ARTIFICIAL INTELLIGENCE TECHNOLOGIES AND SUPPLY CHAIN PERFORMANCE OF MANUFACTURING FIRMS IN KENYA

BY

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MASTER OF BUSINESS ADMINISTRATION (PROCUREMENT AND LOGISTICS MANAGEMENT)

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DECLARATION

I declare that this dissertation is my original work and has not been previously published or submitted elsewhere for award of a degree. I also declare that this contains no material written or published by other people except where due reference is made and author duly acknowledged.

Student Name: ____________________ Reg No. __________

Sign: ____________________ Date: _________________

I do hereby confirm that I have examined the master's dissertation of

Cate Nkatha Kirimi

And have certified that all revisions that the dissertation panel and examiners recommended have been adequately addressed.

Sign: __________________ Date: _________________

Dr. Jackson Ndolo

DEDICATION

I dedicate this research project to my dad, mum, Edna and Emmy for their support. I will remain forever grateful.

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I would like to thank Dr. Jackson Ndolo for being my supervisor and mentor at KCA University. Without his valuable guidance, critiques and recommendations, completion of this project would not have been possible. I would also like to thank KCA University for offering me the opportunity to study in their institution and all other members of staff for their support and knowledge fulfillment during this study period.

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ABBREVIATION

AI	Artificial Intelligence
ANN	Artificial Neural Network
CPS	Cyber Physical Systems
GDP	Gross Domestic Product
ICT	Information Communication Technology
IOT	Internet of Things
KAM	Kenya Association of Manufacturers
ML	Machine Learning
R&D	Research and Development
TOE	Technology Operation Environment
TRA	Theory of Reasoned Action

DEFINITION OF TERMS

Artificial Intelligence is what is given to a system so that it behaves, thinks, or acts like it has Human-level intelligence.

Internet of Things The Internet of Things (IoT) describes the network of physical objects—"things"—that are embedded with sensors, software, and other technologies for the purpose of connecting and exchanging data with other devices and systems over the internet.

ABSTRACT

Today's manufacturing systems are becoming increasingly complex, dynamic, and connected. The factory operations face challenges of highly nonlinear and stochastic activity due to the countless uncertainties and interdependencies that exist. Recent developments in artificial intelligence have shown great potential to transform the manufacturing domain through advanced analytics tools for processing the vast amounts of manufacturing data generated, known as Big Data. Adoption of artificial intelligence technologies has been taunted as an enabler of organizational performance. Therefore, the current study sought to assess the level of adoption of AI technologies and their effect on the performance of supply chains of manufacturing firms in Kenya specifically in the automobile subsector. The study was based on socio technical theory and technology organization environment theory. The study adopts descriptive design targeting the seventeen automobile companies in Kenya. Census method was used to select all 153 functional officers in; Finance, Human resource, ICT, Logistics, SCM, Legal, R&D, Security and Operations since the population was small. Data was collected through use of questionnaires send via Google form, analyzed through descriptive and inferential statistics. The finding of the study is presented in tables. It's expected that the study findings will find use among researchers, policy makers and managers of the manufacturing firms. Key findings of the study are that; all the three artificial intelligence technologies (IOT, Data analytics, Sensors and Drones) have a positive and significant influence on supply chain performance of manufacturing firms in Kenya. Besides government regulations moderating the relationship between AI technologies and supply chain performance. It is recommended that manufacturing firms need to embrace more AI embedded technologies for better supply chain responsiveness, flexibility, reliability and low operational costs. Further research needs to be undertaken on more AI tools and in other institutions so as to verify the study findings.

CHAPTER ONE: INTRODUCTION

1.0 Background to the Study

Artificial Intelligence (AI) helps computers to learn from experience, adjust to new stimuli, and perform tasks of a human nature. It works by combining large amounts of data with fast, iterative processing and smart algorithms, allowing the program to learn from patterns or features in the data automatically. AI is the human-like intelligence given to systems and demonstrated by machines in doing tasks associated with human intelligence. AI systems can therefore, think like humans, act like humans, think rationally or act rationally. AI systems are not only more powerful and more useful than ordinary computers, but they also solve complex emerging human problems. These systems can be used in areas such as medicine, to conduct guided surgery; transportation, for autonomous vehicle control; face recognition; speech recognition; decision making in agriculture, manufacturing and housing and general wisdom (Fjelland, R., 2020). AI can be classified as weak or strong based on its stage of evolution. Weak AI is equivalent to artificial narrow and general intelligence (Fjelland, R.,2020), while strong AI is a more ambitious version of AI. The present study is a review of the AI technologies and their effect on supply chain perfomance of manufacturing firms in Kenya. AI entails all manner of prediction systems, such as predicting pregnancy disorders among women (Maylawati et al., 2017) .

According to Violi (2020) and Pournader et al. (2021) artificial intelligence tools are used for a variety of supply chain operations to facilitate decision making. Developed countries such as the US have invested in AI research centred in robots and pattern recognition. Microsoft has invested in real-time robots and innovative technologies for image processing. Amazon uses AI to develop autonomous robots to be used in their delivery system (Shavarani et al., 2018). Facebook has come up with an AI technology for facial recognition (Mann & Smith, 2017). Further, robot cars have been developed at Stanford University. Similarly, cleaning and 4-foot walking robots have been developed at Massachusetts Institute of Technology (Bledt et al., 2018). AI has been proven to be capable of supporting sustainable development because of the technologies that have been integrated in vast areas of decision making such as, in social media, search engines, agriculture, medicine, transport, manufacturing, and in judiciary. According to Ng (2017), AI is set to have the same impact like electricity that transformed the world in transport, manufacturing, agriculture and health. AI is one of the most rapidly growing technologies which is also increasingly affecting our lives. Methods AI uses include data mining, machine learning, robotics, natural language processing, expert systems, and computer vision.

AI usage has spanned various sectors notable agriculture, health, housing, transportation, manufacturing among others. In agriculture, data mining as a method of AI has been used for decision making. It was therefore, possible to predict crop yield by integrating seasonal and spatial factors by using GIS technologies. Machine learning method has also been used for enhancing the efficiency of agricultural activities. Techniques such as support vector machines and neural networks have been used as classifiers and k-means have been used for clustering (Behmann et al., 2015) These techniques have been applied to create models that have been used to create applications for early detection of plant diseases based on spectral features and weed detection based on shape descriptors with supervised or unsupervised learning methods (Behmann et al., 2015). Pests and diseases have been eliminated without resorting to indiscriminate use of agrochemicals and in Netherlands, robots have been used to pick fruits and vegetables growing in greenhouses (Masuzawa et al., 2017). In the United Kingdom, robots have been used to harvest strawberry faster than human beings (King, 2017).

AI algorithms such as Artificial Neural Networks (ANNs) have been used in the evaluation of market values for house price properties. In a research conducted in Italy, accurate results were obtained in the evaluation of house property valuation (Morano et al., 2015). Similarly, prizes of old houses have also been predicted to determine their value some years later. Such a prediction was conducted using an AI algorithm known to support vector machine where good results with an acceptable flexibility were obtained (Fu, 2018). Artificial Intelligence has also been utilized in the medical industry. AI, using data mining has been applied in heart disease prediction. In a study conducted in India, Artificial Neural Networks was used and compared with Naive Bayes and Decision Tree. ANNs achieved the best prediction for the heart disease (Chadha et al., 2016).

AI models have been developed which have the ability to better predict patients with heart disease that surpasses medical experts. This gives further evidence that AI is able to improve healthcare in the world. In another study, a large data set of over 80,000 patient records was collected and used to build the model (AI beats doctors at predicting deaths due to heart disease). In a similar study, data was gathered from a wearable heart rate sensor and the model built was able to predict heart disease related conditions such as diabetes and high blood pressure with over 80% accuracy, comparable better than tests made by human experts

(Ballinger et al., 2018). Machine learning has been used to care for individual patients in medical practice. In another study, patients suffering from cancer were assessed using computers. This reduced the diagnosis time and the need for human expert, beside improving patient treatment (Darcy et al., 2016). Similarly, machine learning techniques have been used to model the progression and treatment of cancerous conditions. A study conducted early of diagnosis of cancer where patients were classified accurately as high or low risk by applying machine learning methods and using techniques, such as ANNs, Bayesian Networks, Support Vector Machines and Decision Trees (Kourou et al., 2015).

Artificial Intelligence has grown from science fiction to a technology for improved industry manufacturing. AI is at the centre of the next generation of industrial systems known as Industry 4.0 (Lee et al., 2018). A study conducted in China, proposed a framework of a data-driven optimization of production. The framework allows managers to keep track of activities in a factory without their presence. It provides abstraction tools to enable decision making in addition to automatic allocation of resources, thus enabling the factory to operate almost autonomously (Arvind & Bourne, 2016). Machine learning as an AI method has successfully been applied in manufacturing in areas such as optimization, control and troubleshooting (Wuest et al., 2016). Similarly, data mining has been applied by exploiting vast amounts of data collected from product and process design, assembly, materials planning, quality control, scheduling, maintenance, and fault detection. The useful knowledge extracted from these processes has been of benefit in improving the industrial processes (Choudhary et al., 2008). Efforts have been made towards intelligent manufacturing and new models have been proposed in China. One such model has a life cycle of manufacturing which uses autonomous sensing with interconnection, collaboration, learning, analysis, cognition and decision making to enhance production and improved services to users (Li et al., 2017).

Recently researchers have narrowed down to the following AI technologies; high-level, general framework and key elements in smart manufacturing systems and governmental initiatives around the globe as the consisted constituent technologies such as IoT, cyber-physical systems (CPS), cloud computing, big data analytics, and information and communications technology (ICT) and their interrelationships (Li, B., Hou, B., Yu, W., Lu, X., and Yang, C., 2017; Zhong, R. Y., Xu, X., Klotz, E., and Newman, S. T., 2017). It is evident that there is scanty use of AI technologies in Africa. Not much has been achieved using data mining methods in agriculture, education, or manufacturing. This may be attributed to lack of infrastructure for collecting data. However, attempts have been made in West Africa to improve the economic situation and food security for the people in this area by classifying rural agricultural soils (Heil et al., 2017).

Africa has so far used AI technologies to a very limited extent. Although, large volumes of data are generated, there is lack of planning, investment and policy-making required to reap the full benefit of this game changing technologies. This is because there is lack of infrastructure to collect large volumes of data generated. Government infrastructure is lacking to collect for example student data in education or government databases not available for health records in hospitals and clinics. Thus, volumes of data are present but scattered and therefore not usable. In short there is lack of high quality data that could be fed into the systems.

The main challenges facing Africa can be grouped into two: scarcity of quality data and scarcity of talent. Talent is necessary because AI systems require customization, AI systems cannot be downloaded and applied to a generic problem. The scarcity of experts has limited the number of researchers in Africa that could conduct research and use AI technologies. Limited funding from the African governments is another challenge. African researchers depend to a large extend on funding from external sources. This further hinders relevant research in AI technologies that is applicable locally. Notably, a heavy financial investment is inevitable in data mining projects since they require large volumes of data that are collected over a long period of time in addition to repeated training when developing the technologies. This calls for African governments to invest in research. Another challenge is the lack of policy in data use. Most foreign companies that collect useful data from African citizens, such as communication companies and banks, do not release data to researchers, because it is stored in their databases. Government policies on data availability from such institutions would greatly help to create a level ground on AI research in Africa. These aforementioned challenges forms part of the foundation for the need of the current study.

Various theories have explained the relationship between technology adoption and organizational perfomance, however this study reviews socio-technical system and technology-organisation-enviroment theories. According to Khasawneh (2008) technology adoption is defined as the first use or acceptance of new technology or new system. Technology adoption is clarified by numerous theories and models such as the technology acceptance model (TAM), innovation diffusion theory (IDT), the theory of reasoned action (TRA), Theory of

Planned Behaviour (TPB), technology-organization-environment (TOE); and unified theory of acceptance and use of technology (UTAUT). Zhenhua et al (2008) have categorized adoption into three echelons: organizations, groups, and individuals. TAM, UTAUT, and TOE are extensively used in reviewing the adoption of technology by the side of the organizational level. Studies have argued that UTAUT was designed for foreseeing the adoption of technology at the individual level, however, there are some few studies at the organizational level (Oliveira et al., 2011; Williams et al., 2009; Zhenhua et al., 2008). Hence, the TOE framework was developed as a prevalent theoretical view of technology adoption in IT, numerous authors have verified its variables for the acceptance of numerous technologies (Thiesse et al., 2011; Wang & Chen, 2006). (Oliveira et al., 2011) state that, IDT theories are similar to the organizational context and expertise of the TOE framework, though TOE is more significant than IDT as per the analysis of (Zhu et al., 2003). Therefore current study adopts TOE theory.

Socio-technical theory has at its core the idea that the design and performance of any organisational system can only be understood and improved if both 'social' and 'technical' aspects are brought together and treated as interdependent parts of a complex system. 3.1.1 Concept discussion. The STS theory first coined by Emery and Trist, a classical socio-technical systems theory is a combination of the social and technical dimensions that are susceptible to their operating environments (Appelbaum, 1997). Socio-technical systems are distinguished by a high level of social intricacy and technical complexities intended to fulfil society's important functions (Baxter and Sommerville, 2011; Wu *et al.*, 2015). They are the synergistic union of people, technology, organisational structures and processes, including the operating environment within which all these occur (Carayon *et al.*, 2015). In its modern holistic view, Whitworth (2009) adds that a socio-technical system is not one of two separate and side-by-side systems, but the whole integrated system. It is the interaction between the social (including how teams and individual team members perform tasks) and technical systems (including complex interdependencies of the system development life cycle) (Troyer, 2017). Perhaps a more concise description is provided by Bostrom and (Heinen,1977), and (Walker *et al.*,2007), that STS are made up of humans applying technology solutions to execute work activities through processes within a social structure (organization) to accomplish set goals. It should be noted that the social dimension is equally, if not more, complex even at smaller levels of groupings of people (Troyer, 2017). On the one hand,(Appelbaum, 1997) and (Egan *et al.*, 2004) argue that the main aim of the social dimension is to design work structures that respond to the psychological needs of the employees including taking on meaningful tasks and a sense of belonging and responsibility. On the other hand, the technical dimension is mainly concerned with the provision of tools and techniques used to accomplish organisational goals (Appelbaum, 1997; Egan *et al.*, 2004). It's the most commonly applied theory when designing organizational perfomance that incorporate technology adoption due to its generality and so has the capacity to be "adopted with ease to almost any organizational situation and remains open to continual improvement and revision (Hackman, R.J. and Oldham, G.R., Work Redesign, Addison-Wesley, 1980).

