SUPPLY CHAIN INNOVATION AGILITY, FIRM SIZE AND DEMAND FORECASTING PERFORMANCE OF OIL MARKETING COMPANIES IN KENYA

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A Thesis Submitted in Partial Fulfilment of the Requirements for the Degree of Doctor of Philosophy in Business Administration (Procurement and Supply Chain Management Option) of Murang'a University of Technology

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DECLARATION

Student Declaration

I hereby declare that this thesis is my original work and to the best of my knowledge has not been presented for a degree in this or any other University. I understand what plagiarism is and I am aware of the university policy in this regard. I understand that any false claim in respect to this work shall result in disciplinary action in accordance with the University Anti-Plagiarism Policy.

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Supervisor's Approval

The undersigned certify that they have read and thereby recommend for acceptance of Murang'a University of Technology a Thesis entitled "**Supply Chain Innovation Agility, Firm Size and Demand Forecasting Performance of Oil Marketing Companies in Kenya**".

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DEDICATION

This thesis is dedicated to my mother, Naomi and my brothers, Kevin and Collins, for their love, encouragement and overwhelming support.

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First and foremost, I give all glory and honour to Almighty God for His grace, strength, wisdom, and unfailing guidance in this academic journey. Without His divine provision and steadfast presence, the successful completion of this work would not have been possible.

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ABSTRACT

Demand forecasting performance has remained a challenging subject in supply chain management due to the difficulty involved in accurately planning, tracking, and monitoring demand in unpredictable markets. Innovation plays a critical role in improving forecasting accuracy and enabling real- time demand tracking. The purpose of this research was to determine the significance of actively incorporating agile supply chain innovations in oil marketing companies to enhance the accuracy and timeliness of demand forecasting. Specifically, the study sought to analyse the influence of business process innovation on the demand forecasting performance of oil marketing companies in Kenya; examine the influence of technological innovation on the demand forecasting performance of these companies; assess the influence of network structure innovation on demand forecasting performance of oil marketing companies in Kenya; establish the impact of customer- centric innovation on demand forecasting performance of oil marketing companies in Kenya; and evaluate the moderating influence of firm size moderates the relationship between supply chain innovation agility and demand forecasting performance. The research was guided by four theories: Dynamic Capabilities Theory, Systems Theory, Resource- Based Theory, and Network Theory. A descriptive design with a mixed- methods approach was adopted. The target population comprised 145 registered oil marketing companies in Kenya. A purposive sampling technique was used to select 81 companies. The study utilised both open- ended questionnaires and secondary data sources. Quantitative data were analysed using SPSS version 27, while qualitative data were analysed manually. The adjusted R^2 indicated that 81.1% of the variables accounted for demand forecasting performance, with BPI and TI showing positive but not significant effects, and CCI and NSI demonstrating positive and significant effects. Introducing firm size as a moderator increased the adjusted R^2 to 94.5%. However, after moderation, there was a partial significant effect, and the influence on demand forecasting performance decreased; BPI (β = -0.065, p = 0.018), NSI (β = -0. 078, p = 0.273), CCI (β =- 0.177, p = 0.005) had negative effects, while TI (β = 0.047, p = 0.513) had a positive effect. The study concluded that, individually, the SCIA components were positive and significant; however, when regressed together, they tend to share resources, thereby reducing explanatory power and significance. The study also concluded that firm size moderation was partial and context-specific. The study thus recommends decentralising decision-making, empowering regional units, streamlining internal processes to increase flexibility and responsiveness, and investing in integrated digital platforms, real-time data-sharing systems, and collaborative forecasting practices to improve visibility across the supply chain. It also proposes leveraging advanced customer analytics, market intelligence systems, decentralised customer relationship management, and IoT and digital twin technologies that precisely adjust demand, monitor petroleum consumption rates, and visualise the supply chain to identify trends that may influence future demand.

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ACRONYMS AND ABBREVIATIONS

3D	Three Dimensional
4Pl	Fourth Party Logistics
AI	Artificial Intelligence
BPI	Business Process Innovations
CCI	Customer Centric Innovation
COVID-19	Coronavirus Disease of 2019
CPFR	Collaborative Planning Forecasting and Replenishment
CRM	Customer Relationship Management
CSM	Customer Service Management
DCT	Dynamic Capabilities Theory
DFP	Demand Forecasting Performance
EPRA	Energy Petroleum Report Regulatory Authority
EPSR	Energy and Petroleum Statistics Report
ERP	Enterprise Resource Planning
ESG	Environmental, Social and Governance
ESR	Economic Survey Report
FVA	Forecast Value Added
GDP	Gross Domestic Product
I4.0	Industry 4.0
I5.0	Industry 5.0
IEA	International Energy Agency
IoT	Internet of Things
KMO	Kaiser-Mayer-Olkin
KPI	Key Performance Indicator
NACOSTI	National Council for Science, Technology and Innovation
NSI	Network Structure Innovation
OECD	Organisation for Economic Co-operation and Development
PAF	Principal Axis Factoring
PCN	Primary Healthcare Networks
R&D	Research and Development
RBT	Resource-Based Theory
S&OP	Sales and Operations Planning

SCIA	Supply Chain Innovation Agility
SCI	Supply Chain Innovation
SCLC	Supply Chain Learning Capabilities
SCOR	Supply Chain Operations Reference
SCP	Supply Chain Paradigm
SCV	Supply Chain Visibility
SKU	Stock Keeping Unit
SMEs	Small and Medium-sized Enterprises
SMS	Short Messages Service
SOM	Service Oriented Manufacturing
SRM	Supplier Relationship
TI	Technological Innovation
UNESCAP	United Nations Economic and Social Commission for Asia and the Pacific
USSD	Unstructured Supplementary Service Data
VIF	Variance Inflation Factor
WMS	Warehouse Management Systems

OPERATIONAL DEFINITION OF TERMS

Business Process Innovation	This refers to internal changes, improvements, or modifications in business processes, organisational structures, and marketing practices aimed at creating value for organisations, customers, and stakeholders while enhancing operational efficiency, flexibility, and alignment with customer needs (Qerimi et al., 2024)
Customer Centric Innovation	It comprises integrating customer insights, market trends, and preferences into supply chain decisions and operations, enabling companies to adopt flexible, agile, and responsive supply chain models that align supply with dynamic customer demand patterns (Aslam et al., 2023)
Demand forecasting performance	refers to the effectiveness and accuracy with which forecasting techniques and analytical methods are used to estimate future customer demand, improve inventory management, production planning, and supply chain coordination, thereby reducing uncertainty and enhancing overall operational efficiency and customer satisfaction (Zougagh et al., 2020).
Firm Size	Firm size is the extent of an organisation's economic presence and competitive position within an industry, and it reflects the proportion of industry sales or customers controlled by a firm and serves as an indicator of market dominance, competitive capability, and resource availability (Barney & Hesterly, 2021; Dess et al., 2021).

Network Structure Innovation It encompasses the innovative and agile adoption of new technological solutions within supply chain networks to create value, enhance communication and coordination, and leverage supply chain partners and distribution channels to improve responsiveness and adaptability to market demands (James, 2023).

Supply Chain Innovation Agility It is the dynamic capability of a supply chain to innovate responsively by rapidly generating, testing, and implementing new ideas, technologies, and processes to adapt to changing market conditions, customer needs, and disruptions while sustaining or improving performance (Isaid et al., 2024).

Technological Innovation Involves the integration of advanced digital and smart technologies, including big data, cyber-physical systems, 3D printing, and blockchain, which drive digital transformation that enhances supply chain agility, resilience, responsiveness, and operational flexibility (Lee et al., 2024)

CHAPTER ONE
INTRODUCTION

1.1 Background of the Study

Global oil markets are volatile due to a combination of geopolitical, economic, and technological factors. Revolutions, wars, and political decisions in oil-producing regions, especially in the Middle East, have often caused sharp changes in oil prices. OPEC Organisations influence supply through production quotas and policy disagreements, which can shift market conditions suddenly (Jefferson, 2020). The COVID pandemic in 2020 exacerbated this situation, coupled with the price wars between the USA, Saudi Arabia, and Russia, which reduced demand through lockdowns and travel restrictions, with the transport sector most affected.

The International Energy Agency (2024) reported that the oil market has been experiencing high volatility due to fluctuating crude oil prices. The advanced economies, especially in the USA, have shown a great increase in demand for gasoline, while in China, there was a light contraction of demand, which was attributed to the slump in industrial output. The report further mentions that the supply in June 2024 was not able to keep up with the increase in demand, which led to deficits. The oil inventories fell by 26.2 mb, and the crude oil stocks dropped by 40.9 mb. The global oil demand is set to increase in OECD and Non-OECD countries of the USA, China, India and Brazil by 30kb/d, 300kb/d, 160 kb/d and 30kb/d respectively (IEA, 2025).

The IEA (2025) report also predicted that global demand for oil is set to increase by 5.7 mb/d, which is a slight reduction from the steady increase of 1.5 mb/d that has been experienced over the years. This increase will be attributed to the increased demand for plastics and LPG. The report also informs that Africa will show a magnitude growth in demand for oil in 2025 by 2.1%. Sanctions, pandemics and global crude oil prices have a significant role in the oil demand of a country, while trade liberalisation plays a great role in increasing oil demand.

Oil demand forecasting is an important area for energy planning and economic stability in both oil-importing and oil-exporting countries. The many factors that shape oil demand make forecasting difficult, especially when using traditional models that depend mainly on linear assumptions and historical data. These models often fail to

account for the interaction between internal economic factors, such as GDP growth, income levels, urbanisation, and trade liberalisation, and external shocks like geopolitical conflicts, sanctions, or global crises. For example, the COVID-19 pandemic caused an abrupt decline in global oil demand, showing the need for forecasting methods that can respond to sudden changes (Zhu, 2023).

Oltulular (2024) further explains that countries with large economies like the United States, Saudi Arabia, and Russia have shown that oil consumption rates are volatile to oil prices and there exists a long-term connection between price and consumption. However, Japan took about 20 months for their oil marketing companies and oil consumption to recover from the initial market shock. This cemented the notion that oil consumption and prices are at times specific to a particular country, as some are more responsive to changes while other countries are driven by industrial demand, energy policy and domestic supply. Due to the strict measures imposed during the pandemic, there was a reduction in global transport, which reduced the demand for oil. Mwape et al. (2024) highlighted that, in Kenya and Tanzania, even with the reduction of pump prices, it did not translate to stability of energy costs as the countries were not well-equipped with adequate storage facilities and efficient logistics to take advantage of low global prices.

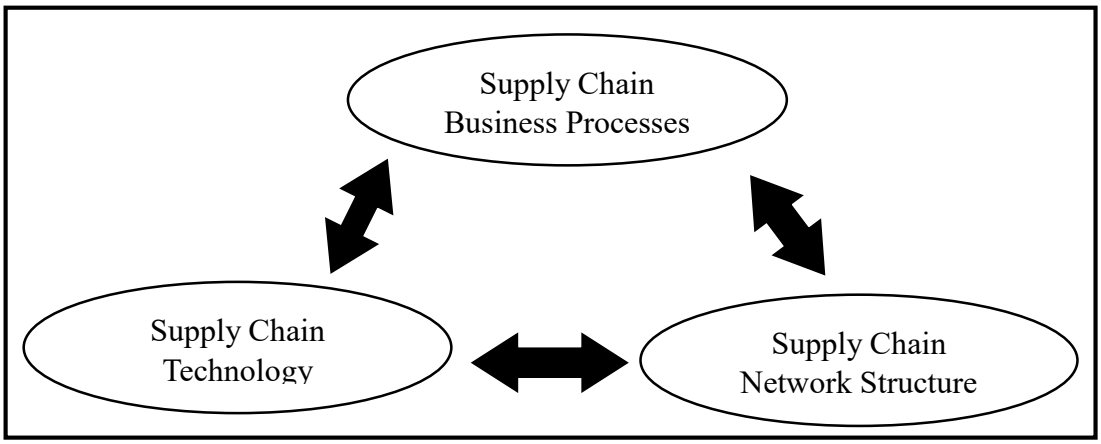
International forecasting benchmarks commonly report Mean Absolute Percentage Error (MAPE) values ranging between 10% and 20%, which translates to forecast accuracies of approximately 80%–90%. In contrast, petroleum supply chains often record forecast accuracies between 65% and 80% because fuel demand is highly sensitive to macroeconomic conditions, seasonal changes, and geopolitical events, highlighting the need for greater adoption of agile supply chain innovations, predictive analytics, and collaborative forecasting systems to improve forecasting performance. (Chukwuemeka et al., 2015; Haque et al., 2023). In 2020, global oil demand fell by 9.1 million barrels per day (bpd), while U.S. crude oil production dropped by over 2 million bpd as supply outstripped demand (IEA, 2021). Globally, the energy price index experienced radical turbulence, plunging during the COVID-19 pandemic to a low of 55.9 in April 2020, before experiencing an aggressive upswing that peaked at an erratic 379.4 in August 2022 (Thugge, 2024). Locally, this volatility was compounded by severe domestic currency distress; between January 2023 and January

2024 alone, the Kenyan Shilling depreciated by a staggering 29% against the U.S. Dollar, dropping from an average of KSh 123.9 to KSh 159.7 (Thugge, 2024). These external shocks severely compromised the accuracy of reactive, calendar-based baseline forecasting methods. When historical statistical averages were applied against such rapid market shifts, the resulting predictive errors directly contributed to significant organisational declines. Major market leaders suffered steep financial contractions, with Total Kenya witnessing a 32.6% turnover drop to KSh 55.7 billion and KenolKobil experiencing a 19.2% revenue decline to KSh 34.8 billion due to high operational costs, mismatched inventory volumes, and stringent regulatory price caps imposed by the Energy and Petroleum Regulatory Authority (Kyalo & Wachiuri, 2024).

Supply chain innovations consider the changes that occur within the supply chain network, process and technology of an organisation or industry to increase value creation (Solaimani &Veen, 2022). Supply chain innovations encompass leveraging and exploring different and existing innovative opportunities in the supply chain for sustainable competition (Li & Li, 2017). It incorporates the essentials of sustainability: economic, social and environmental in its overall decision-making and planning. (Kusi-Sarpong et al., 2019). The Council of Supply Chain Management Professionals (CSCMP) annually awards organisations that show radical or incremental innovative practices and how it impacts the supply chain and sustainability (Arlbjørn et al., 2011).

Supply chain innovation framework developed by Arlbjørn and Hass (2009) in Denmark defined three major components of the SCI framework as business process, technology and network. The framework also included the different innovations that can be adopted in each of the components, from Customer Relationship management (CRM), Warehouse Management Systems (WMS), to Fourth Party Logistics (4PL). The framework was adopted in four different companies in the country to observe how it performed when put into practice. The framework was able to improve SCI language and improved on decision making. Hahn (2020) adopted a similar framework of Arlbjørn et al. (2011) on the incorporation of Industry 4.0 technologies from the supply chain perspective in startups and established companies. The framework measured innovation with similar components. The framework was seen to improve on

outsourcing, reduce transactional costs, differentiation opportunities, flexibility and scalability that essentially improved productivity.



Source: Supply Chain Innovation Framework (Arlbjørn & Hass, 2009)

Figure 1.1: Supply Chain Innovation Framework

The concept of agile methodology originated as a response to the high number of software development projects exceeding their deadlines. In 2001, software developers created and published the Manifesto for Agile Software Development. The management paradigm emphasising flexibility and enabling teams to adapt to necessary changes quickly spread to other industries. Agility focuses on the ability of supply chain operators to respond swiftly to fluctuating or volatile demand, supported by effective relationship management within the supply chain to handle external and internal uncertainties. It allows organisations within the supply chain to capitalise on market opportunities and address threats through sharing information, process integration, and network flexibility (Baah et al., 2020). Agility requires adaptability and concentration to overcome uncertainties and risks arising from changing customer preferences and market trends (Brusset, 2016; Gilgor et al., 2013). The agile approach centres on customer sensitivity, virtual, process, and network integration (Suifan et al., 2019); Ciccullo et al. (2018) mention practices such as risk hedging, flexibility, responsiveness, and innovation adoption through supply chain knowledge. These practices aim to mitigate supply shortage risks while maintaining customer satisfaction by fulfilling evolving demands.

For supply chains, agility is the capability to respond rapidly to unexpected changes and convert these changes into business opportunities (Wang et al., 2024). The

successful exploration of competitive bases, such as speed and flexibility, through the integration of reconfigurable resources and best practices, is crucial for achieving supply chain agility (Susitha et al., 2024). The level of supply chain agility can be measured in terms of production, market, people, information, technology, strategies and organisational management (Garbie, 2011). The adoption of the agile concept improves customer responsiveness in the external supply chain. This is enabled through supplier integration to allow for aggressive response to changing demand (Jermsittiparsert et al., 2019). A conceptual framework of supply chain agility in the oil marketing industry identified twelve factors that showed their inter-relationship, ranging from internal collaborations, integration of ICT, transportation and logistics flexibility to government statutes and regulations and top management support and commitment (Piya et al., 2020). Information is a prerequisite to measuring agility in the supply chain, and as such, imperative that organisations embark on the reliance on sharing of information to reduce costs and also improve customer demand visibility. This enables quick access and response to customer order requirements. (Cicculo et al., 2018).

Agile Supply Chain (ASC) is vital for companies to manage supply networks and adapt to dynamic customer demands. It enhances operational and organisational performance by navigating market volatility and competitive pressures. It relies heavily on digitisation, being inherently information-centric and technology-focused. However, the precise role of digitisation in ASC strategies remains unclear, posing challenges in assessing its impact accurately (Shashi et al., 2022). Agile supply chain management reduces risk through the "Buffer Strategy", which prioritises the increase of resources, in order to mitigate supply chain risks through the establishment of strategic relationships among the diverse parties in the supply chain networks. Therefore, improving the demand management capacity increases product demand control and creates an environment for demand to be realised in time. This strategy allows for the integration of effective warehouse management practices with advanced technology, creating an innovative perspective (Mishra et al., 2016; Kırılmaz & Erol, 2017). Companies that have adopted ASC strategies can rapidly fulfil customer orders, launch new products regularly, and develop strategic relationships with their partners (Um 2017a). Supply chain agility can be achieved through the integration of all companies' capabilities with the supply chain network (Gligor et al., 2015). Due to

the constant demand, ASC strategies must be able to tap into environmental responsiveness and use the available resources to proactively meet reactive demand. This allows suppliers to adjust the quantity and delivery time of orders which ultimately leads to improved overall supply chain performance (Alzoubia & Yanamandrab, 2020; Ahmed & Huma, 2021).

Agility and innovation are mutually reinforcing, particularly in volatile markets. Innovation capacity is viewed as a key antecedent to agility. The relationship is strong because innovation enables firms to explore new solutions to unexpected problems and respond swiftly to changes, leading to the development of more efficient and effective organisational processes. Organisations that focus on innovation also contribute directly to agility by generating innovative solutions to emerging problems (Wang et al., 2025; Kürşad et al., 2025). This relationship is also fundamentally supported by organisational culture, where firms adopt an agile culture that fosters innovation, which centres on a culture that is built on values such as collaboration, continuous learning, and experimentation, which encourage employees to generate innovative ideas. Teamwork and collaboration, elements of agile culture, strengthen organisational commitment and increase innovation within the organisation (Kürşad et al., 2025; Munachi et al., 2024).

Supply chain innovation and supply chain agility are positively interrelated dynamic capabilities that jointly enhance organisational performance in turbulent environments. Aslam et al. (2025) confirm that supply chain agility directly drives supply chain innovation, creating a reinforcing cycle where agility enables faster adaptation while innovation provides new capabilities for responding to disruptions. Lamees and Ramayah (2025) demonstrated that AI-based supply chain analytics significantly boost both agility and innovation, with agility exhibiting a positive effect on innovation performance. Isaid et al. (2024) reiterated that supply chain agility not only helps prevent and repair short-term damage but also promotes innovation in the long term, with the organisation's complementarity with key suppliers moderating this relationship. The study emphasises that setting up the right organisational context is crucial for dynamic capabilities like agility, especially during turbulent times, and that the previously overlooked impact of agility on innovation performance represents a significant theoretical contribution

Digitalisation positively impacts resilience through the sequential mediation of supply chain adaptability and innovation, emphasising adaptability's essential role in translating digital advancements into resilient, innovative supply chains. This suggests that innovation and agility are not independent capabilities but rather co-evolve through digital infrastructure investments (Elmouhib & Idrissi, 2025). Intellectual capital components, such as human, structural, and social, significantly impact the adoption of supply chain analytics that enable both innovation and agility. Cultivating intellectual capital is crucial for utilising supply chain analysis to enhance performance in terms of innovation and agility (Al-Omoush et al., 2025). Alfaqiyah et al. (2025) showcased that Industry 4.0 technologies enhance supply chain resilience through the interplay of agility, adaptability, and customer integration, demonstrating that these capabilities work synergistically rather than independently. The emerging consensus is that supply chain innovation and agility form an integrated capability system where digital transformation, intellectual capital, and organisational context jointly determine their effectiveness in driving competitive advantage

Khan et al. (2023) found that incorporating technological capabilities improves a firm's innovation performance when it’s mediated by supply chain agility, indicating that innovation investments enable firms to respond more effectively to dynamic market conditions. Similarly, Abourokbah et al. (2023) established that digital capability and innovation initiatives positively influence supply chain agility, which subsequently enhances supply chain innovation performance. Raj et al. (2025) concept of "hyperagility," argued that innovative digital capabilities enable supply chains to move beyond traditional agility toward proactive adaptation and continuous innovation.

1.1.1 Global Perspective of Supply Chain Innovation Agility and Demand Forecasting Performance

Brada and Park (2024) postulated that the world’s economy has also recognised the growth in the dimensions of innovations aimed at improving competitive advantage and sustainability. During the Industrial Revolution in the 1800s, emerging technologies played a significant role in improving production, distribution, and automation across different industries. The fourth industrial revolution is driving significant social polarisation, wealth concentration in prominent platform firms and

has transformed global economic competition into a zero-sum struggle. Isaid et al. (2024) outlined that the adoption of artificial intelligence (AI) in Qatar's healthcare systems improved supply chain agility, alignment and adaptation, which assisted the firms in enhancing performance, especially in the complex healthcare industry. The study identified that agility and collaboration are recognised as key enablers of resilience and that technologies, like AI, are adopted by employees to achieve human goals, improve the social world, and advance individual interests. Uyarra et al. (2014) outlined eight (8) barriers to innovation that have been triggered by public procurement in the United Kingdom: lack of demand for innovation, specifications were too prescriptive, contracts were not long or large enough, low capabilities of procurers, inadequate management and poor risk management protocols. Further innovations in the public sector have a low tendency of triggering innovation if persistence is placed on providing standardised products.

The OECD (2021) report showed that during the COVID-19 pandemic in 2020, global supply chains were forced to take measures to ensure that demand was met even with disruption in the network. This generated stress that affected both national and international supply chains and thus perpetuated the mandate for policy development that reinforces supply chains' resilience and agility to prepare for future disruptions. Through investment in enabling digital infrastructure, procurement management and regulatory flexibility, organisations can improve supply chain agility and subsequently promote productivity and competitiveness.

Pakistan's manufacturing sector demonstrated that these firms' supply chain agility enhanced innovation performance, and that close supplier relationships assist in improving agility but hinder innovation, due to over. Internal organisational support also contributes towards developing supply chain agility capabilities that drive long-term innovation, which is considered a strategic outcome from a managerial perspective (Aslam et al., 2025). Similarly, manufacturing companies in India that used traditional methods in supply chain agility were not sufficient, especially during the COVID-19 pandemic. However, Raj et al. (2025) mention that hyper-agile organisations remained sustainable in environments that were highly susceptible to unexpected shocks. Othman and Voon (2018) and Kembro and Norrman (2019) collectively associated major challenges in supply chains with late deliveries, volatile

orders, and the bull-whip effect in communication. These issues are further exacerbated by limited supply chain flexibility and volatile demand. This is due to the instability in demand and unpredictable customer expectations, which are impossible to determine in cases of global supply chain networks (Wee Kwan Tan et al., 2014).

1.1.2 Regional Perspective on Supply Chain Innovation Agility and Demand Forecasting Performance

Most domestic firms in Africa are typically small to medium-sized and often operate outside the global supply chain network. However, these businesses have the potential to make significant contributions to supply chain diversification through vertical or horizontal integration. Vertical integration enables a company to expand into upstream or downstream activities, thereby enhancing its supply chain by acquiring or establishing its own suppliers, manufacturers, distributors, or retail locations, rather than relying on external suppliers (Hayes, 2022). Conversely, horizontal integration enables a company to expand its operations within the same industry level, reaching new markets, diversifying its product offerings, and reducing competition (Kenton, 2022). Both types of integration are more effective when supported by technology services at all stages, from transactional to operational.

Supply chain diversification and resilience are closely linked to digitisation and the adoption of digital technologies. In industries with complex, high-value products and shorter lead times, such as medical devices and electrical equipment, digitisation is essential for production, processes, and supply. Digital technologies—such as advanced automation, additive manufacturing (3D printing), machine learning, artificial intelligence, robotics, the Internet of Things, and blockchain—significantly enhance productivity, distribution, logistics, and procurement efficiency. At the firm level, these technologies lead to increased efficiency, cost reduction, valuation, and competitive advantage. Economic Development in Africa Report (2023) estimated that companies with well-aligned goals efficiently put them into action and anticipate technology-supported manufacturing and delivery to generate productivity gains and cost savings. Therefore, the affordability and access to such digital technologies are crucial for African economies to become attractive partners in supply chain diversification and resilience. Accelerating technological transformation in Africa will

not only boost its supply chain and operational capabilities but also position African firms to capitalise on supply chain opportunities.

Companies looking to expand their supply chains and form partnerships with suppliers in new markets, such as Africa, can do so through joint ventures with local firms or mergers and acquisitions with foreign manufacturers and supply chain service providers on the continent. Creating these partnership opportunities between established global supply chain firms and emerging African firms will result in spillover effects related to specialisation, innovation, digitisation, and skills development, leading to higher-value activities, productivity gains, job creation, and enhanced competitiveness in global supply chains (Sustainable Global Supply Chain Report, 2022).

However, many African countries lack the necessary technology-enabled services and digital platforms for supply chain diversification and resilience due to infrastructure challenges, limited innovation investment, lack of institutional frameworks and regulations, and information asymmetry (Kuteyi and Winkler, 2022). Only a few countries, such as Egypt, Kenya, Mauritius, Nigeria, and South Africa, have developed logistics and smart services for business-to-business platforms. Autonomous supply chains, which are considered the future, are only present in South Africa. The technological advancement in South Africa has driven its competitiveness and integration into global supply chains. Digital transformation in Africa could strengthen producer competitiveness, reduce cross-border trade costs, improve trade-related institutions, and facilitate the African Continental Free Trade Area. Digital transformation also enables firms, including small and medium-sized enterprises, to overcome formal contract enforcement constraints and integrate informal actors, leading to productivity gains, streamlined cross-border trade, and safe and seamless data flow across borders for competitive regional and global supply chains (OECD, 2022a).

South Africa, with one of the largest ICT markets on the continent, is embarking on an extensive skills development program to train one million young people by 2030 in robotics, AI, coding, cloud computing, and networking. This tech boom has enabled the private sector and SMEs to adopt new technologies such as machine-to-machine communication, IoT, cloud computing, big data analytics, cybersecurity, advanced

robotics, AI, smart sensors, augmented and virtual reality, and 3D printing. These technologies are transforming manufacturing in South Africa, placing it among the world's 30 most highly diversified and integrated supply chains (OECD, 2022a). South Africa's technological integration is reflected in its high scores on the frontier technology readiness index and the logistics performance index, ranking first in Africa for both indices. Its frontier technology readiness index was 0.61, above the global average of 0.50 in 2022. Other African countries with above-average scores include Tunisia (0.56), Morocco (0.55), and Mauritius (0.54). South Africa also excelled in logistics performance, with a score of 3.38, compared to the global average of 2.87 in 2018, highlighting its strong supply chain connectivity and logistics (OECD, 2022a).

Despite the significance of technology in the supply chain, most African countries lag behind in trading technology-enabled goods and services. The transformation of raw materials into high-skill, technology-intensive manufactures remains low, limiting opportunities for value addition and participation in global supply chains. High-skill, technology-intensive manufactures accounted for only 7.7% of African exports from 2017 to 2021, the smallest proportion worldwide, behind the Americas (23%), Europe (28%), and Asia (36%) (Economic Development Africa, 2023). In Nigeria, improved digital and data infrastructure alongside increased use of digital communication technology have boosted labour force participation, wage employment, and reduced extreme poverty (World Bank, 2023b). Similar results are observed in other African nations such as Ghana, Kenya, Malawi, Senegal, and Tanzania. Cirera et al. (2021) noted that in Senegal, the utilisation of advanced digital technologies is linked to higher productivity performance. However, barriers to technology adoption, including a lack of capabilities and financing, continue to exist. Suitable policy measures could enhance the diffusion and adoption of cutting-edge technologies in Senegal (Economic Development Africa, 2023).

Saputra (2024) revealed that digital supply chain dimensions, in Moroccan industries, such as digital performance measurement, information technology, and logistics, significantly enhance supply chain agility, which in turn strongly boosts innovation performance. Blockchain technology is becoming increasingly important in optimising supply chain operations in Africa. It enables fast and efficient sourcing and delivery of products, enhances coordination between suppliers and buyers, and

improves access to finance for supply chain participants. Blockchain's transparent, verifiable, and tamperproof nature improves traceability and reduces operational, administrative, and logistics costs. Mining companies in South Africa use blockchain to ensure the traceability of minerals, reducing corruption risks, cutting transaction costs, and increasing profit margins (Akinradewo et al., 2022).

1.1.3 Kenyan Perspective on Supply Chain Innovation Agility and Demand Forecasting Performance

Kenya is an emerging market with significant potential for innovation and digital technologies. It boasts one of the highest rates of digital skill adoption in Africa, with about one-third of its population proficient in using digital devices and applications. By 2030, it is projected that approximately 55% of jobs in Kenya will require digital skills, particularly in the industry and services sectors (International Finance Corporation, 2021a). The country's high digital literacy and its robust information and communications technology sector are key drivers of digital technology adoption, fostering the growth of cutting-edge start-ups and tech-enabled companies. According to the International Telecommunication Union (2021), Kenya has one of the largest and fastest-growing international bandwidths per internet user on the continent, with 566.41 kilobits per second and a compounded annual growth rate of 52% between 2015 and 2019. Emerging technologies such as artificial intelligence, the Internet of Things, and cloud-computing technologies, including blockchain, are increasingly being deployed in Kenya to boost various industries and supply chains, such as innovation, product design, manufacturing, logistics, and supply chain management. This burgeoning tech ecosystem, known as Silicon Savannah, has benefited from supportive policies, a business-friendly regulatory environment, and government-led skills, upgrading and digital technology adoption programs, including the establishment of technology hubs and incubators (International Telecommunication Union, 2021).

The use of technology to streamline purchasing and supply chain processes is gaining momentum in Kenya. Businesses are adopting technology solutions to optimise their supply chain operations, driven by Kenya's position as a regional hub for trade and commerce and its growing economy. This has led to a greater focus on supply chain management to meet the demands of a rapidly expanding market (Murumba & Ngari,

2020). Technology plays a critical role in improving the efficiency and effectiveness of procurement and supply chain processes in Kenyan businesses. The adoption of technology solutions in procurement and supply chain management has led to several benefits, including improved efficiency, transparency, and accountability, as well as reduced procurement costs and increased competition among suppliers. Kagondu (2023) mentions e-procurement systems, which have automated the procurement process in Kenya. These promote transparency while simultaneously mitigating corruption risks. Supply chain management software is being integrated into SCM systems in Kenya to include tools for effective supply chain management. These include inventory management, order processing, and logistics management (Kuria et al., 2021). By adopting such software, organisations improve efficiency while reducing costs through automation, thereby promoting visibility into their supply chains.

The ongoing advancement of technology continues to impact various aspects of business, making it one of the most significant emerging issues in supply chain management. Currently, businesses must consider the impact of technology on their supply chains to manage them effectively. Failure to understand how technology can enhance supply chain activities may result in competitors gaining an advantage. Effective supply chain management involves many players, from raw material sources to the end user.

1.1.4 Demand Forecasting Performance

Demand forecasting is a core concept that enables informed procurement, production planning, stock management, and distribution. Inaccurate forecasting severely hinders a firm's capacity to plan and allocate resources effectively and respond to customer demands (Mutua & Odari, 2025). It also helps organisations reduce stock-holding costs, prevent waste, and ensure products are available in the right quantity and quality when needed (Serenoy et al., 2023). For oil and gas firms to remain viable and competitive in volatile environments, there is a need for these firms to be efficient, which is achieved through innovation by exploring innovative strategies that require firms to produce more at a lower cost (Oliveira et al., 2024).

Serenoy et.al. (2023) noted that accurate forecasting has enabled firms to make informed decisions regarding procurement, production planning, and resource

distribution. Reducing stock-holding costs, minimising operational expenditures, and ensuring products are supplied with the correct timing and quantity, ensures that demand forecasting directly contributes to achieving operational efficiency and competitive advantage. Furthermore, Mutua and Odari (2025) posited that the positive influence of high-quality forecasting is statistically confirmed to enhance overall supply chain performance in demanding sectors, facilitating proactive planning rather than reactive management

In contemporary supply chain management, demand forecasting stands as a foundational element of operational strategy, directly impacting inventory optimisation, production scheduling, resource allocation, and customer satisfaction (Wamoto et al., 2023; Mitra et al., 2022; Yun et al., 2025). Accurate demand prediction directly impacts inventory costs, service levels, and overall supply chain efficiency. This requires adapting various forecasting methods to market characteristics, demand volatility, and data availability. Furthermore, integrating sustainability and resilience considerations into supplier and demand management enhances robustness against disruptions, a growing concern highlighted during events such as the COVID-19 pandemic (Sonar et al., 2022). For increasingly volatile, uncertain, and dynamic global market environments, achieving high predictive accuracy has become crucial for preserving corporate competitiveness (Angos Mediavilla et al., 2022; Yun et al., 2025). When forecasting performance fails or suffers from operational distortions, organisations experience systemic inefficiencies that degrade profitability and performance across downstream departments (Njuguna & Ismael, 2017).

Demand forecasting performance has become a critical determinant of organisational competitiveness due to its influence on inventory management, production planning, procurement, customer service, and overall supply chain efficiency. Ahaggach et al. (2024) postulated that between 2015 and 2019, forecasting performance improved steadily across industries due to increased adoption of enterprise resource planning systems, advanced analytics, and integrated demand planning technologies. During this period, average forecast accuracy improved from approximately 66% to 75%. Organisations increasingly leverage big data analytics, statistical forecasting models, and machine learning techniques to enhance demand visibility and decision-making processes. These developments enabled firms to achieve more accurate predictions of

customer demand and market trends. Improved demand forecasting performance relies on supply chain visibility to allow information sharing within the supply chain network that results in the realisation of mutual benefits (Calatayud et al, 2019).

Coroneo et al. (2023) revealed that the disruption in 2020 following the outbreak of the COVID-19 pandemic introduced unprecedented volatility in consumer behavior, global supply chains, and economic activities, resulting in substantial forecasting errors across industries. Many forecasting models, which relied heavily on historical demand patterns, struggled to capture sudden changes in purchasing behavior and market conditions. Consequently, forecast accuracy declined sharply, with many organisations experiencing forecast errors that exceeded historical averages. Prediction accuracy deteriorated significantly as uncertainty increased and traditional forecasting assumptions became less reliable. Njuguna & Ismael (2017) summarised that the bullwhip effect caused by the vulnerability in the supply chain posed a challenge to maintaining demand forecasting performance where minor fluctuations in consumer demand are progressively amplified as they move upstream through the supply chain. They further emphasised that the adoption of highly accurate forecasting techniques combined with collaborative information sharing across supply network is imperative to reduce order-quantity variability and protect downstream operational performance.

Although forecasting performance began recovering in 2021 and 2022, organisations continued to face challenges arising from supply chain disruptions, inflationary pressures, geopolitical tensions, and changing consumer preferences. During this recovery period, forecast accuracy remained below pre-pandemic levels as firms adjusted to new market realities and adopted more flexible forecasting approaches. From 2023 onwards, demand forecasting performance improved considerably due to advancements in artificial intelligence (AI), machine learning (ML), cloud-based analytics, and real-time data integration. Modern forecasting systems increasingly utilize external market signals, customer behavior data, weather information, and economic indicators to improve predictive accuracy (Coroneo et al., 2023; Ahaggach et al., 2024).

Current oil demand forecasting has improved significantly when modern machine learning approaches incorporate dominant country drivers, especially during volatile

periods. Ditzen, et al. (2026) recognised that with the United States as a global driver and France/Japan as regional hubs, there are statistically significant forecast improvements over traditional autoregressive benchmarks and country-specific models, particularly during increased global volatility. In the oil and petroleum industry, demand forecasting remains particularly challenging because demand is affected by numerous external factors, including global crude oil prices, economic growth, exchange rate fluctuations, government policies, environmental regulations, and geopolitical events. As a result, forecasting performance in the petroleum sector often shows greater volatility than in other industries (Awijen et al., 2025). This challenge highlights the importance of organisational capabilities such as supply chain innovation agility, which allows firms to respond swiftly to market changes and enhance forecasting effectiveness. Organisations with agile forecasting systems, flexible processes, advanced technologies, and strong customer intelligence capabilities are better equipped to sustain forecasting accuracy under uncertain market conditions (Klee & Xia, 2025). According to Saha et al. (2024), artificial intelligence applications in demand forecasting boost scalability, responsiveness, and accuracy, thereby improving supply chain performance. This suggests that innovation agility is becoming a vital factor in determining forecasting success in modern supply chains.

The primary problems facing oil demand forecasting in Africa include the continent's rapidly changing energy landscape and insufficient refining capacity to meet projected demand. Africa's refined oil products demand is projected to increase from about 4 million bpd in 2024 to over 6 million bpd by 2050, with gasoline consumption expected to exceed 2.2 million bpd and diesel consumption increasing by about 880,000 bpd. Current forecasting models struggle with Africa's unique dynamics, including population growth, infrastructure expansion in countries like Angola, Zambia, DRC, and Zimbabwe, and the interplay between increasing domestic production and refining capacity additions of approximately 3 million bpd during the forecast period (OPEC, 2025; African Energy Chamber, 2026).

1.1.5 Oil Marketing Companies

Oil marketing companies are firms that are contained in the energy industry, and their main goal is to produce and distribute oil to the world’s population. This industry is among the largest that contributes to the world’s revenue of about five trillion dollars.

Oil is essential to the world's economy as it influences every aspect of the economy, from transport, electricity production and distribution, manufacturing and also prices of goods and services (Burclaff, 2005a)

Oil marketing industry is categorised into three sections; Upstream which involved the first process of oil discovery where the companies involved explore and produce by recognising reservoirs and drilling oil and gas mines, midstream which is majorly responsible for distribution and transportation of the oil and gas from the mining area to the refineries and downstream which covers refining and marketing (retail and wholesale distribution) of the finished products to the final consumers that is, government, businesses and public consumers (McClay et al.,2022). The energy sector has slow innovation rates since the technologies adopted are vast, complex and last over a particularly long time (International Energy Agency (IEA), 2019).

