ARTIFICIAL INTELLIGENCE INTEGRATION AND BUSINESS MANAGEMENT METRICS IN THE TELECOMMUNICATION SECTOR IN KENYA

BY

CALEB MUNGA

MASTER OF BUSINESS ADMINISTRATION
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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 authors duly acknowledged.

Sign……... Date……17/08/24

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

Caleb Munga

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

Sign……... Date……17/08/24

Dr. Caroline Ntara

ABSTRACT

As a game-changing technology, artificial intelligence (AI) has the potential to completely change a number of industries, including telecommunications. This research investigated how artificial intelligence affects business management metrics in the telecom sector. The main focus was on the effects of AI applications on important KPIs including income generation, productivity, client fulfillment, and predictive analytics. This study's main objective was to examine the influence of artificial intelligence (AI) on business management metrics within the telecommunication sector. The study's specific objectives were: First, to examine the influence of Data Analytics Platform on business management metrics in Telecommunication sector in Kenya. Second, to assess the influence of Natural Language Processing on business management metrics in Telecommunication sector. Third, to examine the influence of Machine Learning Algorithms on business management metrics in Telecommunication sector and finally, to examine the influence of Robotic Process Automation on business management metrics in Telecommunication sector in Kenya. The study utilized descriptive research design. The target population had 427 employees who work at Airtel and Safaricom Companies corporate headquarters under the various functional departments. Stratified random sampling technique was applicable in the selection of the 206 sample size. The study used a semi-structured questionnaire as the data collection instrument with inferential statistics used for data analysis and presentation. The results analysis highlights the critical role of technological advancements, particularly in the areas of Data Analytics, Natural Language Processing, Machine Learning Algorithms, and Robotic Process Automation, in driving improvements in business management metrics within the telecommunications sector in Kenya. The study concludes that the integration of AI technologies is essential for enhancing business management metrics in the telecommunications sector.

Keywords: Artificial Intelligence, Telecommunication, Business Metrics, Information Technology

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DEDICATION

I dedicate this dissertation to my loving and caring grandmother, Mary Mose. She has always motivated me to pursue my studies with dedication as she believes education is the master key to life success.

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ABBREVIATIONS AND ACRONYMS

AI	-	Artificial Intelligence
BSC	-	Balanced Scorecard
IT	-	Information Technology
KPI	-	Key performance indicators
MLA	-	Machine Learning algorithms
NLP	-	Natural Language Processing
RPA	-	Robotic Process Automation
TAM	-	Technology Acceptance Model

DEFINITION OF TERMS

Data Analytics Platform - This refers to an extensive software architecture that allows businesses to gather, handle, examine, and display vast amounts of data from several sources. In order to enhance decision-making and promote business outcomes, it offers tools and capabilities that make data exploration, pattern discovery, and the creation of insightful analysis easier (Loureiro et al., 2021).

Natural Language Processing - Natural Language Processing (NLP) is an artificial intelligence (AI) subfield that studies how computer systems interact with human language. It entails the creation of methods and algorithms that let computers comprehend, interpret, and produce meaningful and practical human language (Loureiro et al., 2021).

Machine Learning Algorithms - This refers to mathematical models and methods allow computers to discover patterns on their own and forecast or make judgments without the need for explicit programming. These algorithms are essential to machine learning, a discipline of artificial intelligence that concentrates on building systems with the capacity to gain insight from and improve upon data (Loureiro et al., 2021).

Robotic Process Automation - The term "robotics" or "bots" refers to the automation of repetitive and rule-based tasks in commercial processes through the use of software. With the use of RPA technology, businesses may automate repetitive and uninteresting jobs that were previously completed by people, freeing up time and resources for more difficult and valuable operations (Loureiro et al., 2021).

Business management metrics - Also known as Key performance indicators, or KPIs, represents quantitative measurements used in company management to assess and monitor the efficacy, performance, and advancement of different business facets. These metrics give management

insightful information on the effectiveness, efficiency, and success of the company, empowering them to decide wisely and take the necessary steps to promote improvement (Loureiro et al., 2021).

CHAPTER ONE

INTRODUCTION

1.0 Overview

This chapter provides the study background on the concept and context from the global, regional and local perspective. The section also provides the statement of the problem, study objectives, research questions, and significance of the research and scope of the study.

1.1 Background to the Study

In today's corporate environment, artificial intelligence (AI) has become an influential force. Artificial Intelligence (AI) integration has emerged as a key transformative force in today's rapidly evolving corporate environment (Wamba-Taguimdje et al., 2020). Kaggwa et al. (2024) in their study on AI in business decision-making, revealed AI as a fundamental component of company progress, providing unmatched chances for creativity and productivity. This shows that AI has changed how businesses function, compete, and provide value to their clients because of its capacity to analyze data, automate processes, and make intelligent judgments.

An overview of the fundamental effects of integrating AI into different business processes and the underlying forces driving this transformation are given in this introduction (Suryadevara, 2023). AI is being used by businesses more and more to solve difficult problems and obtain a competitive edge. The capacity of AI to improve decision-making, spur innovation, and develop new value propositions has defined its trajectory in company strategy. AI's progress in corporate strategy represents a broader shift towards more flexible, data-driven, and technologically sophisticated company practices. This includes improving machine learning capabilities and rethinking the roles of human and machine. AI will probably continue to change the strategic environment as it develops, posing both new opportunities and difficulties for companies all

around the world (Delbufalo et al., 2022). The applications for AI integration are numerous and include natural language extraction, learning algorithms, data analytics, and workflow automation. These AI tools are being used in a variety of sectors to spur innovation, improve consumer experiences, and streamline operations (Aldoseri et al., 2024). The technology known as artificial intelligence has the capacity to completely change a number of facets of corporate operations. The rapid advancement of AI has led to a growing prevalence of its integration into company management operations (Duan et al., 2019).

The application of AI to business processes covers a wide range of applications, including marketing (for content and advertising personalization), client service (for real-time support), supply chain management (for improved logistics and forecasting), finance (for automated risk evaluation and fraud detection), and many more (Pallathadka, et al., 2023). AI's real-world uses are growing, proving its flexibility and applicability in a variety of fields. But there are other issues and concerns to take into account while integrating AI (Duan et al., 2019). Organizations face several challenges in the form of privacy problems, ethical quandaries, and a lack of qualified AI specialists. Additionally, the regulatory environment pertaining to AI is continuously changing, necessitating that firms be aware of the criteria for compliance. The future appears promising for the dynamic and revolutionary integration of AI into corporate operations. Innovations in technology will keep pushing the envelope of what is possible, and companies will have to find a way to combine using AI's promise with making sure its usage is morally and responsibly done. This introduction provides a framework for understanding the critical role AI plays in transforming the corporate world and sets the stage for a thorough investigation of AI integration in the parts that follow (Lu, 2019).

According to Brynjolfsson & Mitchell (2017), the majority of the labor and economic sectors are

only beginning a significant transition brought on by recent advancements in machine learning. In contrast to earlier technological advancements, the latest in artificial intelligence has the potential to impact numerous highly skilled and lucrative professions (Aldoseri et al., 2024). Naturally, there is a great deal of discussion and disagreement over the implications of this for various professions and the nature of labor in general. Some tech experts assert that the AI revolution has the potential to alter society much more than the industrial revolution did (Aldoseri et al., 2024). Conversely, others argue that the impact of AI is widely overestimated.

Globally, Microsoft says that organizations in the UK who employ AI at scale perform 11.5% better than those that do not (Siddharth, et al., 2024), while the International Business Machines Corporation (IBM) reports that AI has saved expenses for 44% of enterprises that have applied it. Furthermore, IBM projects that by 2025, market revenues derived from AI—particularly those impacted by machine and deep learning—will increase by a factor of more than eleven (Hydros & Chaudhry, 2022). According to executive predictions, artificial intelligence (AI) will help businesses develop new smart products and services, enhance internal business processes or manufacturing operations through automation, and transform customer interactions (De Bruyn et al., 2020).

Machine learning and other AI tools are great at turning massive amounts of data into statistical information, which makes it much easier for companies to reach the right consumer base, estimate demand, and forecast sales than they would be if they used manual methods (Sharma & Sharma, 2023). Consequently, while there are currently few businesses investing in AI machine learning (ML), this is starting to change as businesses see the advantages of AI marketing in assisting with strategic decision-making (Kiron et al., 2023). The objective of this research project is to investigate how AI integration affects important company management indicators,

such as operational optimization, productivity, efficiency, fraud detection, risk management, decision-making processes, and the client experience.

In African enterprises with limited resources, AI help in streamlining processes, resulting in better KPIs such as cost reduction, profitability, and resource optimization (Wamba-Taguimdje, et al., 2020). Furthermore, there could be a variety of implications on metrics from the integration of AI into corporate management in Africa. Better operational efficiency, better decision-making, opening up new markets, better customer experiences, optimized supply chain management, skill development and job transformation, and ethical considerations are some of these consequences. Through responsible use of AI technologies and targeted attention to African context-specific issues, enterprises may effectively leverage the advantages of AI integration and enhance their management metrics.

The digital revolution has already produced its effects by transforming the world into a modern one characterized by the supremacy of data in every business activity Data is no longer confined to data centers. With sensors of any kind, any object or environment of objects is henceforth capable of measuring and producing data (Lee et al., 2019). Industrial and digital (information) revolutions have undoubtedly had a financial impact on virtually every aspect of our society, life, business, and employment (Maslej et al., 2023). According to IDC's projections, artificial intelligence (AI) accounts for 40% of digital transformation projects and 75% of commercial applications in the current world (Wamba-Taguimdje et al., 2020). Organizations will depend even more on AI to enhance their performance in order to increase productivity and provide new services. Nonetheless, AI is a market of the future par excellence due to its enormous potential and advantages.

1.1.1 Artificial Intelligence

Artificial intelligence is defined by researchers as mechanisms and programs that exhibit intelligence (Shankar, 2018) or at the very least exhibit human-like behavior and intelligence. Kaplan and Haenlein (2019) proposed a more precise and limited definition of artificial intelligence (AI), characterizing it as the capacity of a system to accurately comprehend and assimilate external input, acquire knowledge from it, and use that knowledge to accomplish five distinct objectives and tasks via adaptable changes. AI was also divided into three phases of development by Kaplan and Haenlein (2019): narrow AI, which is less intelligent than humans, general AI, which is more intelligent than humans, and super AI, which is more intelligent than humans. Currently, there is much discussion surrounding the assumption that super AI would surpass human intellect and render humans obsolete. General AI, on the other hand, is anticipated by some to become a part of our life in order to plan, reason, and solve problems outside of our particular domain, something that narrow AI is unable to accomplish (Kaplan & Haenlein, 2019). Conversely, narrow AI has gained traction and is thought to be the most promising stage from a commercial standpoint (Racounter, 2020; Kaplan & Haenlein, 2019).

1.1.2 Business Management Metrics

Business management metrics are numerical measures that are used to evaluate the efficacy and performance of different areas of an organization's activities (Kathuria & Lucianetti, 2024).

These indicators offer insightful information on the state of the business's finances, effectiveness of its operations, level of client happiness, and general performance. Business metrics encompass a range of functional domains and dimensions, such as accounting, operations, client, employee, and marketing components. A thorough understanding of the company's performance is provided by this all-encompassing approach. Metrics acquire significance when they can be compared to

rivals, industry norms, or past results. This makes it possible to draw insightful comparisons and pinpoint areas for development or competitive advantages. Several studies have examined the effect of business KPIs on firm performance using machine learning algorithms. For instance, Rathnayake and Gunawardana (2023) used machine learning algorithms to investigate the impact of business KPIs on firm performance. Additionally, an experimental approach was employed in a study by Elhajjar et al. (2020) to investigate how company KPIs affects customer satisfaction.

These metrics are quantitative measures and are used to track, monitor, and evaluate the performance or failure of various business processes (Tambare, et al., 2021). They are necessary for organisations to assess their performance, pinpoint areas in need of development, and arrive at wise conclusions. Business metrics can be used to track a variety of aspects of a company's performance, such as revenue, profitability, customer engagement, and employee productivity. They can be categorised by functional area, such as finance, marketing, human resources, and operations. A project's or organization's success in many areas can be measured using performance metrics, which are another name for business metrics. Aspects of financial performance that monitor sales turnover, earnings, expenses, assets, liabilities, and capital are included in financial metrics. Different attributes and measurements can be quantified using a broad range of metrics. This also holds true for business KPIs, which vary greatly and are mostly dependent on the nature of the organisation. As a result, the type of business, industry, and aims of a particular business organisation will determine which business metrics are appropriate (CPI, 2023).

Performance indicators, also known as Key Performance Indicators (KPIs), are what ultimately drive the process performance assessment (Tambare, et al., 2021). KPIs are contemporary tools that facilitate the maintenance of high performance in the production process. Performance

metrics also indicate what will happen in addition to expressing what has already occurred, since they give decision-makers information that will impact the company's competitive position going forward. Business performance indicators serve to drive a change programme, track and monitor operational quality, represent the current state of efficiency, and assess the efficacy of strategic decision-making. The metrics that are most frequently used to assess performance in production systems are quality, cost, delivery time, and adaptability (Tambare, et al., 2021). Notably, real-time quality management and the integration of quality management into technological operations are made possible by contemporary information technology.

1.1.3 Telecommunications industry

The telecom sector is one of the key participants in this digital revolution, which is changing how people and businesses live, work, and communicate with one another thanks to emerging technology (Jercan & Nacu, 2023). To deliver access, connection, and application services, industries pursuing this revolution rely on telecom providers' infrastructures, applications, and productivity gains (World Economic Forum & Accenture, 2017). Businesses in this sector are known for using IT extensively in all aspects of their business operations. They use the aforementioned software applications for distribution, network expansion, and resilience, or frameworks that keep the network operational even in the event of malfunction (Jercan & Nacu, 2023).

The sector is being confronted with several possibilities and risks that might be disruptive (Hanson & Tang, 2020). With its rapid connectivity and low latency technology, 5G is set to revolutionise the industry despite the fact that it is still in the infrastructure developing stage (Di Mascio, 2019). This can lead to the widespread adoption of technologies like cloud computing and the Internet of Things (Nazari Jahantigh, et al., 2020). Furthermore, experts think that 5G and low-Earth orbit

satellite internet might improve the poor rural bandwidth penetration rate as well as the absence of rivalry in the internet sector. The industry's hurdles with relation to 5G will include knowing how to mold consumers' expectations of the technology, ascertaining all of its potential and constraints, and estimating the significant infrastructure expenditure required for its implementation.

1.2 Statement of the Problem

As a way to improve business management procedures, Telecommunication companies probably use AI technology (Javaid et al., 2023). However, the AI integration presents significant risks and challenges such as potential bias in algorithms as well as cybersecurity vulnerabilities, which influence the outcome of various metrics applicable in business management (Jagatheesaperumal, et al., 2021). In some instances the big data sets used by AI systems in businesses contain biased or unrepresentative information; the algorithms may perpetuate and exacerbate those preconceptions. This results in unfair recruiting, promotion, or customer targeting practices, among other decision-making processes. These eventually impacts the metrics used in company management, such as equitable resource allocation, customer happiness, and diversity and inclusion. Furthermore, the presence of malevolent parties targeting AI systems also presents a significant threat. In such cases, adversarial assaults have the ability to alter input data in order to trick AI algorithms or influence their outcome in the wrong way. Such cybersecurity flaws have the potential to affect a number of business management KPIs such as consumer trust, operational effectiveness, and data privacy.