Despite the potential benefits of technology removing the need for human effort, AI also present many challenging safety issues that could negatively affect economic prosperity and national security (directly or indirectly). AI continues to evolve and advance, understanding and interpreting the output of AI tools and related technical details become increasingly exclusive to data scientists and similar professionals with specialized skills in this domain. Often times, this creates a knowledge gap leaving plant managers and production engineers lacking this background with the ability to comprehend and appropriately interpret the meaning of the results from AI models in a manner consistent with the context of the problem area. This highlights a significant challenge of AI in manufacturing, namely the importance of proper interpretation of AI analysis to decision-makers who may not be experts in AI. Without a proper grasp of the analysis that relates to the fundamental physics, users would have no basis to trust and accept the analysis results. Since manufacturing operations are based on what is known physically, not on what might probabilistically occur as indicated by AI models, more transparent, physics-guided process models are required. This has given rise to research into the level of adoption of AI technologies in the Automotive industry in a developing country and its effect on their supply chains from a perfomance perspective.

1.2 Kenya Manufacturing Sector

Across the World, the manufacturing sector has played an important role in driving economic development by stimulating and sustaining high productive growth, boosting employment opportunities for semi-skilled labour and building country competitiveness through exports. Very few countries in the world have managed to industrialize and develop without the manufacturing sector playing a leading role. Kenya, like many other developing countries, has not managed to develop a robust manufacturing sector and growth has been primarily driven by the agriculture and services sectors respectively. The country has thus experienced a premature deindustrialization as evinced by the decline in GDP contribution by the manufacturing sector which was at a paltry 8.4% in 2017 and 9.2% in 2016. Deindustrialization has been characterized by a rising share of the services sector in GDP and fuelled debate as to whether services can replace the manufacturing sector as an engine of economic growth.

The automotive industry in Kenya is primarily involved in the assembly, retail and distribution of motor vehicles and grouped into five main sub-sectors namely: Motor vehicle assemblers, Trailer assemblers, Motorcycle assemblers, parts and components manufacturers, and Body builder's sub-sectors. There are 4 main motor vehicle assemblers in Kenya namely: Trans Africa Limited and Associated Vehicle Assemblers (AVA), in Mombasa, Kenya Vehicle Manufacturers in Thika, and Isuzu East Africa Limited in Nairobi, industrial Area. Combined, they have capacity to assemble about 46,000 units per year (currently operating below capacity utilization) and directly employ over 1,500 people. Total investment by motor vehicles assemblers is estimated at USD 148 million (EAC, 2019). The Assemblers currently operate at a single shift and have a capacity to do three shifts a day.

Finally, the fifth company Mobius Motors Ltd specializes in the design and assembly of Mobius Brand motor vehicles. Mobius motors is the second home-grown Original Equipment Manufacturer (OEM) in the region, with brand recognition across East Africa. Since their incorporation in 2009, Mobius has assembled 53 units. Table 3 shows various brands that are assembled locally.Some of the challenges facing the sub sector include; Research and Development (R&D): Lack of incentives to undertake R&D discourages innovation and new technological development within the automotive sector. Components used for the development of prototypes for R&D are subjected to payment of duties and taxes which is a disincentive to R&D. Technology advancement: Acquisition of the latest technology for assembling and manufacture of spare parts is hindered by the lack of affordable long-term financing options for the sector. According to (KAM, 2020) in the KAM 2022, Automobile sector report some of the challenges include lack of regional policy to regulate the sector and accord certainty to investors and low technological upgradation due to lack of incentives.

1.3 Statement of the Problem

The automobile industry is a pillar of the global economy and a main driver of macroeconomic growth and stability, and technological advancement in both developed and developing countries, spanning many adjacent industries(A. Kearney, 2014). The core automotive industry (vehicle and parts makers) supports a wide range of business segments, both upstream and downstream, along with adjacent industries (figure 1). This leads to a multiplier effect on growth and economic development. According to a 2020 report by the International Labour Organization (ILO), the global direct employment in the industry was estimated at nearly 14 million workers in 2017.Generally, the automotive industry supports in generating government revenue, creating economic development, encouraging people development, and fostering R&D and innovation (figure 2). Therefore, developing a strong automotive sector could potentially result in spill-overs into agricultural and construction equipment manufacturing as well as other specialist equipment Manufacturing.

Kenya's manufacturing sector was negatively impacted by the COVID-19 pandemic, which led to a negative growth rate of 0.1% in 2020 (Economic Survey, 2021). It is critical that Government views the COVID-19 crisis as an opportunity to reshape the economy and revitalize manufacturing for high economic growth and greater equity. The importance of industry in creating shared prosperity is a priority of the Sustainable Development Goals (SDGs). Specifically, SDG 9 on Industry, Innovation and Infrastructure. This entails building resilient infrastructure, promoting inclusive and sustainable industrialization and fostering innovation. The manufacturing sector has traditionally acted as a growth escalator, leading to poverty reduction in countries that have been able to ignite industrialization. The manufacturing sector GDP contribution was 12.05% in 2011 but declined to 7.61 % in 2020 (KNBS, 2020). The manufacturing sector created 293.8 thousand formal jobs in the private sector in 2020 compared to 329 thousand jobs in 2019. One of the governments agenda for the manufacturing sector is enhance digitization of manufacturing; Digital Manufacturing connects manufacturers digitally, much like the Internet of Things (IoT), with a central network that connects digital access across all locations. This allows automation and the ability to learn processes independently, rapidly respond to change, and highlight quality issues.

Local automotive companies have sought to take advance of sophisticated technology to address the competitive pressure and to meet increased customer expectations on quality and cost. Legislation, for instance those relating to emission and recycling, have a strong impact both on vehicle technologies and production.

Artificial intelligence is transforming the global and local industrial landscape by adding value to different businesses. The effect of AI has been felt in different sectors including; logistics, transportation, healthcare, industrial manufacturing and finance. Manufacturers use AI to analyze sensors data and predict breakdowns and accidents. Synthetic intelligence systems aid production facilities in determining the likelihood of future failures in operational machinery, allowing for preventative maintenance and repairs to be scheduled in advance. Similarly, manufacturing companies must continuously develop their production systems and adapt to fluctuating market demands, customer requirements and supply conditions to remain competitive in a globalised environment (Kamble, S.; Gunasekaran, A. Sharma, R. (2018); Drath, R.; Horch, A.(2014). The structure of the manufacturing sector has seen little change over the years despite targeted policy interventions attempting to adjust this. The manufacturing sector's share of GDP has remained stagnant with only limited increases in the last three decades, contributing to an average of 10% from 1964-73 and rising marginally to 13.6% from 1990-2007 and averaging below 10% in recent years.

AI has been taunted as the game changer in solving the challenges facing the manufacturing sector in Kenya. Despite its adoption the perfomance of the sector has still remained stagnant posting an average GDP of 10% to the country's economy. Which begs the question has AI embedded technologies brought the desired supply chain perfomance? Therefore the study sought to assess the level of adoption of AI technologies and their effect on the perfomance of supply chains of manufacturing firms in Kenya.

1.4 Objectives of the Study

1.4.1 General Objective

The general objective of the study was to assess the level of adoption of artificial intelligence embedded technologies and their effect on supply chain performance of manufacturing firms in Nairobi City County, Kenya.

1.4.2 Specific Objectives

The study was guided by the following specific objectives;

a) To evaluate the effect of Internet of things on supply chain performance of manufacturing firms.

b) To determine the effect of big data analytics on supply chain performance of manufacturing firms.

c) To establish the effect of sensors and drones on supply chain performance of manufacturing firms.

d) To determine the moderating effect of government regulations on the relationship between artificial intelligence technologies and supply chain performance of manufacturing firms.

1.5 Research Questions

The study sought to answer the following questions

a) To what extend does Internet of things affect supply chain performance of manufacturing firms?

b) How does big data analytics affect supply chain performance of manufacturing firms?

c) What is the effect of sensors and drones on supply chain performance of manufacturing firms?

d) To what extend does government regulations moderate relationship between artificial intelligence embedded technologies and supply chain performance of manufacturing firms?

1.6 Significance of the Study

The findings of this study will be of great significance to several stakeholders including; management of manufacturing firms, government agencies, researchers and academicians, information technology experts as well as supply chain management practioners in Africa and other less developed economies. The manufacturing firms supply chains continue to be sources of industrial products and agents of development through production of new products, provision of employment opportunities as well as revenue generation to government through taxes and levies.

Government agencies may find this study significant because it will cover in detail the influence of artificial intelligence technologies on manufacturing firms. The findings of this study concerning the performance of the supply chains through the technologies will be a great insight to the government matters crafting legal frameworks that promote adoption of AI.

The management of the manufacturing firms supply chains would find use in the study findings through gaining information on which AI based technology boosts perfomance to a great extent. It will also help them identify challenging areas towards full adoption of AI technologies as well as capacity gaps. To a great extent the study findings will help in crafting a sustainable technology adoption strategy.

Researchers and Academicians; This research acts as a reference material for future researchers on other such and related research topics and will assist academicians who are undertaking studies in similar topics. With more research taking part on this topic, we will be able to expand the argument of enhancing AI technologies as a key part of promotion of supply chain perfomance by providing information and possible solutions.

1.7 Scope of the study

The scope of this study was exploration of AI technologies and their effect on operational performanceofmanufacturing firms supply chains. AI embedded technologies will be limited to; IOT, big data analytics,sensors anddrones and government regulations. The study will focus on the fourKenyan manufacturing firms. Inaddition, previous studies have only focused on financial and telecommunication sectors.

CHAPTER TWO: LITERATURE REVIEW

2.0 Introduction

The chapter reviews different theories related to the study and the empirical literature available from past studies. It also provides a conceptual framework of the study variables and the research gap that necessitates the study.

2.1 Theoretical Review

A theoretical review is a set of interrelated concepts, including theories and models (Ravitch & Riggan, 2016). A theoretical framework directs the study, specifies whatever the investigator will evaluate or measure and the particular statistical links the study will explore. Theoretical frameworks are of major significance in deductive, hypothetical-testing studies. The study theoretical review consists of theories that exhibit the effect of articificial intelligence on supply chain performance of manufacturing supply chains. The socio technical system theory and theory on technology-organization-environment(TOE) are explored to give a basic understanding of the study phenomenon.

2.1.1 Socio-Technical System Theory

Socio-technical system theory as coined by Trist and his colleague in the 1950s in the UK (Trist and Bamforth, 1951) aimed at improving the performance of work system by examining how employees deal with technological difficulty and uncertainty effectively. Accordingly, the socio-technical system has produced a "win-win" situation that employees were more productive and committed, technology was adapted successfully and organisations achieved better performance overall. However, the approach failed to spread widely due to the resistance of leaders to share operational control with employees. Managers complained that workers were not complying with their directions on how the technology was to be operated, while workers insisted that operating the technology directed by engineers was impossible in their working conditions. By the 1970s, Davis and Cherns (1975) incorporated the sociotechnical system in various organisations in the USA and supported the idea of "Quality of Work life". It was adopted to create meaningful work for employees but failed to diffuse further again due to traditional leaders who were concerned giving workers greater control over the design and operation of work systems.

In the early 2000s, researchers (e.g. Hammer and Champy, 2001) redesigned the system by offering firm control for leaders and constructed the lean six-sigma approach to enhance performance by focusing on efficiency and cost saving. In recent years, the burgeoning of digitisation, AI and machine learning has significantly changed the interaction between employees and technologies in the work system, and sociotechnical system has become more relevant than ever before (Pasmore et al., 2019). Sirianni and Zuboff (1989) argued that in the era of smart machines, individuals would face great challenges of either becoming masters of technology or its slaves, and there is a need to design work systems that could fit either of these situations. The socio-technical system developed a hope that organisations could achieve joint optimisation from both technological development and human aspirations.

With the entrance into the era of automation, organisations have employed new ways of working by incorporating AI to enhance organisation-related outcomes, and AI is developed to either make decisions or guide the future decisions (Kaplan and Haenlein, 2019). However, organisations are struggling to keep their social systems in the pace of technology advancement, and they are facing the challenges of navigating high caliber talent, engaging the workforces, developing effective work design and enhancing organisational capabilities (Pasmore et al., 2019). With these considerations, the socio-technical system theory is adopted as the theoretical foundation to analyse how multiple components jointly contribute to the work outcomes. The better fit between social and technical subsystems, the more desired individual and organisational outcomes will be achieved through AI adoption and application.

From the socio-technical system perspective, effective implementation of AI into organisations requires an integrated approach in which development in both social and technical systems is considered (Belanger et al., 2013). This theory incorporates components from four elements that transform work system inputs to desired outputs, including the personnel subsystem in regard to social and people-related factors, the technical subsystem in regard to technology related factors, the organisational structure or work/job design subsystem in terms of organisational structure and work process, and environmental factors external to the work system (Belangeret al., 2013; Hoyland et al., 2019).