The oil marketing companies are undergoing significant changes and facing considerable uncertainty in their business environment (Bergman-Fonte et al., 2023). The COVID-19 pandemic has drastically altered energy demand, leading to fluctuating oil prices, rising exploration and production costs, and technological advancements that are transforming the industry (Shuen et al., 2014; García-Amate et al., 2014). Additionally, challenges such as a limited global carbon budget, the ongoing energy transition, and shifts in consumer practices and expectations are pressing issues for the sector (Bergman-Fonte et al., 2023). This situation arises as companies are under intense pressure to boost shareholder returns while minimising social and environmental impacts, which adds to the uncertainty and disruption in the business environment, impacting their ability to manage these challenges (Shuen et al., 2014; García-Amate et al., 2014). To achieve success and sustainability, the industry must undergo a comprehensive transformation rather than incremental changes (Shuen et al., 2014) identifies several key aspects of oil and gas supply chain design, including strategic vision, competitive strategies, core competencies, organisational processes, and structures.

Lisitsa et al. (2019) outlined strategies that could be used to improve supply chains in the oil industry, highlighting how enhanced logistics can boost efficiency. The application of supply chain management techniques is ideal for the oil industry as it operates globally and requires the incorporation of domestic and international

transportation, inventory control, material handling, and information technology. Growing global demand has increased supply chain complexity, which has provided opportunities for efficiency improvements and cost reductions. Supply chain management software is essential for optimising transportation, warehousing, and inventory management, thereby enhancing overall efficiency and competitiveness(Oke, 2020).

In Kenya, the oil marketing companies are regulated by the Energy Act of 2019 and the Petroleum Act of 2019. These parliamentary acts provide policies and guidelines for oil companies for the establishment of the oil marketing firms and provide regulations for the production, supply and use of Oil, gas and other energy sources. The Energy and Petroleum Regulatory Authority oversee the importation and exportation of electricity and the regulation of upstream oil (World Bank, 2021). The recent discovery of oil deposits in Turkana has urged the growth and development of the area, and in 2019, the country was able to make its first crude oil exportation that garnered Ksh. Twelve (12) billion in the global markets (Kenya Bureau of Statistics, 2020).

The EPRA (2023) report highlighted that 62% of the country's oil was from the domestic market, while the rest (38%) was imported. This is further highlighted by Statista (2025) that Kenya uses about 4.3% of the Gross Domestic Product (GDP) on importation of refined petroleum, implying that Kenya is heavily reliant on oil imports, which make it vulnerable to shifts in global crude oil prices and supply chain disruptions. In 2023, the Kenyan government veered away from the use of open tender systems (OTS) to local, which caused a great depreciation of the Kenyan Shilling and supply reduced; hence, companies were not able to meet the ultimate demand of the customers. Methodological trends in the Kenyan industry suggest a transition from intuitive and naive forecasting toward more robust econometric and machine learning models to improve accuracy, and Lumumba et al. (2024) reported that naive models for petroleum-related forecasting in Kenya often yield an MAPE of approximately 26.8%, indicating a substantial margin of error that necessitates advanced intervention.

The petroleum development plan report developed by EPRA (2025) outlined the updated plans for demand forecasting and showed that the period 2020–2021 was particularly challenging for forecasting performance. COVID-19 restrictions sharply

reduced transport activity, aviation fuel consumption, and industrial fuel demand, creating deviations between pre-pandemic forecasts and actual consumption levels. Demand recovered gradually in 2021 as economic activity resumed; however, forecasters had to continually revise assumptions regarding mobility, tourism, and industrial production. Such conditions typically increase forecast error because historical consumption patterns become less reliable predictors of future demand.

In the downstream petroleum sector of Kenya, firm size often dictates the baseline volume of tangible and intangible strategic assets a company controls. According to RBV, larger oil marketing companies (OMCs) can leverage substantial internal resources such as proprietary software, high-capacity retail networks, and specialised data analysts to enhance baseline operational output (Mukuusi, 2019; Owulaku & Tetteh, 2022). However, because the Kenyan fuel market is subject to intense environmental shocks such as regulatory price caps enforced by the Energy and Petroleum Regulatory Authority (EPRA), unpredictable global crude fluctuations, and localised currency devaluations, static resources alone are insufficient (Kyalo & Wachiuri, 2024).

EPRA report (2024) posited that petrol demand forecasts use assumptions about vehicle population growth, which serves as a key driver of demand projections, where forecasters had to account for elevated fuel prices and exchange-rate depreciation, both of which affected consumption behaviour and purchasing power. The IEA (2025) reports that global oil demand growth was beginning to moderate due to slower economic growth and increasing adoption of alternative energy technologies. Therefore, for Kenyan oil marketing companies, this meant that forecasting systems had to balance domestic growth drivers with emerging structural changes in global fuel consumption patterns.

1.2 Statement of the Problem

The petroleum sector is foundational to Kenya's economic architecture, heavily driving industrialisation, infrastructure, and transport logistics hereby contributing significantly to economic growth (Wambui et al., 2020; Mose, 2022). Oil Marketing Companies (OMCs) are expected to achieve high levels of demand forecasting performance, effectively minimising the variances between projected and actual product consumption. Accurate demand planning is crucial for optimising safety stock

levels, containing inventory holding costs, preventing costly retail stockouts, and ensuring seamless downstream distribution (Kyalo & Wachiuri, 2024; Seroney, 2019). Despite its critical importance, the domestic downstream oil industry has been plagued by extreme volatility and operational inefficiencies characterised by significant external shocks, including severe global crude oil price fluctuations, COVID-19 pandemic disruptions, currency depreciations, and aggressive domestic regulatory price-capping mechanisms (Kikanga et al., 2024; Mutuku, 2023). The oversupply resulting from a fall in global demand led to price instability and market imbalances. These global dynamics had direct consequences for Kenya, where the demand for petroleum products has also fluctuated and as Mwape et al. (2024) further stated, the lack of adequate storage, distribution systems and policy preparedness are some of the issues that have led to East African countries, Kenya and Tanzania, to be unprepared for disruptions as evident during the COVID-19 pandemic. The domestic demand for petroleum products has varied significantly, as reflected in EPRA reports from 2020 to 2024, which show fluctuations in demand. In 2020, it reduced by 9.6%, in 2021, it increased by 2.83%, in 2022 reduced by 3.01%, in 2023, it reduced by 2.10%, and in 2024, it increased by 7.12%. The downstream petroleum sector continues to rely on calendar-based, reactive approaches that fail to integrate real-time telemetry, market sentiment, or macroeconomic variables (Onwong'a et al., 2026). The persistent gap between predicted and realised demand leads to structural supply imbalances, localised fuel crises, and escalating operational expenses. To navigate volatile energy environments, OMCs should leverage innovative agile supply chains by integrating innovation within their network structure, business processes, technology and customer-centric modernisation. Furthermore, demand forecasting execution should be structurally supported by firm size as it is likely to influence how firms incorporate and respond to innovation integration and demand fluctuations through differences in resources, capabilities, and operational scale (Kyalo & Wachiuri, 2024). Previous studies have largely focused on supply chain practices, forecasting techniques, and firm performance independently, with limited attention given to how supply chain innovation agility influences demand forecasting performance (Shalakha, 2015; Seroney, 2019). Despite the growing adoption of supply chain innovation agility, oil marketing companies in Kenya continue to experience challenges in achieving accurate demand forecasts, and similarly, existing studies provide limited evidence on how firm size moderates the relationship between supply chain innovation agility and

demand forecasting performance. The combined influence of these factors remains unclear, creating a knowledge gap that warrants empirical investigation to provide insights that can enhance forecasting accuracy and improve supply chain efficiency within the Kenyan oil marketing sector.

1.3 Objectives of the Study

1.3.1 General Objective

To examine the influence of supply chain innovation agility, firm size on demand forecasting performance of Oil Marketing Companies in Kenya.

1.3.2 Specific Objectives

i. To analyse the influence of business process innovation on demand forecasting performance of oil marketing companies in Kenya
ii. To examine the influence of technological innovation on demand forecasting performance of oil marketing companies in Kenya
iii. To assess the influence of network structure innovation on demand forecasting performance of oil marketing companies in Kenya
iv. To establish the influence of customer-centric innovation on demand forecasting performance of oil marketing companies in Kenya
v. To determine the moderating effect of firm size on supply chain innovation agility on demand forecasting performance of oil marketing companies in Kenya

1.4 Research Hypotheses

H_{01} Business Process Innovation does not have a significant influence on demand forecasting performance of oil marketing companies in Kenya

H_{02} Technological innovation does not have a significant influence on demand forecasting performance of oil marketing companies in Kenya

H_{03} Network structure innovation does not have a significant influence on demand forecasting performance of oil marketing companies in Kenya

H_{04} Customer-centric innovation does not have a significant influence on demand forecasting performance of oil marketing companies in Kenya

H_{05} Firm size does not significantly moderate the relationship between supply chain innovation agility and demand forecasting performance of oil marketing companies in Kenya

1.5 Significance of the Study

This section highlighted and justified the value of the study and how the research outcomes can benefit various stakeholders in order to influence practice, inform future research, support policy formulation or improve industry operations.

1.5.1 Public and Private Organisations

These organisations gain evidence-based guidance on fostering collaboration, innovating infrastructure, and implementing policies that enhance supply chain responsiveness and forecasting accuracy. The study will provide evidence on how innovative and agile supply chain practices enhanced operational efficiency, forecasting accuracy and responsiveness to market fluctuations. Public organisations will be able to apply the results to improve policy implementation, regulatory compliance, and service delivery, while private firms will apply the insights to strengthen competitiveness, optimise inventory management, and improve customer satisfaction. The findings will also help these organisations design strategic interventions to improve overall supply chain efficiency and competitiveness in the oil marketing sector.

1.5.2 Future Researchers

Researchers will gain a strengthened academic foundation, updated empirical data, and a theoretical framework that future scholars can expand upon in related fields such as innovation capability, demand forecasting, and supply chain resilience. They will be able to expand the body of knowledge on supply chain management and organisational agility, particularly within the context of the oil and petroleum industry in developing economies. The findings will identify key variables and relationships that can inform further research, enabling scholars to develop advanced models and innovative approaches tailored to shifting market conditions in oil marketing.

1.5.3 Suppliers and Business Partners

They will be able to gain critical awareness of the operational factors that drive supply chain agility and forecasting accuracy. They will understand how agility within the

network structure can improve coordination, reduce delays, and enhance mutual value creation across the supply chain. Suppliers will recognise the drivers of innovation agility; they can optimise their processes, strengthen communication and coordination with oil marketing companies, and enhance their role in a more agile and demand-responsive supply chain network. The study will also help the partners to appreciate how timely information sharing and adaptive collaboration support can better demand alignment and reduce operational inefficiencies.

1.5.4 Policy Makers

The study will assist in the development of regulatory and innovation frameworks and policy measures on supply chain innovation and forecasting performance. This will contribute to equipping the policy makers in formulating supportive policies that encourage innovation and technological adoption in the petroleum sector, promote efficient supply chain systems, and create enabling environments that stimulate a robust, agile oil marketing supply chain in Kenya. The insights will also guide the formulation of frameworks aimed at promoting sustainable energy distribution and improved demand forecasting practices within Kenya's regulatory landscape.

1.6 Scope of the Study

This study examined the influence of supply chain innovation agility on the demand forecasting performance of oil marketing companies in Kenya. It utilised a population of 145 oil marketing companies registered by EPRA to operate within the country. The research explored four dimensions of supply chain innovation agility: business process innovation agility, technology innovation agility, network structure innovation agility, and customer service innovation agility, as the independent variables, while demand forecasting performance was the dependent variable. Additionally, the study included firm size, measured by market share, as a moderating variable, acknowledging that different firms possess diverse resources, infrastructure, and coordination capacity that could either strengthen or weaken the relationship between innovation agility and demand forecasting performance. The unit of observation was the supply chain officers in licensed oil marketing companies, while the unit of analysis was the OMCs. The study adopted a descriptive research design and purposive sampling, utilising primary data on SCIA and secondary data collected between 2021 and 2024, which was the only data available on demand that was provided by EPRA. This period was

characterised by increased market competition, digital transformation, and evolving supply chain practices within Kenya's petroleum sector.

1.7 Limitations of the Study

The study adopted a four-point Likert scale, which limits respondents to either positive or negative responses without a neutral option. This forced respondents to choose sides even when they are uncertain or indifferent. The study deliberately adopted a four-point Likert scale to encourage respondents to take a definite position on each statement. This design choice was intended to minimise indecisive responses and obtain more decisive opinions that reflect the participants' perceptions more clearly. The study further used qualitative follow-up questions to validate and complement quantitative findings, allowing participants to explain uncertain responses. The use of descriptive design also played a role as a limitation to the study, which prevented the study from examining changes, patterns, or causal relationships between variables over time. This was reduced by the adoption of moving averages in analysing the secondary data, which provides a single point which could then be used to analyse volatility. The study used a purposive sampling where only 81 respondents were selected. This could reduce the statistical power and may limit the ability to generalise findings to the entire population of oil and petroleum firms. This was resolved by using a selected sample size that was determined by the accessibility to their individual demand consumption from 2021-2024, ensuring feasibility while maintaining representativeness of the sector.

1.8 Assumptions of the Study

The study assumed that the management of oil marketing companies (OMCs) in Kenya invests in innovation or agility based on calculated efforts to improve their demand forecasting and overall performance, rather than by random chance or external coercion alone. The OMCs maintain accurate and consistent historical records of sales, stock levels, and market trends. It also assumed that the respondents had a clear and honest understanding of their firm's internal processes and would provide truthful, unbiased information during data collection.

The study presumed that the Kenyan petroleum market was dynamic and subject to fluctuations based on factors such as changes in global crude prices, regulatory shifts

by EPRA, taxation policies, local infrastructure challenges and macroeconomic conditions. The study assumed that these factors apply uniformly across oil marketing companies in Kenya and therefore do not disproportionately bias the relationship under investigation.

The study also presupposed that the size of an OMC is a valid indicator of its resource capacity. It assumes that larger firms have different structural capabilities, such as larger IT budgets or more specialised personnel, compared to smaller independent players. The study assumed that differences in firm size affect technological capability and managerial capacity, which influence how supply chain innovation agility influences demand forecasting performance.

The study postulated that oil marketing companies operating in Kenya have implemented supply chain innovation agility practices such as process innovation, technology adoption, network coordination, and customer-focused innovations and that they are understood and applicable across the various OMCs operating in Kenya.

1.9 Contributions of the Thesis

The study highlighted that not all innovations are equally effective, and their efficiency can vary significantly, suggesting that understanding customer needs and fostering strong external relationships are critical for accurate market prediction, regardless of a firm's internal structure or size. The study indicates that smaller oil marketing companies may derive relatively greater benefits from technological innovation in demand forecasting. Their integral agility and fewer legacy systems might enable faster adoption and more effective integration of new forecasting technologies, allowing them to respond more rapidly to market changes.

In systems theory, the study highlighted that while individual innovations, customer centricity, and network structure work in isolation, their impact changes when the organisation is expanded to include firm size and interaction terms. This affirms that demand forecasting is a systemic outcome and highlights that changing one part of the system has different results depending on the scale of the system or firm. The study also establishes dynamic capability theory by illustrating how firms can organise their innovation strategies based on size, emphasising that firms cannot rely on technology or processes alone, and must possess the dynamic capability to adjust these

innovations as the organisation grows, or risk the negative performance impacts seen in the interaction terms.

The study also reinforces network theory, that reconfiguring external relationships directly translates to better demand performance. When a firm leverages its network position, the flow of information, trust and shared resources within the network, it gains superior market insight. Therefore, a strong network allows for better information exchange with customers and partners, which is crucial for accurate demand forecasting. The study further affirms that innovations are complex and require bundles of resources that are difficult for competitors to replicate, contributing to the firm's performance advantage. This aligns directly with RBT's that a firm's ability to innovate requires core resources for achieving perceived performance.

This study offers empirical evidence on how oil marketing companies can enhance their ability to forecast and react to fluctuations in petroleum demand and supply. Examining how different supply chain innovation agility elements improve demand forecasting, the study can identify specific agile innovations that enable oil firms to adapt swiftly to market uncertainties through advanced technologies, data analytics, collaborative planning, and flexible supply chain processes. Better forecasting accuracy can reduce stockouts, avoid overstocking, and support timely replenishment decisions, thereby boosting fuel availability and market stability during crises. For Kenya, where the economy heavily relies on petroleum products for transportation, manufacturing, and power generation, such insights can help oil marketers, regulators, and policymakers strengthen supply chain resilience and lessen the adverse effects of fuel shortages and price volatility.

1.10 Organisation of the Thesis

Chapter One focused on the relevant background information on supply chain innovation agility, firm size and demand forecasting performance, and their correlation. The chapter identified the problem the research sought to solve, the objectives that linked to the solution, the significance, limitations and the contributions of the study.

Chapter Two highlighted the theories on which the study was based. It also reviewed the literature on supply chain innovation agility variables, and firm size, and a critique

of the literature review. The chapter included a conceptual framework and an operational framework.

Chapter Three presented the research design the study embodied, the sampling design and procedure adopted, the population being investigated, the instruments used in research, the basis for analysis and presentation and the ethical issues that the research considered.

Chapter Four discussed data analysis and presentation, through percentages and means, standard deviations for the descriptive analysis, diagnostic tests for regression assumptions, Correlation for the strength and direction of the relationship between the variables, simple and hierarchical regression to test for the degree of influence, hypotheses and moderation.

Chapter five focused on the summary and conclusion of the findings for each objective, recommendations for policy, management and further research attained from the results of the study.

CHAPTER TWO
LITERATURE REVIEW

2.1 Introduction

This chapter critically analysed the theories that supported this study. The chapter also provided an in-depth review of the variables used in the study. It provided a structure for understanding the concept. It included an empirical review, which illustrated the research gaps and the structural representation of the conceptual framework.

2.2 Theoretical Literature

The study was anchored on four theories that expound on the application of agile supply chain innovation to improve demand forecasting performance. These theories include: dynamic capability theory, systems theory, network theory and resource-based theory (RBT).

2.2.1 Dynamic Capability Theory

The Dynamic Capabilities (DC) Theory was initially formulated by Teece et al. (1997), which addresses the limitations of the Resource-Based View by focusing on a firm's ability to purposefully adapt, renew, and reconfigure its resource base in response to rapidly changing environments. Dynamic capabilities enable organisations to integrate, build, and reconfigure internal and external competencies to sustain competitive advantage in dynamic markets. This theoretical framework recognises a hierarchy of capabilities, distinguishing between ordinary operational capabilities that maintain current business processes and dynamic capabilities that facilitate strategic renewal through sensing opportunities, seizing them via strategic action, and transforming organisational assets (Teece et al., 1997; Nayernia, 2025). The theory also emphasises micro-foundations; managerial cognition, routines, and coordination mechanisms, that enable firms to navigate complexity proactively and sustain innovation-led performance (Nayernia, 2025).

According to Kowshik et al. (2025), knowledge processes form the foundation of dynamic capabilities through what they describe as Knowledge-Based Dynamic Capability (KBDC). The study positions the Knowledge Management Process (KMP), knowledge creation, storage, transfer, and application, as preconditions for developing these capabilities. Among them, knowledge transfer plays a central role in

strengthening absorptive capacity, promoting innovation, and enhancing organisational embeddedness across international networks. The findings show that embeddedness enables knowledge sharing and capability development, while geographical and cultural distances are no longer major constraints due to technological advances. By integrating KMP and DCT, the study reframes knowledge as a dynamic capability that drives learning, agility, and competitiveness, particularly in global contexts where continuous adaptation and resource reconfiguration are vital for long-term success.

DC Theory has been extended into the digital and artificial intelligence (AI) landscape, highlighting how firms cultivate digital adaptability as a form of dynamic capability. Digital adaptability encompasses perceptual adaptability, which relates to keen insight into technological and market shifts, social adaptability, which enhances collaboration and user interaction, and productive adaptability for process optimisation and automation. AI acts as an enabler by augmenting these dimensions, thereby enhancing firms' strategic responsiveness, innovation capabilities, and competitive positioning. For instance, AI-powered data analysis improves perceptual adaptability by enabling firms to detect market trends and customer needs in real time, while social adaptability fosters continuous product evolution through real-time user feedback (Gao et al., 2025). Production adaptability benefits from AI's ability to execute autonomous tasks and optimise operations, increasing innovation efficiency and new product development cycles. Integrating responsible innovation into the dynamic capability framework introduces ethical and sustainability considerations into innovation management. Responsible innovation involves anticipating and mitigating social and environmental risks while engaging stakeholders inclusively throughout the innovation process. This approach aligns with the growing demand for sustainable competitive advantage and the fulfilment of global Sustainable Development Goals (SDGs). Dynamic capabilities thus not only enable digital innovation but also empower firms to embed responsible innovation practices, enhancing legitimacy, social value, and long-term competitiveness in an increasingly agile and ethically conscious business environment (De la Torre & De la Vega, 2025).

Despite its widespread use, DC Theory faces critiques, particularly regarding definitional ambiguity and challenges in operationalising its constructs across

contexts. However, the theory can be enhanced by developing empirical models that can differentiate between ordinary and dynamic capabilities. This will assist in clarifying causal pathways linking dynamic capabilities, innovation, and firm performance. Bridging DC Theory with contemporary issues such as AI adoption, digital transformation, and responsible innovation enriches the framework's relevance for current and future business challenges. These advances form a robust and evolving theoretical framework that supports strategic agility, innovation excellence, and sustainable competitiveness in turbulent environments (Nayernia, 2025; Gao et al., 2025; De la Torre & De la Vega, 2025).

This theory explains how firms constantly adjust and reorganise their operations and resources to improve their ability to respond, stay flexible, and innovate. These qualities are important when dealing with the complexity and uncertainty of global supply networks. The Dynamic Capabilities Theory (DCT) focuses on basic processes such as coordination, learning, and adaptation. These processes are key in supply chains that depend on real-time information, teamwork in solving problems, and aligning technology with strategy. Integrating operational agility with long-term strategic renewal, DCT offers a clear way to understand how firms develop supply chains that are strong, adaptable, and capable of continuous innovation and competitiveness. Digital flexibility and knowledge sharing form part of an organisation's dynamic capabilities that strengthen supply chain innovation by improving how firms sense market changes and reorganise their resources (Gao et al., 2025).

Dynamic capabilities further support demand forecasting performance through organisational learning and innovation. As firms accumulate experience and knowledge from past forecasting outcomes, they develop the capacity to refine forecasting models and respond proactively to demand uncertainties. This continuous learning process enhances forecast accuracy, inventory optimisation, and customer service levels. According to Wilden and Teece (2021), organisations that can rapidly reconfigure resources and technologies in response to market changes are more likely to achieve superior forecasting outcomes than firms relying on static forecasting systems. Therefore, DCTs provide a useful framework for explaining how

organisations enhance demand forecasting performance in volatile and uncertain business environments.

In developing countries, the applicability of DCT is constrained by infrastructural deficiencies, limited technological adoption, inadequate investment in research and development, and shortages of skilled personnel. Many firms, especially small and medium-sized enterprises, lack the financial and technological resources required to sense market changes and rapidly reconfigure operations in response to demand fluctuations. Additionally, institutional weaknesses, regulatory uncertainty, and volatile economic conditions may hinder the development of dynamic capabilities, reducing the theory's explanatory power in such contexts (Teece, 2018). Consequently, the assumptions underpinning DCT may not fully reflect the realities faced by firms operating in emerging markets.

Irrespective of these limitations, the theory remains suitable for explaining supply chain innovation agility because innovation agility reflects an organisation's capacity to rapidly adopt new technologies, processes, and practices in response to environmental changes. Dynamic capabilities provide the mechanisms through which firms continuously innovate, learn, and transform their operations to improve forecasting accuracy and responsiveness. Through sensing and reconfiguring capabilities, firms can integrate advanced forecasting tools, real-time market intelligence, and digital supply chain technologies that support more accurate demand predictions (Teece, Peteraf, & Leih, 2016).

2.2.2 Systems Theory

Systems theory is also known as social systems theory, and it entails the study of complex processes and their interaction with each other (Bertalanffy, 1972). Bertalanffy (1968) advocated for open systems since organisations, both biological and social, require an interaction with the environment to provide inputs necessary for production and sustainability. This makes open systems more flexible for improved output through synergies created by the interaction and collaboration of systems. These elements include inputs, outputs, process and feedback. Systems theory perceives an organisation as a system of interconnected elements that, when linked together generates goods and services. It relies on the mutuality between the different processes in an organisation. The mutuality in this theory includes: i) Pooled, where

every element produces an apparent contribution that is supported by the whole, ii) sequential, where one element completes its contribution before the other takes action, iii) reciprocal, where the output of one element acts as the input of the other (Shook et al., 2009).

Systems theory dominance as a supply chain theory occurred in the 1950s and was used to explain how the supply chains of different organisations work. The theory elaborates on the relationship between the supply chain system components to attain a better comprehension of the value that the supply chain provides. It abridges the complex structures and identifies the stakeholders of the organisation (Lavassani & Movahedi, 2010). The application of systems theory in supply chain requires an integral review of the systems theory properties and their correlation with the supply chain. These properties include: i) Holistic that supply chain is considered a system that comprises of interdependent elements such as suppliers, customers, logistics ii) Complexity and uncertainty that organisations should adhere to making their supply chain agile and resilient enough to be flexible in case of changes in demand, disruptions and price fluctuations iii) Integration and collaborations that organisations need to work together with their supply chain partners to regulate flow of information and feedback (Helou & Cady, 2006)

Systems theory is highly effective for business process innovation because it views organisations as interconnected systems composed of multiple interrelated components. It emphasises the importance of considering both internal and external factors that influence business processes. The theory encourages organisations to be agile and responsive to external stimuli, such as customer demands, technological advancements, and competitive pressures. By adopting this theory, business process innovation becomes not only about improving internal operations but also about aligning with the broader ecosystem in which the business operates. This alignment helps companies stay competitive and adaptable, creating innovation that is resilient and forward-looking.

Systems Theory dictates that demand forecasting performance cannot be treated as an isolated mathematical task; it is an integrated subsystem that processes environmental inputs and feeds output parameters directly into procurement and distribution (Mitra et al., 2022). Without systematic cross-functional synchronisation, local OMCs suffer

from massive information distortion, leading to costly stockouts or localised fuel gluts (Mwaura & Mang'ana, 2024). By viewing supply chain innovation agility through a systems perspective, researchers can evaluate how OMCs integrate modern tracking mechanisms and unified inventory systems across retail and wholesale channels to lower systemic friction and keep the broader organisation aligned with true market consumption patterns.

In developing countries, Systems Theory faces contextual limitations because organisations often operate within fragmented and poorly integrated systems. Many firms experience inadequate information-sharing mechanisms, weak digital infrastructure, unreliable data systems, and limited coordination among supply chain partners. These challenges undermine the interconnectedness assumed by Systems Theory and reduce the effectiveness of system-wide decision-making processes. Moreover, external factors such as inconsistent government policies, infrastructure bottlenecks, and market volatility can disrupt organisational systems, making the theory less effective in explaining performance outcomes in developing economies (Mele, Pels, & Polese, 2010).

However, systems theory dictates that highly integrated systems may increase organisational complexity, bureaucracy, and coordination costs, thereby reducing efficiency (Checkland, 1999). Additionally, excessive interdependence among system components can create vulnerability, where disruptions in one area negatively affect the entire system. These conflicting findings suggest that integration does not always generate positive outcomes and that the effectiveness of systems approaches may depend on contextual factors.

Regardless of these limitations, the theory emphasises that organisational outcomes result from the interdependence of various subsystems, including procurement, inventory management, marketing, transportation, information systems, and customer service. This theory helps explain how business process innovations facilitate coordination and information integration across the supply chain. This systems perspective enables researchers to understand forecasting performance as an outcome of interconnected organisational and environmental factors rather than isolated activities

2.2.3 Network Theory

Network theory is concerned with the ability of an organisation to understand relationships between different members of the supply chain. These members include stakeholders such as suppliers, customers, governments and also the community. The theory assists in providing information to stakeholders on which organisations are lucrative enough to form relationships or alliances with and to engage with (Shook et.al. 2009). The theory focuses on how organisations can create value through multiple relations with different organisations within their environment. It emphasises that effectiveness in the network grows with the increase in diversity, size and range of the network. The relationships enhance the organisations' resource capabilities and individual competencies (Lavassani & Movahedi, 2010). It views organisations as complex networks where resources, information and opportunities are created and shared. It uses graphs to represent the direct and indirect relationships among actors and objects in the supply chain networks. The complex networks form a structural framework that can be used by organisations to determine how networks can grow and sustain by integrating innovations.

The network theory has been used to make decisions in different aspects of the supply chain. Demand planning and make or buy decision where network theory takes into consideration the supply network by locating the firms for production or assembly to enhance information dissemination and flow of resources. It is used to elaborate on their supply capability of meeting customer needs either through in-house production or purchasing from external organisations. The other decision is based category strategy where organisations are assured of the supply of critical goods, and information on technology is shared through relationships. The third decision in supplier selection shows that relationships create value addition, knowledge transfer and competitive advantage. The fourth decision is in contract awards, which emphasises long-term contracts to facilitate future supply of critical goods (Wellenbrock et al., 2013).

Network theory helps organisations restructure their networks in ways that enhance the flow of information, resources, and services, creating more dynamic, adaptable systems that support long-term innovation and growth. This makes it ideal for network structural innovation because it focuses on understanding the relationships and

interactions between various partners in a network. Analysing these connections, businesses can identify key influencers, bottlenecks, or underutilised resources, leading to innovative ways to optimise their network's structure. This can result in more efficient communication, improved collaboration, and the ability to leverage critical partnerships or hubs within the network (Newman, 2018)

For customer service innovation, network theory offers a powerful lens by analysing customer relationships and interactions within a broader ecosystem. This improves how organisations engage with customers, and businesses can enhance service responsiveness, foster loyalty, and anticipate customer needs more effectively. It also highlights opportunities for peer-to-peer support systems, enabling customer-driven innovations through shared knowledge and community interaction, resulting in a more robust, decentralised customer service model (Barabási, 2016).

Network Theory highlights that demand forecasting performance is heavily contingent upon relational density and information integration across these distinct nodes. By leveraging collaborative network structures and deploying advanced predictive frameworks—such as neural networks or hybrid machine learning models—across multi-stage supply chains, firms can effectively mitigate structural inefficiencies (Aldahmani et al., 2024). Ultimately, strong network connectivity and inter-firm synchronisation enable rapid data exchange, which stabilises supply chain fluctuations and optimises collective inventory asset efficiency.

The theory also faces significant contextual weaknesses in developing countries, where supply chain networks are often characterised by information asymmetry, weak institutional frameworks, low levels of trust, and limited technological connectivity. Many firms, particularly in the oil and petroleum sector, may lack the collaborative culture and digital platforms necessary to facilitate effective information sharing among supply chain partners. Additionally, unequal power relationships between large and small firms can limit the benefits derived from network participation, reducing the practical applicability of the theory in emerging economies (Zaheer, Gözübüyük, & Milanov, 2010).

While strong network relationships are generally associated with improved information flow and performance, some studies suggest that overly dense networks

can lead to redundancy, reduced innovation, and groupthink. Firms embedded in highly interconnected networks may become dependent on existing relationships and less responsive to new opportunities (Burt, 2004). Although Network Theory has been criticised for overemphasizing external relationships, the theory is particularly relevant in explaining supply chain innovation agility because innovation often emerges through collaboration and knowledge sharing among supply chain partners. Agile firms are more likely to establish strong networks that facilitate rapid access to market intelligence, technological innovations, and customer demand information. Such networks enable organisations to anticipate market changes more effectively and adjust forecasting processes accordingly, thereby improving forecasting accuracy and responsiveness (Kache & Seuring, 2017).

2.2.4 Resource-Based Theory (RBT)

Resource-Based Theory is a managerial framework that determines strategic resources and how an organisation can exploit them to achieve a competitive advantage. It focuses on how these resources will be deployed and made available to achieve sustainability. The main elements of RBT include tangible and intangible resources and capabilities, where innovation in this context falls in the intangible and capabilities sector. RBT contributes to the investment in technology and innovation to meet organisational goals (Akhter et al., 2018). Therefore, this theory will be used to elaborate on technological innovation. Lavassani & Movahedi (2010) underscored that RBT is primarily concerned with the economic aspects of an organisation's operations and emphasises the importance of value systems and knowledge as factors of production in organisations. It is described in two different schools of thought: Classical, where competitive advantage is achieved through acquisition of organisational economic resources and Modern, where RBT is viewed as an organisational process that promotes growth.

Different stakeholders with a supply chain network aspire to acquire production elements that provide them with a niche against their competitors. Resources in RBT provide strategic advantages through: i) value creation by reducing input costs that influence the total cost of manufacturing, ii) resources could be specific to the organisation, which may not be available outside the organisation, and iii) resources are asset based and they cannot be developed at once thus requiring an accumulation

of input over years (Akhter et al., 2018). RBV further explores that a firm becomes proactive in its sourcing activities by outsourcing in order to seek, explore and transfer knowledge and resources from external partners to the internal controls of the organisation. The relationships accrued from such negotiations avail resources that are imperative for an organisation's sustainability and competitive advantage (Shook et al., 2009).

RBT is highly effective for driving technological innovation because it emphasises leveraging a firm's unique internal resources and capabilities to gain a competitive advantage. This theory's focus on firm-specific assets as drivers of technological advancement helps businesses build and sustain competitive advantages in fast-evolving industries. Focusing on internal resources, businesses can better manage their innovation processes, ensuring that new technologies are not only novel but also aligned with their operational capabilities and market needs.

Firms require technological infrastructure, financial resources, human expertise, and organisational knowledge to develop agile supply chain capabilities. RBT explains how organisations leverage these resources to implement innovative forecasting systems, improve information processing capabilities, and respond effectively to changes in market demand. RBT helps explain how firm size, particularly larger firms, generally possess greater resource endowments, including financial capital, technological infrastructure, and skilled human resources, which may enhance their ability to exploit innovation agility for improved forecasting performance. Conversely, smaller firms may rely on unique organisational capabilities and flexibility to achieve similar outcomes (Barney et al., 2021).

While the theory predicts that superior resources lead to superior performance, several studies have found that resource availability alone does not guarantee success. Some firms with substantial resources fail to outperform competitors, whereas resource-constrained firms often achieve superior performance through innovation, agility, and effective management practices (Newbert, 2007). These contradictions suggest that the value of resources may depend on environmental conditions, managerial capabilities, and complementary organisational factors.

Nevertheless, RBT plays a significant role in explaining technological innovation and the importance of incorporating firm size as firms require advanced forecasting technologies, skilled personnel, data analytics capabilities, innovative supply chain processes and organisational knowledge to develop agile supply chain capabilities, which are critical determinants of demand forecasting performance.

2.3 Empirical Literature Review

2.3.1 Business Process Innovation and Demand Forecasting Performance

Dumas et al. (2018) defined business process as a set of coordinated tasks and workflows, triggered by specific events and managed by various actors, to achieve a defined organisational goal for an end-user. Its development and implementation not only improve efficiency, consistency, and quality but also reduce costs and risks. Business processes occur at all organisational levels, which can be visible to the customer or not. Process innovation is a combination of facilities, skills, and technologies used to produce, deliver, and support a product or provide a service. Business processes are categorised into: i) Management Processes: Planning, organising, coordinating and controlling all management functions, ii) Operational Processes: Core business of the organisation and creates the primary value stream. Supporting Processes: Support the core process for better functionality (Differential, 2020).

Organisations need to respond to market changes by incorporating new ideas into their business processes, which can be complex, dynamic, interactive, and socially constructed, and focusing more on the people. There are extensive studies on process innovation capability or structured business process; however, the study on business process innovation incorporation for demand management is still a point of discussion (Vom Brocke et al., 2016). Due to the nature of the business environment riddled by uncertainty and rapid change; shifts in customers' attitudes, implementation of new laws, technology disruption, natural disaster, pandemic, political aftermath, or terrorist attack, organisations must respond to changes by adopting innovation which can either be product, methods, new market, new supply or new form of competition (Bandara et al., 2021).

Process innovation capability (PIC) is defined as a firm's capacity to acquire, assimilate, and transform technical resources, procedures, and knowledge for

innovation purposes (Frishammar et al., 2012). Organisations need dynamic capabilities in sensing, seizing and transforming to enable the organisation to renew resources, assets and common capabilities to innovate and respond to market change (Teece, 2018). Process innovation can include changes in the equipment and technology used in manufacturing, improving the tools, techniques, and software solutions used to assist in the supply chain and delivery system, sales and warehousing techniques and also accounting and customer service methodologies (Differential, 2020).

Technologically advanced business processes are focused on data, which triggers their execution and influences the decisions that lead towards the overall process goal (Koehler, 2018). Due to the widespread availability of data and technology, business process management (BPM) can be incorporated for an AI application. BPM contains activities that could benefit from AI through automating strenuous and repetitive tasks to allow for more human capacity or allowing new and previously unattainable insights into the process. Data availability provides a mechanism to assist researchers in developing new AI methods that support process development, modelling, implementation, monitoring, and optimisation (Koehler, 2018). Business Process is considered the first component in the supply chain innovation model (de Haas & Munksgaard, 2011). Arlbjorn and de Haas (2009) described business processes as a set of measured activities that have been developed to meet a designated output to meet a certain customer's or market needs. It is also defined as a series of interconnected activities to transfer products and information from the buyer to the vendor to provide requested services (United Nations Economic and Social Commission for Asia and the Pacific, UNESCAP, 2009). Business process involves the interaction between people, machines, procedures and guidelines to meet an organisation's goals (Kaniski &Vincek, 2018).

Schniederjans (2018) quoted the definition of business process innovation (BPI)from (Scannell et al., 2000; Wagner and Bode, 2014) as the ability of an organisation to create new processes from the latest technologies in response to or prediction of customer needs. There are two main types of business processes: Incremental, which are minimum improvements to the organisation's processes and Radical, which are all-encompassing improvements to the processes in the organisation (Schniederjans,

2018). These are strategies for innovation in the supply chain that need to be implemented in specified processes to support innovation, where change or full revision of the practice can be done to improve the supply chain (Fornasiero et al., 2021).

BPI increases value creation, improves buyer-supplier relationships and expands the shift in traditional supply chain (Schniederjans, 2018). Eight supply chain processes have been identified by the Global Supply Chain forum: Customer Relationship Management (CRM), Customer Service Management (CSM), Demand management, order fulfilment, Supplier Relationship Management (SRM), return management, product development and manufacturing Flow Management (Arlbjorn and de Haas, 2009).