Existing studies on AI integration in business management measures provide a general insight (Perifanis & Kitsios, 2023; Bharadiya, 2023; Brynjolfsson & Mcafee, 2017; Davenport, 2018; Chui et al., 2018), but not directly addressing the telecommunications industry. Still unknown, is the extent to which AI integration has affected telecommunication sector business management

measures. Therefore, understanding how AI might impact important KPIs in the telecommunications business requires a focused analysis due to its distinct features, opportunities, and limitations. The percentage of businesses that actually put AI initiatives into practice still lags well behind the number that want to do so. According to the CompTIA IT Industry Outlook 2024 study, 22% of businesses are actively seeking to integrate AI into a variety of technological products and business processes, 33% are implementing AI partially, and 45% are still in the research and development stage (CompTIA IT Community, 2024). This reveals that Artificial Intelligence (AI) is a cutting-edge technology that is gaining popularity and power rapidly, particularly in corporate management applications. Therefore, this study examines how AI integration may influence the outcome of business metrics in the telecommunication sector.

1.3 Research Objectives

1.3.1 Main Research objective

This study's primary goal is to examine the influence of artificial intelligence (AI) on business management metrics within the telecommunication sector.

1.3.2 Specific Research Objective

i. To examine the influence of Data Analytics Platform on business management metrics in Telecommunication sector in Kenya.
ii. To assess the influence of Natural Language Processing on business management metrics in Telecommunication sector in Kenya.
iii. To examine the influence of Machine Learning Algorithms on business management metrics in Telecommunication sector in Kenya.
iv. To examine the influence of Robotic Process Automation on business management

metrics in Telecommunication sector in Kenya.

1.4 Research questions

i. What is the influence of a Data Analytics Platform on business management metrics in the telecommunications sector in Kenya?

ii. What is the influence of Natural Language Processing (NLP) on business management metrics in the telecommunications sector in Kenya?

iii. What is the influence of Machine Learning algorithms on business management metrics in the telecommunications sector in Kenya?

iv. What is the influence of Robotic Process Automation (RPA) on business management metrics in the telecommunications sector in Kenya?

1.5 Study significance

Telecommunications Industry

Examining the effects of AI integration on business management KPIs at Airtel and Safaricom can yield important information on the advantages and difficulties of using AI in the telecom sector. This research can further our understanding of the successful integration of AI into corporate processes.

Policy Implication

The study can provide insight into the relationship between AI integration and important company management KPIs, which comprises revenue growth, cost reduction, operational efficiency, and client satisfaction. Knowing how AI affects these KPIs might help telecommunication companies make informed policies and direct strategic activities that enhance overall business success. Policymakers and regulatory agencies are paying more attention to ensuring the ethical and responsible application of AI as the technology advances. Examining the impact of AI integration

at Airtel and Safaricom can help advance the conversation on optimal procedures, regulations, and policies for AI adoption in the telecom industry. Policymakers might use the findings as guidance for creating policies that safeguard consumer interests, encourage innovation, and perhaps solve ethical issues.

Academic Implication

The study's results can add to the volume of information already available on the integration of AI in corporate management. It can also promote cooperation and the sharing of ideas and experiences amongst academics, business professionals, and other interested parties. The study may serve as a springboard for additional investigation into AI integration in the telecom industry and other sectors.

1.6 Study Scope

The study focuses on the topic; the influence of artificial intelligence integration on business management metrics in the telecommunication industry. The geographical scope will be telecommunication companies in Nairobi City County, with focus on Safaricom and Airtel companies. The time scope; the study will be conducted in the year 2024.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter describes the research's theoretical foundations and provides an overview of the pertinent empirical literature from earlier studies. The conceptual framework and chapter summary are also described in this chapter.

2.2 Theoretical Framework

2.2.1 Technology Acceptance Model (TAM)

The elements impacting people's acceptance and adoption of new technologies are explained by Davis' (1989) Technology Acceptance Model (TAM). It implies that two important factors influencing the adoption of technology are perceived utility and simplicity of use (Silva, 2015). The Technology Acceptance Model (TAM) may be utilized to comprehend managers' and employees' perceptions of the utility and user-friendliness of AI technologies, which in turn impacts their adoption and utilization when it comes to AI integration in company management.

In order to understand and predict technological behavior, this model is crucial. The core tenets of TAM are perceived utility, perceived usability, attitude, intentions, and behavior during real use. In this instance, the user's attitude is determined by perceived utility and perceived ease of use. The TAM model was evaluated on 107 users by Klopping and Mckinney (2004) in order to gauge their intention to use an IT system. In this instance, they discovered that behavior intention was directly impacted by perceived usefulness as well as perceived ease of use.

Technology Acceptance Model is employed in this study in place of the Theory of Reasoned Action's (TRA) attitude variables. Perceived utility and simplicity of use take the place of attitude variables in this instance. The Technology Acceptance Model is used to define the precise factors that influence technology adoption and can be used to explain why organizations deploy AI technology differently (Mohd Amir et al., 2020). The amount of user acceptability among Kenyan telecom firms can be predicted with some degree of accuracy using the Technology acceptability Model. Two theoretical categories are utilized as primary factors of system adoption: perceived usefulness and ease of use.

Perceived usefulness in this context refers to how much employees of the organization think that performance was enhanced by the deployment and utilization of a technical innovation. Conversely, perceived ease of use is concerned with how much staff members think a system will be simple to use. Notably, TAM focuses on prediction in addition to explanation, which generally aids academics and practitioners in determining the reasons why a certain system might not be appropriate and, thus, pursuing the necessary actions (Chem Shing-itan & Chien- Yi, 2011). The theory will support data analytics platform and robotic process automation variables.

2.2.2 Dynamic Capabilities Theory

Teece et al. (1997) established the Dynamic Capabilities hypothesis, which examines an organization's capacity for environment adaptation and response. It implies that in order to attain better performance, organizations with dynamic capacities may take advantage of both internal and external resources. The idea may be used to investigate how businesses build the capacity to successfully incorporate AI technology into their company management procedures, which will enhance metrics (Bleady et al., 2018).

The Dynamic Capabilities Theory is based on various fundamental principles (Bleady et al., 2018).

These entail such aspects as the ability to perceive and recognize shifts, patterns, and possibilities in the outside world. In order to do this, one must actively monitor the surroundings, collect data, and decipher signals that could have an effect on the performance and strategy of the company. Also the capacity to grasp or seize chances found through sensing. To take advantage of the opportunities that have been recognized, the organization must make strategic decisions and act pro-actively. Then organizations must be able to adapt to changing conditions by reconfiguring their current organizational structures, competences, and resources. This entails having the flexibility to reassign resources, change procedures, combine skills, and adjust to shifting market conditions (Gremme & Wohlgemuth, 2017).

The idea of dynamic capacities places a strong emphasis on how adaptive and flexible organizations must be when faced with shifting conditions. This entails accepting ambiguity, being open to trying new things, and being prepared to modify plans of action as necessary. Organizations that are flexible can react to new possibilities and challenges with speed and efficiency (Gremme & Wohlgemuth, 2017). Organizations can establish distinctive and valued capabilities that are hard for rivals to copy or replicate by consistently sensing, seizing, and reconfiguring. The cornerstone for sustained success and exceptional performance is dynamic capabilities. The theory will support natural language processing and machine learning algorithm variables.

2.3 Empirical Literature Review

2.3.1 Data Analytics Platform and Business Management Metrics

Khokhar and Chitsimran (2019) endeavoured to examine the components that facilitate the application of artificial intelligence in marketing. According to Krsteva (2016) and Siau (2017), the marketing business has an unparalleled future due to the numerous inventive applications of

AI. However, Vishnoi and Bagga (2019) have provided comprehensive insights into the AI ecosystem and the embedded technologies that facilitate these marketing endeavors.

Thiraviyam (2018) suggested methods to improve digital marketing strategies, whereas Cosmin TĂNASE (2018) examined the impact of AI on programmatic advertising, considering the scope and relevance of online advertising in contemporary marketing. These studies' findings may not be applicable to all contexts because they are based on specific industries, regions, or sectors. Insufficient theoretical foundation of the investigations can pose challenges in comprehending the underlying mechanisms and interrelationships among variables. The knowledge of AI's influence on marketing strategies could be improved by incorporating accepted ideas or creating new frameworks. In terms of the knowledge gap, research mostly concentrate on the short-term impacts of AI on marketing strategies, ignoring long-term repercussions. Furthermore, the studies concentrate on particular areas or sectors. Comparing different cultures, however, may make it easier to pinpoint the components of AI's influence on marketing strategies that are both universal and culturally particular.

Research on the impact of artificial intelligence (AI) on digital marketing has been conducted recently in a number of specialised study settings, including consumer experience and intellectual marketing (Chandra, 2020; Elhajjar et al., 2020). Elhajjar et al. (2020) used an interview-based methodology to look into what makes students interested in artificial intelligence (AI) in marketing courses, whereas Chandra (2020) looked at a few contemporary applications from the perspective of consumer and customer service positions, like Amazon Flywheel Approach and Amazon Collaborative Filtering.

Elhajjar et al. (2020) and Chandra (2020) research provides significant insights into the elements influencing students' interest in artificial intelligence (AI) in marketing courses and its modern

applications in customer service and consumer roles. However, there are still knowledge and methodological gaps that can be filled through future study, such as long-term consequences, cross-cultural comparisons, and ethical concerns.

Exclusive research by Mogaji et al. (2020) evaluated the impact of AI-enabled digital marketing campaigns on financially vulnerable clientele. The study proposes a theoretical model that may function as a crucial bridge between financial services marketers and consumers who have been identified as financially vulnerable—a market that is underserved in the financial services industry—in addition to emphasising the value of interpersonal relationships in ensuring the highest levels of client engagement and experience. Nonetheless, a number of evident knowledge gaps exist in this investigation. Because the study uses secondary data sources, it might not be possible to fully comprehend how AI-enabled digital marketing strategies affect susceptible consumers. Obtaining primary data via questionnaires, interviews, or studies may yield more detailed information. Measurement inaccuracies may arise from the use of subjective evaluations or self-reported measures. Standardised scales or objective measurements could yield more accurate data. A strong theoretical foundation for comprehending the effects of AI-enabled digital marketing initiatives on susceptible consumers is not provided by the study. The knowledge of AI's influence on marketing strategies could be improved by incorporating accepted ideas or creating new frameworks.

Further, a separate qualitative research study employing fuzzy-sets comparative analysis by Capatina et al. (2020) categorized the newly developed correlated configurations of artificial intelligence-powered software in social media marketing into three distinct groups in the framework of internet marketing agencies: audience, sentiment assessment, and image. The ethical ramifications of AI-powered social media marketing tools, including privacy issues, bias, and even

detrimental effects on employment, are not adequately covered by the study. To guarantee responsible AI deployment, these ethical issues should be addressed in the current research.

In his research, Ng (2017) brought up a crucial point about the use of AI into marketing plans in order to maximize value creation. According to him, relying just on the deployment of AI technology will not ensure success; rather, marketing managers must develop the best plan in order to ensure the intended outcomes. When compared to technology, mastering the acquisition of real data and professional labor is actually scarcer in the market since, while top AI teams can quickly recreate the necessary software, obtaining other people's insights and data might be challenging (Ng, 2017). The analysis is based on secondary data sources, which may not provide a complete picture of the influence of AI on marketing strategy. Obtaining primary data via questionnaires, interviews, or studies may yield more detailed information. Moreover, the research offers restricted actionable suggestions for companies looking to maximise their AI tactics.

Chatterjee et al. (2024) conducted a study on how business analytics contribute to organizational performance and business value. This article's goal was to pinpoint the ways in which organizations can increase their company value by enhancing their performance and acquiring business analytics capabilities. These were quantitatively evaluated by gathering information from selected participants in India's service and goods-based industry sector. The research utilized survey questionnaires. The study made clear that acquiring business analytics capabilities might increase an organization's commercial value by bolstering its organizational efficiency, with the assistance of two essential components: data acquisition and tool acquisition. The findings of the research also revealed that gaining business analytics skills has a big impact on how well business processes and decisions are performed inside an organization, which in turn has a big impact on how well the company performs as a whole. Additionally, an organization's

performance progressively raises its business worth.

2.3.2 Natural Language processing on business management metrics

Study by Wang et al. (2023) focuses on the application of voice-based AI technology and its effects on customer service in contact centers. In particular, it offers the results of a real-world field test designed to assess how well voice-based AI can boost customer satisfaction and call center efficiency. The results of the research show that the voice-based AI system fared better than human operators in a number of areas. In comparison to calls handled by humans, it produced faster response times, increased call resolution rates, and better customer satisfaction. The artificial intelligence system proved to be more accurate and efficient in comprehending client inquiries, delivering pertinent information, and resolving problems. The study also investigates the underlying mechanisms that support voice-based AI's effectiveness in contact center customer support. It pinpoints elements that enhance the efficacy of the AI system, like enhanced speech recognition skills, natural language comprehension, and real-time data integration. A comprehensive theoretical foundation for comprehending the effects of AI on customer service is not provided by the study. The knowledge of AI's influence on marketing strategies could be improved by incorporating accepted ideas or creating new frameworks. Furthermore, the study may not be representative of other contact centres because it is based on confidential data from a single telecommunications provider.

Patel et al. (2023) in their study, used a language representation model for sentiment analysis to examine the Airline reviews dataset. A variety of Machine Learning (ML) algorithms have been employed to investigate sentiment analysis performance such as Support Vector Machine as well as Decision Tree. However, the results of these techniques vary. This study tested the performance of various ML algorithms with Google's BERT algorithm. The Bert architecture, which had been

pre-trained on sentence prediction and masked language modeling—was also examined in this paper. Because it performed the best out of all the machine learning models, the "Random Forest" served as a benchmark for comparing the "BERT Model" outcomes. Based on performance metrics including recall, reliability, precision, and F1-score, BERT was found to perform better than the other ML approaches. The study fails to provide a coherent theoretical foundation for comprehending how sentiment analysis affects services offered by airlines. Understanding how AI affects marketing strategies could be improved by incorporating accepted theories or creating new frameworks.

In their study, Wang, Li, and Singh (2018) employed bag-of-words, TF-IDF, and the approach of singular value decomposition (SVD), a technique for resolving data sparsity in highly dimensional information, in order to identify functional resemblance based on customer feedback and app specifications of each app on the iOS App Store. Another often used technique for quantifying word attributes in documents is bag-of-words. Wu et al. (2019) used bag-of-words to identify patent terms in patent abstracts gathered from the NBER Patent Citation Data File in order to measure innovation and take use of the fact that innovative ideas can be discovered through vocabulary shifting. The "novelty score" was then determined by the authors by calculating the age of each word based on its initial appearance in related technological sectors.

Cui, Gallino, Moreno, and Zhang (2018) measured endorsement using valence in addition to the sentiment and informativeness of Facebook comments. The quantity of words, phrases, and unique words in a comment determined its informativeness. Social media comments are typically brief and made by a diverse range of people, making it impossible to classify them with precision using basic sentiment analysis. In order to categorize each comment into good, negative, or neutral categories, the authors used the recurrent neural tensor network (RNTN) on top the data from the

Stanford Sentiment Treebank corpus.

Hoberg and Phillips (2018) examined corporate descriptions found in 10-K filings to determine the extent to which product language crosses over within and across industries. Based on the content in each company's product description, they created word vectors for each company; however, they left out frequent terms that are utilized by more than 25% of all companies. Then, to determine how similar two word vectors were to one another both inside and across industries, the cosine similarity was computed. In essence, there are many different problems and uses for NLP in OM research. For text categorization, OM research has employed deep learning techniques in addition to conventional word frequency analysis. In strategy research, creating association rules between texts and strategies is essential to utilizing NLP for the extraction of precise information. This can be accomplished by deep learning, which makes it possible to extract and analyse pertinent texts in order to identify capture techniques. Lastly, it is important to note that method selection has a major role in the effectiveness of NLP application because operations management studies cover a wide range of study themes. Scholars in operations management research must consult the literature in other fields with pertinent study subjects in order to identify applicable and efficient analytical techniques.