2.1.2 Technology-Organization-Environment (TOE) Theory

Technology-organization-environment (TOE) framework was developed by Tornatzky (1990) to study the technology adoption of numerous IS and IT services and products at the organizational level. It has risen as an extensive theoretical viewpoint on IT adoption (Zhu et al., 2004). The addition of organizational, technological, and environmental variables had made TOE beneficial over other models used in the study of the adoption of technology, the use of technology, and worth creation from innovation in technology (Hossain & Quaddus, 2011; Zhu, K. and Kraemer, 2005). Moreover, it is free from restrictions on business and organization’s size (J. Chen et al., 2010). Hence, it offers a complete image of the user's adoption of technology, its execution, the expected obstacles, its effect on value chain operations, the dissemination amongst companies after adoption, factors impacting business innovation adoption choices, and to grow better organizational capabilities utilizing the technology (Salwani et al., 2009; Zhu et al., 2004).

According to Tornatzky (1990), There are around three types of contexts that can have an effect on technology; acceptance, creativity, and implementation. These three TOE framework contexts are explained as follows: The technological context includes the variables that affect a person, an organization, and the adoption of innovations by a business (Claycomb et al., 2005). It comprises some innovation characteristics from IDT, that impact the possibility of adoption (Dedrick & West, 2003). Apart from innovation qualities, investigators have incorporated a few different variables also. The studies establish that system integration, complication, perceived intended benefits, perceived unintended benefits, and standardization are important variables while observation is found irrelevant (Hossain & Quaddus, 2011; Musawa & Wahab, 2012). Studies based on TOE framework have numerous restrictions. As indicated by Dedrick & West (2003), TOE framework is only a scientific classification for classifying variables and it doesn't represent the integrated theoretical framework or well-established theory, therefore, there is a need for a strong framework to examine technology adoption in organizations. Low et al., (2011) moreover presented that TOE framework does not have main constructs in a model and variables in one and all context. The TOE framework is insufficient in its descriptive capacity of the adoption of technology, while it can be realized in the circumstance of EDI adoption where nearly half of the levels of EDI acceptance fluctuation stay mysterious (Musawa & Wahab, 2012). Similarly, (Wang et al., 2008) claimed that the TOE framework partakes uncertain key concepts, as well as TOE framework variables that fluctuate in context. Therefore, certain variables, such as sociological variables, psychological variables, technical readiness should be integrated to advance the TOE framework, factors notable to the nation setting, for example, government strategy/guideline, innovation framework and culture (Hossain & Quaddus, 2011; Zhu et al., 2004).

2.2 Empirical Review

2.2.1 Internet of Things and Supply Chain Performance of Manufacturing Firms

In most of the modern enterprises, regular supply chain processes are managed by software packages such as enterprise resource planning (ERP) and advanced planning and scheduling (APS). However, these systems are not enough to face the increasing challenges of today's supply chains; such as flexibility, responsiveness and agility (Reaidy et al. 2015). Hence, new approaches have been introduced to meet these challenges. With the imminent global shift towards Industry 4.0 and smart organizations, IoT technology is playing a vital role in this transition. The core concept of IoT is that "everyday objects can be equipped with identifying, sensing, networking and processing capabilities that will allow them to communicate with one another and with other devices and services over the Internet to achieve some useful objective" (Cortés et al., 2015). IoT infrastructure is based on many technologies such as radio frequency identification (RFID), Wi-Fi, Bluetooth, sensors, and cloud computing. IoT can be useful in improving the performance of the whole supply chain and transforming it to be a smart one; for example, it can be used for monitoring, tracking products, creating an intelligent transportation system, and demand forecasting. Inventory is a one of the significant areas where cost reduction can be achieved in a supply chain (Ibrahim et al., 2011). Specifically, IoT can reduce inventory costs as well as the bullwhip effect across the supply chain.

IoT is an emerging technology advancement in this era, which can help create a bigger leap ahead in the Information and Communication Technology (ICT) sectors in the existing and future. IoT is the extension of networking and web technologies into the physical realm via sensors, actuators, and digital devices for the betterment of automation services (Miorandi et al., 2012). IoT enabled devices are used in all sectors and industries such as transport, healthcare, farming, commerce, tourism, food production, education, and engineering. While the number of connected objects to the wireless devices increase, data provided by those objects also increase, which may increase the quality and reliability of the results of those collected data, all these processes could happen without human intervention (Torgul ˘ et al., 2016). All these collected data send to the cloud storage by the connected devices. Cloud Computing (CC) providing unlimited, on-demand storage, and donkey years (Botta et al., 2015; Rojas, 2015). This IoT and CC combination creates a superhighway that enables possibilities to integrate any sectors with ICT to increase productivity and efficiency without human interaction.

The advancement of ICT applications introduces multiple technologies to increase efficiencies such as IoT, CC, drone, and artificial intelligence (AI). These technologies working in various steps during the FPP; such as nutrition analysis, quality control, packing, supply chain, and food safety. IoT enabled systems food distribution can help to automate food supply chain process during the process (Bhushan et al., 2016)(Accorsi et al., 2017). Meanwhile, food safety and its freshness can be monitored with mobile based IoT application in real time (Witjaksono et al., 2018). And, an IoT based application used to analyze the food ingredients and that uses sensors for food nutrition quantification (Sundaravadivel et al., 2018). Similarly, sensor technologies are used in AI-based packing (Popa et al., 2019). Computerized systems used in food industries to check weight and find leakages of the foods that goes down the line (Srivastava et al., 2015). But, all the technologies using by the food industries require more development in terms of safety and supply process. Research based development created a sensor based IoT system to manage the restaurant food waste (RFW) that includes generation, collection, transportation, and disposal of the food wastes; and this work was provided positive feedback on RFW management processes (Wen et al., 2018). Likewise, Food waste throughout the entire food production process could be reduced using IoT based monitoring system with the help of dynamic shelf-life prediction based on the kinetic Arrhenius model (Ostojic et al., 2017). Similarly, another study has investigated and believed that food safety through IoT was significantly possible in a Chinese restaurant (Yun Gu et al., 2012). Further, a smart food security system architecture has been proposed that could be developed based on big data and IoT, which helps to create food safety information and carry out the information on the monitor and analyze the collected data where it assists to realize monitoring from food source to the final consumer (Parvin et al., 2019). Similarly, Block chain technologies implemented IoT devices were proposed to increase food safety during the food supply chain (Lin et al., 2018).

2.2.2 Data Analytics and Supply Chain Performance of Manufacturing Firms

In the manufacturing sector, big data analytics has improved the performance of businesses (Sun, S., Cegielski, C. G., Jia, L., & Hall, D. J., (2016). Big data analytics are more than just a data mining technique that uses mobile development units, social media platforms, increase Internet bandwidth, and different analysis techniques. Big data analytics are intended to bolster the performance of companies along several dimensions (Kwon, O., Lee, N., & Shin, B., 2014). The different benefits include creating openness, adapting offers and replacing decision making with automated algorithms. In addition to this, it can increase the competitive advantages of different companies in both, developed countries and emerging economies (Brown B, Bughin J, Chui M, Dobbs R, Hung Byers A, Manyika J, et al., (2011).

A successful smart factory needs to manage data-related processes along the entire data life cycle, including data collection, storage, distribution, analysis, use, and deletion, to ensure high data quality at all times. This includes processes related to the design, deployment, and use of hardware and software; the planning, implementation, and monitoring of intra-organizational procedures; and the inter-organizational practices in the value chain. The comprehensive quality control of all important factors is an effective measure against unfit, erroneous, unintelligible, or otherwise unreliable data. Mainly due to this convergence and to technological advances achieved throughout the last two decades, manufacturing related data is being generated at exponentially growing rates (Shao, G., Shin, S.-J., & Jain, S., 2014). Still, there are few manufacturing sectors that truly capitalize on such amount of collected data, by extracting meaningful insights for supporting improvements on their businesses, processes and products (Jain, S., Shao, G., & Shin, S.-J., 2017). Recently, the application of Data Analytics to manufacturing data has been presented as a solution for the issue of capitalizing on ever-growing manufacturing data (Lade, P., Ghosh, R., & Srinivasan, S., 2017). Manufacturing Data Analytics can be defined as the process of finding useful information from analysing manufacturing generated raw data, whether for decision making support or for optimisation of business and production processes, among other objectives((Bang, S. H., Ak, R., Narayanan, A., Lee, Y. T., & Cho, H., 2019); Ren, S., Zhang, Y., Liu, Y., Sakao, T., Huisingh, D., & Almeida, C. M. V. B., 2019) present the main objectives for applying Big Data Analytics (BDA) in smart manufacturing. It is envisioned that future BDA applications will be able to assist enterprise managers to learn everything about what they did today and to predict what they will do tomorrow. This future vision is based on a taxonomy of data analytics approaches for manufacturing, which entails four types of analytics processes: descriptive, diagnostic, predictive and prescriptive analytics (Shao, G., Shin, S.-J., & Jain, S., 2014); Dai, H.-N., Wang, H., Xu, G., Wan, J., & Imran, M., 2019). Both descriptive and diagnostic analytics methods are reactive while predictive and prescriptive analytics approaches are proactive. Descriptive analytics is an exploratory analysis of historical data to tell what happened. During this stage, most of data mining and statistical methods can be used to reveal the data characteristics, recognise patterns and identify relationships of data objects. Diagnostic analytics is a deeper look at data to attempt to understand the causes of events and behaviours. The diagnostic analysis of machines and other equipment can help to identify the possible faults and predict the failures to reduce the machine down-times. Predictive analytics mainly utilises historical data to anticipate the trends of data (i.e., what will occur in the future). Finally, prescriptive analytics extends the results of descriptive, diagnostic and predictive analytics to make the right decisions in order to achieve predicted outcomes. The prescriptive methods typically include simulation, decision-making, optimisation and reinforcement learning algorithms. Although the three first types of data analytics are not new research trends, the fourth, prescriptive analytics, is seen as a future challenge in Manufacturing Data Analytics (G. Shao, S.-J. Shin, S. Jain, 2014; H.-N. Dai, H. Wang, G. Xu, J. Wan, M. Imran, 2020), and is closely linked to simulation (digital twins) and optimisation. Regarding the maturity of data analytics in the manufacturing sector, an empirical study of 2017, that researched 100 manufacturing companies, located mainly in Germany and Switzerland, found that in most companies the amount of data that was exploited, was quite smaller that the available amount of data. The problem for this focuses mainly on the processing step of the data and on the information extraction (S. Groggert, M. Wenking, R. Schmitt, T. Friedli, 2017).

2.2.3 Sensors and Drones and Supply Chain Performance of Manufacturing Firms

Recent advancement in technologies challenge the way companies manufacture and deliver products. For example, additive manufacturing technologies change the processes used to manufacture customized products, collaborative robot technologies enable new assembly processes, augmented reality technologies offer new ways to train operators, and artificial intelligence replaces or assists human operators in customer service processes (Deradjat and Minshall., 2017, Fox., 2010, Hedelind and Jackson, 2011, Steenhuis and Pretorius, 2017). In manufacturing facilities, drones compete with conventional technologies that can be mounted to fixed installations (such as floors, pillars, walls, or ceilings) or moving installations (such as cranes, conveyors, or vehicles). While outdoor drones can use conventional global positioning systems (GPS) for localization, positioning, and routing, indoor drones require complex technologies, such as laser rangefinders (e.g., simultaneous localization and mapping (SLAM)), ultra-wideband radio signals (a form of “indoor GPS”), or more expensive technologies, such as motion capture systems (e.g, Khosiawan and Nielsen, 2016). Safety, noise, and privacy also remain of considerable concern. Moreover; doors, cables, cranes, equipment, and people limit the maneuverability of drones and the confined spaces in manufacturing facilities can create turbulence. However, indoors also have advantages. Indoor settings are not subject to governmental legislation regarding open air flight (Floreano and Wood, 2015) and weather conditions are irrelevant.

The accurate measurement (Dias, T., 2012) of the data is an important basic necessity of any manufacturing industry. Here the measurement system is collecting all the required information and feeding it to the microprocessor for controlling the whole system. The measurement system mainly consists of sensors, transducers and signal processing devices. In general, sensor is a device which gives a usable output from a specified measuring device. The main objective of the introduction of sensors is to carry out production process automatically with ease of process monitoring. With the help of sensor, alarm and light glows, the operator can find out failure part in any of the process in the manufacturing system and helps the operator for better productivity with preventive measures for avoiding deterioration in the quality of the end product. The technological development (A. Bedeloglu, A. Demir, Y. Bozkurt, N.S. Sariciftci, 2009) made automation a basic need for achievement of optimum quality for customer satisfaction without more human intervention. Most of the machineries of all sectors of textiles are dependent for achieving highest level of productivity with better efficiency and optimum quality. It has been observed (E.G. Fisher, 1976) that it is difficult to maintain product uniformity and standard quality parameters in the manufacturing of micro-denier fiber with extrusion method, especially critical parameters has to be emphasized viz, continuous fiber diameter monitoring, constant and continuous control of temperature and pressure, and critical monitoring of polymer solution properties. Drone applications in manufacturinmg varfy from 'see','sense','transform' etc as reviewed.