Liu and Chen (2024) investigated how business process management (BPM) influences environmental performance in heavily polluting industries, highlighting the mediating role of IT capabilities. Their survey included 248 manufacturing managers and experts in China. Structural equation modelling revealed that BPM directly and positively affects environmental performance. Additionally, BPM enhances IT capabilities, which in turn significantly improve environmental outcomes, with IT mediating 45% of the variance. The study underscores that environmental sustainability hinges on deeply integrating IT into core processes. A key limitation is its focus on a single industrial city and reliance on cross-sectional data. Complementing this, Kithinji and Misuko (2022) examined how deliberate organisational innovation strategies impact SME operational performance in Nairobi County, Kenya. They employed a descriptive survey method targeting 398 SMEs, using structured questionnaires and multiple linear regression. Analysing product, service, marketing, and process innovations collectively, their regression results showed all four positively relate to SME performance, with marketing innovation being most influential, accounting for 66.6% of the variance. This extends Liu and Chen (2024) findings by indicating that while process innovation matters, marketing and product innovations might be even more potent drivers for resource-limited SMEs. Schniederjans (2018) identified eight supply chain processes amenable to innovation, providing a structural framework supporting the empirical work of Liu and Chen (2024) and Kithinji and Misuko (2022). However, a notable contradiction

arises: Liu and Chen (2024) identified IT capability as a key mediator, whereas Kithinji and Misuko's (2022) framework omits IT, suggesting that IT's role might depend on context or that the Kenyan study overlooked an important transmission mechanism.

Hahn (2020) adopted three categories of business process: Orchestrate, operate and support, covering supply chain infrastructure, human resources, procurement, and risk. Contrary to the consistently positive results reported by Liu and Chen (2024) and Kithinji and Misuko (2022), Hahn discovered that business processes focused on value creation and transport while overlooking warehousing and inventory management, suggesting that process innovation is unevenly applied. However, Hahn also found increased use of 'predictive analysis' and 'real-time response approaches,' indicating improved scalability and flexibility. The study employed descriptive analysis, though measurement and operationalisation clarity were lacking.

Paunov et al. (2023) expanded the analysis to family-owned firms in Serbia with a study of 207 newly-established companies, utilising descriptive statistics, t-tests, ANOVA, and correlation analysis. Supporting Kithinji and Misuko (2022), SME research, they found that family firms implemented innovations in production and distribution, with a positive link between BPI and customer satisfaction and retention. However, they did not specify which innovations were introduced nor examine mediating mechanisms, especially since Liu and Chen (2024) highlighted IT capability as a key mediator. The study's focus on newly-established Serbian family firms limits broader applicability. Separately, Shukla and Sengupta (2021) investigated Business Model innovation in India’s agriculture supply chain at the bottom of the pyramid, using participatory observation. They emphasised stakeholder benefits over organisational focus, concluding that resource pooling and incentive contracts are essential for success. While process innovation is widely agreed to enhance performance, their work introduces new aspects: stakeholder inclusivity and incentive alignment, not explored in earlier research.

Abdelaziz et al. (2023) further explored how mediating mechanisms influence Egyptian SMEs by examining how supply chain learning capabilities (SCLCs) enable supply chain and process innovation amid technological turbulence. Using interviews and surveys from 189 SME CEOs, the study found that SCLCs positively impact

process innovation, with a moderate positive link between turbulent technology and process innovation. This aligns with Liu and Chen's (2024) focus on IT capability, suggesting that learning capabilities play a similar mediating role, which may have been overlooked in Kithinji and Misuko's (2022) study. Wang et al. (2022) shift their investigation to examine how AI and blockchain technologies drive business innovation, gathering empirical data across sectors. They presented profound evidence of BPI's contribution to demand forecasting, with improvements of 97.1% in demand forecasting accuracy, 96.3% in analysing customer behaviour, 98.9% in business development, 98.3% in product quality, and 97.2% in customer satisfaction. These high effect sizes highlight the potential for stronger performance relationships when advanced technologies are applied, though the limited respondent pool across sectors restricts broader applicability.

Research shows that business process innovation (BPI) positively impacts organisational performance across various contexts, including environmental performance in China, SME performance in Kenya, customer satisfaction in Serbia, supply chain flexibility, and demand forecasting accuracy. Theories support these findings, with mediators like IT capability, supply chain learning, AI, and blockchain identified, though contradictions exist: the importance of innovation types varies by context, mediating mechanisms are inconsistently recognised, and application of BPI is uneven, with some areas neglected. Effects may depend on organisational factors and location, but these are underexplored. Most studies are cross-sectional and limited to a single country. For demand forecasting, BPI improves performance via process efficiency, data integration, predictive analytics, learning capabilities, and automation through AI and blockchain. The conflicting findings suggest future research should explore specific mechanisms, use longitudinal methods, and compare regions to better understand context-specific and universal patterns.

2.3.2 Technological Innovation and Demand Forecasting Performance

The Oxford Dictionary (2020) defines technology as the practical application of scientific knowledge in industry and as a branch of knowledge that deals with applied science. Adopting technology in any industry or organisation protects market share and improves sustainable competitive advantage and market penetration (Patterson et al., 2003). Innovation plays a significant role in the supply chain by adopting

innovation into the supply chain networks and procedures for effective and efficient performance. Through the Internet, IoT, Tracking System, AI and Big Data, supply chain partners have observed a surge in workload through automation of production and document management simplification (Pagano & Liotine, 2019). Technological innovation may be defined as the conception and production of new and elaborate solutions to real or perceived needs. The solution must be something that is feasible or sustainable and can be produced. Technological innovations are essentially the product of solving a problem in an area of discipline to sustain and maintain set goals. Technological innovations are categorised into: radical innovations that require drastic changes, incremental innovations that are merely progressive modifications on products, processes or services, revolutions which are pervasive and affect different branches of the economy and systems which show interrelationships between the economy and technology (Coccia, 2021).

Technological innovation is vital to meet customer needs, attain organisational goals and resolve problems of users towards directed support of social, economic, corporate, and industrial change towards competitive advantage and general productivity (Coccia, 2019a). The rapid growth of technology, the dwindling consumer market and extremely volatile trade market have led to an increase in the prerequisites for the expansion of enterprises. Presently, there has been an increase in research on technological innovation of enterprises; however, technological innovation has only resulted in short-term performance growth. This is because in a highly unpredictable environment, a widespread management cannot meet the growth needs of enterprises (Shao et al., 2016).

Technological innovation is, however, a slow process through incremental adjustments and adopting a linear approach, it simplifies its stages of research, development, demonstration and deployment. This innovation, moreover, does not advance in a void; it covers all aspects of a country's economy from the SMEs to government investments, and they all influence the extent to which the new technologies are created and implemented. It also assists in reducing the costs incurred when developing technologies for organisations (IEA, 2019). New technologies such as Internet of Things (IoT), virtual reality, 3D printing, Blockchain, Internet of Everything (IoE) Bid Data analytics, cloud computing, Machine Learning, have been

adopted in the field of supply chain to increase visibility, reduce costs, predict demand and also provide pre-emptive corrective measures. Technological innovations are inspired by digitalisation, and it helps in reducing labour input in logistics processes via automated vehicles and equipment advance towards a new phase of integration in the internet (Maddikunta et al., 2022).

Technological Innovations are problem-driven and follows distinctive process of identifying a pattern where resolution is required, collecting data associated with the problem, instinctively identifying solutions and finally extensive exploration of the problem and improvements initiated. Therefore, technological innovation results from solving problems within a research or technological area to attain and maintain organisational goals (Coccia, 2016a, 2017c). Consequently, organisations and developed countries support their technological innovations through research and development (R&D) labs to necessitate competent decision-making and problem-solving tasks grounded in capable scientific staff and cutting-edge equipment for achieving specific goals (Coccia, 2017d, 2019c).

The rapid spread and growth of the use of digital technologies has been necessitated by the capacity and the opportunities of technology through the management of communication technologies (ICT). These technologies constitute information that is processed, well communicated through innovation, which has progressed via essential transformations in business models and processes of goods and services, for customer and stakeholder relationships (Olszak & Ziemba, 2012). This allows for sharing and duplication for interactive working environment. Through the technology innovation, partners within the supply chain network can interact and share information both in real-time and securely to support creative and strategic solutions and additionally improve competition within the arbitrary market. The convenience of computers that can multitask different operating systems, separating simultaneously to solve specialised and complex problems without freezing capital in infrastructure-related assets, has perpetuated the increase of workflow and reduced redundant activities within the organisation (Dasí et al., 2017).

Lee et al. (2018) studied how supply chain management affects technological innovation, considering the moderating role of guanxi across 197 Malaysian manufacturing companies. Using partial least-squares structural equation modelling,

they found that all SCM practices positively and significantly relate to technological innovations, with effective information gathering aiding managers in devising strategies to boost innovation. A key limitation is the lack of focus on specific technologies linked to SCM strategies, which restricts practical guidance for managers aiming to enhance innovation. In contrast, Dash et al. (2019) explored AI's role in automating supply chain processes. They concluded that AI helps reduce waste, enables real-time production monitoring, and shortens order cycles. The study highlights AI's ability to analyse market trends for accurate demand forecasting and optimise order and purchase processes, cutting costs in transportation, warehousing, and supply chain administration. The study mentions several companies that have adopted AI to predict supply-demand fluctuations and prepare inventory accordingly. While supporting Wang et al. (2022) findings on AI and blockchain benefits, this study mainly relies on general observations and theoretical insights without rigorous empirical evidence on AI's practical impact on demand forecasting.

Anser et al. (2020) researched the role of technological innovation across 102 countries within a dynamic environmental supply chain model. They focused on intelligent logistics as a key technological indicator to enhance logistics performance by reducing carbon damages. This approach contrasts with the organisation-level focus of Lee et al. (2018) and Dash et al. (2019), as Anser et al. examined effects at the national level, finding that technology, logistics indices, and growth triggered carbon damages. However, the study does not specify which technological innovations contributed to carbon damage, only listing relevant technological factors, and it lacks policy implications. Singhry (2015) studied in Nigeria how supply chain technology, collaboration, and innovation capability influenced manufacturing companies' performance. This directly complements Lee et al. (2018), as it explores similar relationships in an African context, highlighting how innovation capability affects the link between supply chain technology and performance, and its mediating role. Using questionnaires and structural equation modelling, the research showed that manufacturing firms could adopt advanced manufacturing and information technologies to improve processes and collaboration, boosting supply chain performance. Significantly, a positive relationship was found between innovation capability and supply chain collaboration for demand forecasting, an aspect not explicitly examined in other technological innovation studies. However, the study only

considered two types of technology, limiting exploration of additional technological options.

Sun et al. (2021) examined the link between technological innovation, transition trajectories, and organisational performance using a structural equation model. They emphasised innovation's novelty and openness, concluding that both positively influence innovation trajectory and organisational performance. Nonetheless, the study offers limited practical guidance for those aiming to enhance innovation processes and organisational outcomes. In contrast, Zhu et al. (2021) provided direct evidence connecting technological innovation with demand forecasting, specifically in the pharmaceutical supply chain. They applied machine learning to improve demand predictions, utilising cross-series training and downstream inventory data. Their results indicated that training series significantly increased forecast accuracy, especially for low-volume drugs. While downstream information was helpful, past inventory data did not add value, challenging the assumption that more information always improves forecasts. This nuance was overlooked by Dash et al. (2019) and Wang et al. (2022), who reported high accuracy gains from AI and blockchain without addressing these distinctions.

Research consistently shows that technological innovations improve organisational performance, supply chain efficiency, and demand forecasting. Technologies like AI, machine learning, advanced manufacturing, and information tech enhance forecasting and operations, but there's variability. Studies claim AI and blockchain lead to improved performance boosts, though these may be inflated, unlike more cautious estimates elsewhere. The mechanisms driving value vary; some focus on capability, others on specific technologies or characteristics such as openness. Analysis levels differ, complicating synthesis. A key gap is the lack of clear linkages between specific technologies and outcomes, as well as limited implementation guidance. Technology boosts forecasting via AI analytics, collaboration, and innovation, but contradictory findings highlight the need for future research to identify specific tech contributions, consider organisational factors, and guide practitioners.

2.3.3 Network Structure Innovation and Demand Forecasting Performance

The concept of network structure innovation for oil marketing companies (OMCs) encompasses both the physical infrastructure for product distribution and the

organisational design for market responsiveness and agility (Dias et al., 2025). Adaptable network structures allow for the effective sharing of resources, knowledge, and software across different business units (Silicon Valley Innovation Centre, 2024). Operational network structures cover the physical infrastructure and IT integration. Developing robust networks helps to improve reliability and redundancy. This, in conjunction, helps to minimise downtime, enhance operational efficiency and improve safety and compliance as communication in the networks assists in solving issues that arise in real time and thus ensures that companies are in adherence to regulations. The adoption of IT provides remote control on processes, which reduces operational costs, improves uptime and boosts overall performance. (Moxa, 2023). Retail network structures include service stations and convenience stores, and focus on capitalising on the market and agile response to market changes. (Rubeis et al., 2021). This is mostly achieved by using data-driven analytics and AI to determine the best locations for new sites and to optimise the product mix within each convenience store, moving beyond limited fuel and lubricant offerings (Accenture, 2023; Gosling, 2025). Oil marketing companies also structure the retail network to incorporate digital media screens and advertising platforms in order to create new revenue streams and enhance marketing synergies with other business lines (Rubeis et al., 2021; Gosling, 2025).

Network structure innovation shapes technological advancement through organised connections in inventor and inter-industry networks. Firms in the United States gain generative appropriability from integrated intrafirm inventor networks that speed follow-on inventions. China's strategic emerging industries, studied using 8.7 million patents from 2012-2021, show relational and structural embeddings in inter-industry networks drive collaborative performance (Argyres et al, 2025). Network embeddings enhance collaborative innovation via broader and deeper knowledge acquisition from partners. Intra-industry density had a positive impact, as seen in China's high-performing sectors such as AI and new energy. Global manufacturing GVCs, drawn from 50 economies' PCT patents, rise with GIN embedding breadth and depth, especially for leaders like the U.S., Germany, and Japan (Zhang et al., 2025). U.S. firms lead through internal networks, Chinese industries via cross-sector ties, and developed economies dominate GINs while developing their risk lock-in without strong IPR. These insights from U.S. corporate data, Chinese patents, and global 50 economy analysis offer a holistic view of network-driven innovation (Shi & Xiao,

2024). The innovation in network structures across Africa is primarily driven by the transition from isolated entities to integrated, collaborative ecosystems. This structure is designed to foster open collaboration and the development of African-made solutions by connecting entrepreneurs, tech hubs, and institutional funders. This network innovation relies heavily on information and communication technology (ICT) to bypass traditional governance weaknesses (Asongu et al., 2025; Afrilabs, 2019). Network restructuring, particularly through improved digital and organisational linkages, enhances collaboration and efficiency across institutions. Network transformation in public sector institutions has modernised network structures, which have improved communication, reduced information silos, and supported faster decision-making across ministries and agencies. Shifting from fragmented and hierarchical structures to more integrated network arrangements enables organisations to respond more effectively to complex and dynamic operational demands (Too et al., 2025). The health sector in Kenya also illustrates that network structure innovation improves system-level performance through coordinated network design. Adopting a hub-and-spoke network structure has strengthened linkages among health facilities, improved referral systems, and enhanced coordination of resources such as supply chains and information systems. Integrating multiple actors within a defined network reduced fragmentation and improved service delivery across counties in Kenya (Amboko et al., 2025). This suggests that innovative network structures, when effectively coordinated, enhance visibility, responsiveness, and overall performance, particularly in environments characterised by uncertainty and resource constraints. In the supply chain, structural innovation focuses on the innovations included within the supply chain network. It is concerned with the vertical structure, which comprises of the number of suppliers or customers, horizontal structure, which focuses on the number of tiers in the supply chain network. The network structure includes the following elements: outsourcing, third- and fourth-party logistics providers (3PL &4PL), Partnerships and collaborations and distribution channels (Arlbjorn & de Haas, 2009).

Cao et al. (2023) studied how regional innovation networks and government R&D spending influence innovation efficiency in China, distinguishing between technological R&D and commercialisation. Using data from 30 provinces (2011–2019) and a two-stage Data Envelopment Analysis, they found that high technological

R&D efficiency doesn't ensure commercialisation success. An innovation network improves R&D efficiency, but not commercialisation, and government R&D boosts R&D but hampers market-driven commercialisation. Regions with weak networks can compensate by increasing public R&D. They see innovation as a two-stage system with varying policy impacts over time. A key gap is the lack of macroeconomic, external covariates and micro-level data, especially regarding small and medium enterprises.

Li et al. (2022) studied 362 HEM enterprises on how structural innovation influenced organisational performance, focusing on absorption and transformation capabilities. They found that innovation networks improve R&D efficiency, with two indicators mediating between structural innovation and performance, confirming previous findings. The positive impact of structural innovation is noted, but the sample's specific context limits generalizability. Hahn (2020) introduced business architecture as crucial for network structure, highlighting three aspects: product concentration, platform, and service. Industry 4.0 solutions mainly target product focus (90%) for established firms, while startups focus more on service (56%) and platform (33%). However, the measurement and significance of these differences are unclear, showing methodological weaknesses compared to Cao et al. (2023) and Li et al. (2022).

Dixit et al. (2020) shifted focus to viewing supply chain resilience as a network property. They assessed how resilience before and after disasters depended on network structure parameters: density, centrality (position), and size. Using a conditional value-at-risk approach, they found that companies with low network density and centrality, but high connectivity and network size, tend to be most resilient in the market. This contrasts with Cao et al.'s (2023) emphasis on network connectivity, indicating that different structures may be optimal for different goals: high density for innovation, low density for resilience, meaning network design strategies cannot be one-size-fits-all. Building on network structural dynamics, Garvey and Carnovale (2020) explored how ripple effects influence inventory control, developing the 'Rippled Newsvendor,' a modern single-period model that prioritises supply chain severity and incorporates network disruption dynamics. Using a Bayesian Network approach, they demonstrated the model’s performance and explored ideal ordering policies. Additionally, Li and Zobel (2020) examined how network structures affect resilience from a

multidimensional quantitative perspective, challenging Dixit et al.'s conclusion by showing that short-term resilience is more affected by network type than long-term resilience, due to the ripple effect. They also found resilience could be bolstered more effectively by enhancing node risk capacity than by structural changes, aligning with Singhry's (2015) emphasis on innovation capability in technological development.

Zhang et al. (2025) studied how global innovation networks influence manufacturing industries in different economies. Their research extends network structure literature (Cao et al., 2023; Dixit et al., 2022) by examining the evolution of Global Innovation Networks and how two metrics—embedding breadth (geographical spread) and embedding depth (interaction frequency)—affect positions in global value chains across 50 economies from 2007 to 2021. Using patent co-invention data and fixed-effects regression, they found that both metrics positively impact a nation's GVC position. However, heterogeneity analysis showed developed economies leverage tech leadership for GVC upgrades, while developing economies face "low-end lock-in" risks when embedding depth is too high. Stronger intellectual property rights benefit developed economies but hinder developing ones by creating tech barriers. The study concludes that gains from global innovation are uneven and depend on local absorptive capacity and institutional standards. It also notes a limitation in using patent filings alone, ignoring informal knowledge and digital services that also shape manufacturing value chains.

Wang et al. (2022) explored how digital twin-driven architectures can transform smart supply chains by enhancing connectivity, visibility, agility, integration, and intelligence. Their work extends the network structure literature by showing that digital twin architectures combine virtual simulation with live physical networks, overcoming traditional data silo issues. The study indicated that using multi-level simulation models allows logistics systems to predict disruptions with an average accuracy of 96%, and data-driven optimization cut response times by around 50%, reducing the evaluation of nearly 200,000 SKUs from days to under an hour. A key limitation is the reliance on a qualitative framework and a single case study of a large corporation, which may limit applicability to smaller, resource-constrained firms. Meanwhile, Ran, Zhang, and Li (2024) assessed how digital network innovation affects firms' market value and their findings supported Cao et al. (2023) and Zhang

et al. (2025), that digital technology innovation significantly and positively boosts market value, a result consistent across different endogeneity adjustments. However, this effect is driven mainly by digital invention patents, while utility model patents do not significantly impact market capitalisation. Mechanism tests identified three channels—accelerating broad digital transformation, increasing total factor productivity, and improving product market profitability—through which digital innovation enhances value. Heterogeneity analysis revealed that the benefit is especially strong in non-state-owned enterprises, larger firms, technology-heavy or capital-intensive industries, and companies with low internal control costs.

Research shows mixed findings on how network configurations affect performance. Consistently, network structure boosts innovation, R&D efficiency, organisational performance, GVC position, and market value. Contradictions arise where efficiency gains in R&D but not commercialisation, and linking structural innovation to organisational performance can be done through absorption and transformation capabilities, suggesting that the value of network structure depends on the performance dimension being examined. However, the benefits of network embedding vary by economy, and resilience depends on network type and firm maturity. Methodological gaps include heavy reliance on limited generalizability and poor operationalisation of network constructs. Large-scale studies and qualitative insights improve rigour but still face limitations. For demand forecasting, network innovation improves capabilities through better information flows, enhanced resource absorption, digital twin technology, and other digital innovations, but effectiveness depends on absorptive capacity and context. Overall, the network structure influences demand forecasting and supply chain performance, when mediated by firm capacity and institutional factors, requiring more detailed, long-term research.

2.3.4 Customer Centric Innovation and Demand Forecasting Performance

Customer centric innovation combines the attributes of customer centric technologies and sensitivity towards customer needs. It focuses on creating a culture that centres on the customer through understanding and responding to the customer's perspective. It involves creating and delivering products, services, and experiences that are finely tuned to meet customer expectations and address their pain points. This innovation approach acknowledges the importance of being sensitive to the diverse and evolving

needs of customers in order to stay competitive and foster long-term relationships. Its components include data-driven decision making, agile responsiveness, customer-centric designs, continuous feedback and customer experience management (Thorpe & Kalra, 2021)

Customer centric innovation involves introducing new methods, technologies, strategies, or processes to improve customer service quality and effectiveness, aiming to meet customer needs, expectations, and resolve issues innovatively. It focuses on delivering excellent experiences, efficient issue resolution, and stronger business-customer relationships. There are fourteen key elements of customer service innovation to include: Technological Integration, to simplify customer communications, quick feedback, and improve the service experience. omni-channel support: to support customers through multiple channels. Proactive problem resolution: recognising and delivering potential issues before customers' awareness. self-service resources and tools for customer interactions. personalisation by customising based on the customer's preference, purchase history and performance. Personalised customer service contributes to a more engaging and relevant experience. real-time communication between customers and support teams. Feedback mechanisms to collect customer views, suggestions, and insights. Use of social media platforms to engage and support customers. Predictive analytics to predict customer needs and conduct x) collaborative support platforms that provide employees and customers a seamless environment to solve problems. Continuous training and development for customer service teams to be abreast with new trends, innovation and strategies. Emotional intelligence, by providing empathy and emotional support, elevates customer experiences. Mobile customer service, such as applications USSD or SMS support and gamification of customer service, which fosters positive performance, encourages mutual feedback and overall interaction (Jain, 2023).

Due to the growth of customer knowledge of the services they prefer, customers have been able to advance their individual tastes and thus task organisations to be more ingrained in meeting their different and personalised demands. Manufacturing firms are moving towards service-oriented manufacturing (SOM), which combines service provision with manufacturing. SOM centres on its ability to predict customer demand and apply it during production. Therefore, customer satisfaction is a factor that is

considered in SOM due to its impact on customer demand (Cao et al., 2016). Innovative customer service strategies often involve the adoption of agile methodologies that depend on predictive data analytics. This allows firms to be flexible in responding to changing environments, customer comments and market trends. The flexible strategies provide firms with better decision-making that is centred on trends, metrics and insights from the customers. Customer service innovation provides a competitive advantage as it assists organisations to foster customer loyalty and consequently makes the firms more sustainable and successful in meeting their target goals and objectives (Jain, 2023).

Bindroo et al. (2020) examined the level of customer satisfaction and services provided and how they affected consumer behaviour towards the provider, using empirical research in five multinational companies. The results showed a positive and linear effect between product services and customer intention, while also revealing a decrease in customer sensitivity on product and service satisfaction, with over-reliance on satisfying one aspect considered counterproductive. This finding suggests that while customer-centric innovation is beneficial, a balanced approach is necessary—a caution that resonates with later findings on trade-offs in customer-centric structural alignment. Adopting a different perspective on innovation enablers, Rivas and Wu (2019) highlighted the potential benefits of team-working in contributing to innovation success across technological, commercial, and entrepreneurial dimensions. This introduces a human capital dimension not addressed in other customer-centric studies, suggesting that team-working may contribute to innovation success. However, the research lacks empirical evidence to support these claims and would benefit from a more robust theoretical framework, representing a significant methodological limitation compared to the empirical approaches of other studies.

Walambra (2025) examined how customer-centric strategies affect manufacturing firms in Kajiado Central, focusing on customer relationship management, internal and external integration, and customer segmentation. Using a descriptive approach with 330 respondents from 16 firms, the analysis showed that interactive CRM, customer segmentation, and external integration significantly enhanced firm performance. Internal integration had a positive but statistically insignificant effect, possibly due to technological or contextual factors. The study emphasised the critical role of CRM

software, employee training, loyalty programs, customer segmentation, and external integration in boosting performance. Limitations included a focus on only one Kenyan region and manufacturing companies. Wünderlich et al. (2025) developed a comprehensive conceptual framework to explore how emerging service technologies can enhance customer centricity in the B2B manufacturing sector, complementing Walambra's (2025) empirical work with the CCTECH framework. This framework identifies the influence of three technology groups on four key customer-centric processes: interactive CRM, customer integration, internal integration, and external integration. However, the study questioned Walambra's conclusions regarding internal integration, suggesting it as a core process, and implying that either the Kenyan context differs from other B2B environments or the findings were context-specific. The framework offers a practical tool for manufacturers to align technology adoption with a customer-focused marketing strategy. Nevertheless, the research was mainly empirical and theoretical, focusing on manufacturing, which may have overlooked technologies relevant to other industries.

Tuominen et al. (2023) examined how a customer-centric strategy—covering customer orientation and customer relationship orientation—affects firm innovativeness and business growth in international markets. Using an empirical, quantitative method, they analysed 416 responses from Italian export-focused companies via an online survey and employed a structural model to explore relationships. Results show that both orientations are distinct strategic approaches that significantly boost innovativeness. However, contrary to expectations, neither directly impacts business growth; instead, their effect was mediated through innovation, which must precede growth. This supports Singhry (2015)’s view of innovation capacity as a key mediator and clarifies why customer-centric strategies eventually enhance performance, as shown by Kithinji and Misuko (2022). The study recommends export firms adopt a dual strategy focused on understanding customer needs and fostering long-term relationships to drive innovation and succeed internationally.

Lee et al. (2012) examined the financial impacts of customer-centric organisational structures in Fortune 500 companies. Their comprehensive study, covering 13 years of data from 1998 to 2010, analysed 1,651 observations from 174 firms using SEC filings, Compustat, and the American Customer Satisfaction Index. They employed

advanced Bayesian and Latent Instrumental Variable methods. Findings showed a clear trade-off: aligning organisations customer-wise boosts firm value by enhancing satisfaction but also raises internal costs and overhead, which can negatively affect financial performance. This conflicts with earlier positive reports by Walambra (2025) and Bindroo et al. (2020), suggesting that a firm's existing structural qualities influence outcomes. For firms with high complexity or narrow focus, restructuring tended to harm performance due to redundancy and administrative complexity. Conversely, companies with simpler structures or broader markets benefited financially from customer-centric reforms. The study emphasises that organisational alignment is a critical strategic factor affecting firm equity, and executive decisions should consider whether existing structures support effective customer integration.

The literature confirms that customer-centric strategies generally improve firm performance and demand forecasting, with consensus on the positive impact of customer relationship management, external integration, segmentation, and orientation on innovation, satisfaction, and outcomes. However, contradictions exist where internal integration was insignificant, and it was listed as a core process, suggesting that effectiveness varies by technology or context. Customer-centric orientations affect growth indirectly via innovativeness, and there were direct effects on firm value, as well as negative impacts on costs, indicating trade-offs. These findings imply that the value of customer-centric innovation varies based on organisational traits, strategy, and operationalisation. Methodologically, most studies are single-country and for demand forecasting, customer-centric innovation improves market intelligence and responsiveness through innovativeness and structural alignment, yet trade-offs and inconsistent findings highlight the need for further research into specific mechanisms, longitudinal analysis, cross-cultural comparisons, and practical guidance for firms.

2.3.5 Firm Size and Demand Forecasting Performance

Firm size is commonly operationalised through various proxies, including the number of employees, total assets, total sales, or market share (Mansikkamäki, 2023; Bhattacharya et al., 2022). The choice of proxy is critical, as different measures can lead to varied conclusions regarding the impact of firm size on other organisational outcomes (Li & Dang, 2013). Revenue market share has been shown to predict firm

profit; however, unit market share may not, highlighting the importance of specific market share metrics (Bhattacharya et al., 2022). This variability underscores the need for researchers to clearly articulate their chosen definition and its rationale. Larger firms often possess greater market power, economies of scale, and access to resources, which can translate into competitive advantages (Asif et al., 2023). Research consistently links firm size to performance, innovation, and strategic behaviour (Sabitu et al., 2024; Damanpour, 2010). Larger firms may have more robust financial management strategies and be better positioned to invest in information technology or research and development (Al Hashimy, 2025). Conversely, smaller firms might exhibit greater agility, specialised focus, and closer customer relationships. Firm size is therefore crucial for developing comprehensive theories in strategic management, organisational behaviour, and industrial organisation (Udayasankar, 2008).

Firm size frequently functions as a moderating variable, influencing the strength or direction of relationships between other constructs, which alters the nature of the relationship between an independent variable and a dependent variable (Cheah, et al., 2023). This is evident across diverse research domains, providing nuanced insights into complex organisational phenomena. Recent studies highlight its moderating role in various contexts, such as the relationship between liquidity, profitability, and firm value (Tanaya & Wirianta, 2025). Firm size can influence the relationship between variables, suggesting that different mechanisms may operate differently depending on the firm's scale (Sang et al., 2024). These findings underscore that firm size is not merely a descriptive characteristic but a critical contextual factor that shapes how other organisational variables interact and influence outcomes.

Kitenga et al. (2020) explored how dynamic capabilities affect the performance of food manufacturing firms in Kenya, also examining whether firm size influences this relationship. Their survey of 190 respondents across 70 firms, combined with multiple regression analysis, revealed that dynamic capabilities significantly boost firm performance. However, firm size did not have a significant effect nor did it moderate this relationship. Similarly, Aury et al. (2025) studied the connection between financial performance and tax avoidance in Indonesian healthcare firms and whether firm size moderates these effects. Analysing data from 16 firms between 2019 and 2023 using PLS-SEM, they found that profitability positively affects tax avoidance, while

leverage and profit growth do not. Again, firm size did not moderate these relationships. Both studies suggest that firm size may not be a universal moderator across different sectors and contexts, reinforcing the idea that the impact of organisational factors remains consistent regardless of firm size.

Contradicting these findings, Mungai et al. (2025) examined how firm size influences the link between corporate sustainability and performance in Kenya's commercial banking sector. They used stratified random sampling across 39 banks, surveying 200 senior managers, and analysed data via hierarchical regression. Their results showed that sustainability greatly boosts performance, with firm size acting as a moderator—larger banks benefit more thanks to economies of scale, while smaller banks face limitations. This challenges the conclusions of Kitenga et al. (2020) and Auryn et al. (2025), suggesting that firm size may be a key moderator in some contexts, like banking and sustainability, but not universally. Similarly, Ochoi et al. (2025) examined the moderating role of firm size in the relationship between inclusive business models and MSE survival in Nyamira County, Kenya. They surveyed 298 respondents using stratified random sampling and hierarchical multiple regression. Their findings indicated that firm size significantly influences the relationship by improving innovation and value chains, aiding larger MSEs through economies of scale. These results extend Mungai et al.'s findings, showing that firm size enhances the effectiveness of business models in the MSE sector, highlighting a pattern that firm size positively moderates when assessing organisational strategies, but not when focusing on internal capabilities or financial metrics.

Inrawan et al. (2025) explored how firm size moderates the link between profitability and firm value in Indonesia's heavy construction sector. Analyzing secondary data from 17 firms between 2019 and 2023 through moderated regression, they found that profitability does not significantly directly influence firm value. However, firm size negatively moderates this relationship, suggesting that larger firms' managerial complexities, such as increased bureaucracy and coordination costs, can weaken the positive impact of profitability on firm value. This contrasts with the positive moderation effects reported by Mungai et al. (2025) and Ochoi et al. (2025), implying that, under certain conditions, larger firm size may hinder strategic effectiveness. Extending this discussion to leverage-performance dynamics, Alabdulkarim et al.

(2024) examined how firm size affects the nonlinear relationship between leverage and performance using data from Saudi listed firms. Their panel threshold regression analysis of 700 firm-year observations from 2010-2019 confirmed that firm size is significant—leverage negatively impacts performance in both small and large firms, with a more substantial adverse effect on smaller firms, indicating greater financial distress risk in smaller entities. These findings complement Inrawan et al.'s (2025) negative moderation and showed that smaller firms bear a heavier burden from leverage's negative effects, highlighting how the relationship between firm size and performance depends on the specific strategic variable studied.

Bhattacharya et al. (2022) explored how market share influences financial performance mechanisms. Analysing 3,058 firm-year observations from 244 firms between 2000 and 2013 using fixed-effects autoregressive models, they found that market share's positive impact on profit is mainly mediated by market power and signalling quality. In contrast, operating efficiency showed little support, indicating economies of scale are linked more to overall firm size than market share. This highlights that the key to competitive advantage lies in mechanisms like market power and signalling, not size itself. In a different context, Wirianata et al. (2024) studied how firm size affects the relationship between financial metrics and tax avoidance among Indonesian firms. Using data from 69 observations across various sectors and multiple regression methods, they found that firm size does not directly influence tax avoidance but does moderate and even reverse the effects of leverage and capital intensity on it. This supports some prior research by showing that size can influence certain relationships despite having no direct impact.

Feng et al. (2025) contribute significantly to understanding the ESG-innovation link by examining how ESG criteria impact innovation outcomes in Chinese listed firms. Using a large panel dataset of 47,360 observations from 2013 to 2022 and employing firm-and-year fixed effects alongside Two-Stage Least Squares, their findings reveal that both supply chain resilience and ESG performance positively influence corporate innovation. Additionally, their interaction analysis shows that firm size enhances this relationship, suggesting that larger firms leverage their resources to convert sustainability efforts into innovations. This supports the findings of Mungai et al. (2025) and Ochoi et al. (2025) regarding firm size as a moderator in complex

organisational initiatives. Similarly, Kijkasiwat and Phuensane (2020) analysed innovation models and SME performance across 29 transition economies. With data from 12,890 SMEs and PLS-SEM analysis, they confirmed that product and process innovations significantly boost SME performance, with financial capital serving as a positive mediator. Notably, firm size directly moderates the innovation-performance link, while also negatively affecting baseline performance. This indicated that smaller firms use operational flexibility to achieve higher performance from targeted innovations compared to larger, less flexible firms. These findings clarify that while firm size positively moderates innovation's impact on performance, smaller firms tend to perform better relative to their size due to their flexibility.

The review shows firm size is a conditional moderator, a variable across relationships, industries, regions, and performance aspects. Internal capabilities and financial metrics are unaffected by size, suggesting stability. In contrast, strategies like sustainability, inclusive models, ESG, and innovation benefit larger firms, while profitability and leverage relationships show negative effects, with larger firms facing managerial complexities and smaller firms' higher financial risks. Market share and efficiency are less influenced by size, but market power and signal quality are significant. Methodologically, most studies are cross-sectional and single-country, with few longitudinal or multi-country works. Demand forecasting research suggests that larger firms leverage resources for better results, while smaller firms rely on flexibility and customer proximity. These conflicting findings indicate that future research should differentiate performance types, use longitudinal designs, and include cross-cultural studies to help firms adapt strategies based on size.

2.4 Critique of Existing Literature

The collection of studies provides a broad, multidimensional view of innovation across different organisational levels and industry contexts, ranging from highly innovative strategies to deeply organisational structures. However, the studies lack clarity on how critical agile supply chains and innovation metrics are measured and operationalised. The frameworks suggested by Schniederjans (2018) and Hahn (2020) do not offer detailed operational indicators or measurement techniques for their core variables, which significantly undermines the potential for replication and the overall scientific rigour of their findings. Similarly, the study by Paunović et al. (2023) was

unable to specify the precise types of innovations introduced within their sampled organisations, resulting in descriptive obscurity.

Furthermore, several studies rely on restrictive or highly aggregated data proxies that fail to capture realistic operational dynamics. Zhang et al. (2025) relied exclusively on patent-centric co-invention filings to evaluate innovation networks, entirely omitting informal knowledge transfers, tacit operational workflows, and service-digital components that define modern supply chain interactions. Conversely, Wang et al. (2022) and Rivas and Wu (2019) utilise entirely qualitative frameworks or isolated single-case narratives from large corporate entities, creating an empirical void due to a lack of quantitative verification or statistical testing. Mungai et al. (2025) noted that prior studies in developing African markets frequently omit moderated regression frameworks, ignoring how structural organisational traits condition performance links. This models a false uniformity across organisations of varying scales. Additionally, the systematic exclusion of macroeconomic, regional, and external institutional covariates exposes many structural equation models, such as those by Cao et al. (2023) and Liu and Chen (2024), to omitted variable bias. While several studies are limited by localised geographic bounds or specific data collections, the essential requirement is a model that properly captures sector-specific operational realities using clearly defined indicators and robust moderated regression analysis.

The existing literature presents highly fragmented and inconsistent findings, especially regarding the direct outcomes of technology adoption and the specific role of organisational scale. A core contradiction concerns the moderating effect of firm size. While Mungai et al. (2025), Ochoi et al. (2025), and Feng et al. (2025) argue that larger firms utilise substantial resource bases and economies of scale to enhance innovation returns, other empirical studies reach opposite conclusions. Kitenga et al. (2020) and Auryn et al. (2025) find that firm size has no significant direct impact on performance and completely fails to moderate organisational capabilities, whereas Kijkasiwat and Phuensane (2020) report a significant negative baseline relationship, suggesting smaller enterprises use their operational flexibility to outperform larger, more rigid corporate structures. Inrawan et al. (2025) also reveal highly inconsistent moderation patterns, demonstrating that the interaction between organisational size and performance remains unclear.

Additionally, there is a clear lack of linking supply chain innovation directly to demand forecasting performance metrics. Most of the reviewed literature considers performance as a broad, general concept covering market share, overall profitability, or customer satisfaction (Kithinji & Misuko, 2022; Walambra, 2025; Paunović et al., 2023). Studies that explicitly mention advanced technologies—such as Dash et al. (2019) on artificial intelligence or Lee et al. (2018) on technological innovation—rely on broad observations and theoretical ideas rather than examining how these interventions influence data synchronisation, forecast accuracy, or inventory optimisation. Likewise, the concurrent analysis of multiple mediating paths remains underexplored; Bhattacharya et al. (2022) highlight a significant lack of empirical models that directly track why performance relationships change across different competitive environments, leaving a gap in understanding the specific operational mechanisms that connect agility to demand forecasting success.

