Total	228.581	196			

a. Dependent Variable: Adoption of Big Data

b. Predictors: (Constant), Perceived Ease of Use

Source: Research Data (2023)

The ANOVA results in Table 4.18 for the study conducted at the automotive companies in Kenya display the analysis of variance for the regression model with perceived ease of use as the predictor variable. The highly significant F-statistic of 142.777 ($p < .000$) indicates that the regression model effectively explains the variance in the adoption of big data. The sum of squares for the regression (96.620) significantly exceeds the sum of squares for the residual (131.961), underscoring the model's capability to account for a substantial proportion of the variability in big data adoption. These findings highlight the importance of perceived ease of use as a predictor, offering valuable insights into the factors influencing the adoption of big data technologies within the automotive companies in Kenya.

4.6.4 Regression Coefficients of Perceived Ease of Use

The study's goal was to determine how the dependent variable, adoption big data, related to the factors (Perceived ease of use). The results are summarized in Table 4.19.

Table 4.19: Regression Coefficient of Perceived Ease of Use

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.061	.239		4.444	.000
	PEU	.708	.059	.650	11.949	.000

Source: Research Data (2023)

From the Table 4.18 data was used to produce the regression equation that follows:

$$\mathbf{Y = 1.061+0.708X_3}$$

The coefficients presented in Table 4.16 from the study at the automotive companies in Kenya contribute to the understanding of the regression equation predicting the adoption of big data, with perceived ease of use (PEU) as the predictor variable. The constant term (B = 1.061) signifies the estimated adoption of big data when perceived ease of use is zero. The coefficient for perceived ease of use (B = 0.708) indicates that for every one-unit increase in perceived ease of use, the adoption of big data is expected to increase by 0.708 units. The standardized coefficient (Beta = 0.650) underscores the relative importance of perceived ease of use in explaining the variance. The highly significant t-statistic (t = 11.949, p < .000) confirms that the coefficient for perceived ease of use is significantly different from zero. In summary, the regression equation $Y = 1.061 + 0.708X_3$ provides a quantitative representation of the impact of perceived ease of use on the adoption of big data within the automotive companies in Kenya, offering valuable insights into the factors influencing big data adoption.

4.6.5 Regression Coefficients

The study's goal was to determine how the dependent variable, adoption big data, related to the factors (perceived usefulness, perceived ease of-use and innovative culture). The results are summarized in Table 4.10.

Table 4.20: Regression Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.034	.305		3.387	.001
	Perceived Usefulness	.270	.057	.335	4.774	.000
	Innovative Culture	.089	.056	.108	1.572	.119
	Staffs Perceived Ease-of-Use	.458	.060	.547	7.644	.000

Source: Research Data (2023)

From the Table 4.10's data was used to produce the regression equation that follows:

$$\mathbf{Y = 1.034+0.270X_1 +0.089X_2+0.458\ X_3}$$

Adoption of big data would be 1.034 if factors (perceived usefulness, perceived ease of-use and innovative culture) were maintained; the perceived usefulness would increase adoption of big data by 0.270; innovative culture would increase adoption of big data by 0.089; staff's perceived ease-of-ease would increase adoption of big data by 0.458.

Table 4.20 demonstrates that there were noteworthy correlations between adoption of big data and perceived usefulness of the data (p0.000<0.05), the factor was significant, innovative culture and adoption of big data (p0.119>0.05), the factor was insignificant. Staff's perceived ease-of-ease of data and adoption of big data (p0.000>0.05), the factor was significant with the acceptance of innovation. From the findings, the relationship between perceived usefulness, perceived ease of-use and innovative culture and acceptance of big data was statistically significant.

CHAPTER FIVE: DISCUSSION

5.0 Introduction

Chapter five discusses findings from present study analyzed factors influencing adoption of big data in the automobile industry in Kenya. Specifically, the discussion focuses on three main factors, namely, perceived ease-of-use, innovative culture, and perceived usefulness, indicating their influence on adoption of big data in the automotive industry. Additionally, the researcher links and compares the current findings with the reviewed literature.