"See" is the capability of collecting visual data; often in the forms of images and videos. In the manufacturing industry, examples are; the visual inspection of equipment, such as gas flare, silos, boilers, drums, tanks, chimneys, and pipelines (both above and below ground). These are common tasks in many process industries (e.g., petrochemical industry, offshore and onshore oil platforms). Drones that "see" are 15 also used to monitor the safety of staff, such as during maintenance operations where fixed cameras are not economically feasible. Some large plants apply drones to monitor security instead of closed-circuit television (CCTV) or human patrols. Drones are also tested in applications used to monitor of safety, ergonomics, and regulatory compliance. "Sense" is the capability of collecting data and transforming it into the other forms of data or structured data (i.e., information) without performing additional physical operations. Some relevant examples in manufacturing include the following: the thermal inspection of equipment, machines, chimneys, and stacks; gas detection and noise monitoring to identify hazards in the oil, gas, and petrochemical industries; non-destructive tests such as measuring the thickness and detecting corrosion of equipment; cycle counting, tracking and trace, and finding lost pallets and slots for inventory management; 3D factory planning and process mapping for the optimization of factory layouts and material flows. “Move” is the ability of a drone system to grasp and carry objects or perform physical operations (e.g., spraying). A typical example in manufacturing consists of intra-logistics operations, such as delivering light components, spare parts, or tools especially during maintenance operations. Drones can also be used to spray paint on the corrosion in equipment and buildings and to spray foam during fires. “Transform” is the ability of a drone system to collect data and transform them into information while performing physical operations (e.g., carrying objects). It combines the capabilities of see, sense, and move. Current examples of “transform” in industry are scarce, but a few promising pilot studies are underway. For instance, a drone system with a camera can simultaneously inspect equipment and perform simple repair operations using mounted tools (e.g., patching, painting, and sealing). Drones can perform pick up operations in a warehouse. Both examples are technically complex and not economically feasible in the current state of the technology. For example, in e-commerce warehouse management, order picking and order sorting require advanced drones that grasp items and carry them reliably. This operation also requires multiple sensors (e.g., barcode, data matrix, or RFID readers) to manage inventory and update warehouse management systems in real time. An efficient operation would require a swarm of autonomous drones with the capability of recognizing obstacles and applying avoidance algorithms.

Sensors and drones pose a lot of benefits in manufacturing. First they can increase productivity and hence reduce the costs of manufacturing. In particular, in manufacturing plants in inspection intensive process industries, drones can bring a significant cost saving.

Inspections carried out by drones reduce the amount of labor intensive work and eliminate the need for scaffolding. Regarding an extreme non-manufacturing example, one interviewee reported that in an inspection project on one of the biggest oil platforms in the North Sea, the introduction of drones reduced a 700 person-day inspection of 14 objects to 28 person-days. Furthermore, the inspection of flare exhausts required a shut down in which time was an extremely precious resource valued at USD 7 million per day. Another frequently reported example was the use of drones to count stocks in large warehouses. The cost savings in this application were derived from replacing human work, eliminating rework due to human errors, and improving order fill rates, thus increasing customer satisfaction and decreasing safety stock levels. Similar findings were reported by Hoffmann (2017), in which an estimated annual operating cost savings of USD 300,000 was derived in scanning 1,000,000 barcodes per year in a warehouse of 500,000 square feet. A related potential benefit is the increased speed of performing tasks. Using drones for the inspection of hard-to-reach equipment and installations speed up the operations because of the shorter setup time and higher maneuverability compared to traditional processes involving scaffolding, ladders, and rope access. Shorter setup times and higher maneuverability can also increase the frequency of inspections, allowing for the faster detection of incidents such as gas leakages. Another example is the use of drones for the inventory management of bulk raw material, in which light detection and ranging (LiDAR) scanning with drones can increase the speed and efficiency of inventory counting compared with handheld scanners. Drone users can also increase the capability of data collection using multiple sensors. For example, drones can be used to provide digital 3D models of factory floors to support layout planning and redesign

(Barth and Michaeli., 2018, Melcher et al., 2018). In general, the increased amount of accurate data collected by drones can be used to support managerial decision-making.

Use of drones and sensors comes with a myriad challenges; The organizational challenges include the need for skilled drone pilots, who not only must be able to fly drones safely but also must have a deep understanding of the tasks and missions involved. Human issues such as workers' knowledge and technical experience, training, and involvement in planning are key determinants for the success of technology adoption (Chung,(1996), Walton, (1987), McCutcheon and Wood,(1989), Pagell et al., 2000). s legislative rules and regulations. Although the number of drone applications is increasing, the regulations concerning their use is lagging. A main benefit of using drones in indoor applications is that the regulations are more relaxed compared with outdoor applications. There are large variations between countries in terms of drone legislation. The licenses (or the lack of them) define how, where, and what applications the manufacturer can use drones. As in many emergent technologies, it has been difficult to regulate drones, which is because of the rapid improvement of the technology, safety and security issues, the lack of clarity of who should draft the regulations, and the lack of knowledge about many real applications (Khanna, 2018). For instance, flying beyond the visual line of sight (BVLOS) is prohibited in many countries, which reduces the applications of drones as well as the areas of coverage in outdoor applications; however, some countries make exceptions for flying BVLOS. societal and mental challenges related to the use of drone applications in manufacturing. For example, the common use of drones as a military weapon affects public opinion. Many members of the public have negative perceptions of drones as a new technology. People are also concerned about the safety of drone technologies, the intimidating appearance and noisiness of drones, and the invasion of personal data.

2.2.4 Artificial Intelligence Embedded Technologies, Regulations and Supply Chain Performance of Manufacturing Firms

One of the greatest pillars for effective and economical supply chains is that of seamless exchange of knowledge from suppliers which is attributed to end customers (Blos et al., 2009; Dang, Yan, and Lai 2015; Glenn Richey, Skipper, and Hanna 2009; Tomlin, 2006). Data is ideal for decision-making and generates prices for organizations. Improper management of knowledge might result in irreparable injury to organizations (Michelberger and Labodi, 2009). Over the past decades, organizations have faced challenges in applying transport security (Hutter, 2016), because of the fast development of the technological setting (Hutter, 2016). Organization’s area unit currently involved in the transport security of hardware and instrumentality due to the augmented use of mobile devices, together with computers, phones, laborious drives and USB, that makes them susceptible to theft (Carney, 2012; Scott, 2014). Theft of mobile devices is not the sole approach hackers and attackers will use to get the information they require. Hackers will get vital and sensitive knowledge by connecting a USB or a tiny low memory card to computers while not having to travel into the company database (Scott, 2014).

The latest developments of data technology applied to production, transport and consumption of products has introduced mechanical automation, reduced personnel and thereby provided important cost-savings to supply chains. Massive enterprises that are keen to maintain a dominant position within the supply chain in distribution markets ought to promote the appliance of advanced information systems (Dang, Yan, and Lai 2015). The adoption of advanced information systems in supply chains means that sharing and analyzing massive amounts of information among multiple players. Integrated supply chain relationships are vital and integral to the organization's prosperous structure. Supply chain management will be outlined as processes and practices aimed to economical and economical flow of each material and knowledge between the corporate, suppliers and customers (Lancaster and co., 2006). The exchange of data and communication between partners provide the potential for feedback from customers. Therefore, to explore for solutions to organization issues, can beyond any doubt have a positive impact on the organization's performance and outputs.

Information elements typically include several documents proving regulatory compliance or cargo authenticity. However, there is an overall increased attention towards the security of information systems, raising the opportunity to highlight these issues within the supply chain and logistics scientific communities. While these systems may improve supply chain efficiency, it has also been proven that security can be affected (Urciuoli, Mannisto et al., 2013). Harris, (2013) explained that it is difficult to protect corporate data, networks and systems, with the increasing use of computers and smart mobile phones. Almost 74,000 staff, suppliers and contractors were exposed to data penetration in 2014 during the theft of laptops that contain essential and sensitive records about their companies (Scott, 2014).

The dynamic nature of the current environment has contributed to the increase of costs that companies incur because of fraud, sabotage and theft (Hutter, 2016). Earthquakes, volcanoes, floods, and lightning, fire or dust waves are external threats that arise from natural disasters not influenced by human activities (Al-Qahtani, 2015). Such disasters could cause serious damage to information systems and could lead to the interruption of electronic services altogether (Hutter, 2016). There is a great need for an information security structure. Information exchanged by 2017, with supply chain partners is one of the most important assets for organizations. Until information is shared, organizations need to make security arrangements. (Kollurum and Meredith 2005; Chang and co., 2008; Qingxiong, 2008; Merete, 2008; Douglas, 2009; Ramesh, 2010; Suhazimah and Ali 2012; Zahra, 2013; Metalidou, 2014; Sindhuja, 2014).

The risk of security incidents and breaches increases due to increased reliance on information technology, and organizations are increasingly vulnerable to various types of cyber-attacks (Jouini et al., 2014). Security breaches can cause significant financial losses, disrupt and stop operations. As a result, Information Security Management (ISM) has become an important and required function for all organizations.

Some researchers suggest that proper information management may also improve the flexibility of supply chains (Glenn Richey, Skipper, and Hanna, 2009). Lee and Özer (2007) find that by timely downstream sharing of information, upstream disruptions may be promptly avoided or their negative consequences minimized. Tomlin, (2006) suggests that advance information could be used to deal with certain risks, for instance, labor disputes: if a firm has advance information that a strike is imminent, then mitigation inventory may be built in advance. Usage of information sharing in supply chains is an effective approach to deal with supply chain disruptions, for example, those caused by financial, strategic, operational and hazard vulnerabilities (Blos et al., 2009).

Bag et al., (2020) had made a study on "An integrated artificial intelligence framework for knowledge creation and B2B marketing rational decision making for improving firm performance". They have examined the influence of artificial Intelligence on firm performance through customer knowledge creation, user knowledge creation, external market knowledge creation. They have considered primary data from B2B companies functioning in the South African mining industry. The study concluded that Artificial Intelligence influences the firm value significantly. Mikalef and Gupta (2021) had conducted a study on "Artificial Intelligence Capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance." The investigation has analyzed the association between Artificial Intelligence capability with organizational creativity and performance through a conceptual research model. They have confirmed that Artificial Intelligence proxies have a positive influence on organizational performance.

Other studies have documented similar findings, Artificial Intelligence drives business flexibility and performance (Mishra and Pani, 2020; Mikalef and pateli, 2017; Benitez and Ray, 2012; Liu et al., 2020, Rout et al., 2018), amplifiers of an intrapreneurship culture (Benitez, Llorens-Montes, and PerezArostegui, 2010; Mikalef and Krogstie, 2020), as a technique to minimize trade-offs (Goh and Arenas, 2020). Wamba-Taguimdje et al., (2020) had analyzed the impact of artificial Intelligence on firm performance by using 500 case studies from different International IT companies. They have highlighted that artificial

Intelligence improves performance at both organizational and process levels. By employing AI technology, firms can enhance their business value and capability. It is possible when organizations adopt the technologies to reconfigure their processes. Oke (2008) and Miller (2017) have also supported the above statement and found that artificial Intelligence positively influences organizational performance. Sharad (2018) examined Artificial Intelligence's concepts & their influence on accounting by focusing on the digitization accounting process in corporate. He concluded that artificial Intelligence would not enhance the accounting process, but it will help achieve corporate success. Zehong and Zheng (2018) examined the impact of artificial Intelligence on accounting fraud and accounting information quality. They have concluded that Artificial Intelligence will help to evaporate the accounting frauds and will also enhance the quality of accounting information. Margaret (2018) investigated the relationship between Artificial Intelligence & accounting and finance. The study has found that AI transforms the audit and contract functions.

2.3 Conceptual Framework

According to Hammond and Wellington (2012), a conceptual framework is a description of the basic link amongst variables in research. This allows the researcher to see the projected relationship clearly. The study sought to explore the effect of AI technologies; IOT, data analytics, sensors and drones as independent variables and supply chain performance of manufacturing firms in Kenya as dependent variable being moderated by government regulations. This is illustrated in figure 2.1.

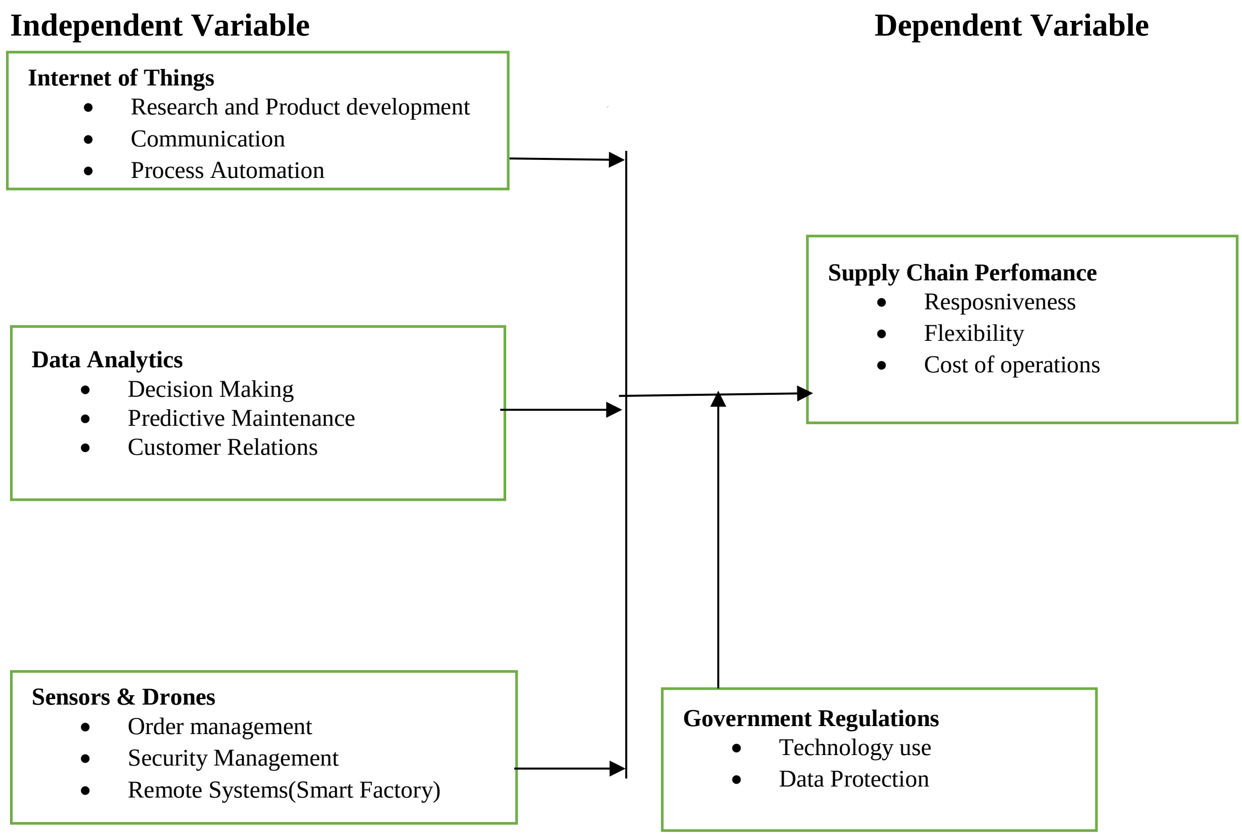

FIGURE 2.1

Conceptual Framework

2.4 Research Gaps

Most of the studies identify and measure the relationship between AI and supply chain perfomance; Wamba-Taguimdje (2020) identified a positive association between artificial Intelligence and performance at both organizational and process levels. Oke (2008); Miler (2017); (Zehong and Zheng, 2018); Margaret (2018) have also found a positive association.