The reviewed literature is heavily skewed toward developed Western economies, East Asian transition contexts, or specific monolithic sectors, leaving the unique realities of sub-Saharan Africa's energy sectors largely unexamined. The vast majority of the empirical baseline is situated in countries such as China (Liu & Chen, 2024; Cao et al., 2023; Ran et al., 2024), Serbia (Paunović et al., 2023), India (Shukla & Sengupta, 2021), Malaysia (Lee et al., 2018), or Italy (Tuominen et al., 2023). These geographical environments operate under institutional frameworks, regulatory pressures, and market-standard alignments that are vastly different from those in developing East African markets.

Contextually, current research treats the business environment as a monolithic entity or concentrates largely on the general manufacturing sector (Kithinji & Misuko, 2022; Walambra, 2025; Wünderlich et al., 2025), commercial banking (Mungai et al., 2025), or the pharmaceutical industry (Zhu et al., 2021). This cross-sector focus overlooks the specific operational complexities of oil marketing companies. The petroleum industry operates under strict regulatory constraints, driven by agencies such as the Energy and Petroleum Regulatory Authority (EPRA) in Kenya. It deals with high demand volatility, complex international supply chains, and intense cash preservation pressures. As a result, concepts like customer-centric integration or digital twin frameworks (Wang et al., 2022) cannot be applied uniformly without sector-specific

restructuring. The lack of research examining how supply chain innovation agility influences demand forecasting within the oil and gas sector highlights a significant thematic and contextual gap.

The current study is strategically positioned to address these methodological, empirical, and thematic deficiencies. Methodologically, the study replaces generic constructs with precise operational definitions, utilising clear metrics for innovation agility and demand forecasting performance. By deploying a rigorous quantitative framework centred on moderated regression analysis, the study addresses the modelling gaps highlighted by Mungai et al. (2025), testing how firm size actively conditions the relationship rather than treating OMCs as a monolithic group.

The study directly addresses the firm size moderation controversy by examining it within a highly capital-intensive and asset-driven industry, thus testing whether economies of scale or operational flexibility are more dominant in the petroleum sector. Moreover, instead of employing broad organisational performance metrics, the study specifically concentrates on demand forecasting performance as the primary dependent variable, addressing the empirical gap identified in technology and process innovation research (Dash et al., 2019; Lee et al., 2018). This study shifts focus from the over-studied manufacturing sector and Western contexts to the downstream petroleum industry in Kenya. By analysing OMCs operating under local market dynamics and EPRA regulations, it offers sector-specific insights. While the research utilises a cross-sectional data design, providing a focused view of the current industry landscape. It enhances the analytical depth by examining how internal innovation capabilities interact with structural asset scales to influence forecasting outcomes under real-world conditions.

Table 2.1: Summary of Existing Gaps in Literature

Gap Category	Specific Gaps Identified	Key Supporting Citations	Limitations of Prior Studies	Current Study Contribution
Methodological	• Ambiguous variable operationalisation. • Reliance on narrow proxies or qualitative blueprints. • Omission of moderated models and external covariates.	Schniederjans (2018); Hahn (2020); Zhang et al. (2025); Wang et al. (2022); Mungai et al. (2025); Cao et al. (2023)	Impedes replication; introduces omitted variable bias; lacks multi-firm empirical validation.	• Establishes structured SCIA definitions. • Adopts a quantitative multi-firm survey design. • Employs moderated regression for firm-size analysis.
Empirical & Findings	• Conflicting results on firm-size moderation. • Lack of direct linkage between innovation and demand forecasting. • Focus on broad financial/customer metrics.	Kitenga et al. (2020); Auryn et al. (2025); Mungai et al. (2025); Ochoi et al. (2025); Dash et al. (2019); Lee et al. (2018); Inrawan et al. (2025)	Leaves scale-flexibility interactions unresolved; fails to quantify forecast optimisation outcomes.	• Evaluates firm-size moderation in capital-intensive sectors. • Links innovation agility directly to demand forecasting metrics.
Thematic & Contextual	• Geographic concentration in Western/East Asian economies. • Sectoral bias toward general manufacturing. • Neglect of unique petroleum sector constraints.	Liu & Chen (2024); Paunović et al. (2023); Shukla & Sengupta (2021); Tuominen et al. (2023); Walambra (2025); Wünderlich et al. (2025)	Limits generalisability to Sub-Saharan Africa's regulated downstream petroleum sectors.	• Focuses on Kenyan oil marketing companies. • Integrates sector-specific supply and regulatory dynamics into operational models.

2.5 Conceptual Framework

A conceptual framework is defined as a network or plane of interlinked concepts that collectively provide a comprehensive understanding of a phenomenon. (Jabareen, 2009). It organises key concepts into a coherent structure to facilitate holistic analysis and provide a theoretical basis for empirical investigation. The objective of a conceptual framework is to synthesise and clarify the foundational dimensions of a complex phenomenon, guiding research, practice, and policy (Waqar et al., 2020). The model showcased the independent variable (Supply Chain Innovation Agility) and the dependent variable (demand forecasting performance). The model will also include a moderating variable (Firm size).

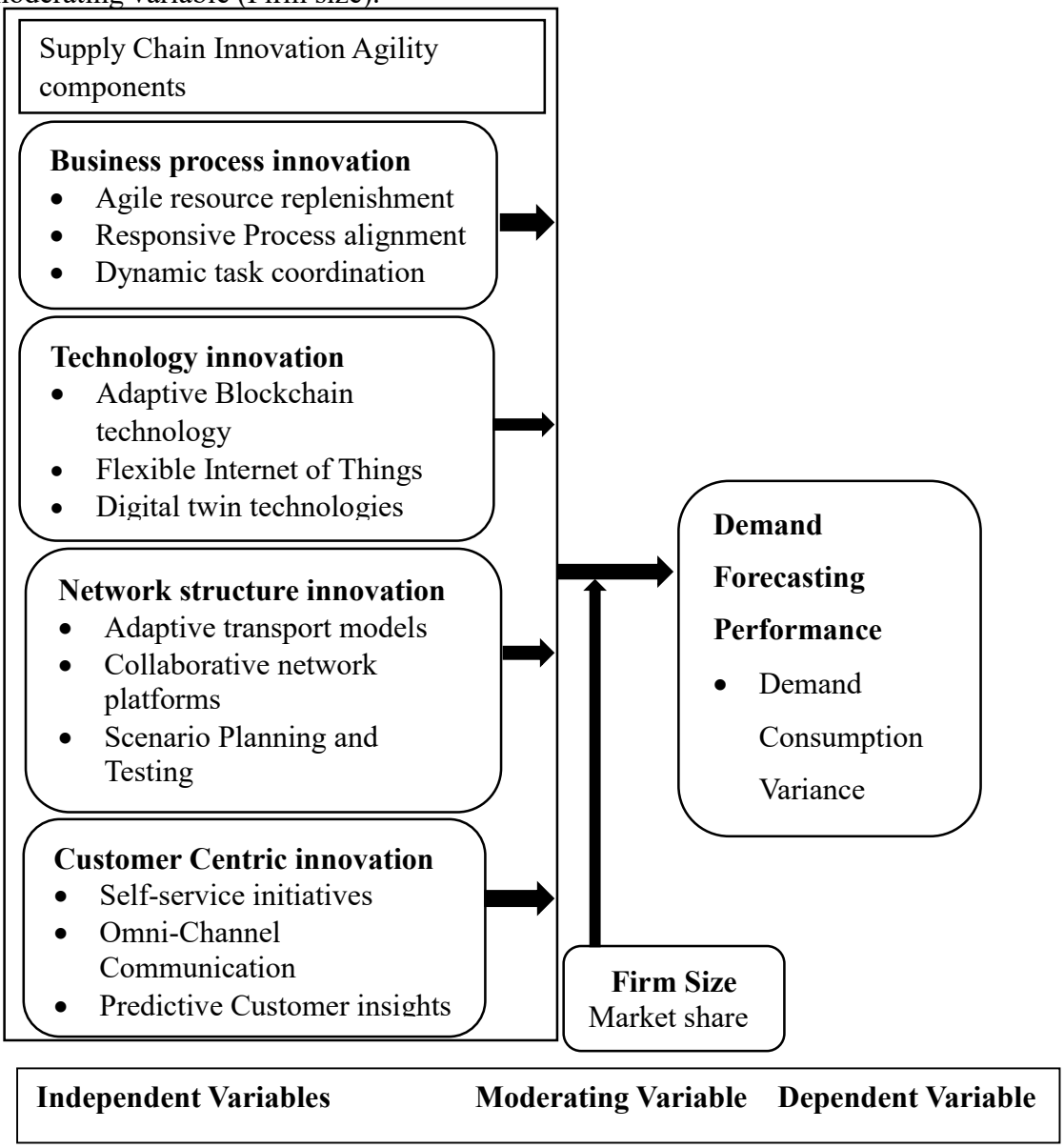


Figure 2.1: Conceptual Framework

2.6 Operational Framework

An operational framework provides the key components, processes, and activities required to achieve the research objectives. It connects theoretical concepts to practical methods, which enabled data collection, analysis and results. The framework in Table 2.2 ensured the research was organised, efficient, and replicable.

Table 2.2: Operationalised Framework

Variable	Indicators	Measuring Tools
Demand forecasting performance	Demand Consumption variance	$\frac{\sum(xi - \bar{x})^2}{N}$
Business Process Innovation	Agile response replenishment Responsive Process alignment Dynamic task coordination	Scale Low (0-24%), Partial (25-49%), Moderate (50-74%), High (75-100%)
Network Structure Innovation	Adaptive transport models Collaborative network platforms Scenario Planning and Testing	Scale Low (0-24%), Partial (25-49%), Moderate (50-74%), High (75-100%)
Technological Innovation	Digital twin technology Block chain Internet of Things	Scale Low (0-24%), Partial (25-49%), Moderate (50-74%), High (75-100%)
Customer centric Innovation	Self-service initiatives Omni-Channel Communication Predictive Customer Insights	Scale Low (0-24%), Partial (25-49%), Moderate (50-74%), High (75-100%)
Firm Size	Market Share	Average Market Share

2.6.1 Business Process Innovation

Business process innovation represents a radical departure from traditional, incremental improvements by fundamentally reimagining workflows to achieve dramatic performance gains (Sayuti et al., 2025). This approach fosters a "generative capacity" within organisations, allowing them to reconfigure their operations to meet

shifting digital demands continuously (Mendling et al., 2020). The implementation of Business Process Re-engineering (BPR) has transformed fragmented bureaucratic systems into an efficient "one-stop shop" model, significantly enhancing public service delivery (Otwoma et al., 2021). Adopting new software and technical techniques is a primary driver of stellar growth and competitive advantage (Kihiko et al., 2024). Successful innovation often requires integrating structured project management tools, such as the Critical Path Method, to mitigate the risks of complex redesigns (Nkomo & Marnewick, 2021). The effectiveness of these innovations is frequently tied to organisational culture and leadership, which act as catalysts for performance improvements in sectors ranging from local government to commercial banking (Mukoya & Mwanzia, 2025). Successful business process innovation can generate significant competitive advantages, including cost reduction, enhanced customer satisfaction, and increased organisational agility (Davenport, 2013). In supply chain management, process innovations are particularly associated with improved responsiveness to market changes, stronger risk management capabilities, and a higher level of customer satisfaction (Christopher, 2016). The adoption of digital technologies such as real-time tracking systems, predictive analytics, and automation has been shown to reduce lead times, minimise inventory holding costs, and enhance supply chain visibility and resilience (Gunasekaran et al., 2017; Waller & Fawcett, 2013). Organisations that embrace supply chain process innovation are better positioned to adapt to global challenges, including logistics disruptions and fluctuations in consumer demand, thereby improving overall supply chain resilience and performance (Ivanov, 2020). Business process innovation serves as a vital socio-technical strategy for maintaining relevance in an increasingly automated global market

Akwalu (2022) revealed that process alignment had a positive influence on the performance of pharmaceutical firms, and including customers in these alignment plans further enhances performance. Jerab (2024) showed that effective coordination had a positive impact on performance and that coordination is a critical performance factor. focused on integrating advanced digital frameworks and artificial intelligence to manage supply chain disruption. Ajayi-Kaffi (2025) emphasises the role of synchronised replenishment strategies. Aligning operational practices with agile principles allows for more responsive resource allocation, particularly in high-stakes

environments where demand volatility is a constant challenge, emphasising the necessity of flexible supplier assignment and real-time inventory adjustments to maintain supply chain resilience. These studies collectively suggest that agile resources. Responsive process alignment seeking to maintain strategic coherence in turbulent digital environments. Martusewicz et al. (2024) illustrate that by aligning internal processes with broader sustainability goals and digital readiness, ensuring that firms can rapidly reconfigure their operations as needed. Dynamic task coordination, Tarasova et al. (2025), addresses the problem of decentralised adaptive task allocation in large-scale, heterogeneous agent systems, proposing architectures that allow autonomous agents to self-organise through advanced cognitive planning.

2.6.2 Technological Innovation

Technological innovation involves transforming new inventions into usable applications to solve problems and create competitive advantages for organisations (Coccia, 2021). This complex process is underpinned by systems of knowledge and tools that satisfy human needs while driving economic progress (Coccia, 2021). Research indicates that technological innovation is significantly influenced by supply chain dynamics, where high-quality information sharing and strategic partnerships act as critical antecedents (Lee et al., 2018). In modern logistics, the integration of artificial intelligence serves as a vital mediator, amplifying the impact of technical advancements on digital supply chain performance (Dalain et al., 2025). Innovation plays a pivotal role in environmental sustainability, helping countries navigate the environmental supply chain curve by reducing carbon footprints through cleaner production methods (Anser et al., 2020). The adoption of these innovations is often modelled through structural equation approaches that evaluate how digital transformation affects corporate governance and market outcomes (Sun et al., 2021). In industrial operations, specific mechanisms such as *guanxi* or social capital can further facilitate the successful implementation of new technologies by smoothing interpersonal and inter-firm transitions (Lee et al., 2018). While radical innovations disrupt established competencies, incremental changes refine existing processes to maintain operational efficiency (Coccia, 2021). The synergy between technical infrastructure and managerial skills is essential for achieving the full "generative capacity" of digital tools (Dalain et al., 2025). As organisations adopt Internet of Things (IoT) and big data, the focus shifts toward real-time responsiveness and data-

driven decision-making (Sun et al., 2021). Ultimately, technological innovation remains the primary engine for wealth creation and societal development in the 21st century (Coccia, 2021). Continual investment in these capabilities ensures that firms remain resilient against environmental threats and global market shifts (Anser et al., 2020).

For adaptive blockchain mechanisms to address limitations in scalability, security, and efficiency, especially in dynamic and adversarial settings. Dutta and Puthal (2025) proposed an adaptive consensus architecture using a graph-based Proximal Policy Optimisation (PPO) reinforcement learning agent that allows the blockchain to adjust consensus logic, detect malicious activity, and optimise validation in real-time, boosting throughput and reducing latency. Similarly, Ghosh et al. (2025) explore adaptive governance, including stakeholder participation in decision-making, enabling flexible policy updates and network evolution. The integration of flexible Internet of Things (IoT) architectures with Digital Twin (DT) technologies aims at creating highly responsive and intelligent cyber-physical systems. Huzzat et al. (2025) highlight the transformative potential of DTs in smart cities, emphasising their role in urban development through real-time data collection via IoT and predictive analytics. These flexible frameworks are crucial for enabling continuous monitoring, real-time data analysis, and predictive insights, which are essential for optimising complex systems across various industries. The concept of Digital Twin, surveyed by Duran et al. (2025), points towards future directions where DTs are offered as scalable services, emphasising the need for flexible architectures that can support diverse applications and data storage requirements to meet the evolving demands of intelligent environments.

2.6.3 Network Structure Innovation

Network structure innovation involves the strategic reconfiguration of interorganisational relationships to facilitate the flow of knowledge and resources essential for competitive advantage. Research indicates that both the breadth and depth of global innovation networks (GINs) are significant determinants of a manufacturing industry's position within the global value chain (Zhang et al., 2025). By embedding themselves deeply within these networks, organisations can overcome boundaries to secure technological gains and mitigate risks (Zhang et al., 2025). Innovation

networks function as heterogeneous models where diverse stakeholders engage in collective actions to bring new technologies to market (Dias et al., 2025). The structural properties of these networks, such as centrality and the presence of "structural holes," directly influence an entity's ability to access unique information and drive performance (Dias et al., 2025). In the public sector, network transformation is increasingly utilised to enhance institutional productivity and service delivery (Too et al., 2025). This is exemplified by the emergence of Primary Health Care Networks (PCNs) in Kenya, which utilise a "hub-and-spoke" model to integrate health services and improve coordination across diverse county contexts (Amboko et al., 2025). Collaborative networks demonstrate how connecting innovation hubs across the continent can foster a community-driven ecosystem for entrepreneurs (AfriLabs, 2019). The success of these structural innovations is often contingent upon information technology thresholds and effective governance dynamics that support structural transformation (Asongu et al., 2025). Innovating the network structure allows organisations to transition from isolated silos to integrated systems that are more resilient to the complexities of the modern digital and economic landscape.

Adaptive transport models focus on developing intelligent systems capable of dynamically responding to real-time traffic conditions and environmental factors to enhance urban mobility and logistics efficiency. Gheorghe and Soica (2025). It extends to broader logistics and supply chain resilience. Research by Nibbrig et al. (2025) [10] introduces an adaptive resilience improvement framework for supply chain networks, designed to dynamically sustain material flow in response to emerging disruptions. TU Delft (2025) emphasises the integration of optimisation, behavioural modelling, and machine learning methodologies to create systems that are not only efficient but also adaptable to changing demands and unforeseen circumstances. Collaborative network platforms foster innovation, enhancing supply chain resilience, and facilitating circular economy transition. Alzate Rendón et al. (2025) examine how horizontal collaborative networks and collaborative risk management practices, supported by social technologies, contribute to supply chain resilience. Antelo et al. (2025) explore collaboration patterns in circular economy innovation ecosystems, emphasising the need for robust ecosystems that foster collaboration among diverse actors to facilitate the transition to CE models. Collaborative network platforms are not merely tools for communication but strategic enablers for complex, multi-

stakeholder initiatives, driving efficiency, resilience, and sustainability across various sectors. Scenario planning and testing are critical for navigating uncertainty, evaluating complex systems, and preparing for future challenges, particularly in dynamic fields Wright et al. (2020). Mannucci (2024) discusses the role of scenario planning in resilience and adaptation, emphasising its utility in facilitating strategic decision-making for sustainable and resilient planning, especially in a complex and uncertain environment.

2.6.4 Customer Centric Innovation

Customer-centric innovation is a strategic approach where the development of new products and services is driven primarily by a deep understanding of customer needs and behaviours. This strategy is built on two distinct and complementary pillars: customer orientation, which focuses on satisfying current needs, and customer relationship orientation, which emphasises long-term engagement. Integrating these orientations, firms can significantly boost their overall innovativeness, which serves as a critical mediator for business growth in competitive international markets (Tuominen et al., 2020). Adopting customer-centric strategies—such as personalised service and responsiveness—has been shown to directly enhance organisational performance by building sustainable competitive advantages (Walambra, 2025). Furthermore, emerging service technologies like artificial intelligence and digital platforms are increasingly leveraged to deepen this centricity, allowing manufacturers to transition from product-focused to service-oriented models (Wünderlich et al., 2025). The successful implementation of these innovations requires an "outside-in" perspective, where market intelligence is used to proactively anticipate latent customer desires rather than just reacting to feedback (Walambra, 2025). Wünderlich et al. (2025) suggest that while technical capabilities are important, the strategic alignment of human resources and organisational culture is what ultimately ensures that technological tools deliver value to the end user. Customer-focused innovativeness is not just a marketing tactic but a survival mechanism that helps navigate the complexities of global trade (Tuominen et al., 2020). Through customer experience prioritisation, organisations can create a virtuous cycle of feedback and improvement that sustains long-term loyalty (Walambra, 2025). Customer-centric innovation allows firms to remain resilient by evolving alongside the changing preferences and digital habits of their target audience.

Self-service initiatives focus on understanding customer adoption, optimising user experience, and leveraging advanced technologies to enhance efficiency. Zungu et al. (2025) highlight how self-service tools are transforming customer interactions by offering personalised and efficient solutions. Deliverect (2025) provides statistics on the significant growth of self-serve systems, indicating a strong trend towards greater automation and user autonomy. Zheng and Iryna (2025) outlined that omni-channel communication focuses on creating seamless and integrated customer experiences across multiple touchpoints to enhance engagement and drive business outcomes. Manhattan Associates (2025) points to the need for greater flexibility in omnichannel commerce technology and processes for retailers to thrive in a challenging market. Bojur &Andreea (2026) highlighted that predictive customer insights enable proactive strategies for personalisation and retention. Leveraging predictive analytics, anticipate future customer actions and trends with remarkable accuracy and provide forecasting behaviour, churn, and future buying patterns, demonstrating how explainable predictive analytics can provide valuable insights for customer segmentation and retention strategies.

2.6.5 Firm Size on Supply Chain Innovation Agility

Larger firms often possess greater resources, including financial capital and technological infrastructure, which can facilitate the adoption of advanced digitalisation strategies within their supply chains (Ozdemir et al., 2022; Li et al., 2025). This digitalisation enables agility, which allows organisations to respond more swiftly to market shifts and disruptions (Raj et al., 2025). However, smaller and medium-sized enterprises (SMEs) can also exhibit remarkable agility due to their inherent flexibility and less complex organisational structures, enabling quicker decision-making and implementation of innovative practices (Ozdemir et al., 2022). The correlation between firm size and the ability to leverage data network is crucial for enhancing supply chain agility, as larger firms might have more extensive data sets, while smaller firms might be more adept at rapid data utilisation (Wong et al., 2024). Ozdemir et al. (2022) confirm that ultimately, innovation is a key determinant of how effectively firms of varying sizes can achieve and maintain supply chain agility and it plays a crucial role in fostering supply chain agility and resilience in different firm sizes. While larger firms might have more diversified supply bases and robust risk management frameworks, potentially making them more resilient to disruptions,

smaller firms can often adapt more quickly due to their leaner operations and closer relationships with a limited set of suppliers. The COVID-19 pandemic showcased how firms of different sizes navigated supply chain disruptions, where larger companies might more efficiently apply risk management strategies. Furthermore, the concept of supply chain flexibility, which supports both innovation and agility, is explored in terms of its dimensions and impact on firm performance, emphasising that a rigid, universal approach is detrimental in modern supply chains (Vázquez-Bustelo & Avella, 2005).

2.6.6 Demand Forecasting Performance

Demand forecasting performance is a pivotal determinant of supply chain efficiency, directly impacting operational costs and customer satisfaction levels (Mutua & Odari, 2025). High-performing forecasting models allow organisations to minimise stock holding costs while ensuring products are available in the right quality and quantity to meet market needs (Serenoy et al., 2019). Traditional methods often struggle with market volatility, but the integration of machine learning and supply-chain information has been shown to significantly reduce error rates, particularly in complex sectors like the pharmaceutical industry (Zhu et al., 2021). Furthermore, the accuracy of these forecasts is often enhanced by utilising hierarchical and aggregation approaches, which balance data granularity between individual SKU levels and strategic long-term horizons (Babai et al., 2022). Empirical evidence from Kenyan SMEs suggests that robust demand forecasting practices are positively correlated with overall business performance and competitive advantage (Mutua & Odari, 2025). In the petroleum sub-sector, effective forecasting acts as a safeguard against shortages and waste, which are critical for maintaining supply chain reliability (Seroney et al., 2019). However, achieving superior performance requires overcoming data limitations, often through sophisticated models that capture hidden market factors (Zhu et al., 2021). The choice between temporal or cross-sectional aggregation also plays a vital role in optimising forecast precision for inventory replenishment (Babai et al., 2022). Consequently, organisations that prioritise data-driven forecasting can better manage the "bullwhip effect" and improve their procurement outcomes (Serenoy et al., 2019). Ultimately, demand forecasting performance serves as the analytical foundation for resilient, cost-effective, and responsive supply chain management (Mutua & Odari, 2025).

2.7 Chapter Summary

This chapter reviewed the theoretical and empirical literature underpinning the study on supply chain innovation agility and demand forecasting performance. The study was anchored on Dynamic Capability Theory, Systems Theory, Resource-Based Theory and Network Theory, which collectively explain how organisational capabilities, strategic resources, integrated systems, and collaborative networks enhance organisational responsiveness and improve demand forecasting performance in dynamic business environments.

The empirical review synthesised previous studies on business process innovation, technological innovation, network structure innovation, customer service innovation, and the moderating role of firm size. Although the literature generally supports a positive relationship between innovation and organisational performance, the findings remain inconsistent due to variations in research contexts, methodologies, and performance measures. Furthermore, limited empirical evidence exists on demand forecasting performance within Kenya's oil marketing industry, and few studies have examined supply chain innovation agility as a multidimensional construct while considering the moderating influence of firm size. The chapter also identified theoretical, methodological, contextual, and empirical gaps that justify the present study in order to contribute to the existing body of knowledge on supply chain innovation agility and provide empirical evidence on its influence on demand forecasting performance among oil marketing companies in Kenya.

CHAPTER THREE
RESEARCH METHODOLOGY

3.1 Introduction

This chapter elaborated on the methodology that was applied, including the research design, the target population, the sample and sampling procedure, the pilot study, the data collection tools and the method of data analysis. The chapter also outlined the ethical issues of research, the reliability and validity of the research instruments and the diagnostic tests for regression assumptions.

3.2 Research Design

Research design refers to a combination of decisions made throughout the research process that enable the researcher to answer the research question and draw the intended conclusions (Hunziker and Blankenagel, 2024). Research design helps the researcher to comprehend the dependencies and thereby provides an elaborate roadmap throughout the research while simultaneously identifying every significant detail (Bairagi & Munot, 2019). The study adopted a descriptive research design to accurately depict the characteristics of a population, phenomenon, or situation without manipulating variables, thereby offering a high level of objectivity and validity, essential for planning and generating hypotheses for further investigation (Aggarwal and Ranganathan, 2019).

The study further incorporated a mixed-methods approach, where quantitative data provided breadth through statistical generalisations and qualitative data offered depth by exploring underlying meanings and contexts (Creswell and Creswell, 2018). This synergy was crucial for achieving stronger inferences and validating findings and provided more robust evidence base than single-method approaches (Wasti et al., 2022). Therefore, for this study, a descriptive research design was crucial for accurately characterising the current state of these complex supply chain innovation agility dimensions. The integration of a mixed-methods approach further strengthens this inquiry by allowing for the statistical analysis of performance metrics alongside in-depth exploration of the contextual factors and perceptions driving innovation agility, thereby providing a comprehensive understanding. This combined methodology ensured that the research not only identified existing patterns and levels

of performance but also uncovered the nuanced reasons, offering actionable insights for the Kenyan oil sector.

3.3 Research Philosophy

A research philosophy guides researchers in selecting the most appropriate and fundamental methodologies, which ensure there is alignment between the worldview and the research process. A research paradigm is achieved through combining the components of ontology and epistemology with axiology and methodology (Park et al., 2020). Bryman (2021) primarily emphasises objective measurement, hypothesis testing, and observable phenomena while often limiting the exploration of contextual and practical organisational realities. Interpretivism philosophy mainly focuses on subjective meanings, social interactions, and qualitative understanding of phenomena from participants' perspectives (Sekaran & Bougie, 2020); however, it may not adequately support the statistical analysis, hypothesis testing, and objective performance measurement required in this study.

Park et al. (2020) posit that the positivist approach emphasises objectivity, replicability, and the use of quantitative methods to generate generalizable findings and is commonly applied in studies that seek to examine causal relationships and test theoretical propositions. Ryan et al. (2002) alluded to the purpose of positivism as to eliminate bias during the research process, make the research replicable by other researchers, and draw general conclusions based on the results obtained. Pervin and Mokhtar (2022) characterise interpretivism as a paradigm that focuses on reality as multiple and socially constructed, requiring researchers to engage in deep reflexivity and relational ethics to understand complex social phenomena. Pragmatism focuses on the practical consequences of research and emphasises the use of methods that best address the research objectives rather than adhering strictly to a single philosophical orientation (Saunders et al., 2023).

Therefore, the pragmatic research philosophy was deemed most appropriate because it allowed the researcher to integrate objective statistical analysis with practical organisational insights, thereby enhancing the comprehensiveness, applicability, and methodological rigour of the study. This approach ensured that it provided the methodological flexibility and supported the integration of both quantitative and qualitative approaches in addressing the complex relationship between supply chain

innovation agility, and demand forecasting performance in the Kenyan oil marketing industry.

3.4 Area of Study

The study was conducted on oil marketing companies registered under the Energy and Petroleum Regulatory Authority. These were the companies that solely focus on the downstream activities of the oil sector, which include storage, distribution, and marketing of refined petroleum products.

3.5 Target Population

A population comprises the participants that a researcher wishes to study, and it requires careful selection (Bairagi & Munot, 2019). This study targeted oil companies in Kenya registered by the regulatory commission. The Energy and Petroleum Authority (EPRA) report for the Financial year 2024-2025 indicated there were 145 registered oil marketing companies in Kenya. The study selected one supply chain officer per company as the unit of observation, yielding a total of 145 respondents. Supply chain officers were selected because they possessed substantial operational and strategic knowledge concerning procurement coordination, demand planning, innovation implementation, and forecasting systems within their organisations. Their positions provide direct exposure to supply chain innovation practices and organisational performance indicators, making them suitable informants for the study

3.6 Sampling Frame

Saunders et al. (2023) refer to a sampling frame as the list or source from which a study's sample is drawn and represents all the accessible elements of the target population that meet the study's inclusion criteria and are eligible for selection. Hair et al (2022) emphasised that an accurate sampling frame minimises selection bias and sampling errors, and Creswell and Creswell (2023) argue that an effective sampling frame should be comprehensive, current, and accurate to ensure that the selected sample adequately represents the target population.

The study's unit of analysis comprised the 145 Oil Marketing Companies (OMCs) licensed by the EPRA register of licensed petroleum marketers and operating in Kenya during the study period. This sampling frame ensured the representativeness of

the study, minimised coverage errors, and provided a reliable basis for selecting firms that meet the inclusion criteria.

3.7 Sampling Design and Sample Size

A sample design is the system adopted to select a sample unit from the target population (Agarwal, 2015). The study employed purposive sampling, which was appropriate in studies where the researcher intentionally selects participants or units that can provide the most relevant and reliable information for achieving the study objectives (Saunders et al., 2023). The firms included in the study were selected based on the availability of complete longitudinal records from 2021 to 2024, operational continuity, and accessibility of EPRA performance data. The firms included in the study were selected based on the availability of complete longitudinal records from 2021 to 2024, operational continuity, and accessibility of EPRA performance data. The exclusion of firms with incomplete operational or financial records prompted the existence of survivorship bias. However, firms lacking complete longitudinal data were omitted because missing observations could compromise trend analysis, forecasting consistency, and statistical validity. The retained firms provided complete and verifiable datasets necessary for valid statistical inference and analysis (Hair et al., 2022). Therefore, only 81 firms met the inclusion criterion of having complete demand forecasting data for the period 2021–2024, making them the accessible population for the study.

3.8 Data Collection and Research Instrument

3.8.1 Research Instrument

The study utilised a semi-structured questionnaire consisting of both closed-ended and open-ended questions. Closed-ended items employed a four-point Likert scale to facilitate quantitative analysis. The four-point Likert scale was adopted because it eliminated neutral responses and minimised central tendency bias by compelling respondents to make definitive judgments regarding the study variables. This helped to improve response discrimination and enhance measurement precision in organisational research (Sekaran & Bougie, 2020; Saunders et al., 2023). The open-ended questions enabled respondents to provide additional qualitative insights regarding supply chain innovation. This was to provide clarity of the data by ensuring more definitive options and reducing ambiguity in interpretation (Gandhi, 2024).

3.8.2 Data Collection Procedure

Data collection assists the researcher with the relevant information that could be analysed to provide meaningful information (Godwill, 2015). Data can be collected either as primary, which is first-hand data that is collected by the researcher, or secondary data, which is information that has already been collected (Benedictine University, 2024). The study adopted both primary and secondary data, with primary data collected from supply chain officers in oil marketing companies regarding supply chain innovation agility practices and their level of adoption. The secondary data was acquired from the EPRA database and published reports, including the demand consumption and market share of the companies. covering the period 2021–2024. The secondary data collection process involved verification of completeness, consistency, and authenticity of the records before analysis. Cross-validation procedures were conducted to ensure the reliability of the secondary data sources. The researcher distributed the questionnaire via drop-and-pick and via Google Forms. This helped reach all respondents who might not be within the organisation.

3.9 Pilot Test

A pilot study is defined as a smaller study to assess the research procedures, data collection tools, sampling strategies and other practices to prepare for the main study. It helps to identify any limitation areas in the research before embarking on full practice implementation and assists the researcher in familiarising themselves with the research procedures (Hassan et al., 2006). A pilot study is usually undertaken to confirm the feasibility, reliability and validity of a research study by evaluating its respondents and the research instruments. It is often conducted on a reduced number of the population to ascertain proper planning and adjustments of the main study (In, 2017).

The pilot study involved 10 respondents, representing approximately 12.3% of the target sample size of 81 respondents. This proportion falls within the methodological recommendations suggesting that pilot samples should constitute between 10% and 20% of the target population for preliminary testing purposes (Creswell & Creswell, 2023). The pilot study re-evaluated question clarity, response consistency, instrument completion time, and the overall appropriateness of the questionnaire structure. The 10 OMCs selected using convenience sampling were drawn from companies with

complete 2021–2024 demand data, and they were intended to check whether the 2021-2024 demand data could be reliably obtained and analysed from firms meeting the inclusion criteria.

3.9.1 Reliability of the Instrument

Reliability is concerned with the degree to which a measurement can provide consistent and stable results under repeated tests (Taherdoost, 2014). Reliability measures the consistency of a measure to provide similar results over time (Habib et al., 2014). There are two categories of reliability: Test-retest which outlines the correlation of responses give consecutive tests over a given time frame, and internal consistency, which highlights the consistency of responses in the different items of measure in the instrument (Mukherjee, 2019). Reliability was assessed using Cronbach's Alpha coefficient to determine the internal consistency of the questionnaire items. A Cronbach's Alpha threshold of 0.70 and above was considered acceptable for establishing reliability, consistent with contemporary methodological standards (Hair et al., 2022).

3.9.2 Validity of the Instrument

Validity is the extent of accuracy in the measure (Habib et al., 2014). It shows the credibility of the study results in depicting the findings of similar respondents outside the researcher's scope (Patino &Ferreira, 2018). Internal validity represents the degree to which a variable is responsible for any change in the dependent variable (Habib et al., 2014). It can be compromised due to erroneous measurement or respondents. External Validity showcases the accuracy of the results to conform to generalisations beyond the study in question. (Patino & Ferreira, 2018).

Validity is categorised into four forms including; Face validity, which covers whether the scale used is appropriate or suitable in measuring the content being researched (Middleton, 2019), Content validity shows the degree to which the measurement covers all attributes of the concept under study, Construct validity encompasses the adherence of a measure to the existing theory and knowledge being studied, Criterion Validity assesses the accuracy to which the results can predict an outcome (Taherdoost, 2014). Face validity was evaluated by examining whether the questionnaire items appeared appropriate and relevant to the study objectives. Content validity was

established through expert review by supervisors and academic specialists in supply chain management and research methodology.

Construct validity was assessed using exploratory factor analysis (EFA). Prior to factor extraction, the data were examined for suitability using the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity. The KMO statistic was used to determine whether the correlations among items were sufficient for factor analysis, whose minimum threshold is 0.50, while Bartlett's test assessed whether the correlation matrix differed significantly from an identity matrix, whose minimum requirement is significance of less than 0.05 ($p<0.05$). Principal axis factoring was employed as the extraction method. Direct Oblimin rotation was applied to obtain a more interpretable factor solution, and items with factor loadings of .50 or higher were retained for further analysis. A factor loading of 0.50 or higher is generally considered acceptable, while loadings of 0.70 or above are regarded as ideal because they indicate that the construct explains at least 49% of the variance in the observed variable (Hair et al., 2022). The study adopted a minimum factor loading threshold of 0.50, which ensured that retained indicators sufficiently explained the latent constructs under investigation.

3.10 Diagnostic Tests

Regression diagnostics is one of a set of procedures available for regression analysis that seek to assess the validity of a model in any of a number of different ways. Assumptions of linear regression models were validated so that the ordinary least squares (OLS) can provide reliable estimates of the parameters (Statistical Solutions, 2024). This study evaluated these assumptions by testing for linearity, autocorrelation, multicollinearity and heteroscedasticity.

3.10.1 Linearity Test

There must be a linear relationship between the outcome variable and the independent variables. Prior to performing linear regression analysis, the study tested the data for linearity to find out whether data sampled from a population that relates the variables of interest are in a linear fashion. The study conducted a linearity test, where a deviation from linearity ($p>0.05$) suggested that the variables had a linear relationship. However, if the deviation from linearity had a p-value less than 0.05 ($p<0.05$), it indicated a violation of the assumption and the variable would be

removed (Leard Statistics, 2018). Where non-linearity was detected, appropriate transformations, including logarithmic transformation and polynomial terms, were considered before excluding variables from the analysis. Outliers and influential observations were assessed using Cook's Distance and standardised residuals. Observations with excessively large Cook's Distance values were examined further to determine their influence on the regression estimates.

3.10.2 Heteroscedasticity Test

Heteroscedasticity occurs when the standard errors of a variable are not constant, and it can be conditional, related to the period volatility or unconditional, not related to the period volatility (Hayes, 2024). The linear regression model assumes that the volatility that has occurred in the model should be uniform in nature (homoscedasticity). The study utilised the Breusch-Pagan test, where a non-significant result ($p > 0.05$) indicated the absence of heteroscedasticity (Gujarati & Porter, 2021). Residual plots were also visually inspected to confirm the random distribution of residuals around zero.

3.10.3 Autocorrelation Test

Autocorrelation tests were conducted to determine whether the residuals from the regression model were independent across observations. Autocorrelation violates the assumption of error independence and may lead to biased standard errors and misleading statistical inferences (Wooldridge, 2020). The Durbin-Watson statistic was used to test for autocorrelation in the regression model. Durbin-Watson values ranging between 1.5 and 2.5 indicated the absence of serious autocorrelation problems in the dataset (Hair et al., 2022).

3.10.4 Multicollinearity Test

Multicollinearity occurs in multiple regression where some of the independent variables are significantly correlated among themselves (Mugenda &Mugenda, 2012). This makes its regression results unstable and unreliable, making it challenging to validate interpretations for drawing meaningful conclusions (Bandhari, 2024). Multicollinearity was assessed using the Variance Inflation Factor (VIF) statistics. VIF values below 10 indicated the absence of problematic multicollinearity among predictor variables (Hair et al., 2022).