5.1 Discussion of Results

5.1.1 Innovative Culture and Adoption of Big Data

From the findings, a correlation was established between innovative organizational culture and adoption of big data ($r=0.574$, $p < .01$). The implication of the findings was that organizational culture was vital in enhancing embrace of big data in automotive industry in Kenya. The findings corroborate the institutional theory's claim on culture as explained by Meyer and Rowan in the 1970s. As per the institutional theory, the organizational norms influence the behavior and conformity. In other words, any innovation an organization chooses is influenced by its internal norms and values. The findings of this study are also aligned with several reviewed secondary sources. For instance, Graf-Vlachy et al. (2018) and Moktadir et al. (2018) established that organizational culture, particularly, supportive government policies, strong leadership, and the support for new ideas, influence the adoption of technology in organization. These findings have also been validated by Kumar et al. (2021) and Muriithi et al. (2016) who established how enhancing privacy and creating an innovative culture help in adoption of various innovations, including the big data. Thus, the findings of the current study correspond with the institutional theory and the reviewed literature that underscored the importance of innovative culture in influencing decisions to adopt technologies in organizations. Thus, to foster increased acceptance and use of big data in the automotive industry in Kenya, managers need to invest more in creating an innovative culture, particularly, through strong leadership, improving privacy of

information, and working together with government to formulate supportive technology policies.

5.1.2 Perceived Usefulness and Adoption of Big Data

Results indicated a strong association between perceived usefulness and the adoption of big data ($r=0.849$, $p < .01$). From the findings, the perceived usefulness of the big data, including decision-making, improved quality, and enhanced efficiency, played a significant role in fostering the acceptance and use of the big data in the automotive industry. The findings validate the claims by Davis (1989) Technology Acceptance Theory (TAM) that supports the role of perceived usefulness in the integration of big data. According to TAM, if technology is perceived as useful in solving certain challenges, minimizing wastage, and fast-tracking processes, it is more likely to be adopted. Findings of the present study also corroborate the reviewed literature. For instance, Kshetri (2014) found that if employees perceived a technology vital in improving quality and fostering efficiency, they were more likely to support its adoption. Furthermore, Sayem et al. (2022) and Li et al. (2019) determined that if big data was perceived effective in understanding customer behavior and in decision-making, it received significant support in an organization. These findings are similar to that of the current study demonstrating a significant reliability of the findings and emphasizing the importance of perceived usefulness in the integration of big data. Thus, to foster the acceptance and continuous use of data analytics in the automotive industry, managers must ensure the technology actually helps to solve challenges and to improve performance. The perceived benefits of the big data will play a significant role in its use in the long term.

5.1.3 Perceived Ease-of-Use and Adoption of Big Data

Results indicated a strong correlation between the perceived ease-of-use and adoption of big data in the automotive industry in Kenya ($r=0.650$, $p < .01$). From the findings, it is apparent that the presence of skills and knowledge regarding ease of use of technology, increased level of competency, and supervision are vital in enhancing the integration of big data in the automotive industry in Kenya. From TAM theory, the perceived ease-of-use is vital in influencing acceptance and use of technology in organizations. According to Davis

(1989), if people perceive technology as easy to use or requiring minimal supervision, they are more likely to support its adoption and use. Furthermore, if employees have the right skills and competency in the relevant technology, they will support adoption of technology. Additionally, the findings of the present study are corroborated by the reviewed literature. Li et al. (2019) and Chauhan et al. (2021) argued that the integration of technology is influenced by how easy it is for the employees to use. Other studies indicated that organizations that prepare employees in terms of training and equipping them with necessary technical skills foster a positive attitude towards the adoption (Raj et al., 2019; Kshetri, 2014. As per Carswell (2015) employee autonomy is also key to the adoption of technology in the sense that employees require little supervision. Thus, to enhance the acceptance and integration of big data technology in the automotive industry in Kenya, it is fundamental that managers ensure that the technology is simple to use, interpret, easily accessible, and requiring little supervision. Furthermore, there is a need to equip the users of technology with the relevant knowledge and skills.

5.2 Summary

From the findings, the perceived ease-of-use, organizational culture, and perceive usefulness are major factors that affect acceptance and integration of technology in the automotive industry in Kenya. Thus, managers in the automotive industry need to ensure that users of big data have the right knowledge and technical skills. By ensuring that the big data helps to improve decision-making, fast-tracking processes, and proving vital information about customer behavior, the big data will be perceived as beneficial, hence, likely to be adopted and used in the automotive industry.

CHAPTER SIX: CONCLUSION AND RECOMMENDATIONS

6.0 Introduction

Chapter six highlights the major conclusions and recommendations of the study that aimed to examine the factors effecting the integration and use of the big data in the automotive industry. The section will also highlight the areas of improvement and the suggestions for further research.

6. 1 Conclusions

6.1.1 Innovative Culture and Adoption of Big Data

Findings of the present study established a strong correlation between innovative culture and integration and use of big data. The research indicated that factors such as leadership, innovative environment, and supportive government policies motivate organizations to adopt the big data. Thus, it is apparent that innovative culture is a strong determinant when it comes to decisions on adoption of the technology in the automotive industry.