However, Sharad (2018) contradicts the above findings, and he inferred a negative association between artificial Intelligence and organizational performance. Most of these studies are done from a developed nations point of view which leaves the developing countries context. From the past literature also, most of the studies have been done basically in a theoretical context. The current study will undertake a field study where primary data will be collected analysed and deductions established. Despite available studies documenting the existence of the relationship between AI technologies and supply chain performance the moderating role of government regulations has been neglected yet in the Kenyan context use of as well as disposal of AI technologies is highly regulated. The current study seeks to evaluate the moderating effect of government regulations on Adoption of AI technologies and Supply chain perfomance. Besides most of the reviewed studies have adopted exploratory and explanatory study designs. The current study adopted descriptive design since it allows establishment of relationships among study variables.

CHAPTER THREE: RESEARCH METHODOLOGY

3.1 Introduction

This chapter outlines the research design, the study target population, the sampling frame, the sampling technique, the research instruments, and the procedures used for data compilation, analysis and presentation. Eventually, the chapter also outlines the statistical analysis model that was used for the analysis of the data.

3.2 Research Design

A research design is the arrangement of the conditions for the compilation and breakdown of data in a manner that seeks to combine significance for the research purpose with economics in the process, and thus provides the conceptual framework through which the study is performed as a blueprint for data collection, processing, measurement plus analysis (Merriam & Tisdell, 2015). The research study adopted a descriptive research design.

3.3 Target Population

According to Weber (2015), a population is defined as a collection of objects, individuals, entities or items out of which samples are drawn for analysis. The target population of this study are the seventeen automobile manufacturers in Kenya (KAM, (2022), Manufacturing sector report).

3.4 Sample and Sampling Method

A census is a study of every unit, everyone or everything, in a population. Census technique based on regions was used to include all the seventeen automobile manufacturing firms in

Kenya. The units of analysis will be functional officer from each of the nine functions (Human Resource Management, Logistics, Supply Chain Management, Operations, Information Communication and Technology, Research and Development, Legal, Finance and Security) from the seventeen automobile manufacturing firms making a total of one hundred and fifty three (153) functional personnel. The population of 153 functional officers is small hence a census study was carried out.

TABLE 1

Sampling Frame

Categorization	**Number**
Human Resource Management officer	17
Logistics Officer	17
Supply Chain Officer	17
Operations Officer	17
Research and Development Officer	17
Information communication and technology	17
Legal officer	17
Finance Officer	17
Security Officer	17
Total	**153**

3.5 Data Collection Method

Research instruments refer to the techniques, materials and resources used in the research to gather information (Zikmund, Carr & Griffin, 2013). Data was obtained by means of a semi structured questionnaire. The questionnaire is a research tool that collects data from a broad sample and tries to turn the research goals into concrete questions, and the answers to each question are generated by the hypotheses test data (Mugenda & Mugenda, 2003). The research questionnaire consisted of open and closed questions, which captures the independent variables, the moderating variable and the dependent variable. It tends to reduce subjectivity and help qualitative and quantitative analysis to be done (Wilson, 2010). Permission was sought from KCAU Board of Postgraduate Studies (BPS) before obtaining of a research permit from National Council of Science, Technology and Innovations (NACOSTI). Questionnaires were send through Google form with a span of two weeks and an extension of one more week was allowed on the respondent's request.

3.6 Pilot Test

Cooper and Schindler (2011) noted that the pilot study is undertaken to identify flaws in the design, composition as well as to provide proxy data for the selection of the probability sample. In this case, the methods used in the pre-test of the questionnaire should be the same as those used in the actual analysis or data collection. Pilot studies are imperative in detecting vagueness and help in assessing the type of responses given to assess if they assist the investigator to meet the objectives laid down for the study (Viechtbauer, Smits, Kotz, Budé, Spigt, Serroyen & Crutzen, 2015).

According to Mugenda and Mugenda (2003), the pre-test number is expected to be low, around one (1) percent to ten (10) percent of the target population. In this investigation, the research questionnaires was tested on ten percent of the total sample size. The pilot study therefore included 16 respondents from 2 firms which were randomly selected from the list. The firms respondents who took part in the pilot shall not constitute the actuall field study.

3.7.1 Reliability Test

According to Bryman and Bell (2015), reliability is accuracy given measurement consistency or measurement reliability over a variety of conditions within which the same results can be obtained. In this research, the internal approach to consistency was followed since it is more robust than other approaches (Cooper & Schindler, 2011). Internal consistency is measured using the Cronbach Alpha statistic. In order for the test to be internally consistent, Drost (2011) recommends that the reliability figures should be based on average inter-relationships between all the individual test objects. The value should be above 0.7 where Cronbach's Alpha Coefficient is used for the measure of reliability (Drost, 2011). The alpha (α) of the Cronbach will be determined as follows:

$$\alpha = K / (K - 1)$$

$$[1- (\Sigma\sigma k^2 / \sigma total^2)]$$

3.7.2 Validity Test

Mugenda and Mugenda (2003) described validity as the degree to which the study findings accurately reflect the phenomenon under investigation. Validity also refers to how well the system measures what it wants to measure (Mugenda, 2008). This study adopts content validity. Bryman and Bell (2015), posit that content validity is a qualitative form of validity where the scope of the definition is made very clear and the analysts or judges decide if the test is entirely within the scope. In essence, there are two methods of determining the validity of the content, i.e., asking a number of questions about the instrument or test and/or asking expert judges in the field for their opinion (Drost, 2011). Two supply chain perfomance and information communication technology experts were engaged for this exercise. The research supervisor also helped.

3.8 Data Analysis and Presentation

The analysis of data requires the use of logic to analyze the data collected in order to define specific patterns and to summarize the relevant details contained in the sample (Ho, 2006). Kothari (2004) poised that data processing requires the editing, sorting and tabulation of data obtained in such a way that they can be analyzed. Entry of data transforms information obtained through secondary or primary methods into a tool for viewing and processing. Descriptive and inferential statistics were applied to analyze the information. Correlation coefficient by Pearson's was used to establish the relationship between the independent variables and the dependent variable since it is used in bivariate relationships (Levin, Fox & Forde, 2010).

The F-test was used to test the hypothesis. Multivariate analysis was employed in the analysis of data. Multivariate analysis is a set of techniques applied to the analysis of data sets that comprise of many variables. The level of confidence for the study will be 95%. The proposed multiple linear regression models will be used to test the significance of the influence of the independent variables on the dependent variable as well as the effect of the moderator. Multiple regression models basically reveal linear relationship between the predictors and the dependent variable. The particular multiple regressions equation took the following form;

$$\mathbf{Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \epsilon}\text{--Equation 1}$$

Where;

Y represents Supply Chain Performance

X_1 represents Internet of things

X_2 represents Data analytics

X_3 represents Sensors and Drones

ε represents refers to the error term

In the model, β_0 = the constant value while the coefficient β_i = 1...3 is the slope of the coefficients showing effect of independent variables X_1, X_2, X_3 on the dependent variable (Y). The error (ε) term shows the unexplained factors in the model.

3.8.1 Moderating government Regulations

Moderation occurs when the linkage between two variables is interacted by another variable (Dawson, 2014; Fairchild & MacKinnon, 2009). Moderation is also described as the individual differences or conditions that influence the power of the relationship linking predictor and outcome element (Bryman, 2015). This research employed Kenny and Baron (1986) approach to check for moderation. Variation in R^2 shall confirm the presence of the moderating special effects of organizational culture. Therefore, the model took the following form;

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_1 X_1 * M + \beta_2 X_2 * M + \beta_3 X_3 * M + \varepsilon \text{ ------------Equation 2}$$

Where;

Y represents Supply Chain Performance of manufacturing firms

X_1 represents Internet of things

X_2 represents Data analytics

X_3 represents Sensors and Drones

M represents Moderator (Regulations)

ε represents Error term.

The results were summarized using tables.

3.9 Diagnostic Tests

The subsequent assumption of the study model was tested. Diagnostics are undertaken before running any model to ensure that correct model coefficients are attained.

3.9.1 Normality Test

Normality test was checked by employing the Kolmogorov-Smirnov (Saunders & Lewis, 2012). The null hypothesis states that data which is normal will not be rejected if the K-S values are larger than 0.05 (Park, 2015).

3.9.2 Linearity Test

Scatter plots was employed to check the linearity of data prior running the model. Linearity tests helps to ensure that data under investigation observes a straight line across the observation under study. The scatter plot tests the linkage existing between predictor and outcome variables.

3.9.3 Test for Multicollinearity

Multicollinearity is usually a situation in which there is a high degree of association between independent variables and dependent variable. Failure to account for perfect multicollinearity results into indeterminate regression coefficients and infinite standard errors while existence of imperfect multicollinearity results into large standard errors (William *et al.* 2013). Large standard errors affect the precision and accuracy of rejection or failure to reject the null hypothesis. During estimation, the problem is not the presence of multicollinearity but rather its severity. Presence or absence of multicollinearity was checked by employing VIF (variance inflation factor) where VIF ≥ 10 denoted presence of multicollinearity (Field, 2013).

3.9.4 Heteroscedasticity

Heteroscedasticity was checked by employing Breusch-Pagan/Godfrey method. The null hypothesis; error variance is homoskedastic (Koenker, 1981). Rejecting null hypothesis shall mean that error variance heteroscedastic and this phenomenon shall call the prediction of FGLS model.

3.10 Hypothesis Testing

Hypothesis testing was conducted by employing p-value. The acceptance/rejection rule is that a p-value smaller than 0.05 will lead to the rejection of H_0 (Bonett & Price, 2002).

CHAPTER FOUR: FINDINGS AND DISCUSSION

4.1 Introduction

Results from the examination of data gathered using questionnaires are presented in this chapter. The goal of the current study was to determine how artificial embedded technologies affected Kenyan manufacturing companies' supply chain performance. Descriptive and inferential statistics were used to analyze the data, and the results were tabulated for discussion and presentation.

4.2 Response Rate

A total of 153 questionnaires were distributed to heads of Human Resources Management, Logistics, Supply Chain Management, Operations, Research and Development, Information Communication Technology, Legal services and Security management. Out of the population covered, 119 were responsive representing a response rate of 78%. This was above the 50% which is considered adequate in descriptive statistics according to (Mugenda & Mugenda, 2018).

TABLE 4.1

Response Rate of Respondents

Response	Frequency	Percentage
Actual Response	119	78
Non-Response	34	22
Total	**153**	**100%**

4.3 Pilot Study

The Cronbach's alpha was computed in terms of the average inter-correlations among the items measuring the concepts. The rule of thumb for Cronbach's alpha is that the closer the alpha is to 1 the higher the reliability (Serekan, 2019). A value of at least 0.7 is recommended. Cronbach's alpha is the most commonly used coefficient of internal consistency and stability. Consistency indicated how well the items measuring the concepts hang together as a set. Cronbach's alpha was used to measure reliability. This was done on the five objectives of the study. The higher the coefficient, the more reliable is the test. The research tool was found to be reliable since all Cronbach alpha coefficients ranged from 0.93 to 0.976. Hence the tool was recommended for use in the field study.

TABLE 4.2

Reliability Results

Variable	No of Items	Respondents	α=Alpha	Comment
Internet of Things	9	15	0.893	Reliable
Data Analytics	9	15	0.987	Reliable
Sensors and Drones	9	15	0.974	Reliable
Government Regulations	9	15	0.976	Reliable

4.4 Demographic Information

This section presents the personal details of the respondents and it provides data regarding the study and is necessary for the determination of whether the individuals in a particular study are a representative sample of the target population and testing appropriateness of respondent in answering the questions for generalization. The study sought to determine the demographic characteristics of the respondents as they are considered as categorical variables which give some basic insight about the respondents. The characteristics considered in the study were; gender, age, their highest level of education attained and their work experience.

4.4.1 Distribution of Respondents by Gender

The gender of the respondents was also established by the survey. The results are shown in figure 4.1, with 43% of respondents being women and 57% of respondents being men. The figures might bring up the question of gender equity in the nation's manufacturing companies, but that is outside the purview of this investigation. Women and men are equally capable of doing jobs, according to a research of American firms, but they approach supply chain management from different perspectives (William, 2020). The figure below shows distribution of respondents by Gender.