3.10.5 Normality Test

These tests are used in research to detect whether data follows a normal distribution, in order to appropriately test the assumptions of the study (Dagster, 2024). This study employed the use of the skewness and kurtosis to determine whether the dependent variable and independent variables followed a normal distribution. If the values range between +1 and -1, the study would conclude that the dependent variable and independent variables follow a normal distribution, and hence fitting a linear model to the data was justified. The study also added quartile plots to supplement the kurtosis and skewness results.

3.11 Data analysis and Presentation

Data analysis entails the use of statistical methods that assist in describing, interpreting and presenting the data gathered. Data is processed through different levels of editing, coding, and classification (Godwill, 2015). Primary data consisted of responses collected through questionnaires administered to supply chain officers and mainly collected data on supply chain innovation agility (independent variable), while secondary data on demand consumption and market share (dependent and moderating variable) was obtained from EPRA reports.

The questionnaire data were cross-sectional because they were collected at a single point in time. Descriptive statistics: percentages, mean and standard deviation were used. This allowed the presentation of data in a meaningful way for an advanced understanding and interpretation (Singpurwalla, 2013). Conversely, the demand forecasting performance and market share data covering 2021–2024 were longitudinal, as they captured observations across multiple periods. Moving averages were utilised to smooth fluctuations in longitudinal demand forecasting data before aggregation into firm-level indicators for regression analysis. This approach enhanced trend stability and reduced short-term volatility within the forecasting data. Temporal differences between primary and secondary datasets were addressed by aggregating longitudinal performance indicators into firm-level averages and growth trends corresponding to the period during which the questionnaire data were collected. This harmonisation ensured consistency between the datasets used in the final analysis.

Open-ended responses were analysed using thematic content analysis. The responses were reviewed, coded, and grouped into categories based on similarities in meaning.

Related categories were then combined to generate themes that reflected respondents' views regarding supply chain innovation agility. The resulting themes were interpreted and used to complement the quantitative findings of the study. The findings were presented narratively and, where appropriate, supported by direct quotations from respondents to enhance credibility and authenticity of interpretation (Braun & Clarke, 2022; Saunders et al., 2023).

Inferential analysis of data was conducted using multiple regression and Pearson's correlation. Multiple regression was used to show the relationship between the supply chain innovation agility components and demand forecasting performance, and the moderating role of firm size within the study. This was done by adopting three equations:

To show the direct relationship between the variables

$Dfp = \beta o + \beta_1 Bpi + \beta_2 Ti + \beta_3 Nsi + \beta_4 Cci + e$ …….. *Equation I*

Where, Dfp = Demand forecasting performance

βo =constant

Bpi = Business process innovation

Ti = Technology Innovation

Nsi = Network Structure Innovation

Cci = Customer Centric Innovation

E = Error term

To find out the Moderating effect of firm size on the relationship between the independent variables and the dependent variable.

$Dfp = \beta o + \beta_1 Bpi + \beta_2 Ti + \beta_3 Nsi + \beta_4 Cci + \beta_5 Fs + e$ ……..*Equation II*

Where;

Dfp = Demand forecasting performance

βo =constant

Bpi = Business process innovation

Ti = technology innovation

Nsi = network structure innovation

Cci = Customer service innovation

Fs = Firm Size

e = Error term

To find out the Moderating effect of firm size and its interaction with the dependent and independent variables

$$Dfp = \beta o + \beta_1 Bpi + \beta_2 Ti + \beta_3 Nsi + \beta_4 Cci + \beta_5 Fs + \beta_6 Bpi.\ Fs + \beta_7 Ti.\ Fs + \beta_8 Nsi.\ Fs + \beta_9 Cci.\ Fs + e \ldots\ldots\ldots\ldots\ldots\ldots \text{Equation III}$$

The study used Statistical Package for the Social Sciences (SPSS) version 27 to assist in transforming, coding, and analysing the quantitative information acquired.

3.12 Hypothesis Testing

The study used ordinary Least Squares regression to test the hypotheses. This method was used to determine whether the relationships between the variables are linear. The null hypothesis H_0 was accepted if the p value was greater than 0.05($p>0.05$), and rejected if the p value was less than 0.05 ($p<0.05$).

Table 3.1: Hypothesis Table Summary

Hypothesis	Hypothesis Test	Regression Model
Hypothesis 1: H_{01}: Business Process Innovation did not have a statistically significant influence on demand forecasting performance of oil marketing companies in Kenya	H_0=0 $H_a \neq 0$ Reject H_0 if p <0.05, Otherwise, fail to reject the H_0	$Dfp = \beta o + \beta_1 Bpi + e$ *Dfp*=Demand Forecasting Performance β_0= intercept (Constant) β_1 = Coefficient for *Bpi* *Bpi* = Business Process Innovation *e* = Error term
Hypothesis 2: H_{02}: Technological Innovation did not have a statistically significant influence on demand forecasting performance of oil marketing companies in Kenya	H_0=0 $H_a \neq 0$ Reject H_0 if p <0.05, Otherwise, fail to reject the H_0	$Dfp = \beta o + \beta_1 Ti + e$ *Dfp*=Demand Forecasting Performance β_0= intercept (Constant) β_1= Coefficient for *Ti* *Ti* = Technological Innovation *e* = Error term
Hypothesis 3: H_{03}: Network Structure Innovation did not have a statistically significant influence on demand forecasting performance of oil marketing companies in Kenya	H_0=0 $H_a \neq 0$ Reject H_0 if p <0.05, Otherwise, fail to reject the H_0	$Dfp = \beta o + \beta_1 Nsi + e$ *Dfp*=Demand Forecasting Performance β_0= intercept (Constant) β_1 = Coefficient for *Nsi* *Nsi* = Network Structure Innovation *e* = Error term

Hypothesis 4: H_{04}: Customer centric Innovation did not have a statistically significant influence on demand forecasting performance of oil marketing companies in Kenya	H_0=0 $H_a \neq 0$ Reject H_0 if p <0.05, Otherwise, fail to reject the H_0	$Dfp = \beta o + \beta_1 Cci + e$ *Dfp*=Demand Forecasting Performance β_0= intercept (Constant) β_1 = Coefficient for *Cci* *Cci* = Customer Centric Innovation *e* = Error term

3.13 Ethical Considerations

Ethical considerations involve the moral principles guiding researchers in designing, conducting, and reporting research with human participants (Bhandari, 2021). Following ethical standards boosts the credibility, integrity, and trustworthiness of the research while protecting participants' rights and well-being (Creswell & Creswell, 2023). Before collecting data, the researcher obtained approval from the Murang'a University of Technology Board of Postgraduate Studies and a research permit from the National Commission for Science, Technology and Innovation (NACOSTI). These approvals permitted the researcher to carry out the study and ensured adherence to national research regulations. Participants were informed that their involvement was voluntary, and declining to participate would not lead to any negative consequences (Saunders et al., 2023).

Before administering the questionnaire, respondents were provided with adequate information about the purpose of the study, the nature of their participation, the expected duration, potential benefits, and measures protecting their rights. Respondents were informed that completing the questionnaire meant their consent to participate. This ensured informed decisions based on accurate information (Creswell & Creswell, 2023). Anonymity was preserved by not requesting personal details like names or contact information, preventing responses from being traced back to individuals. Confidentiality was maintained by limiting access to the data to the researcher and academic supervisors. Completed questionnaires and datasets were

securely stored on password-protected, encrypted devices accessible only to the researcher. Data were used solely for academic purposes and not shared without permission. Findings were presented objectively, with no manipulation, falsification, fabrication, or misrepresentation. Plagiarism detection ensured originality and academic compliance.

3.14 Chapter Summary

This chapter presented the research methodology adopted to examine the influence of supply chain innovation agility on demand forecasting performance among oil marketing companies in Kenya. The study was guided by the pragmatic research philosophy, which supports the integration of quantitative and qualitative approaches to provide a comprehensive understanding of the research problem. A descriptive research design within a mixed methods approach was adopted to facilitate the collection and analysis of both quantitative and qualitative data. Purposive sampling was employed to select respondents with the knowledge and experience necessary to provide relevant information on the study variables.

The chapter further described the data collection procedures, measurement of variables, and the techniques used to establish the quality of the research instruments. Reliability was assessed using Cronbach's alpha coefficient, while construct validity was established through Exploratory Factor Analysis (EFA). Quantitative data were analysed using descriptive statistics, correlation analysis, and multiple regression analysis to examine the relationships among the study variables and test the research hypotheses. Diagnostic tests were conducted to verify that the assumptions underlying the regression model were satisfied, thereby ensuring the validity of the statistical results. Qualitative data were analysed using thematic analysis to complement and enrich the quantitative findings.

The methodology adopted provided a rigorous and systematic framework for generating valid, reliable, and credible evidence to address the study objectives and examine the relationships between supply chain innovation agility, firm size, and demand forecasting performance.

CHAPTER FOUR
RESULTS AND DISCUSSION

4.1 Introduction

This chapter covered the analysis and findings of the study. The main aim of this study was to determine the influence of supply chain innovation agility on the demand forecasting performance of oil marketing companies in Kenya. The chapter will outline the demographic analysis, pilot study analysis and inferential statistics analysis.

4.2 Response Rate

The researcher distributed 71 questionnaires to supply chain officers in oil marketing companies, and 51 respondents completed and submitted them, resulting in a 71.83% response rate. 20 respondents did not submit their responses, accounting for 28.17% of the non-response rate, as shown in Table 4.1. Babbie (2020) states that a response rate of 50% is adequate, 60% is good, and 70% is very good. Baruch and Holtom (2008) additionally reported average response rates of 35.7% for organisation-level surveys, citing the busy schedules and organisational policies on information sharing. The 51 valid responses obtained represented 71.83% of the accessible population, which surpassed the response rates typically deemed acceptable in organisational research, thus providing a sufficiently representative basis for reliable conclusions about the target population (Baruch & Holtom, 2008; Saunders et al., 2023).

Table 4.1: Response Rate

Item	Frequency	Percentage
Respondents	51	71.83
Non-respondents	20	28.17
Total	**71**	**100%**

4.3 Pilot Study Results

A pilot study was conducted to establish the reliability and validity of the instrument. Therefore, this study's 10 oil marketing companies were considered appropriate to conduct a pilot study. The 10 oil marketing companies were not included during analysis. From the pilot study, the researcher conducted reliability and validity tests of the questionnaire to assess the instrument's adequacy for its intended purpose.

4.3.1 Reliability Test

Reliability is the ability of the research instrument to produce consistent results under consistent conditions (Anderson et al., 2024). Reliability was assessed using Cronbach's Alpha coefficients, and according to Hair et al. (2022), Cronbach's Alpha values of 0.70 and above indicate acceptable internal consistency reliability for research instruments. This test ensured that the questionnaire items consistently measured the intended constructs. The Cronbach alpha outcome for the variables in Table 4.2 was all above 0.70.

Table 4.2: Reliability Test

Variable	Cronbach's Alpha	Item
Business Process Innovation	.773	8
Technological Innovation	.799	8
Network Innovation	.740	8
Customer Service Innovation	.854	8

4.3.2 Validity Test

The study evaluated the instrument's validity through content validity, face validity, and construct validity procedures. Content validity was assessed through expert review involving supervisors and two specialists in supply chain management. Face validity was established by evaluating whether the questionnaire items appeared relevant and understandable to respondents. Construct validity was assessed using factor analysis procedures to determine whether the questionnaire items adequately represented the latent variables under investigation.

4.3.2.1 Explanatory Factor Analysis

Construct validity was assessed using EFA due to the relatively small sample size, and Principal Axis Factoring with Varimax rotation was employed as recommended for small-sample exploratory studies. The Kaiser-Meyer-Olkin (KMO) measure and Bartlett's Test of Sphericity were used to determine sampling adequacy and suitability of the data. The exploratory factor analysis (EFA) conducted in this study utilised Principal Axis Factoring (PAF) as the extraction method and Direct Oblimin with Kaiser Normalisation as the rotation method to examine the underlying structure of four innovation dimensions. The choice of PAF is methodologically justified as it

focuses on the shared variance among items, effectively partitioning out unique and error variance to reveal latent constructs rather than merely reducing data volume (Hair et al., 2019). PAF is considered more appropriate for social science research aimed at identifying common factors underlying the observed variables (Tabachnick & Fidell, 2021). Furthermore, the application of Direct Oblimin rotation is justified by the theoretical assumption that innovation dimensions are likely to be interrelated in real-world contexts. Oblique rotations like Direct Oblimin allow factors to correlate, thereby providing a more realistic and simpler structure that accurately reflects the complexity of the data (Field, 2024; Howard, 2023).

Table 4.3 showed that the EFA results for the four variables indicated that the data were suitable for factor analysis, as demonstrated by the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy, which was 0.812, exceeding the recommended threshold of 0.50. Bartlett's Test of Sphericity was statistically significant ($\chi^2 = 81.666$, df = 6, $p < .001$), demonstrating that the variables were significantly correlated and suitable for factor analysis. Therefore, the data satisfied the assumptions for factor analysis, and factor extraction was considered appropriate.

Table 4.3: KMO and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.812
Bartlett's Test of Sphericity	Approx. Chi-Square	81.666
	df	6
	Sig.	.000

In the social and behavioural sciences, where constructs are often complex and multidimensional, a cumulative explained variance of 40% or above is generally considered acceptable, particularly when Principal Axis Factoring (PAF) is employed to extract only the common variance among observed variables (Hair et al., 2022). Therefore, the extracted variance exceeding 40% in this study was considered sufficient to support the underlying factor structure and the construct validity of the measurement scales. The Pattern Matrix obtained after Direct Oblimin rotation was used to evaluate the relationship between the observed variables and their underlying latent factors.

Factor Analysis for Business Process Innovation

Table 4.4 below shows the total variance explained in Business Process Innovation. The first factor, with an eigenvalue of 3.167, and the second factor, with an eigenvalue of 1.187, together explained 40.67% of the cumulative variance after extraction, which was within the recommended threshold.

Table 4.4: Total Variance for Business Process Innovation

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.167	39.582	39.582	2.599	32.488	32.488
2	1.187	14.838	54.420	.655	8.184	40.672
3	.921	11.511	65.931			
4	.712	8.896	74.827			
5	.664	8.296	83.123			
6	.583	7.291	90.415			
7	.417	5.212	95.627			
8	.350	4.373	100.000			
Extraction Method: Principal Axis Factoring						

Table 4.5 shows that all the 8 items on business Process innovation were considered for analysis as the factor loadings ranged from approximately 0.41 to 0.80, indicating meaningful relationships with the latent construct. Negative loadings merely reflect factor orientation.

Table 4.5: Pattern Matrix for Business Process Innovation

Variable Statements	Component	
	1	2
BPI_1	.414	-.022
BPI_2	.200	-.379
BPI_3	.304	-.424
BPI_4	.613	-.068
BPI_5	.553	-.141
BPI_6	.028	-.773
BPI_7	.796	.137
BPI_8	-.096	-.690
Extraction Method: Principal Axis Factoring		

Factor Analysis for Technological Innovation

Table 4.6 below shows the total variance explained in Technological Innovation. The Technological Innovation dimension also yielded two factors with eigenvalues of 3.430 and 1.107, respectively, accounting for 45.11% of the cumulative variance.

Table 4.6: Total Variance for Technological Innovation

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.430	42.870	42.870	2.924	36.544	36.544
2	1.107	13.834	56.704	.685	8.564	45.108
3	.901	11.260	67.964			
4	.808	10.106	78.071			
5	.669	8.357	86.427			
6	.421	5.262	91.689			
7	.371	4.633	96.322			
8	.294	3.678	100.000			
Extraction Method: Principal Axis Factoring.						

In Table 4.7, the 8 items on technological innovation, the factor loadings ranged from 0.42 to 0.93. All indicators demonstrated acceptable loadings and theoretical relevance; therefore, all items were retained.

Table 4.7: Pattern Matrix for Technological Innovation

Variable Statements	Component	
	1	2
TEC_1	.340	.450
TEC _2	.603	.062
TEC _3	.037	.484
TEC _4	.421	.209
TEC _5	.931	-.153
TEC _6	.570	-.033
TEC _7	.479	.109
TEC _8	-.069	.933
Extraction Method: Principal Axis Factoring.		

Factor Analysis for Network Structure Innovation

In Table 4.8, the total variance explained in Network Structure Innovation. Two factors were extracted with eigenvalues of 3.354 and 1.064, explaining 41.03% of the cumulative variance.

Table 4.8: Total Variance for Network Structure Innovation

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.354	41.928	41.928	2.820	35.246	35.246
2	1.064	13.299	55.227	.463	5.786	41.031
3	.939	11.735	66.962			
4	.777	9.718	76.680			
5	.614	7.675	84.356			
6	.507	6.336	90.691			
7	.473	5.909	96.600			
8	.272	3.400	100.000			
Extraction Method: Principal Axis Factoring.						

In Table 4.9, the 8 items on network structure innovation, their factor loadings ranged between 0.44 and 0.90, supporting adequate construct representation. All items were retained because they satisfied recommended loading thresholds. This suggested that network structure innovation is a multidimensional construct in this dataset, requiring a nuanced interpretation of how different items contribute to the overall network innovation capability (Goretzko et al., 2021).

Table 4.9: Pattern Matrix for Network Structure Innovation

Variable Statements	Component	
	1	2
NET_1	.586	.195
NET_2	.547	.303
NET_3	-.104	.471
NET_4	.198	.346
NET_5	.156	.437
NET_6	.224	.564
NET_7	.898	-.183
NET_8	.436	.263
Extraction Method: Principal Axis Factoring.		

Factor Analysis for Customer Centric Innovation

In Table 4.10, the total variance explained in the Customer-centric Innovation dimension demonstrated the most robust internal structure, with two factors accounting for 53.69% of the variance. Although the second eigenvalue was slightly below one (0.904), the extraction sums of squared loadings supported retaining two factors to maintain consistency and theoretical depth.

Table 4.10: Total Variance for Customer Centric Innovation

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4.049	50.607	50.607	3.605	45.060	45.060
2	.904	11.297	61.904	.691	8.632	53.693
3	.876	10.955	72.859			
4	.744	9.296	82.154			
5	.457	5.711	87.865			
6	.418	5.227	93.092			
7	.308	3.854	96.946			
8	.244	3.054	100.000			
Extraction Method: Principal Axis Factoring.						

In Table 4.11, the 8 items on customer-centric innovation had factor loadings ranging from 0.44 to 0.90. All items showed satisfactory measurement properties and were retained.

Table 4.11: Pattern Matrix for Customer Centric Innovation

Component	Component	
	1	2
CUS_1	.692	.203
CUS_2	.065	.925
CUS_3	.552	.116
CUS_4	.885	-.127
CUS_5	.741	-.105
CUS_6	.464	.165
CUS_7	.586	-.067
CUS_8	.693	.099
Extraction Method: Principal Axis Factoring.		

4.4 Demographic Analysis

The demographic characteristics of the respondents were based on their years of operation and level of experience in the oil marketing industry, which was presented in percentages. These characteristics were considered important because they indicated the respondents' familiarity with supply chain operations and demand forecasting practices. The information also helped to establish the credibility of the responses and demonstrates that the respondents possessed adequate organisational and industry knowledge to provide reliable data for the study.

4.4.1 Years of Operation

Table 4.12 shows the number of years the organisations have been in operation. The results of the study show that 31.4% of the companies had been in existence between 11-15 years, which comprised the majority of the respondents, 21.6% were between 16-20 years, 19.6% were between 6-10years, 15.7% were below 5 years, and 11.8% were above 21 years. This shows that the majority of the companies have been sustainable for over 5 years, suggesting that they have been able to keep up with the steady competition of the market.

Table 4.12: Years of Operation

No. of Years	Frequency	Percentage
Below 5 Years	8	15.7%
6-10 Years	10	19.6%
11-15 Years	16	31.4%
16-20 Years	11	21.6%
Above 21 Years	6	11.8%

4.4.2 Level of Experience

The respondents were asked to indicate the number of years they have worked in their profession as supply chain officers. The study results in Table 4.13 show that 29.4% of them have worked for more than 15 years, 27.5% have experience between 6-9 years, 13.7% were between 2-5 years, and 15.7% have less than 1 year of experience. These findings suggest that most of the respondents had a firm understanding and expertise in supply chain innovations and agility, as well as what influences increases or decreases in demand or consumption rates. This was important because it enabled the researcher to gather relevant and relatable information essential to the study.

Table 4.13: Level of Experience

No. of Years	Frequency	Percentage
Below 1 Year	8	15.7%
2-5 Years	7	13.7%
6-9 Years	14	27.5%
10-14 Years	7	13.7%
Above 14 Years	15	29.4%

4.5 Descriptive Analysis

Descriptive analysis was used to determine and explain the current situation of innovation adoption in the oil marketing companies. The data collected was analysed using frequencies, Percentages, means and standard deviation. The responses collected were categorised into the scale of Low (0-24%)-L, Partial (25-49%)-P, Moderate (50-74%)-M, High (75-100%)-H These were further simplified into very low (L), partial (P), Moderate (M) and high (H) for easier understanding.

4.5.1 Business Process Innovation

The respondents were required to indicate to what degree the specific business process had been innovated to ascertain flexibility in their supply chains. The responses were categorised into the scale of Low (0-24%)-L, Partial (25-49%)-P, Moderate (50-74%)-M, High (75-100%)-H. The mean (M) and percentage mean (PM) were used to accurately indicate the collective cumulative average degree of innovation adoption. Table 4.14 shows that the degree of adoption of business process innovations was relatively moderate, with most of the agile functionalities within the moderate level of between 50-75%, the highest being the alignment between customer orders and warehouse dispatches, which is automated (M=3.02, PM=75.5%, SD=.812). The lowest was digital oversight existence in managing supplier compliance (M=2.67, PM=66.8%, SD=.973). The table also showed that departments adjust to align with changing operational priorities, automated systems detect and correct process deviations to reduce delays and monitoring of supplier risk in real time to ensure timely replenishment, have a relatively higher degree of adoption towards agility at (M=2.98, PM=74.5%, SD=.860; M=2.98, PM=74.5%, SD=.761; M=3, PM=75%, SD=.872) respectively. Operational tasks such as order processing and delivery scheduling digitisation were also adopted at a moderate level (M=2.78, PM=69.5%, SD=.856). Most companies' BPI rates vary between low and moderate. The positive impact of supply chain automation, especially in downstream processes such as order-to-dispatch linkages, aligns with Govindan et al. (2022), who found that automation improves order accuracy, reduces cycle times, and enhances process stability, as evidenced by SCOR® metrics and neural network predictions of performance gains. Departments' adaptability and problem-solving skills further support this view, as highlighted by Rasool et al. (2021), that AI- and IoT-driven flexibility aligns with findings on internal resilience during disruptions. However, Hofmann and Osterwalder (2022) note significant contradictions in real-time supplier risk monitoring and coordination gaps, and highlight strengths in detection but point out delays in execution for upstream metrics. Lower inventory and digitisation generally align with calls for broader adoption to address manual bottlenecks. Ambulkar et al. (2019) reinforce this agreement, showing that automation KPIs predict overall improvements without conflicting with ongoing gaps, such as supplier compliance. The high variability, therefore, indicates a shared need for consistent oversight.

Table 4.14: Descriptive Analysis for Business Process Innovation

Statement	L	P	M	H	M	PM	SD
Inventory levels adjust in response to changes in the market	2 3.9%	16 31.4%	21 41.2%	12 23.5%	2.84	71%	.834
Departments adjust to align with changing operational priorities	2 3.9%	13 25.5%	20 39.2%	16 31.4%	2.98	74.5%	.860
Cross-functional teams coordinate dynamically to respond to emerging changes	1 2.0%	12 23.5%	29 56.9%	9 17.6%	2.90	72.5%	.700
Operational tasks (e.g., order processing, delivery scheduling) are digitised	3 5.9%	16 31.4%	21 41.2%	11 21.6%	2.78	69.5%	.856
Automated systems detect and correct process deviations to reduce delays	0 0.0%	15 29.4%	22 43.1%	14 27.5%	2.98	74.5%	.761
Our company monitors supplier risk in real time to ensure timely replenishment	2 3.9%	13 25.5%	19 37.3%	17 33.3%	3.00	75%	.872
Alignment between customer orders and warehouse dispatches is automated	2 3.9%	10 19.6%	24 47.1%	15 29.4%	3.02	75.5%	.812
Digital oversight exists in managing supplier compliance	6 11.8%	17 33.3%	16 31.4%	12 23.5%	2.67	66.8%	.973

4.5.2 Technological Innovation

The respondents were required to indicate to what degree the specific technological innovation has been adopted to provide flexibility in their supply chains. The responses were categorised into the scale of Low (0-24%)-L, Partial (25-49%)-P, Moderate (50-74%)-M, High (75-100%)-H. The mean (M) and percentage mean (PM) were used to accurately indicate the collective cumulative average degree of innovation adoption.

Table 4.15 indicates that none of the companies had been able to extensively use digital twin technology to simulate operational scenarios and digitally visualise entire supply operations for agility decisions, as none reported a high use of the technology and simulations of supply chains at (M=2.16, PM=54%, SD=.644) and (M=2.16, PM=54%, SD=.674). However, they have been able to actively track the authenticity and integrity of fuel products using digital tools (M=2.69, PM=67.3%, SD=.707). It also showed that Internet of Things (IoT) tools are more intensively used to monitor fuel inventory and vehicle conditions (M=2.55, PM=63.8%, SD=.783) than integrated with the forecasting and dispatch models for prediction (M=2.37, PM=59.3%, SD=.720). the table also shows that they moderately use digital twin technologies to collect sensor data for predictive maintenance of assets at (M=2.37, PM=59.3%, SD=.644) Blockchain technology had also been relatively adopted at a moderate level as majority of the companies have low adoption in its functionalities in fuel visibility in the supply chain (M=2.41, PM=60.3%, SD=.726), and in the verification of logistics and payment transactions (M=2.35, PM=58.8%, SD=.770) respectively. This indicated that a higher percentage of their technology is directed towards maintaining fuel integrity and visibility, and monitoring fuel inventory and vehicles. The findings indicate that technological innovation, specifically blockchain, the Internet of Things (IoT), and digital twins, is becoming a cornerstone of operational strategies for oil marketing companies (OMCs). A high level of consensus was observed in the use of digital tools to track the authenticity and integrity of fuel products. This aligns with Park and Li (2021) that blockchain-based supply chains are highly effective at reducing the risk of counterfeit or unlicensed products through decentralised record-keeping systems. Furthermore, the data shows that the value of IoT lies in real-time monitoring of inventory and vehicle conditions. Aslam et al. (2023) & Roumeliotis et al. (2024) support this, noting that IoT-based monitoring provides the real-time data streams necessary for enhancing supply chain accountability and transparency in the oil and gas sector. However, the findings also revealed areas of lower adoption regarding digital twin technology and agile decision visualisation, both of which tied for the lowest mean. While digital twins are theoretically praised for providing a digital mirror to simulate and optimise complex supply chain scenarios (Wang et al., 2022), their lower scores in this study may reflect the significant technical complexity and high initial investment often cited as barriers to implementation (Achouch et al., 2022). Additionally, while blockchain for end-to-end visibility and transaction

verification received moderate support, Teodorescu & Korchagina (2021) warn that the rigidity of smart contracts and organisational readiness remain critical hurdles that can hinder widespread implementation. These results suggest that while OMCs are eager to adopt digital verification tools, they remain more cautious about the more complex, resource-heavy simulation and visualisation technologies.

Table 4.15: Descriptive Analysis for Technological Innovation

Statement	L	P	M	H	M	PM	SD
Our company use blockchain for end-to-end visibility in the fuel supply chain	4 7.8%	25 49.0%	19 37.3%	3 5.9%	2.41	60.3%	.726
IoT supports real-time monitoring of fuel inventory and vehicle conditions	4 7.8%	20 39.2%	22 43.1%	5 9.8%	2.55	63.8%	.783
Digital twin technology has been deployed to simulate operational scenarios	7 13.7%	29 56.9%	15 29.4%	0 0.0%	2.16	54%	.644
Our systems collect sensor data for predictive maintenance of assets	3 5.9%	28 54.9%	18 35.3%	2 3.9%	2.37	59.3%	.662
Our company tracks the authenticity and integrity of fuel products using digital tools	1 2.0%	20 39.2%	24 47.1%	6 11.8%	2.69	67.3%	.707
IoT systems are integrated with the forecasting and dispatch models	6 11.8%	21 41.2%	23 45.1%	1 2.0%	2.37	59.3%	.720
Our company can visualise entire supply operations digitally for agile decisions	8 15.7%	27 52.9%	16 31.4%	0 0.0%	2.16	54%	.674
Blockchain records are used to verify logistics and payment transactions	6 11.8%	24 47.1%	18 35.3%	3 5.9%	2.35	58.8%	.770

4.5.3 Network Structure Innovation

The respondents were required to indicate to what degree the specific network structure innovation has been adopted to establish flexibility in their supply chains. The responses were categorised into the scale of Low (0-24%)-L, Partial (25-49%)-P, Moderate (50-74%)-M, High (75-100%)-H. The mean (M) and percentage mean (PM) were used to accurately indicate the collective cumulative average degree of innovation adoption.

Table 4.16 illustrates that most of the companies (30, 58.8%) collaborate with logistics partners on capacity sharing or joint deliveries at a moderate at a mean (M=2.82, PM=70.5%, SD=.623). The companies can moderately change their routes dynamically to respond to disruption and are agile enough to onboard new suppliers during peak demand at (M=2.76, PM=69%, SD=.681). They were able to moderately exchange information with stakeholders in real time during emergencies (M=2.71, PM=67.8%, SD=.701), and their structure is flexible in maintaining service levels under regional fuel shortages (M=2.69, PM=67.3%, SD=.678). Decentralisation of the distribution system and scenario planning for supply chain uncertainties have also been moderately adopted but at significantly lower degrees than the rest at (M=2.65, PM=66.3%, SD=.688) and (M=2.59, PM=64.8%, SD=.779). However, the ability to adjust sourcing or fulfilment plans based on simulation outputs was the lowest in adoption, as the majority of the companies had low adoption, and very low adoption rates (30, 58.8%) compared to those with moderate and high adoption rates (21, 41.2%). This consequently reduced the mean for simulation to (M=2.29, PM=57.3%, SD=.782). This also signifies that the companies have yet to fully integrate aspects of scenario planning and simulation to increase supply chain flexibility. The findings reveal moderate to high agreement among respondents on supply chain agility practices in Kenyan oil marketing companies, indicating consistent perceptions of capabilities such as dynamic route changes, logistics collaborations, and real-time information exchange during emergencies. These results suggest embedded resilience strategies, aligning with studies showing that supply chain agility, through decisiveness, swift action, and alertness, significantly enhances competitiveness in Kenya's liquefied petroleum gas sector (Sabdio & Samson, 2018). Similarly, risk reduction strategies, including collaboration and flexibility, positively influence supply chain resilience in the Kenyan petroleum industry, supporting the observed

high endorsement of partner sharing and scenario planning (Lambaino, 2019). However, the slightly lower mean for simulation-based adjustment implies implementation gaps, potentially contradicting findings that innovative practices, such as just-in-time and integration, are widely adopted and drive performance in oil marketing firms, although they are challenged by training deficits and technology underinvestment (Shalakha, 2015). This partial divergence highlights context-specific barriers in Kenya, such as infrastructure limitations, which Okitte et al. (2024) identify as hindering logistics efficiency despite positive correlations with storage and transport capabilities. Overall, the findings affirm the role of agility but justify the need for targeted investments to bridge the variances with broader empirical evidence (Barua, 2010).

Table 4.16: Descriptive Analysis for Network Structure Innovation

Statements	L	P	M	H	M	PM	SD
Transport routes can be dynamically changed in response to disruptions	0 0.0%	19 37.3%	25 49.0%	7 13.7%	2.76	69%	.681
Our company use scenario planning to prepare for supply chain uncertainties	3 5.9%	21 41.2%	21 41.2%	6 11.8%	2.59	64.8%	.779
Our company collaborates with logistics partners on capacity sharing or joint deliveries	0 0.0%	15 29.4%	30 58.8%	6 11.8%	2.82	70.5%	.623
Our company network is agile in onboarding new suppliers during peak demand	2 3.9%	13 25.5%	31 60.8%	5 9.8%	2.76	69%	.681
The distribution system is supported by decentralised or backup nodes	1 2.0%	21 41.2%	24 47.1%	5 9.8%	2.65	66.3%	.688
Our firm adjusts sourcing or fulfilment plans based on simulation outputs	8 15.7%	22 43.1%	19 37.3%	2 3.9%	2.29	57.3%	.782
Information exchanged with stakeholders is in real time during emergencies	1 2.0%	19 37.3%	25 49.0%	6 11.8%	2.71	67.8%	.701
The network structure is flexible in maintaining service levels under regional fuel shortages	1 2.0%	19 37.3%	26 51.0%	5 9.8%	2.69	67.3%	.678

4.5.4 Customer Centric Innovation

The respondents were required to indicate to what degree the specific customer service innovation has been adopted to provide flexibility in their supply chains. The responses were categorised into the scale of Low (0-24%)-L, Partial (25-49%)-P, Moderate (50-74%)-M, High (75-100%)-H. The mean (M) and percentage mean (PM) were used to accurately indicate the collective cumulative average degree of innovation adoption.

Table 4.17 outlines that the ability to adjust delivery schedules or inventory based on customer segmentation insights had the highest moderate rate of adoption (43.1%), which collectively improved its overall extent of adoption (M=2.78, PM=69.5%, SD=.730). This was followed closely by their ability to use customer feedback systems to improve decision making, (M=2.75, PM=68.5%), using loyalty programs to give customer rewards, (M=2.73, PM=68.3%, SD=.802), frequent updates of customer communication tools to meet changing preferences (M=2.17, PM=67.7%, SD=.642) and the use of multiple channels to engage with customers (M=2.67, PM=66.8%, SD=.554). The responses indicate that the companies rarely use customer data models to predictive and anticipate future service needs, with the majority (54.9%) which implies the inadequate use of predictive tool to anticipate customer needs (M=2.43, PM=60.8%, SD=.781). However, it also indicated that the majority companies (94.1%) have not fully progressed into self-service apps/kiosks that help customer with their transactions (M=2.39, PM=59.8%, SD=.802). The findings showed that oil marketing companies (OMCs) are increasingly shifting toward a customer-centric innovation model, characterized by high adoption rates for multi-channel and personalized loyalty rewards. The data indicates that the respondents agreed that their company uses multiple channels such as, social media and live chat to engage customers, a strategy that aligns with contemporary views on omnichannel marketing. Rubeis et al. (2022) and Chari (2025) argue that in the modern energy retail sector, survival depends on expanding the value chain beyond the pump, utilizing digital technologies to create a synthesis where digital automation corresponds with the human ability to build trust and immediacy. Furthermore, the high mean score for personalized loyalty programs is supported by Tavor et al. (2023) and Ali and Shabn (2024) that targeted engagement and personalized communication are crucial for increasing Customer Lifetime Value (CLV) and fostering emotional

connections in a market where brand switching is common. While OMCs view automation as an efficiency gain, Roberts et al. (2024) argue that automated customer assistance is not a substitute for true service, as it often involves a transfer of labor from the firm to the customer, which can be detrimental to those with physical or technological limitations. Similarly, although the data reflects a positive trend in using predictive data models there is a noted discrepancy between strategic adoption and operational effectiveness. While machine learning is recognized as a powerful tool for forecasting customer behavior and reducing churn in the energy sector, its successful implementation is often hindered by organisational inertia and a lack of a customer-centric culture (Masoud & Basahel, 2023). This suggests that while OMCs are innovating technologically, the "human element" of service remains a questioned and critical limit for achieving true customer satisfaction (Rosak-Szyrocka et al., 2022).

Table 4.17: Descriptive Analysis for Customer Centric Innovation

Statement	L	P	M	H	M	PM	SD
Self-service platforms (apps, kiosks, etc.) are advanced in assisting customers with transactions	7 13.7%	20 39.2%	21 41.2%	3 5.9%	2.39	59.8%	.802
Our company uses multiple channels (e.g., social media, live chat) to engage with customers	0 0.0%	19 37.3%	30 58.8%	2 3.9%	2.67	66.8%	.554
Customer complaints or queries are resolved through automated systems	2 3.9%	26 51.0%	20 39.2%	3 5.9%	2.47	61.7%	.674
Customer data models are predictive in anticipating future service needs	5 9.8%	23 45.1%	19 37.3%	4 7.8%	2.43	60.8%	.781
Loyalty program offers personalised rewards based on past behaviours	4 7.8%	13 25.5%	27 52.9%	7 13.7%	2.73	68.3%	.802
Our company frequently updates customer communication tools to match changing preferences	1 2.0%	17 33.3%	29 56.9%	4 7.8%	2.71	67.7%	.642
Insights from customer segmentation are used to adjust delivery schedules or inventory	0 0.0%	20 39.2%	22 43.1%	9 17.6%	2.78	69.5%	.730
Feedback systems are integrated with service enhancement decision-making	3 5.9%	16 31.4%	23 45.1%	9 17.6%	2.75	68.7%	.821

4.5.5 Demand Forecasting Performance

The study sought to examine the volatility of petroleum demand among oil marketing companies in Kenya. It utilized demand data obtained from the Energy and Petroleum Regulatory Authority (EPRA) energy reports. Moving averages were calculated using longitudinal demand forecasting data collected over the period 2021–2024. The moving averages were used to smooth short-term fluctuations and identify stable forecasting trends over time. The analysis of secondary data from the EPRA reports, supported by the moving average method, provided valuable insights for forecasting future demand in Kenya's oil and petroleum sector. The results revealed notable fluctuations in petroleum product consumption. Despite periods of travel restrictions and economic slowdowns, overall demand for Premium Motor Spirit (PMS) and AGO experienced marginal increased in 2021 followed by a consistent decline in total domestic petroleum consumption, which indicated a sustained downward trend in demand for traditional petroleum products.

The graph in Figure 4.1 shows the annual actual and projected demand for petroleum products in Kenya from 2021 to 2024. The graph shows a clear change in forecasting accuracy and market behaviour between the first and second halves of the period. In 2021 and 2022, the oil marketing companies tended to over-forecast. Predicted demand exceeded actual results, especially in 2022, with a gap of over 600,000 units. This suggests that the initial projections might have been overly optimistic or failed to account for external market slowdowns. Such differences can lead to high inventory costs and possible overinvestment in production capacity, underscoring the need for more cautious estimation models during those periods. On the other hand, the trend reversed in 2023 and 2024, moving toward under-forecasting. In these years, actual demand was about 316,000 and 445,000 units higher than predictions. While surpassing sales goals is usually a good thing, ongoing under-forecasting can lead to problems like stockouts, high shipping costs, and strained relationships with suppliers. The shift from a surplus to a deficit figures points to a volatile market where the current forecasting approach may not be keeping up with real consumption recovery or growth. External shocks such as global fuel price instability, supply chain disruptions, or domestic policy constraints, may have suppressed actual consumption below predicted levels.

The figure illustrated inconsistencies between projected and actual consumption, suggesting that the forecasting models in use may require methodological improvements, particularly in capturing emergent economic, technological, and policy-related variables. Furthermore, it highlights evolving consumption patterns that petroleum industry stakeholders must incorporate into strategic planning, supply chain agility, and investment decisions.