The study conducted by Berman, Melumad, Humphrey, & Meyer (2019) aimed to investigate the evolution of tweeting during and after four major presidential debates in the United States in 2016. Specifically, the researchers looked at modifications to linguistic style, topical content, and robotic detection through these moments of political significance. In a different study, Srivastava, et al. (2018) measured cultural fit by reviewing the electronic correspondence between full-time staff members. They combined these language groups with Jensen-Shannon (JS) variance to assess compatibility with culture, and they used LIWC to assess the style of language.

According to Barlow, Verhaal, and Angus (2019), the most advantageously unique entrance point is at a low threshold of prototype likeness and a high degree of template similarity. Another common characteristic of inexperienced entrepreneurs is their lack of managerial experience. It has been discovered that the guidance provided by their peers affects the performance of their startup (Chatterji, Delecourt, Hasan, & Koning, 2019). It is imperative for established businesses to innovate in order to obtain a competitive edge. In light of this, scholars have examined two crucial aspects of innovation: the extent to which enterprising firms ought to pursue in order to raise their chances of success and the manner in which they ought to integrate the many forms of creativity that they acquire.

2.3.3 Machine Learning Algorithms on business management

Hassan et al. (2023) conducted a study on the role artificial intelligence in modern banking. This research delved at the application of artificial intelligence (AI) in contemporary banking, with a particular emphasis on AI-enabled strategies for improved regulatory compliance, risk mitigation, and fraud prevention. Its goal is to investigate how AI may be used to help the banking sector overcome these obstacles. The study's conclusions demonstrate the important part artificial intelligence (AI) may play in improving financial services in the contexts of risk oversight, fraud prevention, and complying with laws and regulations. The researchers list a number of AI-driven strategies, such as automated compliance surveillance equipment, modeling-based predictive methods, and anomaly detection algorithms, which have demonstrated potential in enhancing these operations.

Martins and Galegale (2023) conducted a study on sales forecasting using machine learning algorithms. The study assessed the primary approaches and determined which had the highest level of sales prediction accuracy. Three primary approaches were assessed: time series, artificial neural

networks, and machine learning algorithms, according to an integrated review of the literature. The results showed that, when it comes to precision, machine learning is more suitable, particularly for models that combine both internal and external variables. It also makes it possible to find sequences in implicit demand that could be utilised to identify emerging markets. However, longitudinal data can be employed more readily and cheaply in markets with predictable demand and few external interferences, thus its usage is not justified in these circumstances.

Machine learning is crucial for forecasting consumer preferences, pricing, and willingness to provide bids. Since pricing and pricing strategies have a significant impact on sales, marketing experts should focus their research in this area. Therefore, Russell and Norvig (2016) suggest that one of the key areas for future research is how artificial intelligence can best determine whether prices are ideal and whether or not currency trading should be made available. Electronic salesmen enhanced their e-commerce marketing approach and offered additional services like personalization, customization, and referrals by using machine learning (ML) to study the behaviour of their clients. Russell and Norvig 2016 asserts that machine learning (ML) is a fantastic instrument for internet marketers to: (i) increase market sales; (ii) comprehend consumer behaviour; (iii) enhance customer contentment; (iv) draw in more clients; and (v) reduce car buy rejections. ML also directs e-commerce operations and has an impact on decision-making.

A study by Syam and Sharma (2018) highlight how machine learning and artificial intelligence (AI) tools give marketers access to more statistical power, which greatly increases their efficiency in tasks like target market identification, market segmentation, and more precise demand and sales forecasting. Thus, AI-integrated CRM enables real-time consumer participation, which supports the creation of contextually appropriate communications with clients. This makes it easier to determine at the end of the interaction exactly what kind of an approach good, or service the

customer is looking for and aids in coming to an appropriate conclusion.

Rashidirad et al. (2017) studied competitive strategy, dynamic capability, and value creation. The study indicated that the telecommunications industry can improve customer retention by using AI and machine learning algorithms to predict client attrition. This study employed a multidimensional methodology, breaking down each construct into its component dimensions, to analyse the intricate linkages between competitive strategies and dynamic capacities and the ensuing influence on value creation. This study used a multidimensional perspective to encourage reconsideration of the relationship between competitive strategy and dynamic capabilities and value creation in businesses.

A study conducted by Barboza et al. (2017) compared the performance of test machine learning models with findings from traditional approaches to predict bankruptcy one year ahead of the event. In contrast to conventional processes, they report achieving significant predicted accuracy and indicate that machine learning approaches can be readily implemented for large categorization accuracy. With the complexity of bankruptcy models, machine learning may prove to be a valuable tool despite reservations about the model's explanatory power. The model's high degree of prediction accuracy as well as its capacity to identify the financial variables most pertinent to the prediction process could be advantageous to a bank.

In their research, Khrestina et al. (2017) suggest a prototype for producing a report that enables the identification of questionable transactions. An approach called logistic regression is used in the prototype. Notably, they have also included an analysis of six software programmes that are being used by different institutions to automate activities related to monitoring and identifying suspicious transactions. The writers mention algorithms, but it's not apparent if machine learning techniques are used in these goods or which algorithms are used in them. Since this was outside

the purview of the report, no more investigation was conducted on these goods. When it comes to protecting against spammers, where their tactics are always changing, an intelligent solution built on machine learning is recognised to be beneficial. Potentially, spam can cause missed productivity, hiccups in communications, virus assaults, and data theft, which can result in financial loss. With Proof point's MLX technology, you can protect yourself from the threat of spam with comprehensive spam detection using cutting-edge machine learning algorithms. The technology can evaluate millions of messages, and it automatically improves the detection algorithm to recognise and detect emerging risks.

Weng et al. (2017) state that the tracking of pertinent data and predictor variable information, along with the selection of AI algorithms that work well for analysis and prediction, are the two main components of stock market prediction. In light of this objective and the identified research need, the current work will offer a thorough analysis of the machine learning models utilised in predicting. The study discusses other sub-techniques that are employed in conjunction with machine learning to enhance the predictive capacity of the main methods and their variations. The study also includes an analysis of the stock markets concerned, with a focus on the particular variables and types of variables employed in the forecast.

2.3.4 Robotic Process Automation on business management metrics

Rathnayake & Gunawardana (2023) study examines the various ways that generative AI might improve HRM procedures and provides creative fixes for successful and efficient human resource management. Generative AI is revolutionising the recruiting process by providing algorithm-based automated applicant screening, which sorts through submissions and portfolios. According to the findings, the technology helps create objective performance indicators by minimising subjectivity and bias by utilising a variety of data sources. One aspect of AI is

predictive performance analysis, which projects future patterns in employee performance and identifies areas for improvement.

Generative AI adoption in HRM requires a balanced strategy that upholds ethical principles, guarantees openness, and conforms to data protection regulations. In order to reduce any potential biases or mistakes in AI systems, human monitoring is still essential. In conclusion, generative AI is a potent instrument for rethinking HRM procedures, providing scalable, data-driven solutions that are customised to meet the changing demands of the contemporary workforce. The study demonstrates how artificial intelligence (AI) may enhance HRM procedures' efficacy, efficiency, and equity. There are, however, a number of apparent shortcomings and limitations in the study. Because of its reliance on secondary data sources, the study might not offer a thorough picture of how generative AI affects HRM practices. More in-depth information than what the current study would offer could be obtained via primary data collection methods like surveys, interviews, or experiments.

Jain et al. (2019) in their study noted that robots with machine learning (ML) integrated into them are probably going to be significant contributors to customers' lives, serving as pet substitutes, companions, suppliers, or grandkids. Apart from the issues associated with UV that have already been documented, certain studies indicate that interacting with robots that are integrated with artificial intelligence can lead to discomfort and compensatory actions. As per Jain et al. (2019), it is crucial to ascertain whether customers' negative opinions of the robots included in machine learning can be rectified with time. Customer willingness to buy, which measures a customer's propensity to make additional purchases after using a product or service, is a rather accurate psychological predictor of the customer's real propensity for repeat purchases. There is a positive association between the four, according to the ultimate control results, though this connection's

hierarchical structure is distinct.

Hallikainen et al., (2018) in their study noted that despite being a strong instrument, robotic process automation (RPA) can only be used for simple tasks or processes involving digitalized organised information input that are highly rule-based, organised, mature, standardised, repeatable, and extensively reported. In order to address the processes for making decisions including neural networks and integrated intelligence, industries are currently looking for more inventive and clever RPA. Further, according to Zheng et al. (2019), the increasing intelligence of these systems indicates a rise in technological capacity for high-level process digitization and value generation for stakeholders. Although RPA is an established enterprise workflow automation technologies that has gained popularity in the last 10 years, further research and adaption in increasingly complicated and changing commercial settings are still necessary to fully realise its potential.

According to Ng et al. (2017), there has been a significant rise in computational capability, which has led to recent advances in AI. For example, the latest advances in machine learning (ML) technique can speed up the analysis of large-sized datasets in a complicated model. As context-aware computing and real-time data acquisition from internet sources advance, vast amounts of data can be produced for AI training (Lee et al., 2019). Strong graphics processing units improve compatibility while managing intricate reinforcement learning and deep learning algorithms. Together, these elements provide integrated systems that aid in the advancement of AI and embedded intelligence in various engineering applications. RPA may use AI to make cognitive decisions, which can then be used to more engineering applications. In various technical and business applications, the combination of RPA and AI, particularly intelligent automation (IA), could further improve technological skills, readiness for innovation, and operational automation capability.

According to study by Perez et al. (2019), the cognitive decision-making ability of artificial intelligence (IA) can surmount the obstacles associated with the implementation of robotic process automation (RPA) in various domains. These include but are not limited to unstructured data handling, natural language processing, decision analytics, real-time decision-making as well as content-aware computing. Additionally, IA can oversee the execution of rules-based RPA. The integration of artificial intelligence (AI) into process automation offers significant advantages in terms of ROI, productivity, and brand equity.

Sobczak (2019) defined RPA, identified important components of RPA management, and developed a model for managing RPA. To address these three research questions, Sobczak conducted a literature analysis based on SCOPUS and Web of Science. Syed et al. (2020) conducted a systematic literature review (SLR) by examining 125 scientific journals and white papers related to RPA. Six research issues were addressed by the study: what is RPA, why should organisations embrace it, how is preparation for RPA described in the literature, what is RPA's potential, what is the RPA methodology, and which RPA technologies are available now and in the future.

Hindel et al. (2020) conducted a literature review at EBSCO related to the method of examining references discovered in particular source publications. A total of 27 publications were chosen after filters were applied based on conference and publication category. They added a survey and real-world RPA deployment examples to their study in addition to the literature review. The purpose of the study was to bring RPA to reality and validate the theoretical benefits and limitations of RPA based on real-world experience.

Ng et al. (2021) conduct a systematic literature review by examining 63 papers. They addressed five IPA (Intelligent Process Automation) research issues by reading these articles. But it also

makes reference to RPA technology. Wewerka and Reichert (2021) conducted a Systematic Mapping Study in the field of RPA, providing answers to five research questions derived from the examination of 63 publications. What is Robotic Process Automation (RPA) and how is it different from other annexe technologies? What are the jobs that can be automated with RPA and what tools are available? What are the effects of RPA? How can the implementation of RPA be improved? Is AI utilised in conjunction with RPA?

2.4 Research Gaps in Literature

Relatively little research has been done in the literature on the impact of artificial intelligence (AI) on business management metrics in the telecommunications industry in developing countries—Kenya, in particular. There are still information gaps that can be investigated despite the fact that there has been some research on the subject. The research carried out by Chandra (2020) and Elhajjar et al. (2020) offers significant perspectives on the influence of artificial intelligence (AI) on digital marketing within various settings. While Elhajjar et al. (2020) used an interview-based technique, the current study will use a mixed-method approach, which will provide for more information on the sample size, selection criteria, and data analysis procedure.

Chandra (2020) also employed a thorough literature review. Nevertheless, if the author had employed case study analysis and included additional details about the particular cases they looked at and the selection criteria, it may be more enlightening. A method like this might improve the studies' reproducibility and transparency. In the research by Hassan et al. (2023), a possible knowledge gap could be the scant examination of the real-world obstacles and practical application of AI adoption in the banking sector. Although the study offers insights into the possible advantages and methods of AI-driven risk management, fraud prevention, and regulatory compliance, it did not fully address the particular challenges, tactics for implementation, and

environmental aspects that banks might encounter when incorporating AI into their daily operations. To gain a deeper knowledge of the topic, the current research will concentrate on examining the organisational modifications, practical issues, and implementation difficulties that come up when implementing AI technologies in the banking industry.

Studies by Rathnayake and Gunawardana (2023), Brynjolfsson and McAfee (2017) offer broad insights into the incorporation of AI in company management practices. They do not, however, particularly touch the telecom sector. Therefore, it is still unclear how much AI integration has impacted business management practices in the telecom industry. The adoption and consequences of AI in the telecommunications industry can be greatly influenced by various distinct socio-economic, cultural, and technological circumstances that developing countries frequently possess. These contextual elements, which include inadequate infrastructure, low internet penetration rates, and particular regulatory frameworks, may not be sufficiently captured by the literature now in publication. To fully comprehend how these contextual elements affect the application and results of AI in the telecommunications industry, more research is required.

In order to close this gap, data collection from certain telecoms businesses will be taken into consideration in the ongoing research on the influence of AI integration on business management metrics in the telecommunications industry. In this instance, Safaricom, Kenya, aims to comprehend the unique obstacles, prospects, and effects of artificial intelligence integration on business management strategies in this industry inside the framework of developing nations. The paucity of empirical study on developing countries in the context of the telecommunications industry is a wide knowledge gap. The majority of the literature that has already been written about AI in business management measures tends to have a global viewpoint (Helo & Hao, 2022; Walter, 2023; Wang, et al., 2023) or concentrate on established countries, frequently ignoring the particular

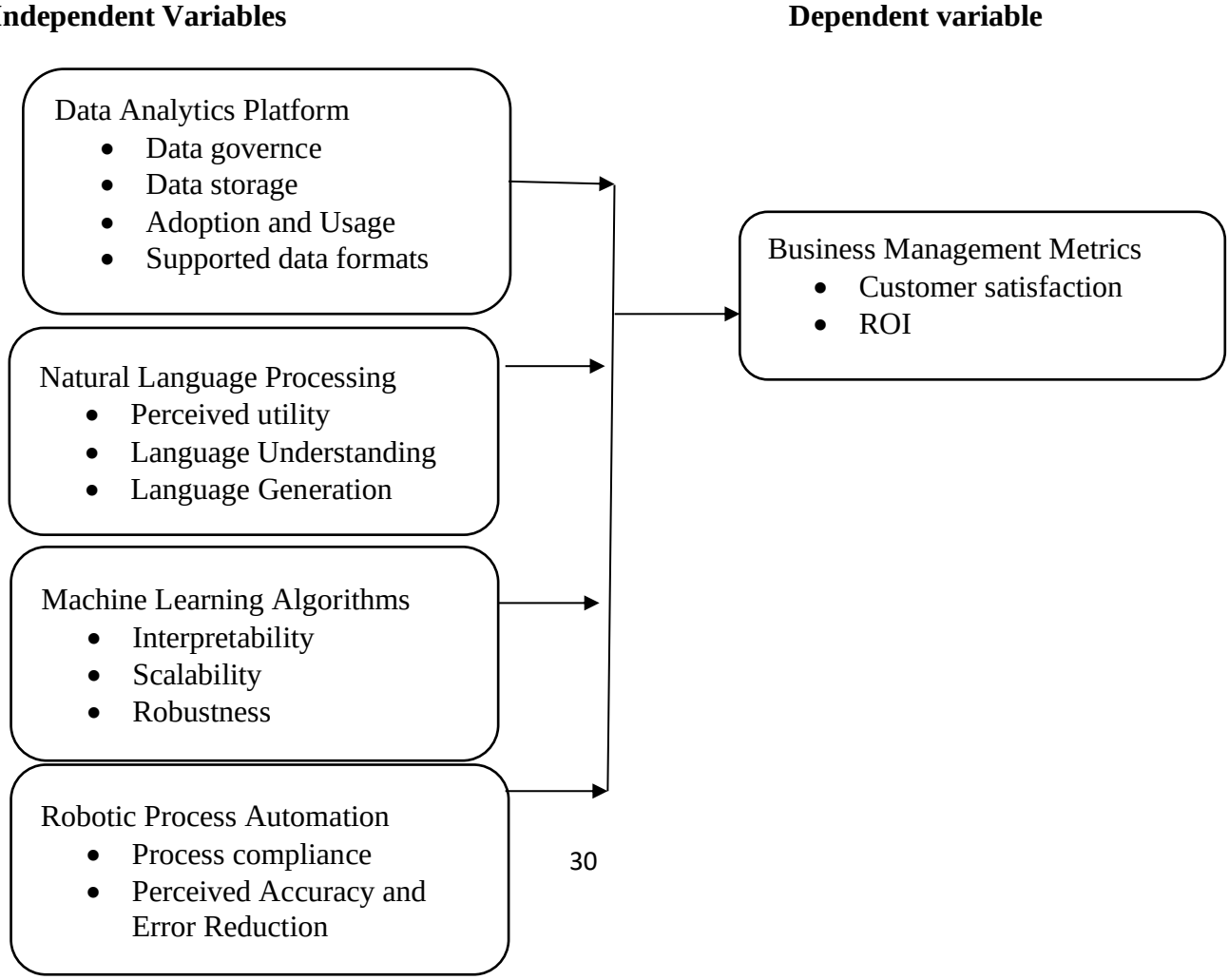
opportunities and challenges that emerging countries face. Furthermore, there might not be enough in-depth case studies or empirical research in the literature to examine the results and real-world use of AI technology in developing countries' telecommunications industries. More qualitative research and field studies might be required to shed light on the difficulties, triumphs, and real-world experiences that telecom firms encounter in these situations.