6.1.2 Perceived Usefulness and Adoption of Big Data

A strong link between perceived usefulness and the acceptance of big data was established by the present study. If the organization views the big data as beneficial in understanding customer behavior, fast-tracking processes, and in improving quality, it is highly likely to accept the technology. Hence, the perceived usefulness has a major effect on the integration and use big data in the automotive industry.

6.1.3 Perceived Ease-of-Use and Adoption of Big Data

A strong correlation between the ease-of-use and adoption of big data in the automotive industry was established. Big data must be simple to use, interpret, and require little or no supervision to operate. Furthermore, organizations must enhance the competence of the users by providing them with the relevant skills. Thus, from the results, the perceived ease-of-use is a strong predictor of the adoption of the big data.

6.2 Recommendations

6.2.1 Suggestions for Improvement

6.2.1.1 Innovative Culture and Adoption of Big Data

The present researched found a significant link between big data and integration of the big data. From research, the automotive industry, particularly the managers at Kenya Vehicles Manufacturers, Associated Vehicles Assemble, and Isuzu East Africa, need to create an innovative culture to foster not just the integration of the big data but also its use in the long term. As indicated by the Kenya Association of Manufacturers, acceptance of big data in the automobile industry remains a major challenge. Leadership needs to support the adoption of big data by creating values and norms that are aligned technology use. Managers should also work closely with the government with a view to improve the privacy regulations. This will help to boost stakeholders' confidence by assuring them of the safety of information. Such measures will enhance the adoption and leverage of the big data.

6.2.1.2 Perceived Usefulness and Adoption of Big Data

A strong relationship between the perceived usefulness and adoption of big data demonstrates the need for Kenya Vehicles Manufacturers, Associated Vehicles Assemble, and Isuzu East Africa to ensure that the big data provides the expected benefits to the organization. That means the need to tailor the big data to the actual needs within these organizations. By determining what specific needs they need addressed by the big data, the managers will acquire the right technology, hence, being able to benefit greatly. Unless the technology adds values, including helping the organization to make better decisions and gaining better understanding of the customers, then it will be perceived negatively. Thus, there is a need to maximize the benefits of the big data by ensuring that the technology is tailored to the needs of the specific organization.

6.2.1.3 Perceived Ease-of-Use and Adoption of Big Data

Studies showed a significant relationship between the perceived ease-of-use and the adoption of big data. Thus, there is a need to improve certain factors, including training and simplification of the technology to foster the adoption of the big data. One of the main

challenges facing the adoption of big data is the complexity of the technology, especially the processing of the complex information and the interpretation of information. Thus, there is a need for managers at Kenya Vehicles Manufacturers, Associated Vehicles Assemble, and Isuzu East Africa to ensure that the technology is easy to use. This can be enhanced by training and equipping the users with the necessary skills and knowledge.

6.2.2 Suggestions for Further Research

While the study achieved its objectives, a few limitations detected can be addressed by future researchers. First, future researchers should use a mixed method. In this study, a quantitative study was applied. The main limitation is that while the quantitative study shows the relationship between variables, it does not help to explain why such a relationship occurs. With a mixed method, the study will provide richer information helping to make better decisions. Secondly, to enhance the generalizability of the findings, future researchers can conduct the research in other industries, including the hospitality and the banking sectors.

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Appendices

Appendix A: Letter of Introduction

Friday, 21 July 2023

RE: FACILITATION OF RESEARCH – MACHARIA EDWIN MURIUKI

This is to introduce Macharia, Edwin Muriuki who is a Master of Business in Administration student at Strathmore University Business School, admission MBA133840/20. As part of our MBA Program, Edwin is expected to do applied research and undertake a project. This is in partial fulfilment of the requirements of the MBA course. To this effect, he would like to request for appropriate data from your organization.

Edwin is undertaking a research paper on **"The factors influencing adoption of big data in the automotive industry in Kenya"**. The information obtained from your organization shall be treated confidentially and shall be used for academic purposes only.

Our MBA seeks to establish links with industry, and one of these ways is by directing our research to areas that would be of direct use to industry.

We would be glad to share our findings with you after the research, and we trust that you will find them of great interest and of practical value to your organization.

We appreciate your support and shall be willing to provide any further information if required.

Appendix B: Consent Form

PARTICIPANT INFORMATION AND CONSENT FORM

STUDY TITLE: INVESTIGATING THE FACTORS INFLUENCING ADOPTION OF BIG DATA IN THE AUTOMOTIVE INDUSTRY IN KENYA

SECTION 1: INFORMATION SHEET – AUTOMOTIVE PERSONNEL

Investigator: EDWIN MURIUKI MACHARIA

Institutional affiliation: Strathmore Business School (SBS)

SECTION 2: INFORMATION SHEET – THE STUDY

2.1: Why is this study being carried out?