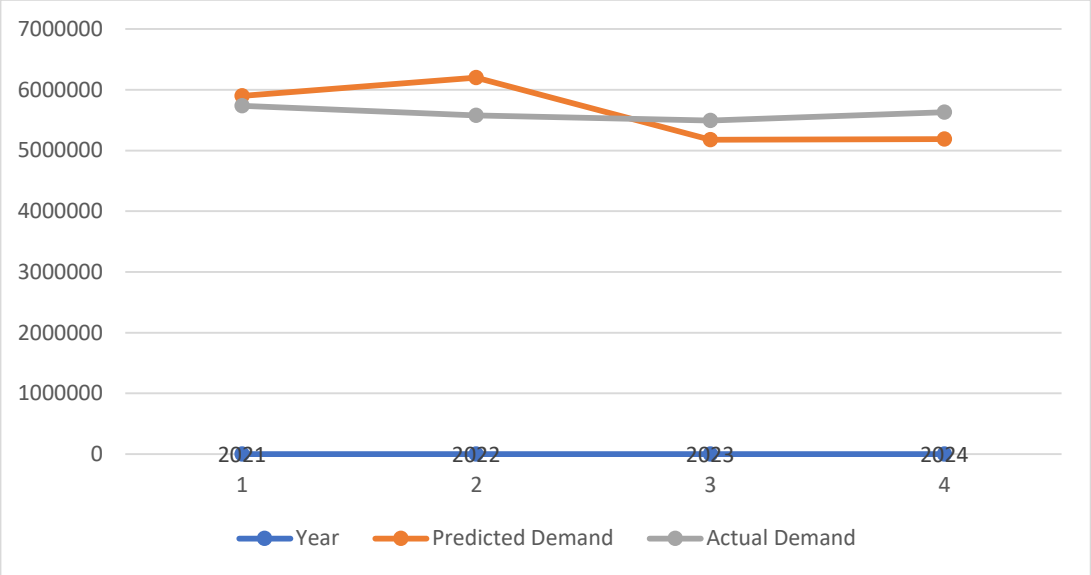


Figure 4.1: Trend of Oil Demand Forecasting Performance

4.5.6 Firm Size/Characteristics

Firm size was selected as the moderating variable for the study, with market share used as its indicator. Market share data was obtained as secondary information from regulatory energy reports. Figure 4.2 revealed that a few firms consistently dominated the market, collectively accounting for about 52% of the total market share. This indicated a high level of concentration and competitive strength among leading firms. Some firms demonstrated a steady growth in market share over the period, which accounted for 40% of the market share. This reinforced their emergence as key players, while others exhibited modest increases or fluctuations. The remaining firms, categorized as "others," held a combined share of about 10%, reflecting reduced market influence and possible consolidation within the industry. Variations in data occurred where some firms were classified under aggregated categories or where information was unavailable certain reporting periods

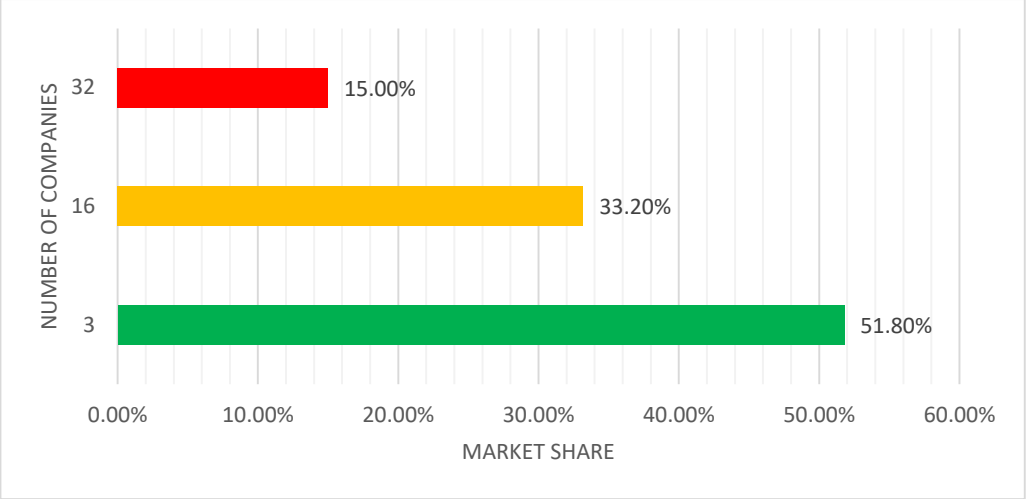


Figure 4.2: Trend Market Share of Oil Marketing Companies

4.6 Qualitative Analysis

Qualitative responses obtained from open-ended questionnaire items were analysed using thematic analysis. The analysis involved coding, categorisation, theme development, and interpretation of recurring patterns within respondents' responses. Braun and Clarke's thematic analysis approach guided the coding and interpretation process to ensure systematic analysis of qualitative data (Braun & Clarke, 2021).

Each variable's qualitative analysis process involved familiarisation with the responses through repeated reading, generation of initial codes from the responses, categorisation of related codes into themes, review and refinement of themes, and eventually interpretation and reporting of the findings. This approach enhanced the credibility and trustworthiness of the qualitative findings.

4.6.1 Business Process Innovation

The study asked respondents to mention some of the strategies their respective companies have adopted to improve process automation and to identify the challenges they have experienced during the automation of such processes.

Examining the responses given, the study was able to identify recurring strategies that have been adopted by these companies. The first was staff workshops and trainings, employees were trained in order to help the company adjust appropriately in an industry riddled by an influx of technologies such as artificial intelligence, machine

learning for decision-making. Improved employee skills increased rat e of management and implementation of process innovations and automations. Al Rob et al. (2024) also confirmed that staff training is as important as it increased the employees to have a willingness to adopt the new tools and technologies and affirms their perceptions on the importance of adopting the new process, which effectively improved the employees quality and efficiency of work.

Secondly, the respondents also mentioned Enterprise Resource Planning (ERP) upgrades, which were done to increase compatibility and integration with other new processes/innovations. These upgrades ensure that oil marketing companies that use legacy software are able to adequately and quickly adjust to the changes in the industry's workflow processes. Nzama (2021) affirms that ERP upgrades ensure that institutional systems are up-to-date with current technology, which eliminates the need to acquire costly projects for future use. However, these upgrades involve reengineering of business processes, which require certain factors, such as top management commitment and employee training, for them to be effectively implemented.

However, lack of full realisation of these innovations was attributed to some challenges that deterred them from fully automating their business processes. The high cost of incorporation and investment in automation tools and systems was identified as one of the major challenges for companies. This alluded to a significant number of oil marketing companies that did not have the capacity or adequate resources to acquire contemporary infrastructure immediately. This can be attributed to the aspect of the age and size of the company, which play a significant role in budgetary allocations and overall cost management. Markwide Research Report (2025), outlined that high initial investment is a challenge that is prominent in oil marketing companies in the Middle East and African countries, especially for medium and small-scale companies, where full system integration is required.

Resistance to change among the employees was also identified as a challenge whose probable cause was a skills gap or fear of redundancy. This was reinforced by Kipkorir, Mutea and Moguche (2023), whose findings also showed that business process reengineering full adoption was not possible due to employees resistance to change.

4.6.2 Technological Innovation

The respondents were required to highlight some of the strategies employed to improve technology adoption in their respective companies. These strategies were meant to identify ways in which the oil marketing companies have been able to ensure they are up-to-date with the market technologies.

Pilot programs are small-scaled controlled implemented of either an innovation, process or technology before they are fully adopted into the organisation. Oil marketing companies use this strategy to test their fuel distribution technologies to identify gaps before full scaling. They adopted this strategy to control costs and to make decisions on whether to modify, expand or drop a technology. Petrilli, Galuppo and Ripamonti (2022) outlined that for new technologies to be properly onboarded, organisations require to facilitate the orientation their employees to the organisation information, conduct meetings, train and gather feedback in order to fully integrate any digital technology into their organisations.

Cashless payments have also identified as a strategy that the oil marketing companies have employed to ensure payment security, reduced wait time while consequently reducing fraud and theft. The payments provide an avenue for oil marketing companies to track fuel expenses, rate of fuel usage and provide data analytics for sale of fuel and other lubricants. The government has advocated for cashless payments to improve on transparency and for tax compliance issues. Owour et al., (2023) affirm that cashless payments increased transparency, reduced operational costs and improved business efficiency.

4.6.3 Network Structure innovation

Strategic collaborations with other partners in the supply chain and with other oil marketing companies. Oil marketing companies have opted to form alliances or mergers with other oil marketing companies to increase their network, this increases their logistics and storage capacity in order to maintain a competitive advantage. Oil marketing companies are able to consolidate their synergies reduce cost of setting up filling stations and storage areas. Muchiri, Ombui and Iravo (2017) confirmed that oil marketing companies did engage in strategic alliances in order to grow their product lines and improve creativity to grow customer reach and access market niches.

Joint research and development with partners was another strategy that the oil marketing companies have adopted to maintain competitiveness in the market. These organisations invest in innovation that focuses on refining for final consumption as it affects their business and their customers. Partnered R&D aligned with knowledge and information sharing on market trends and innovations. Wang (2024)outlines that joint R&D is emphasised by close and concentrated networks promotes innovative ideas and information which can be accessed and shared within the networks.

4.6.4 Customer Centric Innovation

Social media campaigns were used by oil marketing companies to build brand loyalty, trust and also acquire data analytics on customers in order to customise segments that are audience-specific. Oil marketing companies have used social media to gain customer insights on their services and fuel quality, which in turn has assisted in increasing flexibility in decision-making within the volatile market. Espuela et al. (2023) alluded that social media content that is consistent, relevant and engaging promoted repurchase, trust and consequently fostered customer loyalty to respective brand products.

Loyalty applications have been adopted to provide the customer with highly personalised services tailored to their specific preferences. The data collected from these applications has assisted the oil marketing companies in providing data that can be used to predict the demand for fuel types and other products or services. Some of the companies have offered their customers redeemable rewards that can be used to purchase fuel products or services such as car washes or vehicle tunings. Kosasih et al. (2024) highlighted that service innovations such as loyalty apps have enhanced reliability and safety and promoted competitive advantage while consequently reducing operational costs and customer waiting time.

4.7 Diagnostic Tests

Diagnostic tests were conducted to determine whether the data satisfied the assumptions underlying multiple regression analysis. Testing these assumptions is essential to ensure the validity, reliability, and robustness of the regression estimates and to minimise the risk of biased or misleading results. The diagnostic tests undertaken included assessments of normality, linearity, heteroscedasticity,

autocorrelation and multicollinearity. The results of these tests are presented in the following subsections.

4.7.1 Autocorrelation Test

The Durbin-Watson statistic was used to assess autocorrelation among regression residuals. The study used the Durbin-Watson test, which ranges from 0 to 4; values closer to 2 indicate less autocorrelation, while values above 3 indicate high autocorrelation. Wooldridge (2020) reported that values between 1.5 and 2.5 indicated that the residuals were independent and that autocorrelation was not a serious concern in the regression model. Table 4.18 shows that the Durbin -Watson test for the autocorrelation value lies within the range.

Table 4.18: Durbin-Watson Test for Autocorrelation

Model	Durbin-Watson
1	1.608

4.7.2 Heteroscedasticity Test

The study adopted the Breusch-Pagan test, where a p value greater than 0.05 ($p>0.05$) indicates homoscedasticity, while a p value less than 0.05 ($p<0.05$) indicates heteroscedasticity. Table 4.19 indicates that the Breusch-Pagan test p value= .691which ($p>.05$). This indicates that the heteroscedasticity was not present in the dataset, thereby affirming the assumption (Hayes, 2024).

Table 4.19: Breusch-Pagan Test

Breusch-Pagan Test	Chi-Square Value	Sig.
	2.334	0.691

4.7.3 Multicollinearity Test

Multicollinearity was assessed using the Variance Inflation Factor (VIF) statistics and tolerance values. VIF values below 10 and tolerance values above 0.10 indicated the absence of problematic multicollinearity among the independent variables (Hair et al., 2022). This test determines whether the independent variables in a multiple regression exhibited high intercorrelations. VIF assesses collinearity among variables in a multiple regression. Otse (2025) further highlighted that a VIF of 1 indicates that the

variables are not correlated, between 1 and 5 indicates moderate correlation, and 5 and 10 indicate high correlation. Table 4.20 indicates that the VIF for the variables were all below 10 and moderately correlated.

Table 4.20: Multicollinearity Test of the Variables

Model		Collinearity Statistics	
		Tolerance	**VIF**
1	Business Process Innovation	.612	1.633
	Technological Innovation	.360	2.781
	Network Structure Innovation	.417	2.396
	Customer Service Innovation	.415	2.407
	Firm Size	.273	3.662

4.7.4 Normality Test of the Variables

Normality tests are used to ascertain whether the dataset collected has a normal distribution. The study used skewness and kurtosis to assess the normality of the data distribution. Skewness measures the asymmetry of the distribution, while kurtosis measures the peakedness of a distribution, where the rule of thumb is that skewness and kurtosis values that range between +1 and -1 are considered acceptable (Seijas-Macias, 2023). Table 4.21 shows that all the variable values are within range; therefore, the normality assumption is accepted.

Table 4.21: Normality Test

		Statistic	Std. Error
Business Process Innovation	Mean	2.8148	.05791
	Std. Deviation	.52758	
	Range	2.00	
	Skewness	-.502	.264
	Kurtosis	-.505	.523
Technological Innovation	Mean	2.2831	.04734
	Std. Deviation	.43129	
	Range	2.00	
	Skewness	.548	.264
	Kurtosis	.330	.523
Network Structure Innovation	Mean	2.5633	.04277
	Std. Deviation	.38964	
	Range	1.88	
	Skewness	.497	.264
	Kurtosis	.029	.523
Customer Centric Innovation	Mean	2.4714	.05531
	Std. Deviation	.50392	
	Range	2.63	
	Skewness	.458	.264
	Kurtosis	.353	.523

The Q-Q plots were used to assess whether the data follow a normal distribution; for normally distributed data, the points usually fall along a straight diagonal reference. The study, therefore, included quartile plots to supplement the skewness and kurtosis tests for normality to ascertain normal distribution. All three variables exhibited points that generally followed the diagonal reference line with only minor deviations at the tails. This suggests that the variables are approximately normally distributed and supports the results obtained from the skewness and kurtosis statistics.

In Figure 4.3, the Normal Q-Q plot for Business Process Innovation indicates that most of the observed data points closely follow the diagonal reference line, with only slight deviations at the lower and upper ends of the distribution. This pattern suggests that the data are approximately normally distributed and that no serious deviations from normality exist. Therefore, the normality assumption for Business Process

Innovation was considered to have been satisfied, confirming the findings obtained from the skewness and kurtosis statistics.

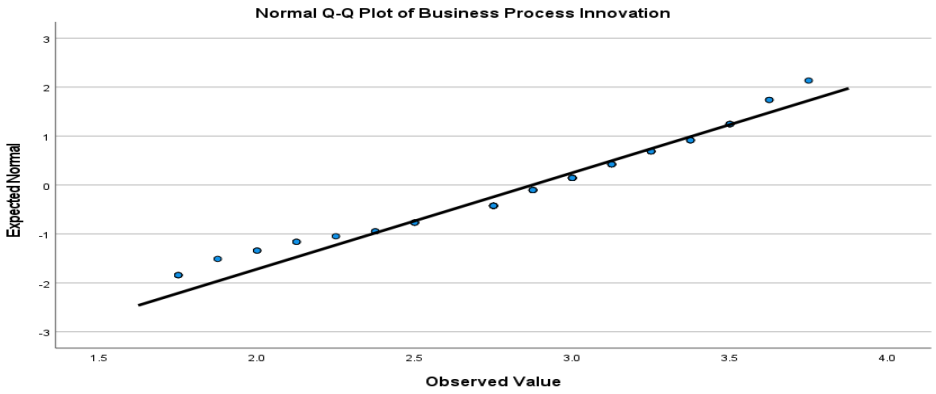


Figure 4.3: Plot of Business Process Innovation

In Figure 4.4, the Normal Q-Q plot for Technology Innovation shows that the majority of the data points lie close to the diagonal reference line, although a few observations at the upper end exhibit minor departures from the line. These deviations are not substantial, and overall, the plot demonstrates that the distribution of Technology Innovation approximates normality, thereby supporting the results of the skewness and kurtosis tests and indicating that the normality assumption was adequately met.

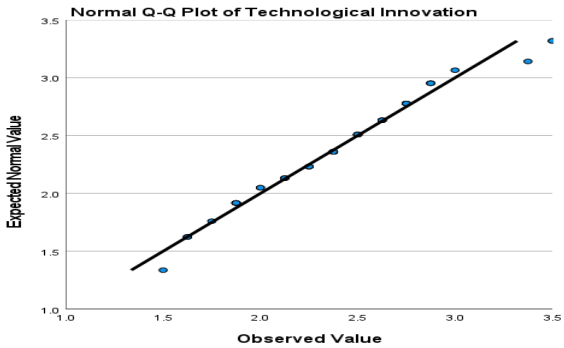


Figure 4.4: Plot of Technological Innovation

In Figure 4.5, the normal Q-Q plot for network structure innovation reveals that the observed values closely align with the expected normal values along the diagonal reference line. Only negligible deviations are evident at the tails of the distribution, indicating the absence of significant non-normality. Consequently, the distribution of Network Structure Innovation can be regarded as approximately normal, which is

consistent with the skewness and kurtosis results and supports the use of parametric statistical analyses.

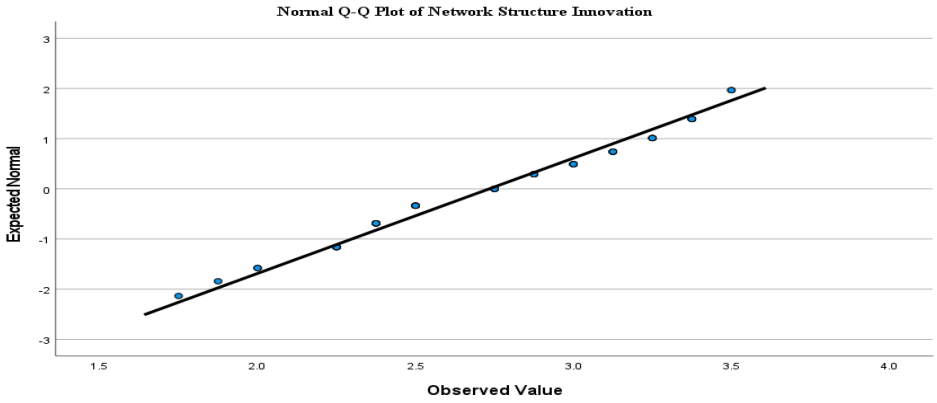


Figure 4.5: Plot of Network Structure Innovation

In Figure 4.6, the Normal Q-Q plot for customer-centric innovation demonstrates that the plotted observations generally follow the diagonal reference line, with only minor deviations occurring at the extreme upper tail. Such slight departures are acceptable and do not indicate serious violations of the normality assumption. Accordingly, customer-centric innovation was considered to be approximately normally distributed, corroborating the skewness and kurtosis statistics and confirming the suitability of the data for subsequent parametric analyses.

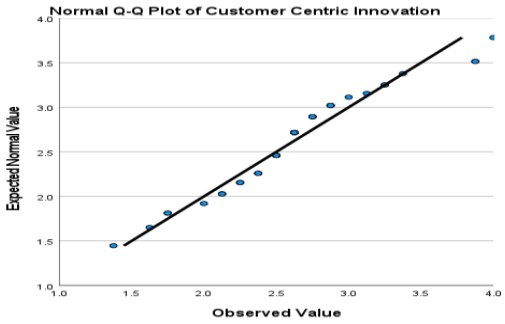


Figure 4.6: Plot of Customer Centric Innovation

4.7.5 Linearity Test

The study used deviation from linearity to assess whether the relationship was linear. A linear relationship is assumed to be likely if the p-value is greater than 0.05 ($p>0.05$); however, if the $p<.0.05$, then it indicates there is a violation of the assumption

(Mindrila, 2023). Table 4.22 outlines the variables that meet the assumption for deviation from linearity, where p>0.05, confirming that the data is linear and the assumption for regression is met.

Table 4.22: Test for Linearity

Variables	Deviation from Linearity (p>0.05)
Business Process Innovation	0.154
Technological Innovation	0.146
Network Structure Innovation	0.082
Customer Centric Innovation	0.226
Firm Size	0.664

4.7.6 Test for outliers of the variables

Outliers are data points that deviate from the overall pattern of the data and may exert undue influence on statistical estimates. This study conducted outlier detection tests to safeguard data integrity before primary analyses. Univariate screening applied the interquartile range (IQR) rule, values exceeding 1.5 times the IQR from the first and third quartiles, alongside z-score thresholds beyond three standard deviations from the mean (Aguinis et al., 2022). Multivariate testing utilised robust principal component analysis (PCA), which projected observations onto principal components and flagged residuals. Cook's distance values were inspected to identify influential observations that could disproportionately affect the regression coefficients. The analysis indicated that none of the cases exceeded the recommended thresholds for standardised residuals or Cook's distance (Osborne, 2023). The finding suggests that the dataset did not contain extreme observations that could distort the regression results.

4.8 Inferential Statistics

The study adopted Pearson's correlation to test for the strength of the relationship, simple linear regression to test for the individual influence of SCIA predictors on demand forecasting performance and multiple regression to test the combined influence of the independent variables (business process innovation, technological innovation, network structure innovation, and customer-centric innovation) on the demand forecasting performance of oil marketing companies in Kenya. The study further used a hierarchical multiple regression model to determine the influence of the

moderating variable on supply chain innovation agility and demand forecasting performance of oil marketing companies in Kenya.

4.8.1 Correlation Analysis

Pearson's correlation coefficient (r) was used to determine the direction and strength of the relationships among the study variables from 51 responses (N=51). Correlation coefficients range from −1 to +1, where the sign indicates the direction of the relationship and the magnitude indicates its strength (Hair, et al., 2022) The strength of the relationships was interpreted according to the guidelines of Schober et al. (2018): negligible (0.00–0.10), weak (0.10–0.39), moderate (0.40–0.69), strong (0.70–0.89), and very strong (0.90–1.00). Statistical significance was assessed at the 5% level ($p < .05$).

Table 4.23 indicates a strong, positive, and statistically significant correlation ($r = .827$, $p < 0.01$) between firm size and demand forecasting performance, which suggests that larger oil firms possess financial and infrastructural resources to implement advanced forecasting systems, which are essential for navigating the volatile energy market (Zhu, 2023). This aligns with the Resource-Based View (RBV), where larger organisations leverage scale-sensitive governance and extensive market reach to maintain stable performance levels even amid global price fluctuations (Venza & Aluoch, 2026). However, Sevil et al. (2022) contradict the notion that larger size is a perpetual advantage; smaller firms may actually outperform larger counterparts following innovation events because they possess the strategic flexibility to adopt new processes more rapidly.

Customer-Centric Innovation shows a strong correlation among innovation variables ($r = .820$, $p < .000$). In the context of supply chain agility, downstream customer data enables oil firms to advance to proactive scheduling. Bennett (2024) supports that integrating real-time customer feedback loops reduces the "bullwhip effect" in fuel distribution, thereby aligning supply more closely with actual consumption patterns. The correlation for technological innovation ($r = .751$, $p < .000$) is supported by Pasupuleti et al. (2024), highlighting that Artificial Intelligence (AI) and Machine Learning (ML) can reduce forecast errors by 20–50% compared to traditional models. While larger firms may have the capital for these high-tech investments, the overall

supply chain agility increasingly depends on the speed of technology adoption rather than the firm's physical scale alone (Zhang et al., 2025).

The strong and significant correlation between network structure innovation and demand forecasting performance ($r = .768$, $p < .000$) outlines that network structure innovation optimises the physical and digital links between refineries, distribution depots, and retail stations. Effective network innovation improves data visibility across the supply chain, thereby enhancing the accuracy of demand predictions (Pasupuleti et al., 2024). This aligns with the concept that oil marketing companies must innovate the way their network is structured to reduce lead times and respond more effectively to regional demand fluctuations. Conversely, a rigid or poorly integrated network structure leads to small changes in consumer demand, resulting in large, inefficient swings in inventory levels upstream.

The data shows that customer centric innovation ($r = .820$, $p < .000$) and technological innovation ($r = .751$, $p < .000$) are also strongly associated with forecasting success. This suggests that oil marketing agility is multifaceted, requiring a combination of advanced technology, customer-focused data, and a flexible network. Ultimately, the findings suggest that while firm size provides the necessary resources, the integration of network, business process, customer-centric, and technological innovations is a driver of the operational agility required for sustainability in the oil industry. The correlation analysis demonstrates that all forms of innovation are interrelated and collectively enhance demand forecasting performance. The positive relationships also imply that innovation practices in business processes, customer engagement, technology adoption, and network management reinforce each other. Furthermore, the size of the firm plays a crucial role in strengthening these innovation effects, consistent with the Dynamic Capabilities Theory, which emphasises the integration and reconfiguration of resources to respond to market changes effectively.

Table 4.23: Correlation Test

		Demand Forecasting Performance	Business Process Innovation	Technological Innovation	Network Structure Innovation	Customer Centric Innovation	Firm Size
Demand Forecasting Performance	Pearson Correlation						
Business Process Innovation	Pearson Correlation	.639**					
	Sig. (2-tailed)	.000					
Technological Innovation	Pearson Correlation	.751**	.578**				
	Sig. (2-tailed)	.000	.000				
Network Structure Innovation	Pearson Correlation	.768**	.491**	.669**			
	Sig. (2-tailed)	.000	.000	.000			
Customer Centric Innovation	Pearson Correlation	.820**	.528**	.637**	.612**		
	Sig. (2-tailed)	.000	.000	.000	.000		
Firm Size	Pearson Correlation	.827**	.539**	.687**	.778**	.736**	
	Sig. (2-tailed)	.000	.000	.000	.000	.000	

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

4.8.2 Simple Linear Regression

The study adopted linear regression to test the research hypotheses. A regression analysis was adopted to determine whether the variables indicated were statistically significant in predicting the influence on demand forecasting performance of oil marketing companies in Kenya.

4.8.2.1 Business Process Innovation and Demand Forecasting Performance

The study sought to examine the influence of Business process innovation on demand forecasting of oil marketing companies in Kenya. The study was guided by the hypothesis that "*Business Process Innovation does not have a statistically significant influence on Demand Forecasting Performance of Oil Marketing Companies in Kenya". The study performed linear regression analysis using the following linear regression model:* Dfp = β0 + β_1*Bpi+e, w*here D*fp*=Demand Forecasting Performance, β_0= intercept (Constant),β_1 = Coefficient for *Bpi, Bpi* = Business Process Innovation, *e* = Error term. The results of the analysis are shown in Table 4.24.

Table 4.24: Regression of Business Process Innovation and Demand Forecasting Performance

Variable	R	R^2	Adjusted R^2	Std Error	F	p	βo	β	t	Sig.
BPI	.639	.408	.396	.44680	33.744	.000	1.931	.783	5.809	.000

The regression analysis shows that only 40.8% of BPI could explain changes in demand forecasting performance among oil marketing companies in Kenya. The ANOVA showed that the p-value was less than 0.05 (F=33.744, p=.000). This indicates that the regression model for business process innovation significantly predicted demand forecasting performance. The coefficient for business process innovation was positive and significant (β =0.783,t=5.809, p=.000). The resultant regression model was as follows: Dfp = 1.931 + 0.783 *Bpi.* This implies that for every unit increase in business process innovation, there is a positive increase in the rate and accuracy of demand forecasting performance of oil marketing companies in Kenya. Liu and Chen (2024) validated that business process management had a positive and statistically significant impact on the performance of corporations, which implies that incorporating information technology into business process innovations significantly

improves the performance of the environment. Paunovic et.al. (2023) also confirmed that there was a positive correlation, they were not able to confirm if the relationship was significant between business process innovation and customer satisfaction within the family-owned businesses in Serbia.

4.8.2.2 Technological Innovation and Demand Forecasting Performance

The study sought to examine the influence of technological innovation on demand forecasting of oil marketing companies in Kenya. The study was guided by the hypothesis that "*Technological Innovation does not have a statistically significant influence on demand forecasting performance of Oil Marketing Companies in Kenya". The study performed linear regression analysis using the following linear regression model: Dfp = β0 + β2Ti +e, where Dfp*=Demand Forecasting Performance, β_0= intercept (Constant), β_2 = Coefficient for *Ti*, *Ti* = Technological Innovation, *e* = Error term. The results of the analysis are shown in Table 4.25.

Table 4.25: Regression of Technological Innovation and Demand Forecasting Performance

Variable	R	R^2	Adjusted R^2	Std Error	F	p	βo	β	t	Sig.
TI	.751	.564	.55	.38328	63.444	.000	1.828	.929	7.965	.000

The regression analysis indicates that the R^2 was .564, implying that 56.4% of BPI could explain the change in demand forecasting performance of oil marketing companies in Kenya. The ANOVA shows that the p value <0.05 (F=63.444, p=.000). This indicates that the regression model for technological innovation significantly predicted demand forecasting performance. The coefficients for technological innovation were positive and significant (*β*=.929, p=.000). The subsequent regression model was as follows: *Dfp = 1.828 +0.929 Ti.* This implies that for every unit increase in technological innovation, there is a positive increase of 0.929 in the rate and accuracy of demand forecasting performance of oil marketing companies in Kenya. Sun et al. (2021) corroborated that technology innovation openness had a positive effect on innovative performance and improved market competitiveness. Ran et al. (2024) also validated that digital technology innovation increased the market share of firms by a significant contribution. This confirmed that technology innovation was

more significant for larger firms, which could adopt capital and technology-intensive measures and lower internal cost controls. Wang et al. (2021) reinforced that innovation output positively influenced the performance of construction companies, where the firms' operational output had a positive correlation with innovation output.

4.8.2.3 Network Structure Innovation and Demand Forecasting Performance

The study sought to examine the influence of network-structure innovation on demand forecasting of oil marketing companies in Kenya. The study was guided by the hypothesis that *Network structure innovation does not have a statistically significant influence on demand forecasting performance of Oil Marketing Companies in Kenya". The study performed linear regression analysis using the following linear regression model: Dfp = β0 + β3Nsi +e, Where Dfp*=Demand Forecasting Performance, β_0= intercept (Constant), β_3 = Coefficient for *Nsi, Nsi* = Network Structure Innovation, and *e* = Error term. The results of the analysis are shown in Table 4.26.

Table 4.26: Regression of Network Structure Innovation and Demand Forecasting Performance

Variable	R	R^2	Adjusted R^2	Std Error	F	p	*βo*	*β*	t	Sig.
NSI	.768	.591	.582	.37154	70.661	.000	1.328	1.055	8.406	.000

The regression analysis illustrates that the R^2 was .591 which indicates that 59.1% of NSI can account for the change in demand forecasting performance of oil marketing companies in Kenya. The ANOVA established that the p value <0.05 (F=70.661, p=.000). This indicates that the regression model for network structure innovation significantly predicted demand forecasting performance. The coefficients for network structure innovation were positive and significant (***β*****=** 1.055, p=.000). The subsequent regression model was as follows: *Dfp= 1.328 + 1.055 Nsi.* This indicates that for every unit increase in network structure innovation, there is a positive increase of 1.055 in the rate and accuracy of demand forecasting performance of oil marketing companies in Kenya. Zhang et.al. (2025) confirmed that global innovation networks did have a significant and positive impact on the global value chain and further suggested that

supporting intellectual property rights on innovations could significantly improve the global value chain in developing economies.

4.8.2.4 Customer Centric Innovation and Demand Forecasting Performance

The study sought to examine the influence of customer centric innovation on demand forecasting of oil marketing companies in Kenya. The study was guided by the hypothesis that *"Customer-centric innovation does not have a statistically significant influence on demand forecasting performance of Oil Marketing Companies in Kenya". The study performed linear regression analysis using the following linear regression model: Dfp=βo + β_1Cci +e,* where *Dfp*=Demand Forecasting Performance, β_0= intercept (Constant), β_1 = Coefficient for *Cci, Cci* = Customer Centric Innovation, *e* = Error term. The results of the analysis are shown in Table 4.27.

Table 4.27: Regression of Customer Centric Innovation and Demand Forecasting Performance

Variable	R	R^2	Adjusted R^2	Std Error	F	p	β_0	β	t	Sig.
CCI	.820	.672	.665	.33254	100.370	.000	1.667	.908	10.018	.000

The regression presents that R^2 was .672, indicating that 67.2% of CCI accounted for changes in demand forecasting performance among oil marketing companies in Kenya. The ANOVA illustrated that the p value <0.05 (F=100.370, p=.000). This indicates that the regression model for customer-centric innovation significantly predicted demand forecasting performance. The coefficients for technological innovation were positive and significant (*β=0*.908, p=.000). The succeeding regression model was as follows: Dfp = *1.667 + 0.908 Cci.* This implies that for every unit increase in network structure innovation, there is a positive increase of 0.908 in the rate and accuracy of demand forecasting performance of oil marketing companies in Kenya. Tuominen et al. (2023) substantiated that customer-centric strategies are a driving force for innovation, and by increasing the innovative maturity of these strategies, export firms have a high chance of increasing the growth of the export firm.

4.8.3 Overall Multiple Regression

A multiple regression model was used to examine the influence of supply chain innovation agility on demand forecasting performance of oil marketing companies in Kenya. The adjusted R^2 was used because it adjusts for the number of predictor variables included in the regression model. Hair et al. (2022) noted that Adjusted R^2 provided a more accurate estimate of model explanatory power, particularly in multiple regression analysis involving several independent variables with a relatively small sample. The following regression equation model was used to show the direct influence of the variables.

$$Dfp = \beta o + \beta_1 Bpi + \beta_2 Ti + \beta_3 Nsi + \beta_4 Cci + e \ldots\ldots\ldots\ldots\ldots\ldots \text{ Equation I}$$

Where, D*fp* = Demand Forecasting Performance

β_o =constant

Bpi = Business Process Innovation

T_i = Technology Innovation

N_{Si} = Network Structure Innovation

Cci= Customer Centric Innovation

e = Error term

The model summary in Table 4.28 below indicates that there was a very strong and positive relationship between supply chain innovation agility and demand forecasting performance (R=.909). The adjusted R^2=.811 corresponds to 81.1% of demand forecasting performance, which can be explained by supply chain innovation agility predictors; business process innovation, technology innovation, network structure innovation and customer centric innovation. This implies that 18.9% of the demand forecasting performance is explained by factors not included in the study.

Table 4.28: Model Summary for Supply Chain Innovation Agility and Demand Forecasting Performance

Model	R	R Square	Adjusted R-Square	Std. Error of the Estimate
1	.909[a]	.826	.811	.24983

a. Predictors: (Constant), Business Process innovation,

The analysis of variance (ANOVA) in Table 4.29 shows that the p value <0.05 (F=54.661, P=.000). This shows that the model was fit to determine the influence of supply chain innovation predictors on demand forecasting performance. This was able to indicate that supply chain innovation had a statistically significant influence on Demand forecasting performance of oil marketing companies in Kenya, thereby rejecting the null hypothesis.

Table 4.29: ANOVA for Supply Chain Innovation Agility and Demand Forecasting Performance

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	13.647	4	3.412	54.661	.000[b]
	Residual	2.871	46	.062		
	Total	16.518	50			

a. Dependent Variable: Demand Forecasting Performance

b. Predictors: (Constant), Business Process Innovation, Technology Innovation, Network Structure Innovation, Customer Centric Innovation

The β coefficients from the regression analysis show the extent to which each predictor influenced demand forecasting performance. Table 4.30 shows that when all predictors are constant, the relationship is positive and significant (β =.659, p=.011). However, when the predictors were all regressed together, business process innovation (β =.189, p=.055), technological innovation (β =.222, p=.062) and had positive relationships but not significant relationship with demand forecasting performance as their p values were greater than .05 (P>.05), network structure innovation (β=.419, p=.001) and customer centric innovation (β=.484, p=.000) has a positive and significant relationship with demand forecasting performance. This suggested that for every one-unit increase in either predictor, there was a positive increase in demand forecasting

performance. The multiple regression analysis reveals that business process innovation and technological innovation had p-values greater than 0.05, indicating that the null hypothesis could not be rejected for each predictor. This outcome suggests that, within the context of this study and the observed data, there is insufficient statistical evidence to conclude that these specific innovation types collectively can significantly explain the variance in demand forecasting performance. This conflicted with Kithinji and Misuko (2022), who found a statistically significant relationship between process, product and service marketing innovation and the organisational performance of small and medium enterprises in Kenya. This could also suggest that, in the context of demand forecasting performance, oil marketing companies tend to share resources, indicating that BPI and TI were moderately correlated. However, their impact could be moderated through other variables not captured in this model. Network structure innovation (β= .419, p=.001) and customer centric innovation (β=.484, p=.000) had a positive relationship, whose relationship was significant (p<.05); the null hypothesis was rejected. This is validated by Cao et al. (2023), where their alternate hypothesis that innovative network structure could positively promote governmental research and development was accepted.

Table 4.30: Coefficients for Supply Chain Innovation Agility and Demand Forecasting Performance

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.
		B	Std. Error	Beta		
1	(Constant)	.659	.247		2.667	.011
	Business Process Innovation	.189	.096	.154	1.968	.055
	Technological Innovation	.222	.116	.180	1.916	.062
	Network Structure Innovation	.419	.121	.305	3.472	.001
	Customer Centric Innovation	.484	.096	.437	5.068	.000

a. Dependent Variable: Demand Forecasting Performance

Therefore, the regression model for Equation 1 was: Demand Forecasting Performance = .659 + .189 Business Process Innovation + .222 Technological Innovation + .419 Network Structure Innovation + .484 Customer-centric Innovation.

Moderating Effect of Firm Size

A moderating variable was introduced to understand the moderating effect of firm size on the relationship between the independent variables and the dependent variable. The research adopted the model below as *Equation II,* where F_i represented the moderating variable 'firm size'.

$$Dfp = \beta o + \beta_1 Bpi + \beta_2 Ti + \beta_3 Nsi + \beta_4 Cci + \beta_5 Fs + e \ldots\ldots\ldots\ldots\ldots\ldots Equation\ II$$

The model summary in Table 4.31 illustrates that the moderator maintained a very strong and positive relationship that slightly increased from (R= .909) to (R=.917). When firm size was introduced as a moderator, the model registered a rise in the adjusted R^2 =.822, which corresponds to 82.2% of demand forecasting performance being explained by BPI, TI, NSI and CCI. This translated into a 0.011 increase in the adjusted R^2, indicating a 1.1% rise in the capacity of the predictors to explain the dependent variable. The remaining 17.8% of demand forecasting performance is accounted for by other factors not mentioned in this study. This suggests that firm size increases the capacity of the independent variables in predicting the demand forecasting performance of oil marketing companies in Kenya. This was affirmed by Wirianata et al. (2024), where the introduction of firm size as a moderator resulted in an increase in the R^2, which implies that firm size was able to increase the financial performance of firms relative to tax avoidance. It is also reinforced by Alabdulkarim et al. (2024), conclusion that firm size was structural in ascertaining the relationship between leverage and firm performance.