2.5 Conceptual Framework

The conceptual framework (Figure 2.1) shows a graphical presentation on the relationship between variables of the study. In this case, the dependent variable (Business metrics) and the independent variables (Artificial Intelligence) were used.

FIGURE 2.1

Conceptual Framework (Author, 2024)



2.5 Operationalization of variables

The process of operationalizing variables entails turning imprecise notions or structures into quantifiable, visible indicators or variables (Stoner et al., 2023). Variable operationalization is critical to ensure data collection and analysis clarity, consistency, and dependability.

TABLE 2.1

Operationalization of Variables

Construct	Variable type	Indicators	Measurable scale	Metrics
Data Analytics Platform	Independent variable	-Automation level -Adoption and Usage	Ordinal scale	-Percentage of automated processes -Time saved due to automation data sources integrated -The processing speed -The accuracy of predictions
Natural Language Processing	Independent variable	-Perceived utility -Language Understanding -Language Generation	Ordinal scale	-BLEU score -ROUGE score -Human evaluations
Machine Learning	Independent variable	Interpretability Scalability	Ordinal scale	-Precision and Recall

Algorithms		Robustness Model Complexity		- Mean Absolute Error (MAE) - Mean Average Precision (MAP)
Robotic Process Automation	Independent variable	-Process compliance Perceived -Accuracy and Error Reduction -Perceived ease of use	Ordinal scale	-Error rate -Cost reduction -Time savings
Business Management Metrics	Dependent variable	-Customer satisfaction -ROI	Ordinal scale	-Cycle time and Efficiency

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

The research techniques used for the study's data collecting and analysis are described in this chapter. The research design, target population, sample design, data collection process, and data collection instruments, as well as data analysis and ethical considerations, are all specifically covered.

3.2 Research Philosophy

This study adopted an epistemological research philosophy guided by the post-positivist paradigm (Tamminen & Poucher, 2020). As to Saunders et al. (2016), epistemology is the theory that explains how knowledge is acquired and expanded into a collection of realities, how something may be known, and what conditions need to be fulfilled before something can be called knowledge. The present study employed the positivist framework, incorporating an aspect of epistemology, as it facilitates the disclosure of observations as well as the explanation of newly acquired information gleaned from the research (Saunders et al., 2016). The purpose of this study is to ascertain the idea regarding corporate governance metrics by fact-finding, fact- measuring, and data-gathering on the impact of artificial intelligence integration at Airtel and Safaricom Kenya, from which performance inferences are made.

3.3 Research Design

This study used a descriptive research design, which offers an overview for addressing the research objectives. According to Venkatesh et al. (2016), research design is the process that an investigator uses to gather data and that helps the researcher to effectively respond to inquiries. The research

design applicable in this study will help improve the ability of the research in conceptualizing the operational plan and variables. The study employed descriptive research methodology, which entails methodically outlining a population, circumstance, or phenomena. This research methodology seeks to address the questions of what, where, when, and how rather than why (Kinyua, 2023).

3.4 Population and Sampling

The study focused on Safaricom and Airtel company headquarters in Nairobi City County. The management staff made up the study's target population. The employees the company served as the unit of analysis. On the other hand, the unit of observation were the two companies departments. The several departments of Safaricom and Airtel telecommunication corporations, collaborate to guarantee the seamless running of the organisations. The employees who work in the corporate headquarters under the various departments were the respondents. In this instance, the population size was made up of 427 professionals, which included heads of departments, senior and mid-level managers, supervisors and subordinate staff from the various departments.

3.5 Sampling Procedure

The process of choosing a representative sample from the target population is called sampling (Saunders et al., 2016). The studyused stratified random sampling techniques to select the sample size. To create an acceptable sample for the aim of gathering empirical data, proportionate stratified random sampling and basic random sampling were sequentially carried out. Stratification guarantees that all significant subgroups of the population are included in the sample, even if they are minor in size. This is crucial when the study question is targeted at certain subgroups or when there are notable differences in the prevalence of the desired result between subgroups. Using stratification, it is possible to investigate the study topic within each subgroup

and gain understanding of how the outcome or exposure of interest differs amongst various population segments. As a result, it makes the sample more representative, raises the accuracy of the estimates, and permits subgroup analysis, all of which contribute to the production of more reliable and insightful research findings.

3.5.1 Sample size determination

Using the Yamane formula, which presumes a normal distribution, a 95% level of confidence, and a precision level of 0.05, the suitable sample size was determined (Yamane, 1967as cited in Adam, 2021).

n = N/1+N*e2

n = 427/1+ 427(0.05)2 = 427/2.0675 = 206

The stratified random sampling formulae was applicable to determine the population size from each category that will be included in this study.

TABLE 3.1

Sample size

Category	Total population	Sample size calculation	Sample size
Customer service	105	(207/427) * 105	51
Finance and Accounting	55	(207/427) * 55	27
Marketing and sales	125	(207/427) * 125	60
Human resources	42	(207/427) * 42	20
Technology and	45	(207/427) * 45	22

Innovation			
Legal and compliance	15	(207/427) * 15	7
Corporate affairs	23	(207/427) * 23	11
Operations	17	(207/427) * 17	8
Total	427		206

(Safaricom & Airtel, 2024)

3.6 Data Collection Methods

The instrument for gathering data for the study was a questionnaire. The study's objectives are all reflected in the instrument's queries (Saunders et al., 2016). Each statement was rated by the responders on a 5-point Likert scale to respond to inquiries about how Airtel and Safaricom Kenya's corporate governance measures are affected by the integration of artificial intelligence.

3.7 Developing Data collection Instrument

The development of the equipment needed for the measurement of variables during the data gathering process is a crucial stage. This is since the procedure makes the required adjustments to fit the study and prevent biased outcomes. In the development of the questionnaire as a quantitative instrument, a number of steps were followed.

First, the conceptualization of the objectives of the study was done to capture the key components of the study. Then a clear definition of the variables as well as the constructs measured in this study. Afterwards, a multi-item questionnaire containing a five-point item scales will be developed. This allowed for the collection of a complete and accurate data in a logical manner. The procedure of using both open-ended and closed ended questions enables the researcher to obtain reliable conclusions from the various observations in the field. Secondly, there was a clear definition of the target population from where the data was collected and the channels applicable

in reaching the respondents. In this case, personal contact was preferred. Thirdly, the researcher settled on the content of the questionnaire whereby open-ended and closed-ended questions taking the form of a Likert scale was applicable. In this case, each question focuses on answering the research questions as established in the research design.

3.8 Data Collection procedure

Self-administered questionnaires were used to collect the quantitative data (Blumberg et al., 2014). The questionnaires were distributed to participants at their respective offices, where they will be completed and subsequently turned in for later collection by the researcher. Prior to answering the questions, participants are required to sign consent forms that are handed out by the researcher.

3.9 Instrumentation

3.9.1 Pilot test

The pilot test is a crucial step in the research process, allowing researchers to evaluate the feasibility, time, cost, risk, and adverse events involved in a study. It serves as a preliminary trial run of the research methodology, ensuring that the instruments and procedures are effective before the full-scale study is conducted. In this context, the pilot test for this study was designed to assess the reliability and validity of the survey instruments used to measure the influence of AI technologies—specifically Data Analytics Platforms, Natural Language Processing, Machine Learning Algorithms, and Robotic Process Automation—on business management metrics in the telecommunications sector in Kenya. The pilot test involved a small sample of participants representative of the target population. The feedback gathered from this group was instrumental in refining the survey questions, ensuring clarity, and eliminating any ambiguities. This process is supported by the Technology Acceptance Model (TAM), which emphasizes the importance of

perceived usefulness and ease of use in technology adoption (Davis, 1989). By ensuring that the survey instruments are user-friendly and clearly convey the intended questions, researchers can enhance the likelihood of obtaining accurate and meaningful responses.

Moreover, the pilot test also aimed to identify potential issues related to data collection procedures. For instance, it allowed researchers to gauge the time required for participants to complete the survey and to assess the effectiveness of the data collection platform. Any logistical challenges encountered during the pilot phase were addressed to streamline the process for the main study. This aligns with the Dynamic Capabilities Theory, which posits that organizations must be adaptable and responsive to changing conditions (Teece et al., 1997). By being proactive in identifying and resolving issues during the pilot test, researchers can enhance the robustness of the study design and ensure a smoother execution during the full-scale research.

The results from the pilot test indicated a high level of reliability for the survey instruments, with Cronbach's alpha values exceeding the acceptable threshold of 0.70, suggesting that the items used to measure each variable were consistently capturing the intended constructs. This is consistent with the findings of Chatterjee et al. (2024), who emphasized the importance of reliable measurement tools in assessing the impact of business analytics capabilities on organizational performance. The pilot test also provided insights into the participants' perceptions of the relevance and clarity of the questions, which helped refine the survey to better align with the research objectives.

3.9.2 Reliability of Instrument

The consistency with which a procedure analyses something under the same conditions is referred to as its reliability. Maintaining this consistency is essential to guaranteeing a precise and consistent result. Internal reliability is crucial when it comes to surveys since it indicates how

effectively the scale's questions relate to one another and to the underlying concept that the scale is meant to assess. The reliability coefficient Cronbach's alpha, represented by α, was employed to evaluate the internal consistency of the questions or items on the questionnaire. Pilot test results were used in this case to test for the reliability.

It was then computed using the overall score variance as well as the variance of the individual items. Greater internal consistency and reliability were indicated by a larger value of α, which had a range of 0 to 1. Cronbach's alpha is a tool used in the construction and validation of questionnaires to assess the internal consistency of the items. When the α score is high, it means that the queries measure the same construct consistently, which is crucial for maintaining the reliability and accuracy of the tool. In this case, all scores were above 0.7 showing that the instrument was reliable.

3.9.3 Validity of Instrument

Validity refers to the extent to which the outcomes of a measure accurately represent the variable for which it was designed. Within the framework of the research, construct and content validity are pertinent and essential for guaranteeing the precision and dependability of your findings. Construct validity, which evaluates how well the test or measure you are using truly represents the theoretical construct or notion you are seeking to measure, is particularly significant in this study. This entails determining if the test items are assessing what they purport to measure and whether there is a meaningful relationship between the test results and the underlying construct. To make sure the test is not measuring anything else unintentionally or unrelated to the concept you are seeking to measure, construct validity is crucial. The validity of the instrument was also ensured with the help of supervision from the supervisors (Blumberg et al., 2014).

3.10 Data Analysis

The quantitative data was analysed using regression, and the results were displayed in tables and charts. Additionally, inferential statistics will be used to analyse the data (Blumberg et al., 2014). In this work, the association that exists between the ordinal outcome parameter and the independent variables will be modelled using the ordinal regression approach. An ordered categorical Likert scale with five points was used to assess the outcome variable. Assuming homogeneity and normality of variance for an ordered categorical outcome is irrational. The ordinal regression approach is used by researchers to quantify the influence of both the independent and the outcome/dependent variable.

The ability of the independent factors to forecast business management metrics was investigated using multiple regression analysis. Simple linear regression is capable of handling one independent variable (X) and one dependent variable (Y), which happens to be a linear function of X. The following formula provides the value of variable Y, yi, for any value xi of variable X:

$$Yi = \alpha + \beta xi + ei \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (i)$$

Multiple linear regression, which is essentially an amalgamation of numerous simple linear regressions, is used when a number of independent variables ($X(X_1,X_2,X_3,...,X_n)$) is linearly dependent on the dependent variable (Y). The following will constitute the overall regression model:

$$Y = \beta o + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \varepsilon \ldots\ldots\ldots\ldots\ldots\ldots\ldots (ii)$$

Whereby:

Y = Business performance metrics X_{1-4} = AI components,

β_1, β_2 and β_3 = Regression Coefficients, β_0 = Constant and ε = Error term

3.11 Ethical Issues in Research

Information was encrypted to safeguard respondents' privacy and confidentiality by encrypting their personal information. In order for respondents to make an informed decision about their willingness to engage in the study, the researcher gave them enough precise information about it. Maintaining a rigorous level of secrecy is imperative for the researcher handling the information given by the respondents. The researcher obtained permission from relevant authorities (NACOSTI) and ethical approval from the institution’s department.

CHAPTER FOUR

RESULTS ANALYSIS AND INTERPRETATION

4.1 Introduction

The integration of Artificial Intelligence (AI) into business management practices has become a transformative force across various sectors, including telecommunications in Kenya. This chapter analyzes the influence of AI integration on business management metrics, focusing on operational efficiency, customer satisfaction, and financial performance.

4.2 Reliability of the Instruments

The questionnaire pilot test results were entered into the statistical programme for social sciences (SPSS), which then calculated the Cronbach's alpha coefficient (table 4.1), a reliability metric. The closer to '1' Cronbach's alpha coefficient is, the higher the internal consistency dependability (Sekaran, 2013). Kurpius and Stafford (2016) recommend that the Cronbach alpha reliability correlation coefficient for a newly built tool be around 0.70.

TABLE 4.1

Cronbach's Alpha Coefficient

Variable	Cronbach's Alpha	No. of Items
Data Analytics Platform	0.878	7
Natural Language Processing	0.758	8
Machine Learning Algorithm	0.859	7
Robotic Process Automation	0.850	10
Business Management Metrics	0.851	6

(Source: Researchers Survey Computations, 2024)

All the variables were above the minimum threshold of 0.7

4.2.1 Response rate

The study aimed to collect data from a sample size of 206 participants. Out of the total sample, 196 individuals responded to the survey, resulting in a response rate of 95.15%.