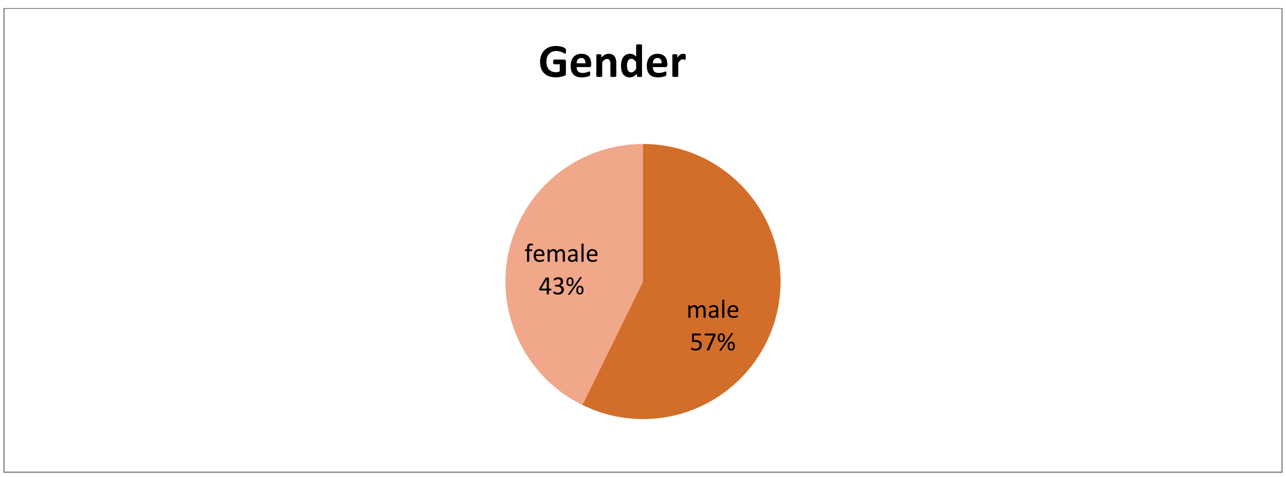

FIGURE 4.1

Distribution of Respondents by Gender

4.4.2 Distribution of Respondents by Age

The age distribution of the respondents was determined by the study. The table below provides a summary of the findings. According to the results, 33.6% of respondents were between the ages of 41 and 50. Aged 31 to 40, respondents made up 26.1% of the sample. 19.3% of the population was between the ages of 18 and 30. The percentage of people over 50 was 21%. Once more, this demonstrates that the interviewees are adults capable of reaching accurate conclusions on their own, and that the study procedure that included them was considered to be valid. The results are consistent with those of Saunders (2021), who found two natural age peaks that connect with employee performance in the late 20s to early 40s.

TABLE 4.3

Distribution of Respondents by Age

Age	Frequency	Percent
18-30 Years	23	19.3
31-40 Years	31	26.1
41-50 Years	40	33.6
50 Years and above	25	21.1
Total	**119**	**100**

4.4.3 Distribution of Respondents by Level of Education

When asked to specify their highest degree of education, the respondents provided the information shown in Table 4.4. Results showed that 23.5% of respondents had a degree certificate, 22.7% had a master's degree, 23.5% had another certificate, and 30.3% had a diploma, making up the majority of respondents. These results support those of Rotich (2021), who found that the majority of persons in charge of public procurement are well educated and that there is proof tying education to manufacturing enterprises' performance.

TABLE 4.4

Distribution of Respondents by Level of Education

Level of Education	Frequency	Percent
Certificate Level	28	23.5
Diploma Level	36	30.3
Degree Level	28	23.5
Master Level	27	22.7
Total	**119**	**100**

4.4.4 Distribution of Respondents by Length of Service

The survey examined how long the respondents had been employed by Kenyan manufacturing companies. According to the results, 28.6% of respondents had spent between six and eight years working for manufacturing companies. 26.9% had been employed for 0 to 2 years. 26.9% had been in the military for 3 to 5 years. 17.6% and higher had been employed for 9 years or more. The study's findings are consistent with a review of the literature by Patron (2021), who noted that an employee's tenure and experience assist him or her to have greater knowledge and abilities, which contribute to performance.

TABLE 4.5

Distribution of Respondents by Length of Service

Length of Service	Frequency	Percent
0-2 Years	32	26.9
3-5 Years	32	26.9
6-8 Years	34	28.6
9 Years and above	21	17.6
Total	**119**	**100**

4.5 Descriptive Statistics

The study set out to seek effect of artificial intelligence technologies on supply chain performance of manufacturing firms in Kenya as moderated by government regulations. To this end, three variables were conceptualized as components of artificial intelligence technologies. These include; Internet of Things, Data Analytics, Sensors and Drones while Government Regulations was identified as a moderator.

4.5.1 Internet of Things

The first objective of the study was to assess the influence of Internet of Things on supply chain performance of manufacturing firms in Kenya. The respondents were asked to indicate to what extent Internet of Things influenced supply chain performance of manufacturing firms in Kenya.

Results indicated that majority of the respondents 33% agreed that it was to a very great extent, 19% said that it was to a great extent, 30% said it was moderate, while little extent was 11% and not all was at 7% respectively.

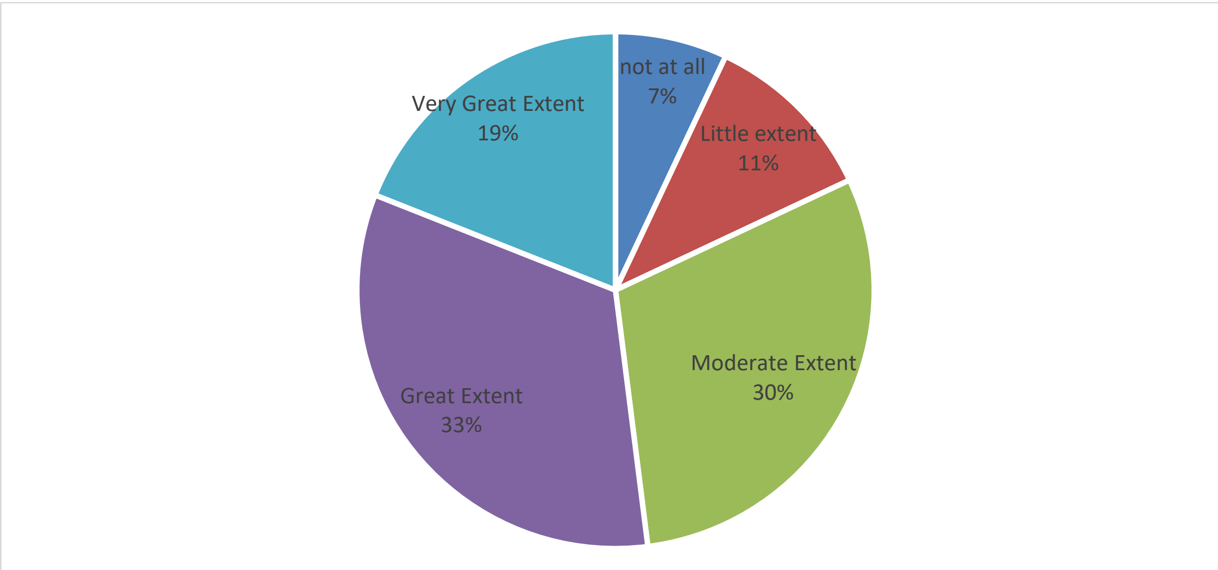

FIGURE 4.2

Internet of Things

The respondents were also asked to comment on statements regarding Internet of Things influence on performance of manufacturing firms. The responses were rated on a likert scale and the results presented in table 4.6 below. It was rated on a 5-point Likert scale ranging from; 1, strongly disagree to 5, strongly agree. The scores of 'strongly disagree' and 'disagree' have been taken to represent a statement not agreed upon, equivalent to mean score of 0 to 2.5. The score of 'neutral' has been taken to represent a statement agreed upon, equivalent to a mean score of 2.6 to 3.4. The score of 'agree' and 'strongly agree' have been taken to represent a statement highly agreed upon equivalent to a mean score of 3.5 to 5.

Results indicated that majority of the respondents as indicated by a mean of 4.2 agreed on the statement that Supply chain process automation level is high reducing on operational costs. The variations in the responses were shown by a standard deviation of 1.0. Results indicated that majority of the respondents as indicated by a mean of 3.6 agreed on the statement that Supply chain operations automation has reduced supply chain operational costs. The variation in the responses was shown by a standard deviation of 1.3. Results indicated that majority of the respondents as indicated by a mean of 3.6 agreed on the statement that process automation has improved our supply chain responsiveness on Internet of things, which improved our communications. The variation in the responses was shown by a standard deviation of 1.3.

Results indicated that majority of the respondents as indicated by a mean of 3.3 agreed on the statement that internet of things has improved our communications. The variations in the responses were shown by a standard deviation of 1.3. Results indicated that majority of the respondents as indicated by a mean of 4.2 agreed on the statement that improvement in our communications has endured us to our clients. The variations in the responses were shown by a standard deviation of 0.9. Results indicated that majority of the respondents as indicated by a mean of 3.8 agreed on the statement that internet of things has improved on our research and development. The variations in the responses were shown by a standard deviation of 0.6.

Results indicated that majority of the respondents as indicated by a mean of 4.1 agreed on the statement that improved on our research and development has led to more customer centric products. The variations in the responses were shown by a standard deviation of 0.6. Results indicated that majority of the respondents as indicated by a mean of 3.6 agreed on the statement that improved on our research and development has led to more customer centric products. The variations in the responses were shown by a standard deviation of 0.6. The average result for statements on Internet of Things was 3.8 while the standard deviation was 1.4. The findings agree with Odundo (2021) that adoption of iinternet of things improves supply chain performance. Ibrahim *et al* (2011) that adoption of IOT leads to reduction in inventory costs as well as the bullwhip effect across the supply chain.

TABLE 4.6

Internet of Things

Statements	N	Mean	Std. Deviation
Supply chain process automation level is high	119	4.2	1.0
Supply chain operations automation has reduced supply chain operational costs	119	3.6	1.3
Process automation has improved our supply chain responsiveness	119	3.8	1.3
IOT has improved our communications	119	3.3	1.4
Improvement in our communications has endured us to our clients	119	4.2	0.9
IOT has improved on our research and development	119	3.8	0.6
Improved on our research and development has led to more customer centric products	119	3.6	1.3
Most of our supply chain tasks are digitalized	119	4.1	3.9
Most of our supply chain operations are cloud based	119	3.9	1.1

Average		119	3.8	1.4

4.5.2 Data Analytics

The second objective of the study was to investigate the influence Data Analytics has on supply chain performance of manufacturing firms in Kenya. The respondents were asked to indicate to what extent did Data Analytics influenced supply chain performance of manufacturing firms in Kenya. Results indicated that majority of the respondents 37% agreed that it was to a very great extent, 33% said that it was to a great extent, 19% said it was moderate, while little extent and not all tied were at 4 and 7% respectively.

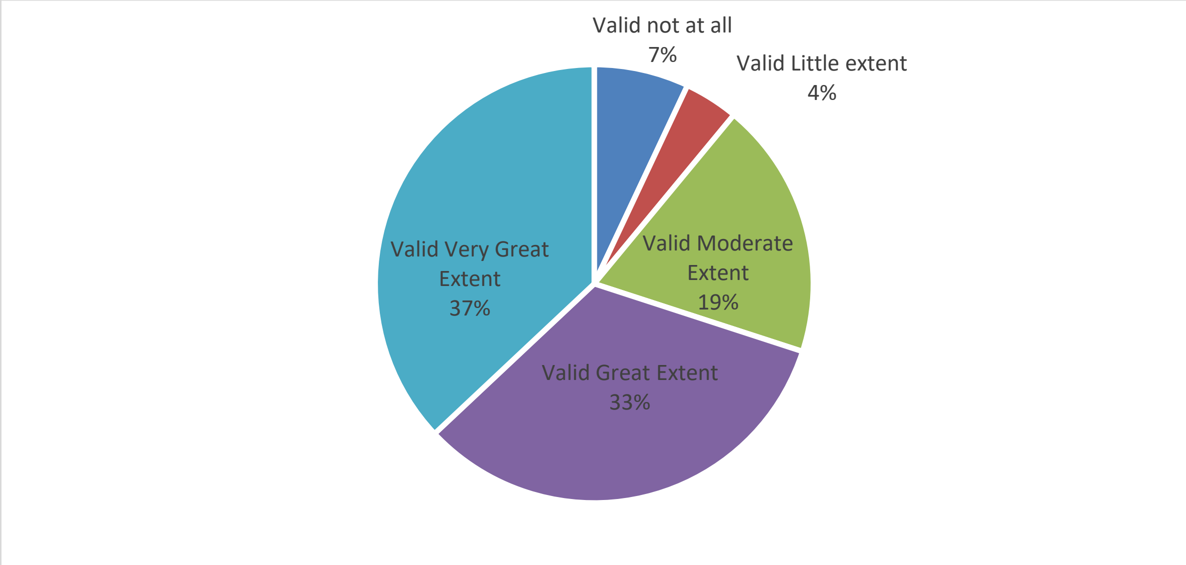

FIGURE 4.3

Data Analytics

The respondents were also asked to comment on statements regarding the influence of Data Analytics on supply chain performance of manufacturing firms in Kenya. Results indicated that majority of the respondents indicated by a mean of 3.8 agreed on statements that data analytics influences our key decisions in our supply chain operations, the variation was 1.2.

Results indicated that majority of the respondents indicated by a mean of 3.5 agreed on the statement that data analytics plays a significant influence in reducing costs, the variation was 1.1. Results indicated that majority of the respondents indicated by a mean of 3.7 agreed on the statement that data based decision making plays a significant influence in reducing costs, the variation was 1.

Results indicated that majority of the respondents indicated by a mean of 3.5 agreed on the statement that big data analytics is a key consideration for our customer relations, the variation was 1. Results indicated that majority of the respondents indicated by a mean of 3.6 agreed on the statement that big data analytics influences the type of customer relations to adopt, the variation was 1.2. Results indicated that majority of the respondents indicated by a mean of 3.5 agreed on the statement that Adoption of maintenance has significantly helped reduce our supply chain operational costs, the variation was 1.3.

Results indicated that majority of the respondents indicated by a mean of 3.5 agreed on the statement that adoption of maintenance has significantly helped reduce our supply chain operational costs, the variation was 1.3. Results indicated that majority of the respondents indicated by a mean of 3.4 agreed on the statement that big data is critical in undertaking repair and maintenance, the variation was 1.4. Results indicated that majority of the respondents indicated by a mean of 3.4 agreed on the statement that big data is critical timely repair and maintenance which in turn improves our supply chain performance, the variation was 0.5.