Table 4.31: Model Summary for the Moderating Effect of Firm Size on Supply Chain Innovation Agility and Demand Forecasting Performance

Model	R	R Square	Adjusted R-Square	Std. Error of the Estimate
1	.909[a]	.826	.811	.24983
2	.917[b]	.840	.822	.24236

a. Predictors: (Constant), Business Process Innovation, Technology Innovation, Network Structure Innovation, Customer Centric Innovation
b. Predictors: (Constant), Business Process Innovation, Technology Innovation, Network Structure Innovation, Customer Centric Innovation, Firm Size

The ANOVA for the moderator, shown in Table 4.32, indicates that the model remained appropriate (F=47.244, p=.000), suggesting that the influence remained significant despite adding firm size as a moderating variable in the regression model. This correlates with Kitenga et al. (2020), where the ANOVA for the firm size as a moderator was statistically significant.

Table 4.32: ANOVA for the Moderating Effect of Firm Size on Supply Chain Innovation Agility and Demand Forecasting Performance

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	13.647	4	3.412	54.661	.000[b]
	Residual	2.871	46	.062		
	Total	16.518	50			
2	Regression	13.875	5	2.775	47.244	.000[c]
	Residual	2.643	45	.059		
	Total	16.518	50			

a. Dependent Variable: Demand Forecasting Performance
b. Predictors: (Constant), Business Process Innovation, Technological Innovation, Network Structure Innovation, Customer Centric Innovation
c. Predictors: (Constant), Business Process Innovation, Technological Innovation, Network Structure Innovation, Customer Centric Innovation, Firm Size

There was a change in the β coefficients when the moderator was included in the regression analysis. Table 4.33 illustrates that when all the predictors are kept constant, the relationship was positive and significant (β =.1.372, p=.003). When the predictors were all regressed together, business process innovation (β =.173 p=.072), Technological innovation (β=.185, p=.111) and customer centric innovation (β =.398,

p=.000) and Network structure innovation (β=.280, p=.046) had positive relationships, however, business process and technological innovation had p values greater than .05 (P>.05), whereas network structure innovation and customer centric innovation remained significant (p<.05). Firm size (β =.031, p=.055), also had a positive but non-significant relationship (p>.05). The regression analysis established that firm size itself has a positive and marginally significant effect on demand forecasting performance (β = .031, p = 0.055). This suggests that larger firms tend to have better demand forecasting performance, independent of the innovation types, or that firm size acts as a proxy for other factors contributing to better performance. This coincides with Kitenge et.al. (2020), where firm size did not have a statistically significant influence on the sustainable performance of manufacturing companies in Kenya. The coefficient slightly decreases for business process innovation (β=.189 to β=.173), and its significance weakens further (p = .072). This indicates that when firm size is accounted for, the direct impact of business process innovation on demand forecasting performance becomes even less distinct. The coefficient for technological innovation also decreases (from 0.222 to 0.185), and its significance drops considerably (p = 0.111). This suggests that some of the positive effects initially attributed to Technological Innovation might be absorbed by firm size, or that its direct impact is less significant in the presence of firm size. This correlates with Zhou et al. (2021), where increasing firm size provided a positive influence on technological innovation, but weakened the performance, while remaining positive. The coefficient for network structure innovation decreases (0.419 to 0.280 and its significance also weakens (p = 0.046), but remains significant, however, less so than before. This substantial change suggests that firm size influences how network structure innovation affects demand forecasting. Larger firms might have more established networks, or the benefits of network innovation are more pronounced in certain firm sizes. Customer-centric innovation coefficient decreases from 0.484 to 0.398, but it remains highly significant (p < 0.000). While its direct impact is still strong, the reduction in the coefficient suggests that firm size might explain a portion of the variance previously attributed solely to Customer Centric Innovation. The study findings also correlated with Wirianata et.al. (2024), where firm size lowered the coefficient values for two of the existing variables, concluding that when firm size is introduced as a moderator, return on assets and corporate social responsibility (CSR) had an indirect relationship with tax avoidance.

The moderation effect was not uniform across all innovation types. Customer-centric innovation, despite a reduced coefficient, remains highly significant, suggesting its fundamental importance regardless of firm size. However, the impact of business process and technological innovation appears more sensitive to firm size, indicating that their benefits might be more reliant on the firm's scale or other factors associated with size. Larger firms typically have more resources to implement and leverage innovations effectively (Kijkasiwat & Phuensane, 2020; Feng et al., 2025), which allows them to absorb the costs and risks associated with innovation, potentially leading to better demand forecasting outcomes. Smaller firms might struggle with the comprehensive implementation required to achieve significant improvements in complex areas such as demand forecasting from certain innovations.

Table 4.33: Coefficients for the Moderating Effect of Firm Size on Supply Chain Innovation Agility and Demand Forecasting Performance

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.659	.247		2.667	.011
	Business Process Innovation	.189	.096	.154	1.968	.055
	Technological Innovation	.222	.116	.180	1.916	.062
	Network Structure Innovation	.419	.121	.305	3.472	.001
	Customer Centric Innovation	.484	.096	.437	5.068	.000
2	(Constant)	1.372	.434		3.160	.003
	Business Process Innovation	.173	.093	.141	1.846	.072
	Technological Innovation	.185	.114	.150	1.624	.111
	Network Structure Innovation	.280	.137	.204	2.052	.046
	Customer Centric Innovation	.398	.102	.360	3.887	.000
	Firm size	.031	.016	.225	1.970	.055

a. Dependent Variable: Demand Forecasting Performance

Therefore, the regression model for Equation II after the moderating variable was introduced was:

Demand Forecasting Performance= 1.372 + .173 Business Process Innovation + .185 Technological Innovation + .280 Network Structure Innovation + .398 Customer Centric Innovation + .031 Firm Size

Moderating Effect of Firm Size and Its Interaction with the Dependent and Independent Variables

To understand the role of the moderating variable when they interrelate with the independent variables, the moderating variable (Firm Size) was introduced to determine whether there was any change when the moderating variable interacted with the other predictors. The following equation was adopted and named *Equation III.*

$$Dfp = \beta o + \beta_1 Bpi + \beta_2 Ti + \beta_3 Nsi + \beta_4 Csi + \beta_5 Gi + \beta_6 Bpi.Fs + \beta_7 Ti.Fs + \beta_8 Nsi.Fs + \beta_9 Csi.Fs + e \ldots\ldots\ldots\ldots\ldots\ldots \text{Equation III}$$

Where: *Bpi.Fs* = interaction between Business Process Innovation and Firm Size

Ti.Fs = interaction between Technological Innovation and Firm Size

Nsi.Fs = interaction between Network Structure Innovation and Firm Size

Cci.Fs = interaction between Customer Centric and Firm Size

The model summary in Table 4.34, Model 3, shows a slight increase in the relationship between supply chain innovation agility predictors and the dependent variable (R=.977). The interaction between the predictors increased the adjusted R^2 to .945, which corresponds the 94.5% of demand forecasting performance being explained by business process innovation, technology innovation, network structure innovation, and customer-centric innovation. This translates to a 0.123 change in the adjusted R^2, which indicates a 12.3% rise in the capacity of predictors to explain the dependent variable. This showed that when firm size interacts with the independent variables, they could account for 94.5% of demand forecasting performance; the other 5.5% of the demand forecasting performance is accounts for by other factors

not mentioned in this study. In Model 1, the predictors alone accounted for 81.1% of demand forecasting performance, while in Model 2, after including the moderating variable, 82.2% of demand forecasting performance could be explained by the predictors and the moderator. This means that by adding the moderator and introducing the interactions between the supply chain innovation agility predictors and firm size, the capacity for the predictors to account for demand forecasting performance increases exponentially.

Table 4.34: Model Summary for Firm Size and Its Interaction with the Dependent and Independent Variables

Model	R	R Square	Adjusted R Square	Adjusted R Square change	Std. Error of the Estimate
1	.909[a]	.826	.811	-	.24983
2	.917[b]	.840	.822	.011	.24236
3	.977[c]	.955	.945	.123	.13533

a. Predictors: (Constant), Business Process Innovation, Technology Innovation, Network Structure Innovation, Customer Centric Innovation
b. Predictors: (Constant), Business Process Innovation, Technology Innovation, Network Structure Innovation, Customer Centric Innovation, Firm Size
c. Predictors: (Constant), Business Process Innovation, Technology Innovation, Network Structure Innovation, Customer Centric Innovation, Firm Size, Business Process Innovation*Firm Size, Technology Innovation*Firm Size, Network Structure Innovation*Firm Size, Customer Centric Innovation*Firm Size

The ANOVA in Table 4.35 illustrates that the p values were all <0.05 in Model 1 (F=54.661, p=.000), Model 2 (F=47.244, p=.000) and Model 3 (F=95.662, p=.000). This shows that despite adding the moderating variable and interacting the independent variables with the moderating variable, the model remained significant. This implies that supply chain innovation, when moderated and interacted with firm size, still has a statistically significant influence on demand forecasting performance of oil marketing companies in Kenya.

Table 4.35: ANOVA for Firm Size and Its Interaction with the Dependent and Independent Variables

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	13.647	4	3.412	54.661	.000[b]
	Residual	2.871	46	.062		
	Total	16.518	50			
2	Regression	13.875	5	2.775	47.244	.000[c]
	Residual	2.643	45	.059		
	Total	16.518	50			
3	Regression	15.767	9	1.752	95.662	.000[d]
	Residual	.751	41	.018		
	Total	16.518	50			

a. Dependent Variable: Demand Forecasting Performance
b. Predictors: (Constant), Business Process Innovation, Technology Innovation, Network Structure Innovation, Customer Centric Innovation
c. Predictors: (Constant), Business Process Innovation, Technology Innovation, Network Structure Innovation, Customer Centric Innovation, Firm Size
d. Predictors: (Constant), Business Process Innovation, Technology Innovation, Network Structure Innovation, Customer Centric Innovation, Firm Size, Business Process Innovation*Firm Size, Technology Innovation*Firm Size, Network Structure Innovation*Firm Size, Customer Centric Innovation*Firm Size

Table 4.36 highlights the coefficients for Model 1 shows that when the predictors were all regressed together, business process innovation (β =.189, p=.055), Technological innovation (β =.222, p=.062) and has positive relationships but not significant relationship with demand forecasting performance as their p values were greater than .05 (P>.05), network structure innovation (β=.419, p=.001) and customer centric innovation (β=.484, p=.000) have a positive and significant relationship with demand forecasting performance.

In Model 2, the moderating variable, firm size, was added to the regression model, and the results show that business process innovation (β =.173, p=.072), technological innovation (β=.185, p=.111) and customer centric innovation (β =.398, p=.000), network structure innovation (β=.280, p=.046), Firm size (β =.031, p=.055) have positive relationships. Business process, technological innovation and firm size have a non-significant relationship (p>.05), while network structure innovation and

customer centric innovation remained significant (p<.05). Firm size (β =.031, p=.055) has a positive but slightly non-significant influence on demand forecasting performance.

In Model 3, the study investigated the interaction between supply chain innovation predictors and firm size. The results from the analysis show that.

i. Business Process Innovation × Firm Size (β = -0.065, p = 0.018): Statistically significant negative moderation. The beneficial effect of process innovation is stronger in smaller firms and diminishes in larger firms.
ii. Technological Innovation × Firm Size (β = 0.047, p = 0.513): Not statistically significant. The benefits of technological innovation are relatively consistent across firm sizes.
iii. Network Structure Innovation × Firm Size (β = -0.078, p = 0.273): Not statistically significant, though the point estimate suggests a trend toward stronger effects in smaller firms.
iv. Customer Centric Innovation × Firm Size (β = -0.177, p = 0.005): Statistically significant negative moderation. The beneficial effect of customer-centric innovation is substantially stronger in smaller firms and significantly diminished in larger firms.

Table 4.36: Coefficients for the Moderating Term of Firm Size and its Interaction with the Dependent and Independent Variables

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.659	.247		2.667	.011
	Business Process Innovation	.189	.096	.154	1.968	.055
	Technological Innovation	.222	.116	.180	1.916	.062
	Network Structure Innovation	.419	.121	.305	3.472	.001
	Customer Centric Innovation	.484	.096	.437	5.068	.000
2	(Constant)	1.372	.434		3.160	.003
	Business Process Innovation	.173	.093	.141	1.846	.072
	Technological Innovation	.185	.114	.150	1.624	.111
	Network Structure Innovation	.280	.137	.204	2.052	.046
	Customer Centric Innovation	.398	.102	.360	3.887	.000
	Firm Size	.031	.016	.225	1.970	.055
3	(Constant)	4.755	.437		10.871	.000
	Business Process Innovation	-.033	.059	-.027	-.557	.581
	Technological Innovation	.052	.118	.042	.445	.659
	Network Structure Innovation	-.001	.123	-.001	-.010	.992
	Customer Centric Innovation	-.137	.107	-.123	-1.280	.208
	Firm Size	.402	.040	2.953	10.026	.000
	Business Process Innovation*Firm Size	-.065	.026	-.369	-2.467	.018
	Technological Innovation*Firm Size	.047	.071	.337	.660	.513
	Network Structure Innovation*Firm Size	-.078	.070	-.607	-1.110	.273
	Customer Centric Innovation*Firm Size	-.177	.059	-1.503	-2.968	.005

a. Dependent Variable: Demand Forecasting Performance

Therefore, the regression model for Equation III, after the interaction between the independent variables and the moderating variable was introduced, was:

*Demand Forecasting Performance= 4.755 - .033 Business Process Innovation + .052 Technological Innovation - .001 Network Structure Innovation - .137 Customer Centric Innovation - .065 Business Process Innovation*Firm Size+ .047 Technological Innovation*Firm Size - .078 Network Structure Innovation*Firm Size - .177 Customer Centric Innovation*Firm Size*

Discussion on the Moderating Influence of Firm Size on Supply Chain Innovation Agility, and Demand Forecasting Performance Of Oil Marketing Companies In Kenya

The purpose of this study was to assess whether supply chain innovation agility (SCIA) in oil marketing companies (OMCs) in Kenya enhances their ability to predict demand more accurately. The regression results from the study showed that SCIA variables, business process innovation, technological innovation, network structure innovation, and customer-centric innovation explained 81.1% of changes in demand forecasting performance when analysed directly. When firm size was introduced as a moderating variable, the predictive power rose to 82.2%. This suggests that collectively, firm size improved the relationship between innovation agility and demand forecasting performance.

Firm size was considered under the assumption that larger firms generally have more resources, broader distribution networks, and stronger market presence. These factors make it easier for them to adopt innovations, process large volumes of data, and refine forecasting models. Smaller firms, on the other hand, may face resource limitations that reduce the impact of innovations on demand forecasting performance. This view aligns with Wirianata et al. (2024), who found that firm size can increase the effect of strategic practices on performance outcomes. Similarly, Alabdulkarim et al. (2024) noted that firm size influences the strength of relationships between financial variables such as leverage and performance. When interactions between firm size and SCIA dimensions were considered, the predictive power increased further to 94.5%. Interestingly, the results showed mixed effects: technological innovation interacted positively with firm size to improve demand forecasting performance, whereas business process innovation, network structure innovation, and customer-centric innovation interacted negatively. This indicated that in large firms, process and technology adoption strongly directed forecasting accuracy, but complexities in

networks and customer systems may create inefficiencies that reduce predictive accuracy.

The findings emphasise that firm size increases resources and influences how innovations affect performance. Larger OMCs benefit more from process and technological innovation because they can scale these practices effectively. However, larger customer networks and extended supply chains may introduce coordination challenges that diminish the benefits of business process, network, and customer-centric innovation. This aligns with Kitenga et al. (2020), where firm size weakened the link between capabilities and sustainable performance. Larger firms are better able to turn innovation into accurate forecasting, while smaller firms may struggle unless they focus on scalable innovations. Market share as an indicator of firm size in innovation studies reflects a firm's ability to capture value and exert influence within its industry (Bhattacharya et al., 2022). The findings highlight a negative moderation effect, suggesting that as firms gain higher market share, they may face organisational inertia and increased complexity. This aligns with Folger et al. (2023), who observed that dominant firms with large market shares become less responsive to radical process or customer-centric changes due to the need to protect existing revenue streams and navigate established bureaucratic structures. The interaction results imply that firms with large market shares often operate across multiple segments and geographies, which suggests that business process innovation in such complex environments may actually lead to bureaucratic inertia, hindering the agility needed for accurate demand forecasting in a volatile market, as Sankur et al. (2024) documented that high market share generates enormous volumes of data, but also introduces significant interference, explaining why the positive impact of customer-centricity on forecasting performance was reduced by interaction with firm size. Customer insights often decline as market share increases, making it harder to translate those insights into precise demand predictions.

The findings also suggest that even though firm size improved the explanatory power of the supply chain innovation agility components collectively, it does not uniformly influence all the dimensions. The moderating role of firm size is therefore contextual and dependent, that is, dimension-specific, on the specific innovation agility capability being implemented. Technological innovation and network structure innovation could

not be moderated by firm size, as was confirmed by Auryn et al. (2025), where firm size was not able to moderate the relationship between financial performance and tax avoidance, affirming this study's findings. This highlights the importance of focusing on the nature of the innovation and the organisational capabilities that support it. These findings, therefore, indicate that firm size partially moderated supply chain innovation agility and demand forecasting performance, suggesting that technological innovation and network structure innovation, which were not moderated by firm size, may operate independently of the organisational size and rely more on information sharing and organisational culture

4.8.4 Hypothesis Test

The study used Model 1 and Model 3 to test and report on the hypotheses of the study. Model 1 reported on the individual hypothesis collectively, and the combined influence and Model 3 reported on the fifth hypothesis.

H_{01} Business Process Innovation does not have a statistically significant influence on Demand Forecasting Performance of Oil Marketing Companies in Kenya

The regression coefficients Table 4.30 shows that business process innovation has a positive but non-significant influence (b=.189, p=.055), suggesting that business process innovation did not have a statistically significant influence on the demand forecasting performance of oil marketing companies in Kenya, thereby there was no sufficient evidence to reject the null hypothesis. This contradicts Wang et al. (2022) findings were combining business innovation with artificial intelligence improved demand forecasting performance.

H_{02} Technological Innovation does not have a statistically significant influence on demand forecasting performance of Oil Marketing Companies in Kenya

The regression coefficients in Table 4.30 illustrate that technological innovation has a positive but non-significant influence (b=.222, p=.062). This showed that technological innovation did not have a statistically significant influence on the demand forecasting performance of oil marketing companies in Kenya, and there was no sufficient evidence to reject the null hypothesis. This contradicts Sukumar et al.

(2022), where technological innovation had a statistically significant influence on the performance of manufacturing firms in Switzerland.

H_{03} Network Structure Innovation does not have a statistically significant influence on Demand Forecasting Performance of Oil Marketing Companies in Kenya

The regression coefficients in Table 4.30 show that technological innovation has a positive and significant influence (b=.419, p=.001). This indicates that network structure innovation has a statistically significant influence on demand forecasting performance of oil marketing companies in Kenya, thereby rejecting the null hypothesis. These findings also correlated with the simple regression results, where network structure innovation was statistically significant. Li et al. (2022) validated that structural innovation had a positive and significant impact on the performance of HEM enterprises.

H_{04} Customer Centric Innovation does not have a statistically significant influence on Demand Forecasting performance of Oil Marketing Companies in Kenya

The regression coefficients Table 4.30 shows that customer centric innovation had a positive and significant influence (b=.484, p=.000). This shows that customer centric innovation did have a statistically significant influence on demand forecasting performance of oil marketing companies in Kenya, thereby rejecting the null hypothesis. Lee et al. (2015) affirmed that customer centric structure was able to significantly enhances financial performance of corporate firms by increasing customer satisfaction.

H_{05} Firm size does not have a moderating effect on supply chain innovation, agility, and demand forecasting performance of oil marketing companies in Kenya

The results from the regression coefficients in Table 4.36 established that, firm size statistically moderated business process innovation (β = -0.065, p= 0.018), firm size did not statistically moderate technological innovation(β = 0.047, p = 0.513) firm size did not statistically moderate network structure innovation (β = -0.078, p = 0.273) and finally, firm size statistically moderated customer centric innovation (β = -0.177, p = 0.005). These findings indicate that firm size partially moderated the influence of

supply chain innovation agility and demand forecasting performance; the study failed to fully reject the null hypothesis, since firm size significantly moderated the relationship between business process innovation and customer-centric innovation, but did not significantly influence technological innovation and network structure innovation. Singh and Khatua (2025) corroborated that firm size provided dimension-specific moderation in financial disclosures, where liquidity and profitability disclosures were significant, and the others, leverage and investor disclosures, were not significant. This affirmed that firm size does not moderate all variables in the same direction or magnitude, but rather exerts influence that is specific to the dimensions being studied.

Table 4.37: Summary of Hypothesis Tests

Hypothesis	Rule	P-value	Verdict
Business Process Innovation does not have a statistically significant influence on demand forecasting performance of oil marketing companies in Kenya	Reject if p-value is less than 0.05 ($p<0.05$)	0.055	Failed to Reject
Technological Innovation does not have a statistically significant influence on demand forecasting performance of oil marketing companies in Kenya	Reject if p-value is less than 0.05 ($p<0.05$)	0.062	Failed to Reject
Network Structure Innovation does not have a statistically significant influence on demand forecasting performance of oil marketing companies in Kenya	Reject if p-value is less than 0.05 ($p<0.05$)	0.001	Rejected
Customer-centric Innovation does not have a statistically significant influence on demand forecasting performance of oil marketing companies in Kenya	Reject if p-value is less than 0.05 ($p<0.05$)	0.000	Rejected
Firm size does not have a moderating effect on supply chain innovation, agility and demand forecasting performance of oil marketing companies in Kenya.	Reject if p-value is less than 0.05 ($p<0.05$)	BPI ($p<0.018$) TI ($p>0.513$) NSI ($p>0.273$) CCI ($p<0.005$)	Partially Reject

4.9 Chapter Summary

This chapter presented and analysed the study findings in relation to the research objectives. The analysis began with the respondents' demographic characteristics, followed by descriptive statistics for the dimensions of supply chain innovation agility, namely business process innovation, technological innovation, network structure innovation, and customer service innovation. The descriptive findings provided an overview of respondents' perceptions of the study variables and established the basis for subsequent inferential analyses.

The chapter further presented the results of the diagnostic tests, which confirmed that the assumptions underlying the regression models were satisfied, thereby validating the use of parametric statistical techniques. Pearson's correlation analysis was then conducted to determine the strength and direction of the relationships between the study variables, while simple regression analysis established the individual influence of each dimension of supply chain innovation agility on demand forecasting performance.

Finally, hierarchical multiple regression analysis was employed to examine the moderating effect of firm size using a three-step modelling approach. The hierarchical models assessed the direct effects of the independent variables, the contribution of the moderator, and the interaction effects between supply chain innovation agility and firm size. The findings provided empirical evidence for testing the study hypotheses and addressing the research objectives.

CHAPTER FIVE
SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1 Summary of Findings

The study's general objective was to examine the influence of supply chain innovation agility on demand forecasting performance in oil marketing companies in Kenya. The study specifically aimed to; establish the influence of business process innovation on demand forecasting performance of oil marketing companies in Kenya, assess the influence of technological innovation on demand forecasting performance of oil marketing companies in Kenya, establish the influence of business process innovation on demand forecasting performance of oil marketing companies in Kenya, analyse the influence of network structure innovation on demand forecasting performance of oil marketing companies in Kenya, ascertain the influence of customer centric innovation on demand forecasting performance of oil marketing companies in Kenya and to ascertain the moderating effect of firm size on the relationship between supply chain innovation agility and demand forecasting performance of oil marketing companies in Kenya.

Supply chain innovation agility, encompassing all dimensions, significantly influences demand forecasting performance in Kenyan oil marketing companies. A holistic approach to innovation is crucial for enhancing forecasting capabilities and achieving a competitive advantage in a volatile market. In the initial regression analyses, each independent variable, business process innovation, technological innovation, network structure innovation, and customer-centric innovation, individually demonstrated a statistically significant positive influence on demand forecasting performance. This initial assessment suggests that, in isolation, each form of innovation contributes meaningfully and independently to a firm's forecasting capabilities. This is an important baseline understanding, indicating the general effectiveness of each innovation type.

When these innovation types were subsequently analysed together within a multiple regression, the individual statistical significance of business process and technological innovations diminished, with only network structure innovation and customer-centric innovation retaining their statistical significance. While each innovation type is

conceptually distinct, its practical implementation within a single organisation often involves overlapping resources, processes, and objectives. For instance, technological innovations might enable more efficient business processes, or customer-centric initiatives might rely on robust network structures for data collection and delivery. This overlap means that a portion of the explanatory power of one innovation type might be accounted for by another when they are considered simultaneously.

The findings demonstrate that firms capable of fostering innovation across their business processes, technological infrastructure, network structures, and customer-centric approaches are significantly better positioned to anticipate market demand fluctuations. This agility translates into a competitive advantage, enabling companies to optimise inventory levels, reduce stockouts and overstock, enhance operational efficiency, and ultimately improve profitability. The study reinforces that in an industry characterised by volatility and external shocks, such as geopolitical events, global price shifts, and local regulatory change, a proactive and adaptive innovation strategy is vital for maintaining market relevance and operational stability. The collective explanatory power of these innovation dimensions underscores the necessity for a holistic and integrated approach, rather than isolated initiatives, to truly utilise the predictive capabilities essential in an agile supply chain.

5.1.1 Business Process Innovation and Demand Forecasting Performance

This study sought to analyse the influence of business process innovation on demand forecasting performance of oil marketing companies in Kenya. The descriptive analysis provided a granular view of the adoption of Business Process Innovation (BPI) within the surveyed oil marketing companies. It was observed that critical operational areas, such as the automation of inventory restocking processes based on demand fluctuations and the adaptability of workflows to accommodate urgent or last-minute supply changes, demonstrated a moderate level of implementation. This suggests a strategic recognition among these companies of the direct link between streamlined internal processes and enhanced operational agility. The integration of systems across procurement, warehousing, and distribution units, while showing moderate adoption, indicates a collaborative effort towards creating a more cohesive and responsive supply chain. However, the study also highlighted persistent challenges that impede the full realisation of BPI's potential. These include the

significant financial expenditure associated with incorporating advanced process automation technologies, inherent organisational resistance to fundamental changes in established workflows, and technical difficulties in integrating new systems with existing infrastructure. Despite these challenges, the preliminary inferential analysis evidently supported the hypothesis that BPI has a statistically significant positive influence on demand forecasting. This finding implies that continuous investment in and refinement of business processes directly contribute to a firm's capacity for more accurate and timely demand forecasting. Optimising the flow of information, reducing manual interventions, and enhancing the speed of decision-making, companies can develop more sophisticated predictive models, leading to optimised inventory levels, reduced carrying costs, and improved responsiveness to market shifts. In Model 1, business process innovation exhibited a positive but non-significant effect ($\beta = 0.189$, $p = 0.055$); therefore, the data were not sufficient to reject the null hypothesis. This suggests that improvements in operational efficiency, workflow optimization and process automation contribute incrementally to enhanced forecasting capabilities but not at a significant level. When firm size is introduced as a moderating variable, the effect of business process innovation slightly diminishes ($\beta = 0.173$, $p = 0.072$), indicating that firm size partially accounts for some variance previously attributed to process innovation. However, the relationship remains directionally consistent and non-significant, suggesting that process improvements retain independent explanatory power even after controlling for organisational scale. The interaction analysis revealed that firm size significantly moderates the relationship between business process innovation and demand forecasting performance ($\beta = -0.065$, $p = 0.018$). This negative moderation coefficient indicates that the beneficial effect of business process innovation is stronger in smaller firms and diminishes in larger organisations. The diminishing returns in larger firms may reflect organisational inertia and the difficulty of achieving coordinated implementation across multiple departments and business units.

5.1.2 Technological Innovation and Demand Forecasting Performance

The second objective of the study was to examine the influence of technological innovation on demand forecasting performance in oil marketing companies in Kenya. The descriptive analysis showed that technological innovation (TI) adoption was moderate. Companies effectively used digital tools for product authenticity tracking

and IoT for real-time monitoring. However, advanced technologies such as blockchain for end-to-end visibility and digital twin technology for simulations saw lower adoption. The initial regression analysis demonstrated a positive and significant influence of TI on demand forecasting performance; the null hypothesis that technological innovation did not have a statistically significant influence on demand forecasting performance was rejected. The findings in the baseline model ($\beta = 0.222$, $p = 0.062$) indicate that TI had a positive but not significant influence on demand forecasting performance, indicating that technological integration improves forecasting accuracy; therefore, the null hypothesis that technological innovation did not have a statistically significant influence on demand forecasting performance failed to be rejected. This aligns with theoretical expectations that advanced technologies enhance the accuracy and sophistication of demand forecasting models. In Model 2, when moderated, technological innovation's effect slightly reduces ($\beta = 0.185$, $p = 0.111$). This suggests that firm size does not substantially confound the relationship between technological innovation and forecasting performance at the main effect level. The interaction term for technological innovation and firm size is not statistically significant ($\beta = 0.047$, $p = 0.513$), indicating that firm size does not significantly moderate the relationship between technological innovation and demand forecasting performance. This suggests that the benefits of technological innovation are relatively consistent across firm sizes, implying that both small and large organisations can derive similar proportional gains from technology adoption. It also suggests that Larger firms' greater financial resources and technical expertise may offset the implementation complexity disadvantages they face with process innovation

5.1.3 Network Structure Innovation and Demand Forecasting Performance

The third objective of the study was to assess the influence of network structure innovation on demand forecasting performance in oil marketing companies in Kenya. The overall descriptive analysis showed that network structure innovation (NSI) had moderate adoption, characterised by an emphasis on collaborative practices and adaptive network designs. Companies exhibited a strong tendency for collaboration with logistics partners, particularly in areas such as capacity sharing and joint deliveries. This highlights an identification of the benefits accrued from inter-organisational cooperation in resource utilisation to improve operational efficiency.

Furthermore, the ability to adjust transport routes in response to disruptions and the agility in onboarding new suppliers during periods of peak demand emphasised a proactive approach to building resilient and flexible supply networks. The ability to reconfigure networks in real-time translates into a more informed and agile forecasting process, reducing lead times and enhancing overall market responsiveness. However, there was a lower adoption in the adjustment of sourcing or fulfilment plans based on simulation outputs. This suggests a gap in leveraging advanced analytical and modelling tools for strategic network optimisation and scenario planning.

In Model 1, network structure innovation yielded a standardised coefficient of $\beta = 0.419$ ($p = 0.001$), which was positive, statistically significant and substantially larger than the effects of business process and technological innovation; the null hypothesis was rejected. The findings suggest that organisational network redesign, supply chain integration, cross-functional collaboration mechanisms, and external partnership development substantially enhance forecasting capabilities. Network structure innovations likely facilitate information flow, reduce communication barriers, and enable knowledge sharing across organisational boundaries. When firm size is introduced, the effect of network structure innovation diminishes to $\beta = 0.280$ ($p = 0.046$), remaining statistically significant but reduced in magnitude. This suggests that firm size accounts for a significant portion of the variance in the effectiveness of network structure innovation. The interaction analysis reveals that firm size does not significantly moderate the relationship between network structure innovation and demand forecasting performance ($\beta = -0.078$, $p = 0.273$). While the coefficient is negative, it fails to achieve statistical significance. This finding suggests that network structure innovation is relatively robust across firm sizes, though the point estimate suggests a potential trend toward stronger effects in smaller firms. However, the lack of statistical significance may reflect high variability in how different firms implement network innovation.

5.1.4 Customer-Centric Innovation and Demand Forecasting Performance

The fourth objective was to establish the influence of customer centric innovation on demand forecasting performance in oil marketing companies in Kenya. The overall descriptive analysis shows that customer-centric innovation (CCI) was moderately adopted, where companies were able to leverage customer insights for operational

adjustments. The practice of adjusting delivery schedules based on customer segmentation insights and the effective utilisation of customer feedback systems for informed decision-making were prominent. This indicated a clear understanding among oil marketing companies of the intrinsic value of customer data in shaping their operational responses and service delivery. Furthermore, the implementation of loyalty programs and the frequent updating of customer communication tools to match evolving preferences were also noted, reflecting a commitment to enhancing customer engagement and satisfaction. However, the study identified areas where CCI adoption was less established, especially in the use of predictive customer data models for anticipating future service needs and the full development and deployment of self-service platforms. This suggests an opportunity for companies to transition from reactive customer engagement to more proactive, data-driven approaches that leverage advanced analytics for foresight.

In Model 1, the standardised coefficient is $\beta = 0.484 (p < 0.001)$, the largest effect among all innovation types. The study's null hypothesis that customer-centric innovation did not have a statistically significant influence on demand forecasting performance was rejected. The finding reflects the fundamental insight that demand forecasting accuracy depends critically on understanding customer needs, preferences, and behaviour. Customer centric innovations directly inform and improve forecasting models. When firm size was introduced, customer centric innovation's effect remains strong and statistically significant ($\beta = 0.398$, $p < .000$), though it decreases from 0.484 to 0.398. This suggests that firm size accounts for some variance but does not substantially confound the customer-centric innovation relationship. The interaction analysis revealed a statistically significant negative moderation effect of firm size on the customer centric innovation-forecasting performance relationship ($\beta = -0.177$, $p = 0.005$). This is the only innovation type where the moderation effect achieves conventional statistical significance. The negative coefficient indicates that smaller firms may derive greater benefits from customer-centric innovation than larger firms, since larger firms experience significantly reduced returns from customer-centric initiatives, and the relationship between customer-centric innovation and forecasting performance is highly size-dependent. This finding emphasises that an understanding of customer behaviour, preferences, and evolving needs is vital for accurate demand forecasting.

5.1.5 Moderating Effect of Firm Size

The fifth objective of the study was to evaluate the moderating effect of firm size on supply chain innovation agility and demand forecasting performance of oil marketing companies in Kenya. Firm size had a direct positive and significant relationship with demand forecasting performance. Its introduction increased the model's explanatory power. The initial inclusion of firm size as a direct predictor in the regression model substantially increased its explanatory power, evidenced by a significant increase in the R-squared value from 81.1% to 82.2%. The findings showed that firm size had a positive moderating influence on supply chain innovation agility and demand forecasting performance, suggesting that an increasing firms size improved demand forecasting performance. This can be attributed to several factors present in larger organisations, such as greater access to financial capital for technology investments, a broader pool of human resources with specialised expertise, and more extensive market reach and data collection infrastructure. In Model 2, firm size exhibits a non-significant direct positive effect on Demand Forecasting Performance (B = 0.031, p = 0.055). This suggests that, without considering interaction effects, larger firms tend to have slightly better demand forecasting performance. However, the significance level is borderline, indicating a weak direct influence.

The interaction effects showed that explanatory power increased R^2=94.5%, the direct effect of firm size becomes highly significant and positive (B = 0.402, p < 0.001), indicating that firm size is a strong predictor of Demand Forecasting Performance when interaction effects are accounted for. Firm size demonstrated significant moderating effects on two key innovation-performance relationships. The interaction term on business process innovation and firm size was statistically significant and negative (B = -0.065, p = 0.018). This implies that as firm size increases, the positive impact of business process innovation on demand forecasting performance tends to diminish. In smaller firms, business process innovation might yield substantial improvements in demand forecasting, but this effect becomes less pronounced or even counteracted in larger organisations. Similarly, the interaction term for customer centric innovation and firm size is significant and negative (B = -0.177, p = 0.005). This suggests that the benefits derived from customer centric innovation in enhancing demand forecasting performance are mitigated in larger firms. Smaller, more agile

firms might be better positioned to leverage customer-centric approaches for forecasting accuracy, while larger firms may face challenges in translating these innovations into proportional gains. Conversely, the moderating effects of firm size on technological innovation (B = 0.047, p = 0.513) and network structure innovation (B = -0.078, p = 0.273) are not statistically significant. This indicates that the relationship between these innovation types and demand forecasting performance does not significantly change with varying firm sizes. This indicates a complex, context-dependent role of firm size in optimising innovation strategies for demand forecasting performance. The study findings showed that firm size moderated specific aspects of supply chain innovation agility, and demand forecasting performance. Therefore, the null hypothesis that firm size does not have a moderating effect on supply chain innovation agility and demand forecasting performance of oil marketing companies in Kenya was partially rejected.

The analysis of interaction effects showed that firm size could positively but not significantly moderate the influence of technological innovation on demand forecasting performance. This implies that larger firms are better positioned to effectively implement technological initiatives; however, some companies suffer from bureaucratic issues. Their ability to absorb high upfront costs, manage large-scale system integrations, and leverage extensive data sets allows them to increase the positive impact of these innovations on their demand forecasting performance accuracy. Firm size negatively and significantly moderated the influence of network structure innovation and customer-centric innovation on demand forecasting performance. This suggests that while these innovation types are inherently beneficial, larger firms may encounter unique challenges or diminishing returns in fully leveraging them.

The existing bureaucratic structures and slower decision-making processes of large organisations might hinder the agility required for dynamic network reconfigurations or the personalised responsiveness to effective customer-centric approaches. This could also be due to the complexities of managing vast, distributed networks and the challenge of maintaining close, individualised customer relationships across a massive customer base. This moderating effect highlights that a standard approach to innovation strategy may not be efficient. Therefore, while all innovation types are

valuable, their relative importance and optimal implementation strategies vary depending on the specific organisational context and scale. Therefore, companies must tailor their innovation investments and implementation strategies to align with their specific organisational scale and characteristics for optimal demand forecasting performance outcomes.

5.2 Conclusion

The study sought to determine whether supply chain innovation agility had an influence on demand forecasting performance in oil marketing companies in Kenya. The study was able to conclude that collectively, business process innovation, technological innovation, network structure innovation and customer centric innovation could account for 81.1% of demand forecasting performance. Introducing firm size as a moderator increased that to 82.2%, and through interaction between firm size and the other variables, it increased to 94.5%. The rest of the remaining variations could be explained by other factors that were not mentioned in this study. This study concludes that supply chain innovation agility is not merely a desirable attribute but a critical determinant of effective demand forecasting performance within the dynamic context of oil marketing companies in Kenya.

5.2.1 Business Process Innovation on Demand Forecasting Performance

Business process innovation has a substantial influence on demand forecasting performance; however, this relationship is weakened by firm size, indicating that it is not uniform across firm sizes, as smaller organisations can derive substantially greater forecasting benefits from process improvements than their larger counterparts. The ability to reconfigure internal workflows, automate routine tasks, and integrate disparate systems allows for a more seamless flow of information, which is crucial for accurate forecasting. When processes are agile, data can be collected, analysed, and disseminated more rapidly, enabling quicker adjustments to demand models. However, challenges such as the high cost of implementation and resistance to change cannot be overlooked, and in order to improve forecasting accuracy, companies need to successfully navigate these challenges by implementing robust agile business process innovations to achieve superior predictive capabilities, leading to more efficient resource allocation and reduced operational waste.