The response rate was calculated as follows:

Response Rate = (Number of Responses / Sample Size) × 100 Substituting the values:

Response Rate = (196 / 206) × 100

= 0.9515 × 100 = 95.15%

A response rate of 95.15% is considered excellent, as it indicates a high level of participation and engagement from the target population. This high response rate suggests that the survey questions were well-designed, relevant, and easily understood by the participants. Additionally, it implies that the researchers effectively communicated the importance and purpose of the study, encouraging respondents to provide their valuable insights.

4.3 Demographic Information

The demographic characteristics of the 196 respondents (Table 4.2) provide valuable insights into the composition of the sample and its implications for the study on the influence of artificial intelligence (AI) integration in the telecommunications sector in Kenya.

Gender Distribution reveals a slight male predominance, with 51.5% of respondents identifying as male and 48.5% as female. This near-equal representation is beneficial, as it allows for a comprehensive understanding of how gender may influence perceptions and attitudes toward AI technologies in business management. The balance suggests that both male and female perspectives are likely to be reflected in the findings, which can enhance the generalizability of

the results across the workforce.

Service Period data indicates that a significant majority of respondents (82.2%) have between 1 to 10 years of experience in the telecommunications sector, with 44.4% falling within the 6-10 year range. This relatively young workforce may be more adaptable to technological changes, including AI integration. However, the presence of 17.9% of respondents with over 11 years of experience adds a layer of depth, as these individuals can provide insights grounded in traditional practices and potentially highlight resistance to change or challenges in adopting new technologies.

TABLE 4.2

Demographic Characteristics of Respondents

Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Female	95	48.5	48.5	48.5
	Male	101	51.5	51.5	100.0
	Total	196	100.0	100.0	

Service Period

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1-5 years	74	37.8	37.8	37.8
	6-10 years	87	44.4	44.4	82.1
	Above 11 years	35	17.9	17.9	100.0
	Total	196	100.0	100.0	

Education level

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Degree	137	59.7	59.7	59.7
	Masters	45	23.0	23.0	82.7
	PhD	14	17.3	17.3	100.0
	Total	196	100.0	100.0	

Job Role

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Customer Service	29	14.8	14.8	14.8
	Sales/Marketing	85	43.4	43.4	58.2
	IT/Technical Staff	45	23.0	23.0	81.1
	Analyst/Researcher	16	8.2	8.2	89.3
	Manager/Supervisor	12	6.1	6.1	95.4
	Executive/Top Management	9	4.6	4.6	100.0
	Total	196	100.0	100.0	

(Source: Researchers Survey Computations, 2024)

The Education Level of the respondents is notably high, with 82.7% holding at least a degree. This educational background is advantageous for the study, as it suggests that respondents are likely to possess the analytical skills necessary to understand and engage with AI technologies effectively. The presence of individuals with advanced degrees (Masters and PhDs) indicates a workforce capable of critically evaluating the implications of AI on business management metrics.

In terms of Job Roles, the largest group of respondents is from Sales/Marketing (43.4%), followed by IT/Technical Staff (23.0%). This distribution is particularly relevant, as it combines customer-facing roles with technical expertise, essential for understanding the multifaceted impact of AI. The relatively low representation of managerial and executive roles (10.7%) raises a concern about the strategic insights that may be missing from the study. Engaging higher management could provide critical perspectives on decision-making regarding AI investments and implementation strategies. The demographic profile of respondents presents a well-rounded view of the workforce in the telecommunications sector in Kenya. The combination of gender balance, diverse service periods, high educational attainment, and varied job roles suggests a rich tapestry of perspectives that can inform the study's findings. However, the limited representation of leadership roles highlights a potential gap that may need to be addressed in future research to ensure a comprehensive understanding of AI's influence on business management metrics.

4.4 Study Variables

Objective 1: To examine the influence of Data Analytics Platform on business management metrics in Telecommunication sector in Kenya.

The descriptive statistics presented in Table 4.3 highlight the perceived influence of Data Analytics Platforms on various business management metrics within the telecommunications sector in Kenya. The responses from the 196 participants indicate a range of opinions on how these platforms impact operational efficiency, network performance, revenue management, business opportunities, and customer service personalization.

The mean scores for the statements range from 2.62 to 2.82 on a scale that likely reflects a Likert-

type format, suggesting a moderate level of agreement among respondents regarding the effectiveness of Data Analytics Platforms. The highest mean score of 2.82 pertains to the statement that "The Data Analytics Platform has improved the overall operational efficiency in our telecommunication company." This indicates that respondents generally believe that these platforms play a significant role in enhancing operational processes, which is crucial for maintaining competitiveness in a rapidly evolving industry.

Conversely, the lowest mean score of 2.62 relates to the perception that "The Data Analytics Platform has improved our ability to identify and target new business opportunities." This suggests that while there is recognition of the platform's capabilities, there may be limitations in how effectively these tools are being utilized to uncover new market opportunities. This could point to a need for further training or strategic alignment to fully leverage the data analytics capabilities available. The standard deviations across the statements range from 1.349 to 1.586, indicating a moderate level of variability in responses. The relatively high standard deviations suggest that while some respondents strongly agree with the statements, others may have reservations or differing experiences regarding the effectiveness of Data Analytics Platforms. This variability highlights the importance of considering individual organizational contexts when interpreting these findings.

TABLE 4.3

Descriptive on the influence of Data Analytics Platform on business management metrics

	The Data Analytics Platform has improved the overall operational efficiency in our telecommunication company.	The Data Analytics Platform has helped us in identifying and resolving network performance issues more effectively.	The Data Analytics Platform has enhanced our ability to predict and prevent network outages.	The Data Analytics Platform has helped us in identifying and addressing revenue leakage.	The Data Analytics Platform has improved our ability to identify and target new business opportunities.	The Data Analytics Platform has increased our ability to personalize and tailor services for our customers.
N	196	196	196	196	196	196
Mean	2.82	2.65	2.68	2.69	2.62	2.68
Std. Deviation	1.349	1.520	1.560	1.533	1.556	1.586
Variance	1.819	2.311	2.435	2.349	2.422	2.517

(Source: Researchers Survey Computations, 2024)

The data suggests that while Data Analytics Platforms are viewed positively in terms of operational efficiency and network performance, there remains room for improvement in areas such as revenue leakage management and the identification of new business opportunities. This analysis underscores the necessity for telecommunications companies in Kenya to not only adopt these

platforms but also to invest in training and strategic initiatives that enhance their effectiveness in driving business management metrics.

Objective 2: To assess the influence of Natural Language Processing on business management metrics in Telecommunication sector in Kenya.

The descriptive statistics presented in Table 4.4 reveal the perceived influence of Natural Language Processing (NLP) on various business management metrics within the telecommunications sector in Kenya. The responses from the 196 participants indicate varying levels of agreement regarding the effectiveness of NLP in improving customer support, extracting insights from customer feedback, enhancing chatbots, analyzing customer sentiment, understanding preferences, automating processes, and improving data analysis.

The highest mean score of 3.41 is associated with the statement "Natural Language Processing has improved the accuracy and efficiency of our customer support interactions." This suggests that respondents generally believe NLP has had a significant positive impact on customer support, which is crucial for maintaining a competitive edge in the industry. The relatively low standard deviation of 1.071 indicates a high level of agreement among respondents on this point.

In contrast, the lowest mean scores are observed for the statements "Natural Language Processing has improved the accuracy and efficiency of our data analysis and reporting" (mea = 1.43) and "Natural Language Processing has increased our ability to extract meaningful information from unstructured data sources, such as social media and customer emails" (mean = 1.65). These findings suggest that while NLP is perceived as effective in customer support, its impact on data analysis and extracting insights from unstructured data sources may be limited. The low means and standard deviations (0.810 and 0.842, respectively) indicate a high level of agreement among

respondents on these points.

TABLE 4.4

Descriptive on the influence of Natural Language Processing on business management metrics

	Natural Language Processing has improved the accuracy and efficiency of our customer support interactions.	Natural Language Processing has enhanced our ability to analyze and extract insights from customer feedback and reviews.	Natural Language Processing has improved the effectiveness of our chatbots or virtual assistants in addressing customer queries and concerns.	Natural Language Processing has helped us in identifying and addressing customer sentiment and emotions more effectively.	Natural Language Processing has improved our ability to analyze and understand customer preferences and behaviors.	Natural Language Processing has enhanced our ability to automate and streamline manual processes within our organization.	Natural Language Processing has improved the accuracy and efficiency of our data analysis and reporting.	Natural Language Processing has increased our ability to extract meaningful information from unstructured data sources, such as social media and customer emails.

Mean	3.41	2.66	2.90	2.47	2.63	2.28	1.43	1.65
Std. Dv	1.071	1.539	1.552	1.622	1.715	1.688	.810	.842
Variance	1.146	2.370	2.410	2.630	2.943	2.849	.656	.710

(Source: Researchers Survey Computations, 2024)

The remaining statements show moderate mean scores ranging from 2.28 to 2.90, suggesting a mixed perception of NLP's influence on enhancing chatbots, analyzing customer sentiment, understanding preferences, and automating processes. The relatively high standard deviations (1.539 to 1.715) indicate a greater variability in responses, suggesting that individual organizational contexts and experiences may play a role in shaping perceptions of NLP's effectiveness in these areas. Overall, the data suggests that while NLP is viewed positively in terms of improving customer support, there is room for improvement in leveraging its capabilities for data analysis, extracting insights from unstructured data sources, and automating processes. This analysis underscores the need for telecommunications companies in Kenya to invest in NLP technologies and ensure they are effectively integrated into their business processes to drive desired outcomes across various management metrics

Objective 3: To examine the influence of Machine Learning Algorithms on business management metrics in Telecommunication sector in Kenya

The descriptive statistics in Table 4.5 provide insights into the perceived influence of Machine Learning (ML) algorithms on various business management metrics within the telecommunications sector in Kenya. The responses from the 196 participants indicate a generally low level of agreement regarding the effectiveness of ML algorithms in enhancing operational

capabilities across several critical areas.

The mean scores for the statements range from 1.54 to 1.79, with the highest mean of 1.79 associated with the statement "Machine Learning algorithms have enhanced our ability to identify and prevent network anomalies and outages." Despite being the highest score, this value indicates a weak perception of effectiveness, suggesting that while there is some acknowledgment of ML's role in network anomaly detection, the overall sentiment is not strongly positive. The standard deviation of 1.058 indicates a moderate level of variability in responses, suggesting that while some respondents may see value in ML for this purpose, others may not share the same view.

TABLE 4.5

Descriptive on the influence of Machine Learning Algorithms on business management metrics

Statistics

	Machine Learning algorithms have enhanced our ability to identify and prevent network anomalies and outages.	Machine Learning algorithms have improved the efficiency and cost-effectiveness of our resource allocation and optimization.	Machine Learning algorithms have increased our ability to personalize and tailor services for our customers.	Machine Learning algorithms have improved the accuracy and effectiveness of our customer churn prediction.	Machine Learning algorithms have enhanced our ability to detect and mitigate fraudulent activities within our organization.	Machine Learning algorithms have improved the efficiency and effectiveness of our marketing and customer acquisition strategies.	Machine Learning algorithms have improved the accuracy and effectiveness of our credit scoring and risk assessment processes.
N	196	196	196	196	196	196	196
Mean	1.79	1.62	1.54	1.55	1.54	1.64	1.77
Std. Deviation	1.058	.865	.780	.786	.793	.921	1.060
Variance	1.120	.749	.609	.618	.629	.848	1.124

(Source: Researchers Survey Computations, 2024)

Conversely, the lowest mean scores are found in the areas of "Machine Learning algorithms have improved the efficiency and cost-effectiveness of our resource allocation and optimization" (mean

= 1.62) and "Machine Learning algorithms have increased our ability to personalize and tailor services for our customers" (mean = 1.54). These low scores reflect a significant skepticism regarding the impact of ML on resource optimization and customer personalization, which are critical metrics for business management in the telecommunications industry. The standard deviations for these statements (0.865 and 0.780, respectively) suggest a relatively high level of consensus among respondents, indicating widespread agreement that ML has not significantly influenced these areas.

The overall low mean scores across all statements, particularly those related to customer-related metrics such as churn prediction and fraud detection (both at 1.54), highlight a concerning perception of ML's effectiveness in enhancing critical business functions. The variances, ranging from 0.609 to 1.120, further emphasize the limited impact that respondents believe ML algorithms have on their operations. In this case, the data suggests that while there is some recognition of the potential benefits of Machine Learning algorithms in identifying network anomalies, the overall influence on business management metrics in the telecommunications sector in Kenya is perceived as minimal. This indicates a potential gap in the implementation or effectiveness of ML technologies within organizations, suggesting that further investment in training, infrastructure, and strategic alignment may be necessary to fully realize the benefits of Machine Learning in enhancing operational efficiency and customer engagement.

Objective 4: To examine the influence of Robotic Process Automation on business management metrics in Telecommunication sector in Kenya

The descriptive statistics presented in Table 4.5 provide insights into the perceived influence of Robotic Process Automation (RPA) on various business management metrics within the telecommunications sector in Kenya. The responses from the 196 participants indicate varying

levels of agreement regarding the effectiveness of RPA in improving operational efficiency, customer service, and process standardization.

TABLE 4.6

Descriptive on the influence of Robotic Process Automation on business management metrics

Robotic Process Automation has improved the accuracy and efficiency of our billing and invoicing processes.	Robotic Process Automation has enhanced our ability to automate repetitive and mundane tasks within our organization.	Robotic Process Automation has improved the speed and timeliness of our customer order processing.	Robotic Process Automation has increased our ability to handle a higher volume of customer inquiries and requests.	Robotic Process Automation has enhanced our ability to streamline and standardize our business processes.	Robotic Process Automation has improved the speed and timeliness of our customer order processing.	Robotic Process Automation has increased our ability to respond to customer queries and concerns in a timely manner.	Robotic Process Automation has increased our ability to handle a higher volume of customer inquiries and requests.	Robotic Process Automation has improved the accuracy and efficiency of our inventory management and supply chain processes.	Robotic Process Automation has improved the overall operational efficiency and cost-effectiveness of our organization.

N	196	196	196	196	196	196	196	196	196	196
Mean	1.89	2.09	2.07	1.75	1.93	2.11	1.85	1.86	2.19	1.95
StdDv	1.206	1.378	1.383	.957	1.098	1.405	1.083	1.038	1.265	1.237
Variance	1.454	1.899	1.913	.917	1.205	1.973	1.173	1.077	1.600	1.531

(Source: Researchers Survey Computations, 2024)

The highest mean score of 2.19 is associated with the statement "Robotic Process Automation has improved the accuracy and efficiency of our inventory management and supply chain processes." This suggests that respondents generally believe RPA has had a positive impact on inventory and supply chain management, which is crucial for maintaining operational efficiency and cost-effectiveness. The standard deviation of 1.265 indicates a moderate level of variability in responses, implying that while some respondents strongly agree with this statement, others may have reservations or differing experiences. In contrast, the lowest mean score of 1.75 is found for the statement "Robotic Process Automation has increased our ability to handle a higher volume of customer inquiries and requests." This finding suggests that respondents perceive RPA as having a limited impact on improving customer service efficiency, particularly in terms of handling a higher volume of inquiries. The relatively low standard deviation of 0.957 indicates a high level of consensus among respondents on this point.

The remaining statements show mean scores ranging from 1.85 to 2.11, suggesting a mixed perception of RPA's influence on improving billing accuracy, automating repetitive tasks, streamlining processes, and responding to customer queries. The standard deviations (1.038 to 1.405) indicate a moderate level of variability in responses, suggesting that individual organizational contexts and experiences may play a role in shaping perceptions of RPA's

effectiveness in these areas.