The purpose of this study is to assess the factors influencing the adoption of big data in the automotive industry in Kenya

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 were interviewed (or required to fill out a questionnaire) to get information pertaining to the study topic.

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

Employees from three major motor companies in Kenya: Kenya Vehicles Manufacturers, Associated Vehicles Assemble, and Isuzu East Africa.

Appendix C: Research Questionnaire

SECTION 1: Demographic Data

Kindly, fill in the questions by indicating X on the correct response

1. What is your gender?

- Male
- Female
- Prefer not to disclose _____

2. How old are you?

- 25-35 Years
- 35-45 Years
- 45-55 Years
- 55-65 Years
- Above 65 Years _____

3. What is your Education Level?

- High School
- College
- Undergraduate
- Graduate
- Doctorate
- Other (Please specify) _____

4. What is your Level in the organization?

- Non-managerial level
- Lower managerial level
- Middle managerial level
- Senior managerial level

SECTION 2: INNOVATIVE CULTURE

		Strongly Agree	Agree	Neutral	Disagree	Strongly disagree
1	We have supportive government policies to help in adoption of big data					
2	Our organization has strong leadership that fosters adoption of big data					
3	Issues of privacy influence the adoption of big data in our organization					
4	Our organization supports new ideas and innovations					
5	Technological innovation is seen as a top priority for the organization's success.					
6	The organization actively encourages employees to propose new technological ideas and solutions.					
7	Technological innovation is integrated into the organization's long-term strategic planning.					

SECTION 3: PERCEIVED EASE-OF-USE

		Strongly Agree	Agree	Neutral	Disagree	Strongly disagree
1	Adoption of big data is influenced by how easy it is to use					
2	Knowledge and skills will influence use of big data in our organization					
3	Adoption of big data can be influence by competency of its users					

4	Big data use requires little supervision					
5	I can complete tasks with technology without feeling frustrated.					
6	Using big data is straightforward and uncomplicated					
7	Big data technologies are user-friendly.					

SECTION: 4 PERCEIVED USEFULNESS OF BIG DATA

		Strongly Agree	**Agree**	**Neutral**	**Disagree**	**Strongly disagree**
1	Big data helps to improve efficiency					
2	Big data helps to understand customer behavior					
3	Big data can help in good decision-making					
4	Big data can help to improve quality					
5	Big data analytics can improve the quality of our products or services.					
6	Using big data has the potential to increase revenue for our organization.					
7	Big data helps us stay competitive and adapt to changing market conditions					

SECTION 5: ADOPTION OF BIG DATA

		Strongly Agree	**Agree**	**Neutral**	**Disagree**	**Strongly disagree**
1	Our organization provides supportive environment for big data adoption					
2	Our organization accepts big data use					

3	Our organization uses big data for various activities					
4	Our organization has integrated technology to its various functions					
5	Big data is actively used to improve our products and services					
6	Big data is employed to gain insights into customer behavior and preferences.					
7	Our organization has invested in the necessary infrastructure to support big data processing.					

Appendix D: IRB Approval

Strathmore UNIVERSITY

18th March 2024

Mr Macharia Edwin,
edwin.macharia@strathmore.edu

Dear Mr Macharia,

RE: Analysis of Factors Affecting Adoption of Big Data in the Automotive Assembly Industry In Kenya

This is to inform you that SU-ISERC has reviewed and **approved** your above **SU-masters** research proposal. Your application reference number is **SU-ISERC2058/24.** The approval period is from **18th March 2024 to 17th March 2025.**

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 72 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 72 hours.
v. Clearance for the 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 the expiry of the approval period. Attach a comprehensive progress report to support the renewal.
vii. Submission of an executive summary report within 90 days of completion of the study to SU-ISERC.