The average of the statements on Data Analytics was 3.6 while the variations in the responses were given at 1.1. These findings agree with P. Lade *et al* (2017) that application of Data Analytics to manufacturing data has been presented as a solution for the issue of capitalizing on ever-growing manufacturing. Furthermore, Brown B (2011) asserts usage of data analytics increase the competitive advantages of different companies in both, developed countries and emerging economies. The opportunities for cost savings can be enormous as the impact on supply chain performance is great.

TABLE 4.7

Data Analytics

Statements	N	Mean	Std. Deviation
Data analytics influences our key decisions in our supply chain operations	119	3.8	1.2
Data analytics plays a significant influence in reducing costs	119	3.5	1.1
Data based decision making plays a significant influence in reducing costs	119	3.7	1.0
Big data analytics is a key consideration for our customer relations	119	3.5	1.1
Big data analytics influences the type of customer relations to adopt	119	3.6	1.2
We have adopted predictive maintenance	119	3.5	1.3
Adoption of predictive maintenance has significantly helped	119	3.5	1.3

reduce our supply chain operational costs			
Big data is critical in undertaking repair and maintenance	119	3.4	1.4
Big data is critical timely repair and maintenance which in turn improves our supply chain performance	119	3.6	0.5
Average	**119**	**3.6**	**1.1**

4.5.3 Sensors and Drones

The third goal also required determining how sensors and drones affected the supply chain performance of Kenyan industrial companies. The respondents were asked to remark on the extent to which sensors and drones affect Kenyan manufacturing companies' supply chain performance. The majority of respondents, 48% agreed that it was to a very great extent, 45% said that it was to a great extent, 2% said that it was moderate, 2% said that it was to a little extent, and 3% stated that it wasn't to all extents.

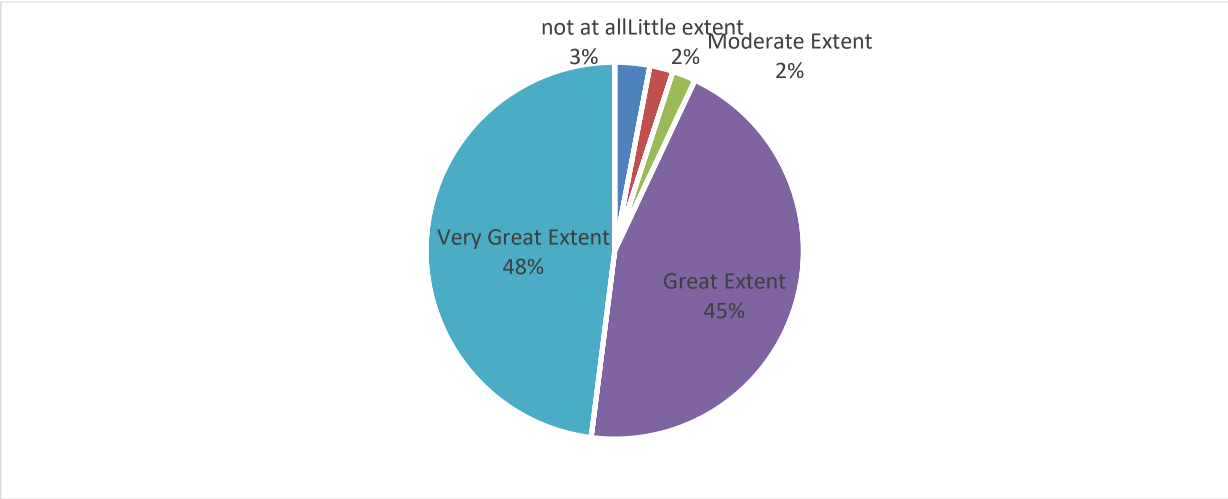

FIGURE 4.4

Sensors and Drones

The respondents were also asked to comment on statements regarding: Sensors and Drones influence supply chain performance of manufacturing firms in Kenya. Results indicated that majority of the respondents as shown by a mean of 4.0 agreed on the statement that the firms use sensors and drones to achieve high order fulfillment levels, the standard deviation for the results responses was 1.1. Results indicated that majority of the respondents as shown by a mean of 4.4 agreed on the statement that the firms use of sensors and drones has led to high responsiveness of their supply chain, the standard deviation for the results responses was 1.3. Results indicated that majority of the respondents as shown by a mean of 3.4 agreed on the statement that they use sensors and drones to achieve high supply chain flexibility, the standard deviation for the results responses was 0.8.

Results indicated that majority of the respondents as shown by a mean of 3.4 agreed on the statement that application of drones in our security management has boosted our supply chain responsiveness to a great extent, the standard deviation for the results responses was 1.3. Results indicated that majority of the respondents as shown by a mean of 3.7 agreed on the statement that drones are applied in our security management to a great extent share; the standard deviation for the results responses was 0.7. Results indicated that majority of the respondents as shown by a mean of 2.8 agreed on the statement that application of drones in our security management has boosted our supply chain responsiveness to a great extent, the standard deviation for the results responses was 7.

Results indicated that majority of the respondents as shown by a mean of 3.2 agreed on the statement that the use of sensors has boosted our supply chain operational efficiency to a great extent, the standard deviation for the results responses was 1.2. Results indicated that majority of the respondents as shown by a mean of 3.4 agreed on the statement that they have adopted smart factory/remote systems to a great extent, the standard deviation for the results responses was 1.2. Results indicated that majority of the respondents as shown by a mean of 3.6 agreed on the statement that adoption of smart factory/remote systems has boosted our operational efficiency, the standard deviation for the results responses was 1.3. The average for all the responses was 3.6 and a standard deviation of 1.2. These findings imply that through Sensors and Drones, manufacturing firms can improve performance (Noor, Guyo & Amuhaya, 2018).

TABLE 4.8

Sensors and Drones

Statements	**N**	**Mean**	**Std. Deviation**
We use sensors and drones to achieve hig orderfulfillment levels	119	4.0	1.1
We use sensors and drones has led to high responsiveness of our supply chain	119	3.4	1.3
We use sensors and drones to achieve hig supply chain flexibility	119	4.4	0.8
Use of sensors and drones has lead to low operational costs	119	4.1	1.0
Drones are applied in our security management to a great extent	119	3.7	0.7

Application of drones in our security management has boosted our supply chain responsiveness to a great extent	119	2.8	1.3
Use of sensors has boosted our supply chain operational efficiency to a great extent	119	3.2	1.2
We have adopted smart factory/remote systems to a great extent	119	3.4	1.2
Adoption of smart factory/remote systems has boosted our operational efficiency	119	3.6	1.3
Average	**119**	**3.6**	**1.1**

4.5.4 Government Regulations

The fourth purpose of the research was to determine the impact that a government regulations has on the relationship between adoption of artificial intelligence technologies and supply chain performance of manufacturing firms in Kenya. Examining descriptive statistics, which provided a synopsis of the observable factors that were used in the process of measuring government regulations, allowed for the accomplishment of this goal. The frequency, percentage, mean, and S.D of three observable factors that ultimately assessed government regulations were included in the descriptive findings.

TABLE 4.2

Government Regulations

Where 5= Strongly Agree, 4=Agree, 3= Undecided, 2 =Disagree, 1= Strongly Disagree

Statements	**5**	**4**	**3**	**2**	**1**	**Mean**	**S.D**
Government Regulations regulates usage of artificial embedded technology which in	30.8 (24)	44.9 (35)	7.7 (6)	6.4 (5)	10.3 (8)	3.79	1.24

turn has improved our supply chain responsiveness							
Government regulations moderate usage of AI technologies which has improved our supply chain flexibility	16.7 (13)	37.2 (29)	28.2 (22)	7.7 (6)	10.3 (8)	3.42	1.17
Government regulations moderate adoption of AI technologies which has reduced our operational costs	39.7 (31)	32.1 (25)	11.5 (9)	6.4 (5)	10.3 (8)	3.85	1.30

From the results in the table 4.9, 30.8% (24) of the respondents strongly agreed that government Regulations regulates usage of artificial embedded technology which in turn has improved their supply chain responsiveness and a further 44.9% (35) agreed on the same statement. Moreover, 7.7% (6) of the respondents were undecided, 6.4% (5) disagreed while 10.3% (8) strongly disagreed. With a mean of 3.79 and a significant S.D of 1.24, implying that the respondents agreed on the statement.

However, 16.7% (13) of the respondents strongly agreed and a further 37.2% (41) agreed that Government regulations moderate usage of AI technologies which had improved their supply chain flexibility. Also, 28.2% (22) of the respondents were undecided, 7.7% (6) disagreed while 10.3% (8) strongly disagreed. With a mean of 3.65 and a significant S.D of 1.07, the respondents were undecided on the statement.

In regards to the statement that government regulations moderate adoption of AI technologies which has reduced their organisational operational costs, 39.7% (31) of the respondents strongly agreed while 32.1% (25) agreed. Moreover, 11.5% (9) of the respondents were undecided, 6.4% (5) disagreed and a further 10.3% (8) strongly disagreed. With a mean of 3.85 and a significant S.D of 1.30, the respondents agreed on the assertion.

4.5.5 Supply Chain Performance of Manufacturing Firms in Kenya

The ascertain the status of supply chain performance of manufacturing firms, the five observable variables' frequency, percentage, mean, and S.D were calculated and presented in the descriptive results. The results indicated the supply chain performance of manufacturing firms in Kenya from an operational standpoint i.e. before and after adoption of artificial intelligence technologies.

Where 5) Greatly improved 4) Improved 3) Constant 2) Reduced and 1) greatly reduced.

TABLE 4.10

Supply Chain Performance of Manufacturing Firms in Kenya

Statements	5	4	3	2	1	Mean	S.D
Supply Chain Reliability	47.4	34.6	10.3	6.4	1.3		
	(37)	(27)	(8)	(5)	(1)	4.21	0.96
Supply Chain Flexibility	34.6	46.2	15.4	2.6	1.3		
	(27)	(36)	(12)	(2)	(1)	4.10	0.85
Supply Chain Cost of Operations	41	44.9	6.4	6.4	1.3		
	(32)	(35)	(5)	(5)	(1)	4.18	0.91
Supply Chain resilience	37.2	41	14.1	5.1	2.6		
	(29)	(32)	(11)	(4)	(2)	4.05	0.98

According to the findings in Table 10, 47.4% (37) of the respondents strongly agreed that their supply chain is very reliable, and a further 34.6% (27) concurred. In addition, 1.3% (1) of the respondents strongly disagreed with the statement that they had a highly reliable supply chain, while 6.4% (5) disagreed and 10.3% (8) were unsure. A large S.D of 0.96 and a mean of 4.21 indicate that the respondents agreed with the assertion.

However, 46.2% (36) and 34.6% (27) of respondents agreed and strongly agreed, respectively, that their supply chain is flexible enough to meet the demands of their customers. As for whether they have a flexible supply chain, 15.4% (12) of the respondents were unsure, 2.6% (2) disagreed, and 1.3% (1) strongly disagreed. On the statement that, they have a supply chain that is responsive to customer needs, 41% (32) of the respondents strongly agreed while 44.9% (35) agreed. However, 6.4% (5) of the respondents were undecided and 6.4% (5) disagreed while 1.3% (1) strongly disagreed that they have a supply chain that is responsive to customer needs. With a mean of 4.18 and a significant S.D of 0.91, the participants agreed on the statement.

According to the finding of the study, 37.2% (29) of the respondents strongly agreed while 41% (32) agreed that their operational costs are within planned levels. Also, 14.1% (11) of the respondents were undecided, 5.1% (4) disagreed and a further 2.6% (2) strongly disagreed that their operational costs are within planned levels. With a mean of 4.05 and a significant S.D of 0.98, the respondents agreed on the statement.

4.6 Correlation Analysis

The level of association and significance of the variables were assessed using correlation analysis, which was also used to forecast the amount of variation in the dependent variable brought on by the independent variables. The correlation method is employed to examine the strength of the relationship between two variables. Table 4.11 provides an overview of the correlation analysis' findings.

TABLE 4.10
Summary of Correlations

		Internet of Things	**Data Analytics**	**Sensors and Drones**	**Government Regulations**	**Performance of manufacturing firms**
Internet of Things	Pearson Correlation	1				
Data Analytics	Pearson Correlation	. 289**				
	Sig. (2-tailed)	0				
Sensors and Drones	Pearson Correlation	.368**	.344**	1		
	Sig. (2-	0	0			

	tailed)					
Government Regulations	Pearson Correlation	.352**	.457**	.520**	1	
	Sig. (2-tailed)	0	0	0		
Supply Chain Performance of manufacturing firms	Pearson Correlation	.479**	.323**	.628**	.676**	1
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	

** Correlation is significant at the 0.05 level (2-tailed).

The connections between each of the independent variables and the dependent variable were all significant at the 95% confidence level, according to the correlation summary in Table 4.10. The Pearson Correlation Coefficient was estimated and assessed at the 5% significance level in the correlation study to determine the impact of artificial embedded technologies on the supply chain performance of manufacturing enterprises in Kenya.

According to the findings, there is a strong correlation between the Internet of Things and Kenyan manufacturing companies' supply chain performance (r=0.479). The association was also discovered to be statistically significant at the 5% level (p=0.000, 0.05) by the researcher. The Pearson Correlation Coefficient was estimated and tested at a significance level of 5% in order to conduct a correlation analysis to ascertain the association between Internet of Things and supply chain performance of manufacturing enterprises in Kenya.

The findings show that Data Analytics and the performance of manufacturing enterprises are positively correlated (r=0.323). The association was also discovered to be statistically significant at the 5% level (p=0.000, 0.05) by the researcher. The Pearson Correlation Coefficient was estimated and assessed at a 5% significance level for the correlation study to determine the association between sensors and drones and the performance of industrial enterprises. The findings show a positive correlation between the performance of industrial enterprises and sensors and drones (r=0.628). The association was also discovered to be statistically significant at the 5% level (p=0.000, 0.05) by the researcher.