It is worth noting that the overall mean scores are relatively low, with none exceeding 2.19 on a scale that likely reflects a Likert-type format. This suggests that while there is some recognition of RPA's potential benefits, the perceived influence on business management metrics is not strongly positive. The variances, ranging from 0.917 to 1.973, further emphasize the limited impact that respondents believe RPA has on their operations. In this case, the data suggests that while Robotic Process Automation is viewed as potentially beneficial for inventory management and supply chain processes, its influence on other critical business management metrics, such as customer service efficiency and overall operational effectiveness, is perceived as limited. This indicates a potential gap in the implementation or effectiveness of RPA technologies within organizations, suggesting that further investment in training, infrastructure, and strategic alignment may be necessary to fully realize the benefits of RPA in enhancing business performance.

4.4.1 Business Metrics (Dependent Variable)

The descriptive statistics in Table 4.6 provide an overview of business metrics performance within the telecommunications sector in Kenya, focusing on key performance indicators (KPIs) related to customer satisfaction, complaint resolution, network performance, customer retention strategies, service level agreements (SLAs), and the use of data analytics for decision-making. The responses from the 196 participants reveal varying levels of effectiveness in these areas.

The highest mean score of 3.42 is associated with the statement "Our organization effectively tracks and manages network performance metrics to ensure optimal service quality." This suggests that respondents generally believe their organizations are proficient in monitoring network performance, which is critical for maintaining service quality in a competitive telecommunications landscape. The standard deviation of 1.181 indicates a moderate level of

variability in responses, suggesting that while many respondents feel positively about network management, some may have differing experiences. Following closely, the statement "Our organization has a well-defined and efficient process for resolving customer complaints and issues" received a mean score of 3.40. This indicates that a significant number of respondents perceive their organizations as having effective complaint resolution processes, which is essential for enhancing customer satisfaction and loyalty. The lower standard deviation of 0.874 suggests a higher consensus among respondents regarding the effectiveness of these processes.

TABLE 4.7

Descriptive on Business Metrics Performance

		Our organization effectively monitors and manages key performance indicators (KPIs) related to customer satisfaction.	Our organization has a well-defined and efficient process for resolving customer complaints and issues.	Our organization effectively tracks and manages network performance metrics to ensure optimal service quality.	Our organization has implemented effective strategies to attract and retain customers in a competitive market.	Our organization consistently meets or exceeds service level agreements (SLAs) with customers.	Our organization utilizes data analytics and business intelligence tools to make informed and data-driven decisions.
N	Valid	196	196	196	196	196	196

Mean	3.12	3.40	3.42	1.49	1.63	1.41
Std. Deviation	1.287	.874	1.181	.748	.835	.622
Variance	1.657	.764	1.394	.559	.696	.387

(Source: Researchers Survey Computations, 2024)

In contrast, the mean scores for statements related to customer attraction and retention strategies, as well as the use of data analytics, are notably lower. The statement "Our organization has implemented effective strategies to attract and retain customers in a competitive market" received a mean score of 1.49, indicating a general perception that organizations are struggling to effectively implement such strategies. Similarly, the statement "Our organization utilizes data analytics and business intelligence tools to make informed and data-driven decisions" scored even lower at 1.41. These low scores, coupled with the standard deviations of 0.622 and 0.748, reflect a significant level of skepticism among respondents regarding their organizations' capabilities in these critical areas. In this case, the data suggests that while telecommunications organizations in Kenya are perceived to perform well in tracking network performance and resolving customer complaints, they face considerable challenges in attracting and retaining customers and leveraging data analytics for decision-making. This highlights the need for organizations to enhance their strategies in customer engagement and data utilization to improve overall business performance and competitiveness in the rapidly evolving telecommunications market.

4.5 Diagnostic Test

4.5.1 Multicollinearity

Multicollinearity refers to the situation in which two or more independent variables in a regression model are highly correlated, potentially leading to unreliable and unstable estimates of the regression coefficients. To assess multicollinearity among the independent variables in this study,

we examine the Tolerance and Variance Inflation Factor (VIF) statistics, as presented in Table 4.8.

TABLE 4.8

Collinearity Statistics

Tolerance	VIF
.499	1.005
.496	1.017
.706	1.416
.686	1.457

(Source: Researchers Survey Computations, 2024)

To assess multicollinearity among the independent variables in this study, we examined the Tolerance and Variance Inflation Factor (VIF) statistics, as presented in Table 4.7. The Tolerance values for the variables ranged from 0.496 to 0.706, indicating that each variable retains a substantial amount of unique variance that is not explained by the other independent variables. Generally, a Tolerance value below 0.10 is considered indicative of problematic multicollinearity, and since all values in this analysis exceed 0.49, it suggests that multicollinearity is not a significant concern.

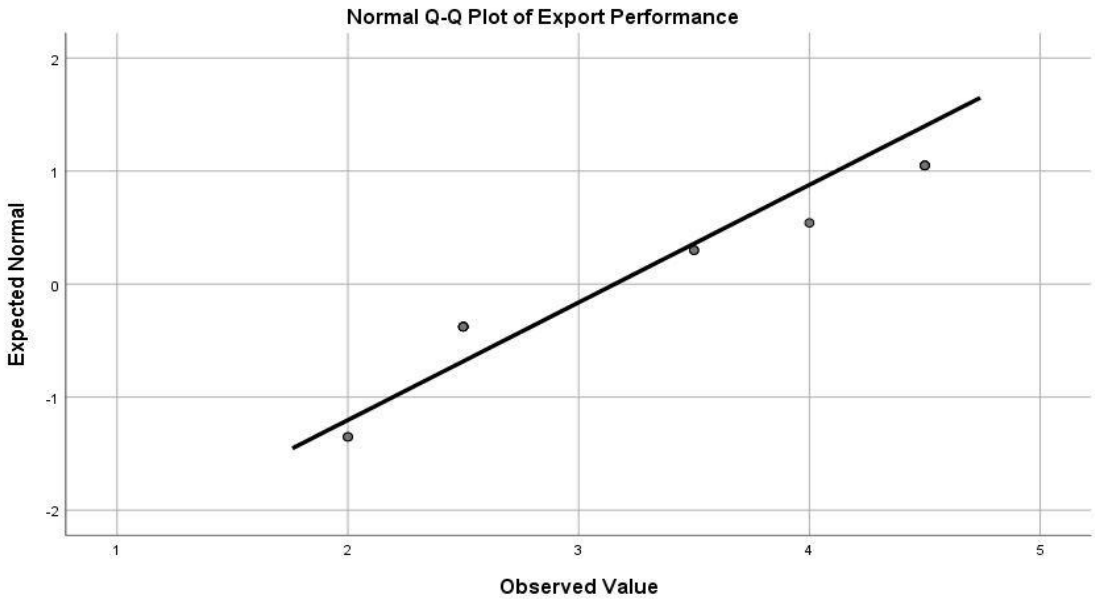
Additionally, the VIF values ranged from 1.005 to 1.457, which are well below the critical threshold of 10 typically used to indicate severe multicollinearity. This further reinforces the conclusion that the independent variables in this study do not exhibit problematic multicollinearity. Overall, the diagnostic tests for multicollinearity indicate that the relationships among the independent variables are stable and reliable, allowing for accurate interpretation of the regression results. Consequently, this enhances the validity of the study's findings regarding the influence of various factors on business management metrics in the telecommunications sector in Kenya.

4.5.2 Normality test

In the test, Q-Q graph representing the normality test clearly indicated a normal distribution since the individual data was considered to have fair distribution around the mean (Figure 4.1).

FIGURE 4.1

Normality Test Plot



4.5.3 Autocorrelation

The Durbin-Watson statistic (Table 4.10) is reported as 1.710, which is used to detect the presence of autocorrelation in the residuals from a regression analysis. Therefore, A value close to 2 suggests no autocorrelation.

4.6 Correlations

The correlation analysis presented in Table 4.9 examines the relationships between business management metrics (BMM) and various technological factors, including Data Analytics (DAn),

Natural Language Processing (NLP), Machine Learning Algorithms (MLA), and Robotic Process Automation (RPA). The Pearson correlation coefficients provide insights into the strength and direction of these relationships.

TABLE 4.9

Correlations

		BMM	DAn	NLP	MLA	RPA
BMM	Pearson Correlation	1				
	Sig. (2-tailed)					
	N	196				
DAn	Pearson Correlation	.423	1			
	Sig. (2-tailed)	.051				
	N	196	196			
NLP	Pearson Correlation	.012	.647**	1		
	Sig. (2-tailed)	.017	.000			
	N	196	196	196		
MLA	Pearson Correlation	.150	.128	.158*	1	
	Sig. (2-tailed)	.004	.073	.027		
	N	196	196	196	196	
RPA	Pearson Correlation	.118	.156*	.160*	.519**	1
	Sig. (2-tailed)	.022	.029	.025	.000	
	N	196	196	196	196	196

**. Correlation is significant at the 0.01 level (2-tailed).

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

(Source: Researchers Survey Computations, 2024)

The correlation between Business Management Metrics (BMM) and Data Analytics (DAn) is significant, with a Pearson correlation coefficient of 0.423 (p = 0.051). This indicates a moderate positive relationship, suggesting that as the effectiveness of data analytics improves, so too does the performance of business management metrics. This finding highlights the importance of data analytics in enhancing business operations within the telecommunications sector. Natural Language Processing (NLP) shows a weak positive correlation with BMM (Pearson c = 0.012), which is not statistically significant (p = 0.017). However, NLP has a strong positive correlation with Data Analytics (0.647, p = 0.000), indicating that organizations that effectively implement NLP also tend to have robust data analytics capabilities. This relationship suggests that NLP can play a crucial role in enhancing data analysis processes, potentially leading to better business management outcomes. Machine Learning Algorithms (MLA) exhibit weak positive correlations with BMM (0.150, p = 0.004) and NLP (0.158, p = 0.027), indicating that while there is some relationship between these variables, it is not particularly strong. The correlation between MLA and DAn is also weak (0.128, p = 0.073), suggesting that improvements in machine learning may not directly translate to enhanced data analytics performance.

Robotic Process Automation (RPA) demonstrates a moderate positive correlation with BMM (0.118, p = 0.022) and stronger correlations with NLP (0.160, p = 0.025) and MLA (0.519, p = 0.000). The strong correlation between RPA and MLA suggests that organizations utilizing RPA are likely to benefit from enhanced machine learning capabilities, which can lead to improved operational efficiency and effectiveness in business management metrics. In this case, the correlation analysis indicates that while there are positive relationships between business management metrics and various technological factors, the strength of these relationships varies.

Data Analytics emerges as a significant contributor to improving business management metrics, while NLP and RPA show potential for enhancing data analytics and machine learning capabilities, respectively. These findings underscore the importance of integrating these technologies to optimize business performance in the telecommunications sector in Kenya.

4.7 Regression Analysis

Regression analysis involves identifying the nature of the relationship between variables. The primary goal is to model the dependent variable (outcome) as a function of independent variables (predictors). The subsection presents the model summary, ANOVA and regression coefficients.

4.7.1 Modell Summary

The regression analysis presented in the Model Summary (Table 4.10) evaluates the relationship between various predictors—Robotic Process Automation (RPA), Data Analytics (DAn), Machine Learning Algorithms (MLA), and Natural Language Processing (NLP)—and the dependent variable, Business Management Metrics (BMM). The results provide insights into the model's explanatory power and the significance of the predictors.

TABLE 4.10

Model Summary

				Std. Error	Change Statistics					
Model	R	R Square	Adjusted R Square	of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.381a	.33	.313	.42843	.033	1.621	4	191	.011	1.710

a. Predictors: (Constant), RPA, DAn, MLA, NLP

b. Dependent Variable: BMM

(Source: Researchers Survey Computations, 2024)

The multiple correlation coefficient (R) is reported as 0.381, indicating a moderate positive correlation between the predictors and the dependent variable. The R Square value of 0.33 suggests that approximately 33% of the variance in Business Management Metrics can be explained by the combined effects of RPA, DAn, MLA, and NLP. This indicates that while the model captures a significant portion of the variance, there remains a substantial amount of unexplained variability in BMM, suggesting that other factors may also influence business management performance. The Adjusted R Square value of 0.313 accounts for the number of predictors in the model and provides a more accurate measure of the model's explanatory power. This value is slightly lower than the R Square value, which is expected when adjusting for the number of predictors. The standard error of the estimate is 0.42843, indicating the average distance that the observed values fall from the regression line, which reflects the model's predictive accuracy.

The Change Statistics indicate a statistically significant change in the model, with an F Change value of 1.621 and a significance level (Sig. F Change) of 0.011. This suggests that the model significantly improves the prediction of Business Management Metrics when including the predictors, indicating that at least one of the predictors contributes meaningfully to explaining the variance in BMM.

In this case, the regression analysis indicates that the model, comprising RPA, DAn, MLA, and NLP, explains a moderate portion of the variance in Business Management Metrics. The significant F Change suggests that these predictors collectively contribute to understanding the factors influencing business management performance in the telecommunications sector in Kenya.

4.7.2 ANOVA

The Analysis of Variance (ANOVA) presented in Table 4.11 assesses the overall significance of

the regression model that predicts Business Management Metrics (BMM) based on the independent variables: Robotic Process Automation (RPA), Data Analytics (DAn), Machine Learning Algorithms (MLA), and Natural Language Processing (NLP).

TABLE 4.11

Analysis of Variance

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.190	4	.297	1.621	.011[b]
	Residual	35.058	191	.184		
	Total	36.248	195			

a. Dependent Variable: BMM

b. Predictors: (Constant), RPA, DAn, MLA, NLP

(Source: Researchers Survey Computations, 2024)

The ANOVA table 4.11 shows that the Sum of Squares for the regression model is 1.190, which represents the variation explained by the predictors. The Residual Sum of Squares is 35.058, indicating the variation that is not explained by the model. The Total Sum of Squares is 36.248, which is the total variation in the dependent variable. The degrees of freedom (df) for the regression is 4, corresponding to the number of predictors in the model. The residual degree of freedom is 191, calculated as the total number of observations (196) minus the number of predictors (4) minus 1 for the intercept. The Mean Square for the regression is calculated as the Regression Sum of Squares divided by its degrees of freedom, resulting in a value of 0.297. The Mean Square for the residual is calculated as the Residual Sum of Squares divided by its degrees of freedom, yielding a value of 0.184.

The F statistic is calculated as the ratio of the Mean Square for the regression to the Mean Square

for the residual, which results in an F value of 1.621. This F value tests the null hypothesis that all regression coefficients are equal to zero (i.e., that the predictors do not explain any variance in the dependent variable). The significance level (Sig.) for the F statistic is reported as 0.011, which is less than the conventional alpha level of 0.05. This indicates that the regression model is statistically significant; suggesting that at least one of the predictors (RPA, DAn, MLA, or NLP) significantly contributes to explaining the variance in Business Management Metrics.

Therefore, the ANOVA results demonstrate that the regression model is statistically significant, providing evidence that the combined effects of Robotic Process Automation, Data Analytics, Machine Learning Algorithms, and Natural Language Processing have a meaningful impact on Business Management Metrics in the telecommunications sector in Kenya. This reinforces the findings from the regression analysis, indicating the importance of these technological factors in enhancing business performance.

4.7.3 Regression Coefficients

The regression coefficients presented in Table 4.12 provide insights into the individual contributions of each predictor variable—Data Analytics (DAn), Natural Language Processing (NLP), Machine Learning Algorithms (MLA), and Robotic Process Automation (RPA)—to the dependent variable, Business Management Metrics (BMM). The coefficients are essential for understanding how changes in each predictor are associated with changes in the outcome variable. The Unstandardized Coefficients indicate the expected change in BMM for a one-unit change in the predictor while holding all other predictors constant. The constant term (intercept) is 2.312, suggesting that when all predictors are zero, the expected value of BMM is 2.312.