5.2.2 Technological Innovation on Demand Forecasting Performance

Technological innovation is essential for improving demand forecasting performance. The moderate use of certain technologies, such as digital twins, IoT, and blockchain, related to real-time monitoring and product integrity, already provides notable gains. This indicates that even small technological advances contribute to improvements. However, the relatively low adoption of more advanced technologies, such as blockchain for comprehensive visibility and digital twins for simulation, reveals significant untapped potential. The advantages of technological innovation are fairly consistent across organisational sizes and seem to be a universally effective approach regardless of company size. Fully utilising these technologies could deliver unprecedented levels of data integrity and predictive accuracy, enabling companies to model complex scenarios and forecast demand more precisely. Continuous investment in and strategic deployment of relevant technologies are not optional but vital for maintaining competitive demand forecasting in a data-driven industry. The future of demand forecasting in the oil sector will increasingly rely on a company's ability to adopt and integrate advanced technological solutions.

5.2.3 Network Structure Innovation on Demand Forecasting Performance

Network structure innovation substantially improves demand forecasting performance; however, as firms change in size, NSI's relationship with demand forecasting is significantly weakened. Collaborative relationships and flexible network designs facilitate rapid information exchange and responses to market changes, leading to more accurate demand anticipation. This underscores the critical role of external collaboration and network flexibility. In an industry where supply chains are inherently complex and global, the ability to dynamically adjust transport routes, collaborate with logistics partners, and agilely onboard new suppliers provides a significant advantage. This is especially relevant for large firms that are susceptible to the bullwhip effect as they expand their networks, leading to misinformation and reduced accuracy. A resilient and adaptable network minimises disruptions and enables information to flow freely across the supply chain, enabling a more holistic view of market conditions and potential demand shifts. A large network increases coordination and logistics challenges, which result in failure to adapt to constant changes within the market, leading to disruptions. Companies should actively cultivate

strong, collaborative relationships with their network partners, fostering an environment of trust and shared information. This collaborative approach, combined with flexible network designs, directly enhances a firm's capacity for accurate, responsive demand forecasting, enabling better strategic planning and operational execution.

5.2.4 Customer-Centric Innovation on Demand Forecasting Performance

Customer-centric innovation positively influences demand forecasting performance. Leveraging customer insights and feedback mechanisms enables a deeper understanding of consumer behaviour, leading to more precise demand forecasting and optimised resource allocation. The moderate adoption of practices like adjusting delivery schedules based on customer segmentation already demonstrates tangible benefits. However, the underutilization of predictive customer data models and self-service platforms represents a significant opportunity for further enhancement. Therefore, a deeper integration of customer data and advanced analytical techniques can unlock even greater predictive power. Positioning the customer at the centre of their innovation efforts, oil marketing companies can gain more understanding of demand drivers, anticipate shifts in consumer behaviour, and tailor their supply chain responses accordingly, leading to improved customer satisfaction and optimised resource allocation. Integrating customer insights directly into their predictive models, oil marketing companies can better anticipate subtle shifts in consumer demand, optimise product offerings, and enhance overall market responsiveness. Increasing the precision and predictive power of customer data, the demand forecast becomes more accurate and reliable, leading to improved resource allocation and enhanced customer satisfaction.

5.2.5 Moderating Effect of Firm Size

Firm size has a significant moderating effect. Larger firms can better utilise TI thanks to their resources, but may face challenges with BPI, NSI and CCI. This suggests that the best innovation strategies for demand forecasting performance depend on firm size and need to be tailored. The findings show that the effectiveness of certain kinds of innovation, especially Business Process Innovation and Customer Centric Innovation, depends on firm size. Managers in bigger organisations should realise that these

innovations might not bring the same proportionate benefits in demand forecasting as they do in smaller firms. This requires a customised innovation strategy, with expected results adjusted to the firm's size. The negative moderating effects indicate that larger firms might struggle to leverage BPI and CCI fully for demand forecasting. This could be due to greater bureaucracy, slower decision-making, or difficulties in implementing widespread changes across complex structures. Larger firms may need to invest more in change management, internal communication, and specialised implementation strategies to overcome these challenges. Smaller firms seem to be more agile in turning BPI and CCI into better demand forecasting. This could give them a competitive edge by allowing quicker adaptation to market changes and customer needs through these innovation pathways. The non-significant moderating effects for TI and NSI imply they may consistently impact demand forecasting performance regardless of firm size. Firm size weakens the relationship between some of the SCIA variables and DFP, and therefore, oil marketing should take their size into account when designing and applying innovation strategies to improve their demand forecasting capabilities. They should also consider the compatibility of the integrated innovations to complement each other's limitations.

5.3 Recommendations

The study sought to determine whether supply chain innovation agility had an influence on demand forecasting performance in oil marketing companies in Kenya. The study was able to make recommendations for policy, managers and further studies. These recommendations were based on the study findings.

5.3.1 Recommendations for Policy

Policy makers should encourage oil marketing companies to use digital technologies that make supply chains more visible and improve how demand is predicted. This can be done by providing financial help, such as grants or tax breaks, for companies investing in these technologies. Governments can also make rules that promote safe and fair sharing of data among companies, helping them respond faster to changes in demand and reducing supply chain problems.

Governments and regulators should create spaces like forums or shared digital platforms where companies can collaborate and share information. This teamwork

helps companies predict demand better and strengthens the whole industry against unexpected challenges. Supporting cooperation with clear rules, policymakers help companies benefit equally and improve services for customers.

There should also be investment and support for the development of innovation capabilities through training, research collaborations, knowledge exchange, and technology transfer while promoting standardised approaches to innovation implementation and performance measurement. These national training programs that will equip supply chain managers, government institutions, and researchers with innovation skills. This will simultaneously prepare new workers and update current employees to manage new technologies. A well-trained workforce is essential for adopting digital tools smoothly and making supply chains more efficient and flexible.

Policy makers should formulate and implement a comprehensive innovation framework that institutionalises supply chain innovation agility within Kenya's oil and petroleum industry. The framework should establish strategic priorities for innovation, facilitate investment in digital and process innovations, strengthen industry-wide collaboration, and provide regulatory incentives that encourage the adoption of agile supply chain practices. The framework would create an enabling environment for oil marketing companies to respond rapidly to fluctuations in market demand, improve demand forecasting performance, enhance supply chain resilience, and strengthen the sector's overall competitiveness in an increasingly dynamic business environment.

5.3.2 Recommendation for Practice

Managers should develop a clear, coordinated strategy for innovation that covers technology, business processes, and networks. Instead of focusing on only one area, they need to make sure all innovation efforts work together to improve demand forecasting. New data collection technology should be paired with business process changes to use data well and network improvements to share information with partners. This integrated approach helps companies get the most benefit from their investments, making demand forecasting more accurate and enabling quicker responses to market changes. Managers should also align innovation with operational capacity, strengthen integration and communication across supply chain innovations.

I. Business Process Innovation

Management should decentralise decision-making, empower regional units, streamline internal processes and opt for cross-functional teams to ensure that business process innovations remain flexible and responsive to market changes. This would enable large firms to maintain the agility required for accurate and timely demand forecasting despite increasing organisational complexity. Organisations can also implement fully automated forecasting systems that enable dynamic adjustments to demand forecasts, based on information added and evaluated collaboratively by stakeholders from different departments involved with the supply chain.

Oil marketing companies should strengthen their agile resource replenishment and responsive process alignment practices and invest in systems that enable real-time monitoring of inventory levels, sales trends, and market demand, allowing resources to be replenished promptly based on actual consumption patterns. Organisations should also ensure that procurement, inventory management, transportation, and distribution processes are closely aligned and responsive to changing market conditions. This can be done by adopting a business process innovation model that integrates financial planning, strategic planning, product and supply chain innovation with demand, market, and supply chain plans. This will ensure that volatility is reduced and forecasts will become more reliable for expenditure decision-making.

They should also consider enhancing collaboration among functional departments and supply chain partners, enabling organisations to respond quickly to emerging demand trends and operational disruptions through coordinated mechanisms and real-time information sharing. This will improve visibility across the supply chain, generate more reliable demand information, and strengthen their ability to accurately forecast demand for oil and petroleum products.

II. Technological Innovation

Companies should invest in IoT to enable the collection of real-time data from interconnected devices, sensors, vehicles, storage facilities, and retail outlets across the supply chain. Oil marketing companies can install IoT sensors in fuel storage tanks, depots, pipelines, and service stations to continuously monitor fuel stocks and consumption rates, enabling companies to detect demand trends early and adjust replenishment plans accordingly. IoT-generated data can be used to monitor vehicle

traffic patterns and anticipate consumption changes, economic fluctuations, or supply disruptions. This will lead to improved forecasting accuracy, reduced stockouts, lower inventory costs, and enhanced supply chain responsiveness.

Blockchain should be integrated to improve the accuracy, reliability and timeliness of information. This reduces information asymmetry, minimises data manipulation, and enhances trust among supply chain participants. This also facilitates end-to-end supply chain visibility and collaborative forecasting, and ease in rapidly identifying demand fluctuations and making informed forecasting decisions, thus providing greater resilience during market uncertainties or supply disruptions.

Digital twin technologies should be effectively adopted to visualise the entire supply chain in real time and identify trends that may influence future demand. This improves forecasting accuracy by allowing managers to base predictions on current operational conditions rather than relying solely on historical data. Through operations simulation, oil marketing companies can model the effects of global crude oil price changes, transportation disruptions, and government policy adjustments on petroleum product demand, enabling them to develop more accurate forecasts and proactive response strategies.

III. Network Structure Innovation

Oil marketing companies should strengthen coordination mechanisms across their supply chain networks to prevent communication bottlenecks and information distortions that may arise from extensive supplier, distributor, and stakeholder relationships. Firms should also invest in integrated digital platforms, real-time data-sharing systems, and collaborative forecasting practices that improve visibility across the supply chain. These measures can help ensure that the benefits of network structure innovation are not weakened by the challenges associated with larger organisational size.

Oil marketing companies should incorporate adaptive transport models that enable them to anticipate regional demand shifts, optimise fuel distribution routes, and respond quickly to unexpected changes in consumption patterns. This enhances forecast accuracy by ensuring that demand predictions are informed by current logistics realities rather than relying solely on historical data. Collaborative network

platforms should be integrated to enable seamless communication among depots, transport providers, fuel stations, and suppliers, allowing firms to generate more accurate demand projections and make proactive replenishment decisions that improve supply chain efficiency and responsiveness, improving demand visibility across the entire supply chain. The firms should also adopt simulation tools to assist in scenario planning, which enables oil marketing companies to prepare for sudden shifts in fuel demand and supply conditions, reducing forecasting errors and enhancing their ability to respond effectively to market volatility and uncertainty.

IV. Customer-Centric Innovation

Oil marketing companies should leverage advanced customer analytics, market intelligence systems, and decentralised customer relationship management approaches to maintain close customer interactions. This would enable firms to translate customer insights into more accurate demand forecasts and preserve the effectiveness of customer-centric innovation regardless of organisational size**.**

Companies should adopt predictive customer insights to accurately analyse historical and real-time customer data and forecast customer contact demand in order to reduce delays and improve customer satisfaction. This can be achieved by integrating data from digital channels such as websites, social media platforms and applications, into short-term demand detection models. It will also provide real-time information on customer intent, which is important information for optimising inventory placement and stock levels. Firms can incorporate customer feedback into their forecasting models by extracting lead indicators of demand change. This will help in the early detection of emerging trends or shifts in customer preferences, where proactive forecasting adjustments can be made. It will also improve on service responsiveness which is aligned with demand fluctuations.

Large firms should develop more localized and segmented customer engagement strategies to prevent the loss of customer responsiveness that often occurs as organisations expand. As firm size increases, customer-centric innovations may become less effective due to standardized procedures, longer feedback loops, and difficulties in capturing diverse customer needs across multiple markets. Oil marketing companies should leverage advanced customer analytics, market intelligence systems, and decentralized customer relationship management

approaches to maintain close customer interactions. This would enable firms to translate customer insights into more accurate demand forecasts and preserve the effectiveness of customer-centric innovation regardless of organisational size

V. Firm Size

Large firms should create small, dedicated and cross-functional teams that can fast-track approval authority to pilot and implement new forecasting technologies. This approach facilitates decentralised innovation, bypassing bureaucratic hurdles to rapidly test and deploy new AI/Machine Learning (ML) models or data sources, and subsequently scale successful pilots across the broader organisation. Firms should make significant investments in innovation whose purpose is to create a single, cloud-based computing system that integrates data from all existing storage facilities, such as ERP, CRM, S&OP systems, and external feeds. This will ensure data-driven consensus by providing a single source of high-quality data for forecasting, which speeds up the critical consensus-building process.

Large firms should formalise innovation portfolio management. Supply chain innovation should be treated as a balanced portfolio, with high-risk, high-reward projects, such as Generative AI forecasting, balanced with low-risk, incremental improvements like process automation. This strategy ensures resource optimisation by spreading R&D investment effectively and maintaining a continuous pipeline of improvements, leveraging the firm's superior resource base. They should also implement Forecast Value Added (FVA) Analysis, which objectively measures the contribution of every manual adjustment and system input to the final forecast. This uses the firm's analytical capacity for bias reduction, identifying and eliminating systemic bias often introduced by large, influential departments, such as sales over-forecasting.

Small firms should leverage cloud-based, subscription-model AI/ML forecasting platforms. This provides low-cost technology access, granting access to advanced technological innovation without the prohibitive upfront capital investment or the need to hire scarce, high-cost data science talent. Prioritizing on external collaboration through formal CPFR protocols with key strategic customers and suppliers should be considered in order to focus on data expansion, compensating for limited internal data

volume by gaining access to richer, more accurate external demand signals from partners, which is crucial for improving DFP.

Smaller firms should leverage their flat hierarchy and small size in order to implement process changes quickly, such as adopting daily or weekly micro-forecasting cycles for key products. This maximises their inherent speed and flexibility, which is a competitive advantage that allows for immediate adjustments to market changes compared to slower, larger rivals. They should also focus on data quality over data volume by effecting simple, cost-effective data cleaning and standardisation tools to ensure that the limited data available is highly accurate and reliable. This establishes a reliable foundation, preventing the "garbage in, garbage out" problem and ensuring that any technological innovation is built on clean data.

5.3.3 Recommendations for Further Studies

Future studies should examine the effectiveness of specific digital twin technologies, IoT and blockchain techniques in enhancing demand forecasting performance within the oil and petroleum industry. Such studies would provide empirical evidence on the most suitable technologies for forecasting petroleum demand in volatile environments and guide oil marketing companies in making informed investments in digital forecasting solutions.

Researchers should examine whether organisational complexity, bureaucratic decision-making structures, communication barriers, resource allocation inefficiencies, or reduced operational flexibility in larger firms diminish the effectiveness of these innovation practices. Researchers may explore organisational and contextual factors such as managerial hierarchy, coordination challenges, information-processing capabilities, organisational culture, and technological integration that may constrain the effectiveness of innovation initiatives in firms.

Future research should also adopt a longitudinal research design to investigate the long-term relationship between supply chain innovation agility and demand forecasting performance. A longitudinal approach would enable researchers to assess how the implementation and evolution of innovation agility practices over time influence forecasting accuracy and organisational responsiveness. This could reveal whether the benefits of supply chain innovation agility are immediate, cumulative, or

subject to diminishing returns across different stages of organisational growth and market development.

Additionally, future studies should expand forecasting models by incorporating external environmental variables such as economic fluctuations, inflation rates, exchange rate movements, geopolitical conflicts, climate-related disruptions, government policy changes, and public health emergencies as moderating or mediating variables to confirm if the effect will be different. The inclusion of these factors would provide a more comprehensive understanding of the determinants of demand forecasting performance and improve the predictive power of forecasting models, and consequently provide resilient and adaptive supply chain systems capable of responding effectively to complex and unpredictable disruptions in the global and local petroleum markets.

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APPENDICES

Appendix 1: Letter to Respondents

WANJIKU NYOKABI RUTH,

MURANGA UNIVERSITY OF TECHNOLOGY,

P.O BOX 75-10200,

MURANG'A, KENYA.

Dear Respondent,

This letter is to request you help me obtain data to facilitate my study titled: ***SUPPLY CHAIN INNOVATION AGILITY, FIRM SIZE AND DEMAND FORECASTING PERFORMANCE OF OIL MARKETING COMPANIES IN KENYA*** by filling out the questionnaire attached.

The information you voluntarily provide will be treated with utmost confidentiality as the final results will be communicated in a general manner. Thanking you in advance for your cooperation and I am looking forward to your positive feedback.

Yours faithfully,

Wanjiku Nyokabi Ruth BE500/5803/2022

Cell numbers: 0703828007/0774277212

Student at Murang'a University of Technology, Kenya

Appendix 2: Primary Data Questionnaire

This survey aims to understand how agile supply chain innovations can transform demand forecasting performance processes in businesses. Your insights will help us analyze current practices, challenges, and potential improvements in leveraging digital tools for more accurate demand forecasting. The questionnaire is anonymous and the information given will be treated as confidential and the results of the study will be used for academic research purposes only.

SECTION A: BACKGROUND INFORMATION

Please indicate the number of years your company has been in operation

Below 5 year☐ ☐6-10 years ☐11-15years ☐above 16 years

Level of experience in the respective field

Below 1 year☐ ☐2-5 years ☐ 6-9 years ☐above 10 years

Please indicate the degree to which you agree with the following statements

SECTION B: BUSINESS PROCESS INNOVATION

Question	Low(L)	Partial(P)	Moderate(M)	High(H)
To what extent does your inventory levels adjust in response to changes in the market?				
How well do your departments adjust to align with changing operational priorities?				
To what extent are cross-functional teams coordinate dynamically to respond to emerging changes?				
To what extent are operational tasks (e.g. Order processing, delivery scheduling) digitized?				
How effectively can your automated systems detect and correct process deviations to reduce delays?				
To what extent does your company monitor supplier risk in real time to ensure timely replenishment?				
How automated is the alignment between customer orders with warehouse dispatches?				
What level of digital oversight exists in managing supplier and compliance?				

What are some of the strategies employed by your company to improve process automation?

……
……
……
……

What are some of the challenges that your organization has faced during automation of these processes?
……
……
……
……

SECTION C: TECHNOLOGY INNOVATION

Question	Low(L)	Partial(P)	Moderate(M)	High(H)
To what extent does your company use blockchain for end-to-end visibility in the fuel supply chain?				
How well does IoT support real-time monitoring of fuel inventory and vehicle conditions?				
To what extent has digital twin technology been deployed to simulate operational scenarios?				
How effectively do your systems collect sensor data for predictive maintenance of assets?				
To what extent does your company track the integrity of fuel products using digital tools?				
How integrated are your IoT systems with your forecasting and dispatch models?				
To what extent does your company visualize entire supply operations digitally for agility decisions?				
How often are blockchain records used to verify logistics and payment transactions?				

What are some of the strategies employed by your company to improve rate of technological adoption?

……
……

……
……

SECTION D: NETWORK STRUCUTRE INNOVATION

Question	Low(L)	Partial(P)	Moderate(M)	High(H)
To what extent can your transport routes be dynamically changed in response to disruptions?				
How often does your company use scenario planning to prepare for supply chain uncertainties?				
To what extent do you collaborate with logistics partners on capacity sharing or joint deliveries?				
How agile is your network in onboarding new suppliers during peak demand?				
How well is your distribution system supported by decentralized or backup nodes?				
How often does your firm adjust sourcing or fulfilment plans based on simulation outputs?				
To what extent is information exchanged with stakeholders in real time during emergencies?				
How flexible is your network structure in maintaining service levels under regional fuel shortages?				

What are some of the strategies employed by your company to improve rate of network structure adoption?

.....
.....
.....

SECTION E: CUSTOMER SERVICE INNOVATION

Question	Low(L)	Partial(P)	Moderate(M)	High(H)
How advanced are your self-service platforms (apps, kiosks, etc.) in assisting customers with transactions?				
To what extent does your company use multiple channels (e.g., social				

media, live chat) to engage with customers?				
How effectively are customer complaints or queries resolved through automated systems?				
How predictive are your customer data models in anticipating future service needs?				
To what extent does your loyalty program offer personalized rewards based on past behaviors?				
How integrated are feedback systems with service enhancement decision-making?				
To what extent are insights from customer segmentation used to adjust delivery schedules or inventory?				
How frequently does your company update customer communication tools to match changing preferences?				

What customer related initiatives has your organisation been able to implement to predict and meet customer preferences?.....

.....

.....

SECONDARY DATA COLLECTION TOOL

This tool is aimed to collect secondary data on supply chain innovation agility, firm size and demand forecasting performance of oil marketing companies in Kenya. The data will be treated with utmost discretion and confidence.

Name of company……..

Indicator	2021	2022	2023	2024
Actual Demand Consumption Metric Tonnes (ADC)				
Forecasted Demand Consumption (Metric Tonnes) (FDC)				
Demand Consumption Variance (ADC-FDC)				
Market Share (%)				

THANK YOU FOR YOUR PARTICIPATION

Appendix 3: List of Oil Marketing Companies in Kenya

NO	LICENCE NUMBER	COMPANY NAME
1	EPRA/PET/3011	ACER PETROLEUM LIMITED
2	EPRA/PET/5688	AFRO PETROLEUM LTD
3	EPRA/PET/4723	AFTAH PETROLEUM(K)LTD
4	EPRA/PET/2459	AINUSHAMSI ENERGY LIMITED
5	EPRA/PET/3973	ALBA PETROLEUM LIMITED
6	EPRA/PET/9814	ANTIC ENERGIES LIMITED
7	EPRA/PET/10946	APPLE ENERGY LIMITED
8	EPRA/PET/4241	ASHARAMI SYNERGY LIMITED
9	EPRA/PET/2621	ASTROL PETROLEUM COMPANY LIMITED
10	EPRA/PET/11560	AVION ENERGY LIMITED
11	EPRA/PET/8584	AWDEER INVESTMENTS LTD
12	EPRA/PET/4819	AXON ENERGY LTD
13	EPRA/PET/9217	AZIFAT ENERGIES LIMITED
14	EPRA/PET/11347	AZKAM OIL LIMITED
15	EPRA/PET/4208	BACHULAL POPATLAL (KENYA) LIMITED
16	EPRA/PET/3840	BE ENERGY LIMITED
17	EPRA/PET/11226	BECZON OIL LIMITED
18	EPRA/PET/3838	BLUE SKY ENERGY LIMITED
19	EPRA/PET/9751	BONGANI ENERGY KENYA LIMITED
20	EPRA/PET/11675	BOSTON PETROLEUM LIMITED
21	EPRA/PET/6823	CITY OIL (K) LIMITED
22	EPRA/PET/4657	COSTALINA ENERGY LIMITED

23	EPRA/PET/5418	DALBIT PETROLEUM LIMITED
24	EPRA/PET/7678	DAWSON SERVICES (K) LIMITED
25	EPRA/PET/5348	DC ENERGY KENYA LIMITED
26	EPRA/PET/10945	DIFAAC GENERAL TRADING LTD
27	EPRA/PET/4385	E3 ENERGY KENYA LIMITED
28	EPRA/PET/4967	EAST AFRICAN GASOIL LIMITED
29	EPRA/PET/3557	ECO OIL KENYA LIMITED
30	EPRA/PET/9518	EGOL ENTERPRISES LIMITED
31	EPRA/PET/11871	ENI KENYA B.V.
32	EPRA/PET/9384	EUROPET LIMITED
33	EPRA/PET/4609	EVON INTERNATIONAL ENERGY LIMITED
34	EPRA/PET/3868	FASTNETT ENERGY LIMITED
35	EPRA/PET/8187	FELEG ENERGY LIMITED
36	EPRA/PET/3931	FINEJET LIMITED
37	EPRA/PET/5068	FORT RETAIL KENYA LIMITED
38	EPRA/PET/3972	FOSSIL SUPPLIES LIMITED
39	EPRA/PET/3917	GALANA ENERGIES LIMITED
40	EPRA/PET/11407	GALLAD CENTER LIMITED
41	EPRA/PET/10183	GAMOIL TRADING LIMITED
42	EPRA/PET/3122	GAPCO KENYA LIMITED
43	EPRA/PET/10506	GAS AND GO PETROLEUM PRODUCTS LTD
44	EPRA/PET/5709	GASLINE PETROLEUM LIMITED
45	EPRA/PET/9952	GOLDPET ENERGIES LTD
46	EPRA/PET/9954	GREAT WALL OIL LIMITED
47	EPRA/PET/7308	GREEN WELLS ENERGIES LIMITED
48	EPRA/PET/6569	GULF ENERGY HOLDINGS LIMITED

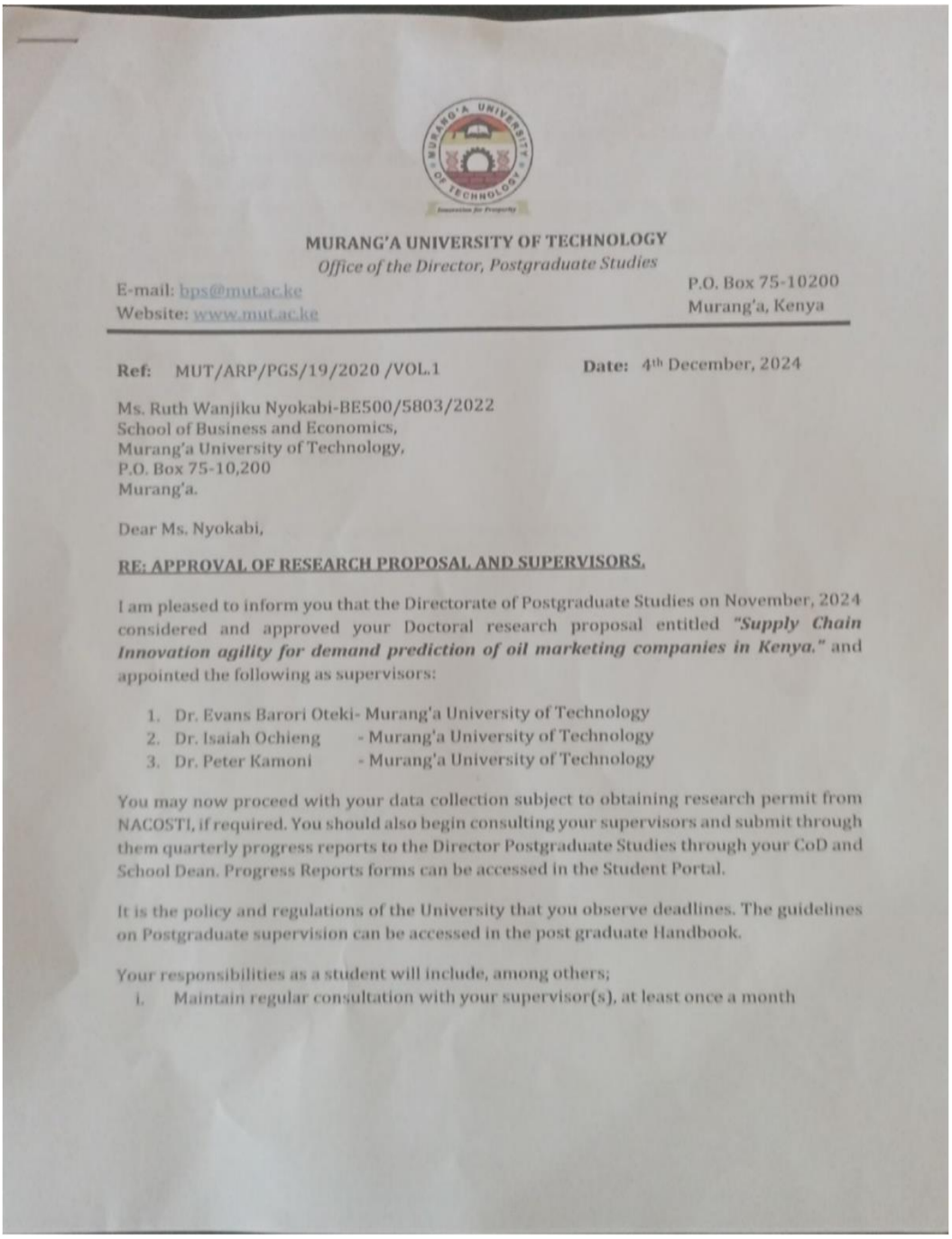
49	EPRA/PET/5167	GULF ENERGY LIMITED
50	EPRA/PET/11188	HARBOUR ENERGY LIMITED
51	EPRA/PET/4253	HARED ENERGY LIMITED
52	EPRA/PET/3956	HASS PETROLEUM KENYA LIMITED
53	EPRA/PET/3828	HELLER PETROLEUM LIMITED
54	EPRA/PET/9161	HERO PETROLEUM LIMITED
55	EPRA/PET/7705	HSON KENYA LIMITED
56	EPRA/PET/4075	ILADE OIL CO. LIMITED
57	EPRA/PET/6973	INDEPENDENT PETROLEUM GROUP KENYA LIMITED
58	EPRA/PET/5900	JAGUAR PETROLEUM LIMITED
59	EPRA/PET/4832	JOJES OIL DEALERS LIMITED
60	EPRA/PET/5037	KAYMAN ENERGY LIMITED
61	EPRA/PET/11225	KOLA ENERGIES LIMITED
62	EPRA/PET/5640	LAKE OIL LIMITED
63	EPRA/PET/7126	LEADWAY PETROLEUM LIMITED
64	EPRA/PET/3739	LEXO ENERGY KENYA LIMITED
65	EPRA/PET/2850	LUQMAN PETROLEUM LIMITED
66	EPRA/PET/11190	M & A ENERGY LIMITED
67	EPRA/PET/7207	MARVISS PETROLEUM LIMITED
68	EPRA/PET/11189	MELON ENERGIES LIMITED
69	EPRA/PET/10295	MERI PETROLEUM DEALERS LIMITED
70	EPRA/PET/11266	MIXOIL ENTERPRISES LIMITED
71	EPRA/PET/4155	MOIL KENYA LIMITED
72	EPRA/PET/7483	MOK PETRO ENERGY LIMITED
73	EPRA/PET/8544	MUNTAZ OIL LIMITED

74	EPRA/PET/11870	NAHR JUBA GENERAL TRADING LIMITED
75	EPRA/PET/4084	NATIONAL OIL CORPORATION OF KENYA
76	EPRA/PET/4115	NET GAS AND ENERGY LIMITED
77	EPRA/PET/7747	NEXUS PETROLEUM LIMITED
78	EPRA/PET/7504	NOMAD PETROCHEM LTD
79	EPRA/PET/11753	NORD ENERGY LIMITED
80	EPRA/PET/11682	NORTHGAS LIMITED
81	EPRA/PET/2952	OCEAN ENERGY LIMITED
82	EPRA/PET/9953	ODHAV GENERAL SUPPLIERS LIMITED
83	EPRA/PET/3648	OIL ENERGY KENYA LIMITED
84	EPRA/PET/2636	OILCOM (K) LIMITED
85	EPRA/PET/6310	OILGEN PETROLEUM LIMITED
86	EPRA/PET/7692	OILHUB LIMITED
87	EPRA/PET/11680	OILWAVE ENERGY LIMITED
88	EPRA/PET/3253	OLA ENERGY KENYA LIMITED
89	EPRA/PET/3817	OLA ENERGY KENYA LIMITED
90	EPRA/PET/3228	OLYMPIC PETROLEUM LIMITED
91	EPRA/PET/4136	ONE PETROLEUM LIMITED
92	EPRA/PET/4107	ORYX ENERGIES KENYA LIMITED
93	EPRA/PET/9395	OYLA EAST AFRICA ENERGY
94	EPRA/PET/3249	PACIFIC PETROLEUM LIMITED
95	EPRA/PET/3955	PETRO OIL KENYA LIMITED
96	EPRA/PET/4744	PETROCAM KENYA LTD
97	EPRA/PET/10713	PINOIL ENERGY LIMITED
98	EPRA/PET/10748	PITOT ENERGY LTD
99	EPRA/PET/11561	PRINSAN GROUP LIMITED

100	EPRA/PET/10296	PRIZE PETROLEUM LIMITED
101	EPRA/PET/12011	PROMPT COMMODITIES LIMITED
102	EPRA/PET/7704	QUALITY PETROLEUM LIMITED
103	EPRA/PET/9059	RAAD ENERGY LIMITED
104	EPRA/PET/4703	RAMJI HARIBHAI DEVANI LIMITED
105	EPRA/PET/10134	RAMMEXJI PETROLEUM LTD
106	EPRA/PET/4615	RANWAY ENERGIES LTD
107	EPRA/PET/4895	REGNOL OIL (K) LIMITED
108	EPRA/PET/4280	RIVA PETROLEUM DEALERS LIMITED
109	EPRA/PET/4040	ROYAL ENERGY K LTD
110	EPRA/PET/6724	ROYAL OIL COMPANY LIMITED
111	EPRA/PET/2425	RUBIS ENERGY KENYA PLC
112	EPRA/PET/6181	SAHARA ENERGY LIMITED
113	EPRA/PET/8474	SAKINA GAS COMPANY LTD
114	EPRA/PET/9847	SEGUTON ENERGY
115	EPRA/PET/7868	SELFOSS PETROLEUM LIMITED
116	EPRA/PET/9418	SHORELINE PETROLEUM LIMITED
117	EPRA/PET/4072	SOCIETE PETROLIERE KENYA LIMITED
118	EPRA/PET/3902	STABEX INTERNATIONAL LTD
119	EPRA/PET/4276	TAAM PETROLEUM LIMITED
120	EPRA/PET/11298	TAKSAN ENERGY LTD
121	EPRA/PET/8430	TALOS ENERGY LTD
122	EPRA/PET/9938	TARITA PETROLEUM LIMITED
123	EPRA/PET/5499	TEXAS ENERGY LTD
124	EPRA/PET/3746	TIBA OIL COMPANY LIMITED
125	EPRA/PET/01426	TOPAZ PETROLEUM LIMITED

126	EPRA/PET/12003	TOPSTAR ENERGY LIMITED
127	EPRA/PET/5039	TORCH ENERGY LTD
128	EPRA/PET/4188	TOSHA PETROLEUM (KENYA) LIMITED
129	EPRA/PET/3987	TOTALENERGIES MARKETING KENYA PLC
130	EPRA/PET/4579	TOWBA PETROLEUM COMPANY LIMITED
131	EPRA/PET/1925	TRINITY ENERGY (K) LIMITED
132	EPRA/PET/9084	TRIPLUS PETROLEUM LTD
133	EPRA/PET/5082	TRISTAR TRANSPORT LIMITED
134	EPRA/PET/7495	TROJAN SIX OIL 2019 LIMITED
135	EPRA/PET/8546	TUPESH ENERGY LIMITED
136	EPRA/PET/10912	UGANDA NATIONAL OIL COMPANY LIMITED
137	EPRA/PET/7770	UNITED ENERGY LIMITED
138	EPRA/PET/11772	UNOP FUEL AND GAS LIMITED
139	EPRA/PET/4639	UPTIME ENERGIES (KENYA) LIMITED
140	EPRA/PET/10116	VITALAC INTERNATIONAL LIMITED
141	EPRA/PET/4206	VIVO ENERGY KENYA LIMITED
142	EPRA/PET/9268	WALD ENERGY LIMITED
143	EPRA/PET/8622	WNINE ENERGY LIMITED
144	EPRA/PET/10031	XENOM ENERGY LIMITED
145	EPRA/PET/4161	ZACOSIA TRADING LIMITED

Appendix 5: Board of Postgraduate Students Approval of Research Proposal



MURANG'A UNIVERSITY OF TECHNOLOGY

Office of the Director, Postgraduate Studies

E-mail: bps@mut.ac.ke
Website: www.mut.ac.ke

P.O. Box 75-10200
Murang'a, Kenya

Ref: MUT/ARP/PGS/19/2020 /VOL.1 **Date:** 4th December, 2024

Ms. Ruth Wanjiku Nyokabi-BE500/5803/2022
School of Business and Economics,
Murang'a University of Technology,
P.O. Box 75-10,200
Murang'a.

Dear Ms. Nyokabi,

RE: APPROVAL OF RESEARCH PROPOSAL AND SUPERVISORS.

I am pleased to inform you that the Directorate of Postgraduate Studies on November, 2024 considered and approved your Doctoral research proposal entitled ***"Supply Chain Innovation agility for demand prediction of oil marketing companies in Kenya."*** and appointed the following as supervisors:

1. Dr. Evans Barori Oteki- Murang'a University of Technology
2. Dr. Isaiah Ochieng - Murang'a University of Technology
3. Dr. Peter Kamoni - Murang'a University of Technology

You may now proceed with your data collection subject to obtaining research permit from NACOSTI, if required. You should also begin consulting your supervisors and submit through them quarterly progress reports to the Director Postgraduate Studies through your CoD and School Dean. Progress Reports forms can be accessed in the Student Portal.

It is the policy and regulations of the University that you observe deadlines. The guidelines on Postgraduate supervision can be accessed in the post graduate Handbook.

Your responsibilities as a student will include, among others;

i. Maintain regular consultation with your supervisor(s), at least once a month

ii. Submit quarterly reports on time, through your supervisors, CoD, Dean and to the Director of Postgraduate Studies;
iii. Ensure quality work all through;
iv. Present your research findings at 2-3 seminars/conferences prior to thesis examination.
v. Publish two articles from your research findings in a refereed journal prior to thesis examination.

For any further clarification please contact the undersigned.

Yours Sincerely,

Prof. Geoffrey Muchiri, PhD
Director, Postgraduate Studies
GM/MMK

DIRECTORATE OF POSTGRADUATE STUDIES
MURANG'A UNIVERSITY OF TECHNOLOGY
04 DEC 2020
P. O. Box 75 - 10200, MURANG'A
Tel: 0771463515, Email: info@mut.ac.ke

Copy to:
1. Registrar, Academics, Research and Students Affairs
2. Dean, School of Business and Economics

Appendix 4: NACOSTI Research Licence Permit

REPUBLIC OF KENYA

NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Ref No: **906785**

Date of Issue: **20/January/2025**

RESEARCH LICENSE



This is to Certify that Miss.. Ruth Nyokabi Wanjiku of Murang'a University of Technology, has been licensed to conduct research as per the provision of the Science, Technology and Innovation Act, 2013 (Rev.2014) in on the topic: SUPPLY CHAIN INNOVATION AGILITY FOR DEMAND PREDICTION OF OIL MARKETING COMPANIES IN KENYA for the period ending : 20/January/2026.

License No: **NACOSTI/P/25/415289**

906785

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See overleaf for conditions

Appendix 6: Publications

This thesis has produced the following publications:

Ruth, W. N., Biraori, O. E., & Mwau, K. P. (2026). Network Structure Innovation and Demand Forecasting Performance of Oil Marketing Companies in Kenya. *International Journal of Supply Chain and Logistics*, *10*(1), 42-61.

Ruth, W., Oteki, E., Mwau, K., & Abilla, O. (2026). Business Process Innovation and Demand Forecasting Performance of Oil Marketing Companies in Kenya. *East African Journal of Information Technology*, *9*(1), 121-136. https://doi.org/10.37284/eajit.9.1.4589