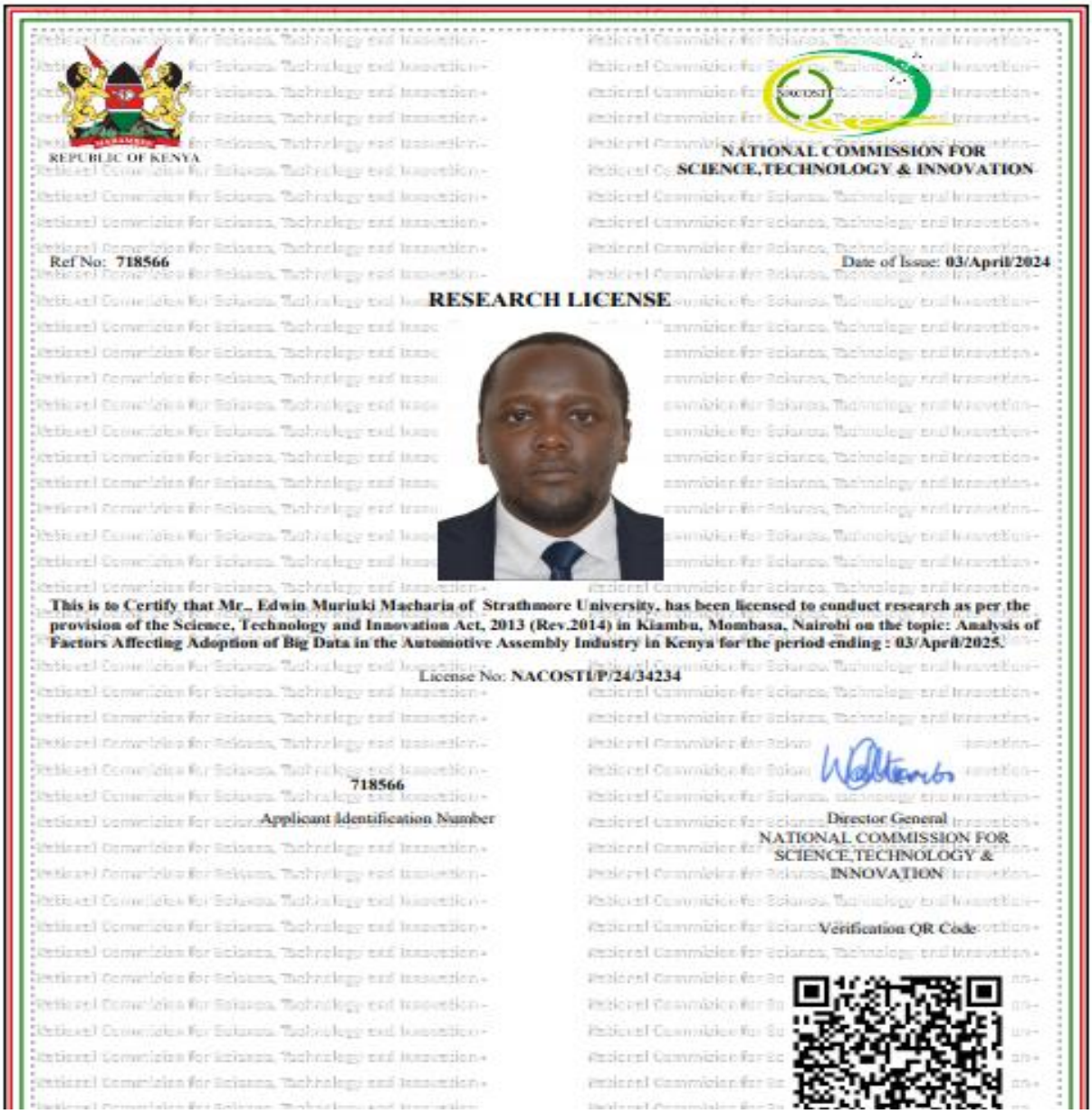
Before commencing your study, you will be expected to obtain a research license from National Commission for Science, Technology, and Innovation (NACOSTI) https://research-portal.nacosti.go.ke/ and obtain other clearances needed.

Yours sincerely,

Mr Ambrose Rachier,
Chairperson; SU-ISERC

STRATHMORE UNIVERSITY INSTITUTIONAL SCIENTIFIC AND ETHICAL REVIEW COMMITTEE
(SU-ISERC)
18-Mar-2024
Email:ethicsreview@strathmore.edu
P.O BOX 59857-00200
NAIROBI-KENYA

Appendix E: NACOSTI Approval



REPUBLIC OF KENYA

NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Ref No: **718566**

Date of Issue: **03/April/2024**

RESEARCH LICENSE

This is to Certify that Mr., Edwin Muriuki Macharia of Strathmore University, has been licensed to conduct research as per the provision of the Science, Technology and Innovation Act, 2013 (Rev.2014) in Kiambu, Mombasa, Nairobi on the topic: Analysis of Factors Affecting Adoption of Big Data in the Automotive Assembly Industry in Kenya for the period ending : 03/April/2025.

License No: **NACOSTI/P/24/34234**

718566

Applicant Identification Number

Director General
NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Verification QR Code