The B coefficient for DAn is 0.423, indicating that a one-unit increase in Data Analytics effectiveness is associated with a 0.423 increase in BMM, holding other variables constant. The

significance level (Sig.) is 0.051, which is marginally significant and suggests that DAn has a meaningful impact on BMM. The B coefficient for NLP is 0.118, suggesting that improvements in NLP are associated with a 0.118 increase in BMM. The significance level is 0.017, indicating that NLP has a statistically significant positive effect on BMM. The B coefficient for MLA is 0.286, indicating that a one-unit increase in the effectiveness of machine learning algorithms is associated with a 0.286 increase in BMM. The significance level of 0.004 shows that MLA has a statistically significant and positive influence on BMM. The B coefficient for RPA is 0.114, indicating a positive relationship with BMM. The significance level is 0.022, suggesting that RPA also has a statistically significant impact on improving business management metrics.

TABLE 4.12

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	2.312	.124		18.588	.000		
	Dan	.423	.037	.061	.608	.051	.499	1.005
	NLP	.118	.047	.038	.377	.017	.496	1.017
	MLA	.286	.051	.144	1.704	.004	.706	1.416
	RPA	.114	.047	.209	2.430	.022	.686	1.457

a. Dependent Variable: BMM

(Source: Researchers Survey Computations, 2024)

The Standardized Coefficients (Beta) provide a way to compare the relative strength of the predictors in the model. The standardized coefficient for MLA (0.144) is the highest among the

predictors, indicating that it has the strongest relative impact on BMM, followed by RPA (0.209), DAn (0.061), and NLP (0.038). Therefore, the regression coefficients reveal that Data Analytics, Natural Language Processing, Machine Learning Algorithms, and Robotic Process Automation all positively influence Business Management Metrics in the telecommunications sector in Kenya. The statistical significance of these predictors underscores their importance in enhancing business performance. The analysis also confirms that multicollinearity is not a concern, allowing for reliable interpretation of the regression results. These findings highlight the critical role of technological advancements in driving improvements in business management metrics.

After applying a regression model to variables measured in their original scales, unstandardized coefficients were generated. Similarly, the application of a regression model to standardized variables generates standardized coefficients (i.e. rescaled variables that have a mean of 0 and a standard deviation of 1). The unstandardized coefficient was used in this case because it helps interpreting individual X's unique impact on Y, whereby a change of units in the result Y is correlated with a change of units in the independent variable X. In the case of standardized coefficients the impact of several predictors Xi are evaluated on the result Y, whereby, a change of 1 standard deviation in X is related to a change of β standard deviations in Y.

Further analysis of the resulting model's beta coefficients reveals that, with gradients of B=0.423 for Data analytics, NLP = 0.118, MLA = .286, and RPA = 0.114 all significantly improve the Business Management Metrics, showing a positive and statistically significant impact.

Based on these, the regression model:

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + e$$

Therefore becomes;

$$Y = 2.312 + 0.423\ X_1 + 0.118\ X_2 + 0.286\ X_3 + 0.114 X_4 + e$$

4.8 Discussion of Findings

Objective 1: Influence of Data Analytics Platforms on Business Management Metrics

The study's results indicate that Data Analytics Platforms have a moderate positive impact on business management metrics, with a mean score of 2.82 reflecting improvements in operational efficiency. This finding aligns with the empirical literature, particularly the work of Chatterjee et al. (2024), which emphasizes that acquiring business analytics capabilities enhances organizational performance and value. Their research highlights that effective data analytics can lead to improved decision-making processes and operational efficiencies, corroborating the positive perceptions reported by respondents in this study.

Chatterjee et al. (2024) quantitatively assessed how business analytics capabilities contribute to organizational performance by collecting data from participants in various sectors. The study found that acquiring these capabilities significantly enhances organizational efficiency, which in turn positively impacts overall business performance. This aligns with the findings of this study, which suggest that telecommunications organizations in Kenya can similarly benefit from enhanced data analytics capabilities to improve their business management metrics.

Additionally, the literature highlights the importance of integrating data analytics with other organizational processes. For instance, Khokhar and Chitsimran (2019) explored the components that facilitate the application of artificial intelligence in marketing, underscoring that data analytics is foundational for successful AI implementation. Their findings suggest that organizations that effectively utilize data analytics can enhance their marketing strategies, leading to improved customer engagement and satisfaction. This reinforces the idea that data analytics platforms are not just standalone tools but integral components of a broader strategy for organizational success.

Furthermore, the Dynamic Capabilities Theory, as discussed by Teece et al. (1997), provides a theoretical framework for understanding how organizations can leverage data analytics to adapt and respond to changing market conditions. The ability to sense and seize opportunities through data analytics allows organizations to make informed strategic decisions, thereby enhancing their competitive positioning. This theoretical perspective supports the notion that investing in data analytics platforms equips organizations with the necessary tools to navigate complex business environments effectively.

Moreover, the findings of this study resonate with the broader empirical literature on the transformative potential of data analytics across various industries. For example, studies have shown that organizations that embrace data-driven decision-making experience significant improvements in operational performance, customer satisfaction, and overall business outcomes (Kokina & Davenport, 2017). This body of research underscores the critical importance of data analytics in driving organizational success and aligns with the conclusions drawn from this study regarding the positive influence of data analytics platforms on business management metrics. The linkage between the study findings and the empirical literature highlights the essential role of Data Analytics Platforms in enhancing business management metrics. By investing in these capabilities, organizations can optimize their operations, improve decision-making, and ultimately gain a competitive advantage in the telecommunications sector and beyond. The integration of theoretical frameworks, such as the Dynamic Capabilities Theory and the insights from empirical studies, further reinforces the significance of data analytics in driving organizational performance and value creation.

Furthermore, the correlation analysis showing a significant positive relationship between Data Analytics and Business Management Metrics (0.423) reinforces the findings of Khokhar and

Chitsimran (2019), who explored the application of AI in marketing, suggesting that data-driven insights significantly enhance business operations. The significant positive correlation between Data Analytics and Business Management Metrics, as observed in this study, aligns with the conclusions drawn by Khokhar and Chitsimran (2019). It suggests that organizations that effectively utilize data analytics capabilities are better equipped to enhance their business management metrics, such as operational efficiency, customer satisfaction, and financial performance. Furthermore, the study by Chatterjee et al. (2024) provides additional support for the importance of data analytics in driving organizational performance. Their research demonstrates that acquiring business analytics capabilities can significantly improve an organization's efficiency, which in turn positively impacts overall business value. This finding is consistent with the positive relationship between Data Analytics and Business Management Metrics observed in this study.

The alignment of these studies underscores the critical role of data analytics in enabling organizations to make informed, data-driven decisions that ultimately enhance their competitiveness and success in the market. By investing in robust data analytics platforms and capabilities, organizations can leverage the power of data to optimize their operations, improve customer engagement, and drive sustainable growth.

Objective 2: The Influence of Natural Language Processing on Business Management Metrics

Natural Language Processing (NLP) was perceived to improve customer support interactions significantly, with a mean score of 3.41. This is consistent with the findings of Wang et al. (2023), who demonstrated that voice-based AI technologies could enhance customer service efficiency and satisfaction in contact centers. Their study indicates that AI systems outperform human

operators in various metrics, highlighting the potential of NLP to transform customer interactions. However, the lower mean scores for NLP's impact on data analysis suggest that while organizations recognize its utility in customer service, they may not fully leverage its capabilities for data-driven decision-making. This observation aligns with the literature's call for a deeper understanding of how NLP can enhance data analytics, as suggested by Patel et al. (2023), who emphasized the importance of integrating advanced AI techniques for better analytical outcomes. While NLP was found to be highly effective in improving customer support interactions, the lower mean scores for its impact on data analysis suggest that organizations may not be fully leveraging its capabilities for data-driven decision-making. This observation aligns with the literature's call for a deeper understanding of how NLP can enhance data analytics, as suggested by Patel et al. (2023). In their study, Patel et al. (2023) used a language representation model for sentiment analysis to examine the Airline reviews dataset. They compared the performance of various Machine Learning (ML) algorithms, including Support Vector Machine and Decision Tree, with Google's BERT algorithm. The study found that the BERT model performed better than the other ML approaches based on performance metrics such as recall, reliability, precision, and F1-score. However, the study fails to provide a coherent theoretical foundation for comprehending how sentiment analysis affects services offered by airlines. Understanding how AI affects marketing strategies could be improved by incorporating accepted theories or creating new frameworks.

The findings of Wang et al. (2023) and Patel et al. (2023) suggest that while NLP has significant potential in enhancing customer service, its application in data analytics remains an area that requires further exploration. Organizations should seek to integrate NLP with advanced AI techniques, such as machine learning algorithms, to unlock the full potential of data-driven

decision-making. By leveraging the strengths of NLP in understanding and processing natural language, combined with the predictive power of machine learning, organizations can gain valuable insights from their data and make more informed business decisions. This approach aligns with the literature's emphasis on the importance of integrating AI technologies for better analytical outcomes and improved business performance.

Objective 3: The Influence of Machine Learning Algorithms on Business Management Metrics

The results indicate a significant positive influence of Machine Learning Algorithms (MLA) on business management metrics, with a coefficient of 0.286. This finding supports the literature, particularly the work of Martins and Galegale (2023), which highlights the effectiveness of machine learning in enhancing sales forecasting accuracy. Their research demonstrates that machine learning provides valuable insights into consumer behavior and market trends, which can drive better business decisions. Additionally, the empirical studies by Syam and Sharma (2018) emphasize that AI tools, including machine learning, empower marketers by enhancing statistical power and improving market segmentation and demand forecasting. These insights align with the study's findings, suggesting that organizations can significantly benefit from integrating machine learning into their operational frameworks.

The empirical studies by Syam and Sharma (2018) provide additional support for the effectiveness of machine learning in empowering marketers. Their research emphasizes that AI tools, including machine learning, enhance statistical power and improve market segmentation and demand forecasting. These insights suggest that organizations can significantly benefit from integrating machine learning into their marketing and operational frameworks, as it enables them to make more informed decisions based on a deeper understanding of consumer behavior and market

trends. The findings of this study and the supporting literature highlight the transformative potential of machine learning algorithms in driving business success. By leveraging the predictive power and analytical capabilities of machine learning, organizations can optimize various aspects of their operations, from sales forecasting to market segmentation and demand forecasting. This, in turn, can lead to improved business management metrics, such as increased revenue, enhanced customer satisfaction, and better operational efficiency.

However, it is important to note that the successful integration of machine learning algorithms requires a comprehensive approach that considers organizational capabilities, data quality, and ethical considerations. As highlighted by Russell and Norvig (2016), one of the key areas for future research is how artificial intelligence, particularly machine learning, can best determine optimal pricing strategies and their impact on sales. This underscores the need for a deeper understanding of the interplay between machine learning, pricing, and overall business performance.

Therefore, the significant positive influence of Machine Learning Algorithms on business management metrics, as observed in this study, is strongly supported by the empirical literature. The work of Martins and Galegale (2023) and Syam and Sharma (2018) provides compelling evidence that machine learning can enhance sales forecasting accuracy, market segmentation, and demand forecasting, ultimately driving better business decisions and improved overall performance. As organizations continue to explore the potential of AI technologies, the strategic integration of machine learning algorithms into their operational frameworks can be a key driver of sustainable success in an increasingly competitive business landscape.

Objective 4: The Influence of Robotic Process Automation on Business Management Metrics

Robotic Process Automation (RPA) was found to have a positive but limited impact on business management metrics, with a mean score of 2.19. This finding suggests that while RPA is

recognized for its potential to streamline processes, its perceived effectiveness may vary across organizations. The literature supports this notion, as highlighted by the Dynamic Capabilities Theory, which emphasizes the importance of an organization's ability to adapt and leverage technology effectively (Teece et al., 1997). Organizations that successfully implement RPA can enhance operational efficiency, as noted in the work of Hassan et al. (2023), which discusses AI's role in improving compliance and operational processes in banking. This suggests that telecommunications firms in Kenya may need to focus on developing their dynamic capabilities to fully harness the benefits of RPA.

Hassan et al. (2023) provide empirical evidence supporting the role of AI, including RPA, in enhancing operational efficiency within the banking sector. Their research highlights how AI-driven strategies can improve compliance and operational processes, suggesting that organizations that effectively implement RPA can achieve similar benefits. This is particularly relevant for telecommunications firms in Kenya, which may face unique challenges and opportunities in their operational environments. The findings indicate that while RPA has the potential to streamline processes, organizations must focus on developing their dynamic capabilities to fully harness its benefits.

Dynamic Capabilities Theory posits that organizations need to continuously adapt their resources and processes to respond to changing market conditions. This involves not only adopting new technologies but also fostering a culture of innovation and flexibility within the organization. The limited impact of RPA on business management metrics, as indicated by the mean score of 2.19, may reflect a lack of organizational readiness or insufficient integration of RPA into broader operational strategies. This aligns with the literature's emphasis on the need for organizations to build capabilities that allow them to effectively implement and leverage new technologies.

Moreover, the literature suggests that organizations must actively monitor their environments to identify shifts and opportunities that can be addressed through RPA. By developing a keen understanding of their operational landscape, organizations can better position themselves to take advantage of RPA's capabilities. This involves not only technological adoption but also strategic decision-making and resource reconfiguration, which are core components of the Dynamic Capabilities framework. In this case, while RPA is recognized for its potential to enhance operational efficiency, its limited impact on business management metrics highlights the need for telecommunications firms in Kenya to focus on developing their dynamic capabilities. By fostering an adaptive organizational culture, investing in employee training, and integrating RPA into broader business strategies, these firms can unlock the full potential of RPA and improve their overall business management metrics. The alignment of this study's findings with the Dynamic Capabilities Theory underscores the importance of adaptability and strategic resource management in successfully leveraging RPA within organizations

The results of this study demonstrate the significant influence of AI technologies—Data Analytics, Natural Language Processing, Machine Learning Algorithms, and Robotic Process Automation—on business management metrics in the telecommunications sector. These findings are well-supported by empirical literature, which underscores the importance of integrating AI into business practices to enhance operational efficiency, customer service, and decision-making processes. The alignment of the study's results with existing research highlights the necessity for organizations to strategically adopt and implement these technologies to gain a competitive edge in the rapidly evolving telecommunications landscape. Future research should continue to explore the long-term impacts of AI integration and the specific mechanisms through which these technologies influence business outcomes.

CHAPTER FIVE

SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

This chapter presents a summary of the key findings from the study, draws conclusions based on the results, and provides recommendations for telecommunications organizations in Kenya as well as suggestions for future research.

5.2 Summary of Key Findings

This section summarizes the key findings of the study based on the defined objectives, reflecting the influence of various AI technologies on business management metrics in the telecommunications sector in Kenya.

Objective 1: To Examine the Influence of Data Analytics Platforms on Business Management Metrics

The study found that Data Analytics Platforms significantly enhance business management metrics, particularly in improving operational efficiency. The descriptive statistics indicated a mean score of 2.82, suggesting that respondents perceive these platforms as effective in streamlining processes and facilitating better decision-making. The regression analysis further supported this finding, with a coefficient of 0.423, indicating a positive and marginally significant impact on business management metrics. This aligns with the empirical literature, such as the work of Chatterjee et al. (2024), which emphasizes the role of data analytics in enhancing organizational performance and value.