The correlation analysis was used to determine the relationship between Government Regulations and performance of manufacturing firms, Pearson Correlation Coefficient computed and tested at 5% significance level. The results indicate that there is a positive relationship (r= 0.676) between Government Regulations and performance of manufacturing firms. In addition, the researcher found the relationship to be statistically significant at 5% level (p=0.000, <0.05). Hence, it is evident that all the independent variables could explain the changes in the performance of manufacturing firms on the basis of the correlation analysis.

The correlation analysis findings are in line with Mikalef and Gupta (2021) that Artificial Intelligence proxies have a positive influence on organizational performance. Furthermore, Bag et al., (2020) asserts that artificial intelligence influences the firm value significantly through customer knowledge creation, user knowledge creation and external market knowledge creation. However the technologies are expensive to acquire.

4.7 Regression Analysis

In this study multivariate regression analysis was used to determine the significance of the relationship between the dependent variable and all the independent variables pooled together. Regression analysis was conducted to find the proportion in the dependent variable (performance of manufacturing firms) which can be predicted from the independent variables (Internet of Things, Data Analytics, Sensors and Drones and Government Regulations.)

Table 4.11 presents the regression coefficient of independent variables against dependent variable. The results of regression analysis revealed there is a significant positive relationship between dependent variable (performance of manufacturing firms) and the independent variables (Internet of Things, Data Analytics, Sensors and Drones and Government Regulations).

The independent variables reported R value of .775 indicating that there is perfect relationship between dependent variable and independent variables. R square value of 0.6 means that 60% of the corresponding variation in performance of manufacturing firms can be explained or predicted by Internet of Things, Data Analytics, Sensors and Drones and Government Regulations, which indicated that the model fitted the study data.

Adjusted R square in table 4.11 is called the coefficient of determination which indicates how performance of manufacturing firms varied with variation in effects of factors which includes; Internet of Things, Data Analytics, Sensors and Drones and Government Regulations. The results of regression analysis revealed that there was a significant positive relationship between dependent variable and independent variable at ($\beta = 0.309$), $p=0.002 < 0.05$).

TABLE 4.11
Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.775[a]	.60	.586	.16769

a) Predictors: (Constant), Internet of Things, Data Analytics, Sensors and Drones and Government Regulations

b) Dependent Variable: Performance of manufacturing firms

TABLE 4.12
ANOVA

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	4.809	4	1.202	42.749	.000[b]
	Residual	3.206	114	0.028		
	Total	8.014	118			

a) Predictors: (Constant), Internet of Things, Data Analytics, Sensors and Drones and Government Regulations

b) Dependent Variable: Performance of manufacturing firms

The significance value is 0.000 which is less that 0.05 thus the model is statistically significance in predicting how Internet of Things, Data Analytics, Sensors and Drones, Government Regulations influence supply chain performance of manufacturing firms in Kenya. The F critical at 5% level of significance was 26.80. Since F calculated which can be noted from the ANOVA table above is 42.749 which is greater than the F critical (value = 26.80), this shows that the overall model was significant. The study therefore establishes that; Internet of Things, Data Analytics, Sensors and Drones, Government Regulations were all important factors influencing performance of manufacturing firms. These results agree with Asaari and Razak (2020) results which indicated a positive and significant effect of artificial embedded technologies on supply chain performance of manufacturing firms in Kenya.

TABLE 4.13
Coefficients of Determination

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.44	0.198		12.317	0.000
	Internet of Things	0.146	0.045	0.214	3.27	0.000
	Sensors and Drones	0.11	0.024	0.334	4.662	0.020
	Data Analytics	0.03	0.033	0.062	0.921	0.030

a) Predictors: (Constant), Internet of Things, Data Analytics, Sensors and Drones

b) Dependent Variable: Supply Chain Performance of Performance of manufacturing firms

The research used a multiple regression model

$$Y= \beta_0+ \beta_1X_1+\beta_2X_2+\beta_3X_3 +\varepsilon$$

Where **Y**= Performance of manufacturing firms in the Manufacturing firms

β_0= Constant

X_1= Internet of Things

X_2= Data Analytics

X_3= Sensors and Drones

ε= Error Term at 95% confidence level.

The regression equation is;

$$Y= 2.44 + 0.146X_1 + 0.03X_2 + 0.11X_3$$

The regression equation above has established that taking all factors into account (Internet of Things, Data Analytics, Sensors and Drones) constant at zero, Supply Chain performance of manufacturing firms will be an index of 2.44. The findings presented also shows that taking all other independent variables at zero, a unit increase in Internet of Things will lead to a 0.146 increase in performance of manufacturing firms. The P-value was 0.00 which is less than 0.05 and thus the relationship was significant.

The study also found that a unit increase in Data Analytics will lead to a 0.03 increase in performance of manufacturing firms. The P-value was 0.03 and thus the relationship was significant. In addition, the study found that a unit increase in Sensors and Drones will lead to a 0.11 increase in the Supply Chain performance of manufacturing firms. The P-value was 0.00 and thus the relationship was significant. The findings of the study show that, internet of things contributed most to the supply chain performance of manufacturing firms in Kenya. This findings are in line with Wamba-Taguimdje et al., (2020) that artificial intelligence improves performance at both organizational and process levels. By employing AI technology, firms can enhance their business value and capability. Besides Oke (2008) and Miller (2017) also found that artificial Intelligence positively influences organizational performance.

CHAPTER FIVE: CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

This chapter provides a detailed summary of the major findings of the actual study; it then draws conclusions and discusses implications emanating from these findings. Finally, it makes some recommendations and suggestions on areas of further study. The main aim of the study was to examine the effect of artificial intelligence technologies on supply chain performance of manufacturing firms in Kenya. It specifically determined the influence of; Internet of Things, Data Analytics, Sensors and Drones and Government Regulations on the supply chain performance of manufacturing firms in Kenya.

5.2 Summary of Findings

The study examined the effect of artificial intelligence technologies on supply chain performance of manufacturing firms in Kenya. The study targeted procurement heads in the manufacturing firms. A total of 119 employees participated. The summary of the study findings presented herein followed the research objectives formulated in chapter one of the study.

5.2.1 Internet of Things

The study assessed influence of Internet of Things on supply chain performance of manufacturing firms in Kenya as the first objective of the study. Most respondents were found to highly agree that the manufacturing firms had embraced Internet of Things with regard to their procurement activities. Eco branding and labeling was common in the manufacturing firms. Correlation and regression results revealed that this was an important variable that could perhaps be explained by the observation from the findings that Internet of Things was an important factor in influencing performance of manufacturing firms.

5.2.2 Data Analytics

The influence of Data Analytics on supply chain performance of manufacturing firms in Kenya was the second objective of the study. Most respondents were found to highly agree that the manufacturing firms had embraced Data Analytics with regard to their procurement activities. Uses of low sulphur fuel and electricity vehicles were common in the manufacturing firms. Correlation and regression results revealed that this was an important variable that could perhaps be explained by the observation from the findings that Data Analytics was an important factor in influencing supply chain performance of manufacturing firms in Kenya.

5.2.3 Sensors and Drones

The study assessed influence of Sensors and Drones on supply chain performance of manufacturing firms in Kenya as the third objective of the study. Most respondents were found to highly agree that the manufacturing firms had embraced Sensors and Drones with regard to their procurement activities. Energy efficient equipment were common in companies in the manufacturing firms. Correlation and regression results revealed that this was an important variable that could perhaps be explained by the observation from the findings that Sensors and Drones was an important factor in influencing performance of manufacturing firms in the manufacturing firms.

5.2.4 Government Regulations

The study assessed the moderating effect of Government Regulations on the relationship between artificial intelligence technologies and supply chain performance of manufacturing firms in Kenya as the last objective of the study. Most respondents were found to highly agree that the firms supply chain responsiveness, flexibility and reliability had improved after adoption of AI with government regulations.

5.3 Conclusion of the Study

Based on the study findings, the study concluded that Supply chain performance of manufacturing firms can be improved by Internet of Things, Data Analytics, Sensors and Drones operating with stipulates of existing Government Regulations. First, in regard to Internet of Things, the regression coefficients of the study show that it has a significant influence of 0.146 on performance of manufacturing firms. This implies that increasing levels of Internet of Things by a unit would increase the levels of performance of manufacturing firms by 0.146. This shows that Internet of Things has a positive influence on performance of manufacturing firms.

With regard to Sensors and Drones, the regression coefficients of the study show that it has a significant influence of 0.11 on performance of manufacturing firms. This implies that increasing levels of Sensors and Drones by a unit would increase the levels of performance of the companies by 0.11. This shows that Sensors and Drones have a positive influence on performance of manufacturing firms.

Thirdly, the regression coefficients of the study showed that it has a significant influence of 0.03 on performance of manufacturing firms. This implies that increasing levels of Data Analytics by a unit would increase the levels of performance of manufacturing firms by 0.03. This shows that Data Analytics has a positive influence on performance of manufacturing firms. Drawing on this research, lack of adoption of Internet of Things, Data Analytics, Sensors and Drones in the manufacturing firms is leading to poor supply chain performance.

Lastly, the adoption of AI technologies by manufacturing firms which affects their supply chain performance is moderated by government regulations. This is expected since usage of such technologies is perceived to be of national security importance. Therefore for manufacturing firms to realize desired supply chain performance then they must seek approval for usage of such technologies more so sensors and drones.

5.4 Recommendations of the Study

For manufacturing firms to have better performance of their supply chains they should focus more on using their Internet of Things to ensure that there is improved responsiveness, reliability, flexibility and cost of operations. Regarding the second objective, it would be constructive for the manufacturing firms to invest more in Data Analytics to improve on cost of decision making and also, boasting the speed of decision making besides having a data-based decision making criteria.

In relation to Sensors and Drones, the organizations should arrange for more application of the same more so in security management, order fulfillment and usage of smart factories and equipment. If the manufacturing firms embrace Sensors and Drones among its production processes, then there will be reducing operational costs and responsiveness. Concerning Government Regulations, there is need for the manufacturing firms to always monitor their compliance to laws so as to avoid non conformity negative effects.

5.5 Areas for Further Research

The study is built on the foundation that AI technologies are enablers to supply chain performance as long as they are applied with stipulated government regulations. The findings demonstrated the important AI in the manufacturing firms to include; Internet of Things, Data Analytics, Sensors and Drone. The current study obtained an R^2 of 60% and should therefore, be expanded further in future in order to include other AI technologies for example, Chat GPT that may as well have a positive significance to supply chain performance of manufacturing firms. Existing literature indicates that as a future avenue of research, there is need to undertake similar research in other institutions in Kenya and other countries in order to establish whether the explored AI tools herein can be generalized to affect supply chain performance in other institutions and countries.

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APPENDICES

APPENDIX I: QUESTIONNAIRE

The questionnaire is developed to collect data on **Artificial Intelligence Technologies and Supply Chain Performance of Manufacturing Firms In Kenya** as part of my masters program research project requirements. Kindly fill it with it honestly and I promise that the responses shall only be used for academic purposes.

Section A: General Information

Please tick (√) where ppropriate

1. **Your Gender**

   Male [ ]

   Female [ ]

   Don’t want to disclose [ ]

2. **Education Level**

   Diploma Certificate [ ]

   Bachelor Degree [ ]

   Postgraduate Degree [ ]

   Others (specify) ……………………………………

3. **Number of years worked for the current county**

   0-5 years [ ]

   6-10 years [ ]

   11-15 years [ ]

16 years and above [ ]

4. **Number of years of experience**

0-5 years [ ]

6-10 years [ ]

11-20 years [ ]

21 years and above [ ]

Section B: Adoption of Artificial Intelligence Technologies in Manufacturing Supply Chains

5. To what extend has the following artificial intelligence technologies been adopted in your company

   Use 1-Very low extent 2- Low extent 3-Moderate extent 4-Great Extent 5-Very great Extent

Artificial Intelligence Embedded technologies	**1**	**2**	**3**	**4**	**5**
Internet of things					
Big data analytics					
Sensors and Drones					
Any other(Please specify)					

Section C: Artificial Intelligence Technologies and Supply Chain Performance of Manufacturing Firms

6. Please Tick (√) only on one number that best reflects your opinion on the influence of artificial intelligence embedded technologies on Supply Chain Performance of Manufacturing Firms**.** Use five point scale: {1 = Strongly Disagree (SD), 2 = Disagree (D), 3 =Neutral (N), 4 = Agree (A), 5 = Strongly Agree (SA)}

Artificial Intelligence Embedded Technologies					
Internet of Things (IOT)	**1**	**2**	**3**	**4**	**5**
Process automation level is high					
IOT has improved our communications					
IOT has improved on our research and development					
Big Data Analytics	**1**	**2**	**3**	**4**	**5**
Data analytics influences our key decisions					
Big data analytics is a key consideration for our customer relations					
We have adopted predictive maintenance					
Big data is critical in undertaking repair and maintenance					
Sensors and Drones	**1**	**2**	**3**	**4**	**5**
We use sensors and drones to achieve high orderfulfillment levels					
Drones are applied in our security management to a great					

extent					
We have adopted smart factory/remote systems					

Section D: Supply Chain Perfomance of Manufacturing Firms

7. Using likert scale 1-5 rate the Supply Chain Perfomance of Manufacturing Firms before and after adoption of artificial intelligence technologies.

Perfomance Indicators	**Greatly Reduced (1)**	**Reduced (2)**	**Constant (3)**	**Improved (4)**	**Greatly improved (5)**
Responsiveness					
Flexibility					
Cost of Operations					
Any other(Please specify)					

Section D: Moderating effect of Government Regulations

8. Using likert scale 1-5 rate the performance of devolved systems of government before and implementing information technology in supply chain management.

Perfomance Indicators	**Greatly Reduced (1)**	**Reduced (2)**	**Constant (3)**	**Improved (4)**	**Greatly improved (5)**
Usage of artificial embedded technology has improved our					

supply chain responsiveness					
Usage of AI technologies has improved our supply chain flexibility					
Adoption of AI technologies has reduced our operational costs					
Any other (Specify)					