Objective 2: To Assess the Influence of Natural Language Processing on Business Management Metrics

Natural Language Processing (NLP) was found to have a notable impact on customer support

interactions, with a mean score of 3.41 reflecting its effectiveness in improving response accuracy and efficiency. However, the study also revealed lower mean scores for NLP's influence on data analysis capabilities, indicating a gap in leveraging NLP for data-driven decision-making. The regression analysis showed a significant positive coefficient of 0.118 for NLP on business management metrics. This finding is consistent with the literature, particularly the study by Wang et al. (2023), which highlights the effectiveness of voice-based AI technologies in enhancing customer service and satisfaction.

Objective 3: To Examine the Influence of Machine Learning Algorithms on Business Management Metrics

Machine Learning Algorithms (MLA) demonstrated a significant positive influence on business management metrics, with a regression coefficient of 0.286. Despite relatively low mean scores in the descriptive statistics, the analysis indicates that improvements in MLA effectiveness are associated with enhanced business performance. This finding aligns with empirical studies, such as those by Martins and Galegale (2023), which emphasize the potential of machine learning in improving sales forecasting and operational efficiency.

Objective 4: To Examine the Influence of Robotic Process Automation on Business Management Metrics

Robotic Process Automation (RPA) was perceived to have a moderate impact on business management metrics, with a mean score of 2.19. The regression analysis indicated a significant positive coefficient of 0.114, suggesting that improvements in RPA effectiveness contribute to better business management performance. This finding is supported by the literature, which highlights the role of RPA in streamlining processes and enhancing operational efficiency, as discussed by Hassan et al. (2023).

The regression analysis presented in Tables 4.9, 4.10, and 4.11 examines the influence of various technological factors, including Data Analytics (DAn), Natural Language Processing (NLP), Machine Learning Algorithms (MLA), and Robotic Process Automation (RPA), on Business Management Metrics (BMM) in the telecommunications sector in Kenya. The Model Summary (Table 4.9) indicates a moderate positive correlation (R = 0.381) between the predictors and the dependent variable. The R Square value of 0.33 suggests that approximately 33% of the variance in Business Management Metrics can be explained by the combined effects of the predictors. The Adjusted R Square of 0.313 accounts for the number of predictors and provides a more accurate measure of the model's explanatory power. The significant F Change (Sig. F Change = 0.011) indicates that the model significantly improves the prediction of BMM when including the predictors.

The ANOVA results (Table 4.10) demonstrate that the regression model is statistically significant ($F = 1.621$, $p = 0.011$), providing evidence that at least one of the predictors significantly contributes to explaining the variance in Business Management Metrics. The regression coefficients (Table 4.11) reveal that all four predictors have positive influences on BMM. Data Analytics has a marginally significant positive effect ($B = 0.423$, $p = 0.051$), suggesting that improvements in data analytics effectiveness are associated with increases in business management performance. Natural Language Processing ($B = 0.118$, $p = 0.017$), Machine Learning Algorithms ($B = 0.286$, $p = 0.004$), and Robotic Process Automation ($B = 0.114$, $p = 0.022$) all have statistically significant positive impacts on BMM. The standardized coefficients indicate that MLA has the strongest relative influence, followed by RPA, DAn, and NLP.

The collinearity statistics (Tolerance and VIF) confirm that multicollinearity is not a significant concern in the model, allowing for reliable interpretation of the regression results. Overall, the

analysis highlights the critical role of technological advancements, particularly in the areas of Data Analytics, Natural Language Processing, Machine Learning Algorithms, and Robotic Process Automation, in driving improvements in business management metrics within the telecommunications sector in Kenya.

5.3 Conclusion

This study examined the influence of various artificial intelligence (AI) technologies on business management metrics in the telecommunications sector in Kenya, focusing on Data Analytics Platforms, Natural Language Processing, Machine Learning Algorithms, and Robotic Process Automation. The findings indicate that these technologies significantly impact operational efficiency, customer satisfaction, and overall business performance. The results reveal that Data Analytics Platforms are perceived as crucial for enhancing operational efficiency, with a significant positive influence on business management metrics.

Similarly, Natural Language Processing was recognized for its effectiveness in customer support interactions, although its potential for enhancing data-driven decision-making was less pronounced. This finding resonates with the benefits of voice-based AI technologies in customer service. Machine Learning Algorithms demonstrated a significant positive influence on business management metrics, despite lower perceived effectiveness in descriptive statistics. This finding underscores the importance of machine learning in sales forecasting and operational efficiency. Lastly, Robotic Process Automation was found to improve operational processes, particularly in inventory management, aligning with the literature that discusses the role of RPA in streamlining business operations.

The conclusions drawn from this study can be effectively linked to the theoretical framework utilized, which includes the Technology Acceptance Model (TAM) and the Dynamic Capabilities

Theory. These frameworks provide a robust foundation for understanding how AI technologies can be integrated into business management practices in the telecommunications sector in Kenya. The study's findings highlight the significant positive influence of Data Analytics Platforms on business management metrics. To capitalize on this, organizations should invest in developing robust data analytics capabilities. This aligns with the TAM, which emphasizes perceived usefulness as a crucial factor influencing technology adoption. By demonstrating the utility of advanced data analytics tools, organizations can enhance their employees' acceptance and usage of these technologies, ultimately leading to improved operational efficiency and decision- making. The effectiveness of Natural Language Processing (NLP) in improving customer support interactions underscores the need for organizations to implement NLP technologies actively. This is supported by the Dynamic Capabilities Theory, which emphasizes the importance of sensing and seizing opportunities in the market. By adopting NLP, organizations can enhance their customer engagement strategies, thereby improving customer satisfaction and loyalty. Additionally, integrating NLP into data analytics processes can provide deeper insights into customer feedback, further driving business performance.

The study found a significant positive influence of Machine Learning Algorithms on business management metrics. This aligns with the TAM, as perceived ease of use and perceived usefulness are critical for encouraging the adoption of machine learning tools. By providing training and demonstrating the effectiveness of these algorithms, organizations can foster a culture that embraces machine learning, leading to enhanced operational efficiency. Robotic Process Automation (RPA) was shown to have a positive impact on business management metrics. This is consistent with the Dynamic Capabilities Theory, which emphasizes the need for organizations to adapt and reconfigure their processes to respond to changing market conditions. By leveraging

RPA, organizations can enhance their agility and responsiveness, ultimately leading to improved business outcomes.

To fully leverage the benefits of AI technologies, organizations must cultivate a culture of continuous learning and innovation. This is crucial for enhancing perceived ease of use, as outlined in the TAM. By providing ongoing training and development opportunities, organizations can empower employees to utilize AI tools effectively, leading to greater acceptance and integration of these technologies into daily operations. Developing dynamic capabilities that enable them to adapt to changing market conditions and technological advancements, aligns with the Dynamic Capabilities Theory. This posits that organizations must sense, seize, and reconfigure resources to maintain competitive advantage. By fostering agility and flexibility, telecommunications companies can better navigate the rapidly evolving landscape of AI technologies and respond effectively to new challenges and opportunities.

The study concludes that the integration of AI technologies is essential for enhancing business management metrics in the telecommunications sector. The findings suggest that organizations should strategically adopt these technologies to optimize performance, improve customer engagement, and maintain a competitive edge in a rapidly evolving market. The empirical literature supports these conclusions, emphasizing the transformative potential of AI in driving business success. Therefore, this study contributes to the growing body of knowledge on AI integration in business management, providing valuable insights for practitioners and researchers alike. The findings underscore the need for telecommunications organizations in Kenya to embrace AI technologies to enhance their operational capabilities and achieve sustainable growth.

5.4 Recommendations

Based on the findings of this study, several recommendations are proposed for telecommunications

organizations in Kenya to enhance their business management metrics through the effective integration of AI technologies. These recommendations are linked to the study results and their significance.

Given the significant positive influence of Data Analytics Platforms on business management metrics, organizations should invest in robust data analytics capabilities. This includes not only acquiring advanced analytics tools but also ensuring that employees are trained to utilize these tools effectively. By fostering a data-driven culture, organizations can make informed decisions that enhance operational efficiency and customer satisfaction.

The study found that Natural Language Processing (NLP) significantly improves customer support interactions. Organizations should actively implement NLP technologies to enhance customer engagement and satisfaction. This includes developing chatbots and virtual assistants that can handle customer inquiries efficiently. Additionally, organizations should explore ways to leverage NLP for data analysis, enabling them to extract valuable insights from customer feedback and enhance decision-making processes.

The positive influence of Machine Learning Algorithms on business management metrics suggests that organizations should adopt and integrate these technologies into their operations. Machine learning can optimize various business functions, such as sales forecasting, fraud detection, and personalized marketing strategies. By utilizing machine learning, organizations can identify emerging market trends and enhance their competitive edge.

Robotic Process Automation (RPA) was shown to have a significant positive influence on business management metrics. Organizations should implement RPA to streamline repetitive tasks, improve process accuracy, and enhance overall operational efficiency. Organizations should focus on identifying processes that can be automated to free up resources for more strategic activities.

To fully leverage the benefits of AI technologies, organizations must cultivate a culture of continuous learning and innovation. This involves providing ongoing training and development opportunities for employees to enhance their skills in using AI tools effectively. The Technology Acceptance Model (TAM) indicates that perceived ease of use and perceived usefulness significantly influence technology adoption. By ensuring that employees feel confident in using AI technologies, organizations can improve adoption rates and maximize the benefits of these tools.

Organizations should focus on developing dynamic capabilities that enable them to adapt to changing market conditions and technological advancements. The Dynamic Capabilities Theory emphasizes the importance of sensing, seizing, and reconfiguring resources to respond to new opportunities. By fostering agility and flexibility, telecommunications companies can better navigate the rapidly evolving landscape of AI technologies and maintain a competitive advantage.

5.5 Suggestions for Further Studies

Future research should consider longitudinal studies to assess the long-term impacts of AI technologies, such as Data Analytics, Natural Language Processing, Machine Learning Algorithms, and Robotic Process Automation, on business management metrics. While this study provides valuable insights into the current state of AI integration, understanding the sustained effects over time can offer deeper insights into the effectiveness and adaptability of these technologies. Longitudinal studies can help identify trends, challenges, and evolving best practices in AI adoption, thereby providing a more comprehensive view of its impact on organizational performance. Also, given the context-specific findings of this study, future research could explore cross-cultural comparisons to understand how AI technologies influence business management metrics in different cultural and economic contexts. Such studies could identify universal

principles and culturally specific nuances in AI adoption and its effects on business performance.

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APPENDICES

APPENDIX I: QUESTIONNAIRE

1. Gender: Male Female Other (please specify)

2. Age range: Under 18 years old 18-24 years old

   25-34 years old

   35-44 years old

   45-54 years old

   55-64 years old 65 years or older

3. Job Role

   Executive/Top Management

   Manager/Supervisor

   Analyst/Researcher

   IT/Technical Staff

   Sales/Marketing

   Customer Service Other (please specify)

4. Years of Experience in the Telecommunication Sector: Less than 1 year

   1-3 years

   4-6 years

   7-10 years

   More than 10 years

5. Educational Background: High School

Bachelor's Degree

Master's Degree

Doctorate/Ph.D.

Other (please specify)

B: Data analytics and Business Metrics

On a 5-point scale, where 1 denotes "strongly disagree" and 5 denotes "strongly agree," rate your degree of agreement or disagreement with each statement. (A= agree, D= disagree, N= neutral, SD= strongly disagree, SA= strongly agree)

Measures	(SD)	(D)	(N)	(A)	(SA)
6. The Data Analytics Platform has improved the overall operational efficiency in our telecommunication company.					
7. The Data Analytics Platform has helped us in identifying and resolving network performance issues more effectively.					
8. The Data Analytics Platform has enhanced our ability to predict and prevent network outages.					
9. The Data Analytics Platform has helped us in identifying and addressing revenue leakage.					
10. The Data Analytics Platform has improved our ability to identify and target new business opportunities.					
11. The Data Analytics Platform has increased our ability to personalize and tailor services for our customers.					
12. The Data Analytics Platform has improved our ability to manage and mitigate risks in the telecommunication sector.					

C: Natural Language Processing

Rate your degree of agreement or disagreement with each statement. (A= agree, D= disagree, N=

neutral, SD= strongly disagree, SA= strongly agree).

Measures	(SD)	(D)	(N)	(A)	(SA)
13. Natural Language Processing has improved the accuracy and efficiency of our customer support interactions.					
14. Natural Language Processing has enhanced our ability to analyze and extract insights from customer feedback and reviews.					
15. Natural Language Processing has improved the effectiveness of our chatbots or virtual assistants in addressing customer queries and concerns.					
16. Natural Language Processing has helped us in identifying and addressing customer sentiment and emotions more effectively.					
17. Natural Language Processing has improved our ability to analyze and understand customer preferences and behaviors.					
18. Natural Language Processing has enhanced our ability to automate and streamline manual processes within our organization.					
19. Natural Language Processing has improved the accuracy and efficiency of our data analysis and reporting.					
20. Natural Language Processing has increased our ability to extract meaningful information from unstructured data sources, such as social media and customer emails.					

D: Machine Learning algorithms

Rate your degree of agreement or disagreement with each statement. (A= agree, D= disagree, N= neutral, SD= strongly disagree, SA= strongly agree).

Measures	(SD)	(D)	(N)	(A)	(SA)
21. Machine Learning algorithms have enhanced our ability to identify and prevent network anomalies and outages.					

22. Machine Learning algorithms have improved the efficiency and cost-effectiveness of our resource allocation and optimization.					
23. Machine Learning algorithms have increased our ability to personalize and tailor services for our customers.					
24. Machine Learning algorithms have improved the accuracy and effectiveness of our customer churn prediction.					
25. Machine Learning algorithms have enhanced our ability to detect and mitigate fraudulent activities within our organization.					
26. Machine Learning algorithms have improved the efficiency and effectiveness of our marketing and customer acquisition strategies.					
27. Machine Learning algorithms have improved the accuracy and effectiveness of our credit scoring and risk assessment processes.					

E: Robotic Process Automation

Rate your degree of agreement or disagreement with each statement. (A= agree, D= disagree, N= neutral, SD= strongly disagree, SA= strongly agree).

Measures	(SD)	(D)	(N)	(A)	(SA)
28. Robotic Process Automation has improved the accuracy and efficiency of our billing and invoicing processes.					
29. Robotic Process Automation has enhanced our ability to automate repetitive and mundane tasks within our organization.					
30. Robotic Process Automation has improved the speed and timeliness of our customer order processing.					
31. Robotic Process Automation has increased our ability to handle a higher volume of customer inquiries and requests.					

32. Robotic Process Automation has improved the accuracy and effectiveness of our data entry and data management processes.					
33. Robotic Process Automation has enhanced our ability to streamline and standardize our business processes.					
34. Robotic Process Automation has improved the accuracy and efficiency of our inventory management and supply chain processes.					
35. Robotic Process Automation has increased our ability to respond to customer queries and concerns in a timely manner.					
36. Robotic Process Automation has improved the overall operational efficiency and cost-effectiveness of our organization.					
37. Robotic Process Automation has increased our competitive advantage in the market.					

F: Business management metrics in Telecommunication sector

Rate your degree of agreement or disagreement with each statement. (A= agree, D= disagree, N= neutral, SD= strongly disagree, SA= strongly agree).

Measures	(SD)	(D)	(N)	(A)	(SA)
38. Our organization effectively monitors and manages key performance indicators (KPIs) related to customer satisfaction.					
39. Our organization has a well-defined and efficient process for resolving customer complaints and issues.					
40. Our organization effectively tracks and manages network performance metrics to ensure optimal service quality.					
41. Our organization has implemented effective strategies to attract and retain customers in a competitive market.					

42. Our organization consistently meets or exceeds service level agreements (SLAs) with customers.					
43. Our organization utilizes data analytics and business intelligence tools to make informed and data-driven decisions.					