RELATIONSHIP BETWEEN DYNAMIC SUPPLY CHAIN CAPABILITIES AND RESILIENCE OF RETAIL CHAIN OF STORES IN KENYA

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Relationship between Dynamic Supply Chain Capabilities and Resilience of Retail Chain of Stores in Kenya

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DECLARATION

This thesis is my original work and has not been presented for a degree in any other University.

Signature ………………………………………. Date ……………………………..

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This thesis has been submitted for examination with our approval as university supervisors.

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DEDICATION

Having learned the subtle art of not giving a fuck. I dedicate this work to no one.

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LIST OF ACRONYMS AND ABBREVIATIONS

AKS	Association of Kenya Suppliers
AMOS	Analysis of Moment Structures
BCP	Business Continuity Planning
BDA	Big Data Analytics
CACGR	Compound Annual Growth Rate
CFI	Comparative Fit Index
CFRR	Center for Retail Research
CPFR	Collaborative Planning Forecasting and Replenishment
CRM	Customer Relationship Management
DCs	Dynamic Capabilities
DCT	Dynamic Capabilities Theory
ECR	Efficient Customer Response
EFA	Explanatory Factor Analysis
FDI	foreign Direct Investment
GDP	Gross Domestic Income
IBM	International Business Machine
KEBS	Kenya National Bureau of Statistics
KFA	Knight Frank Africa
KMO	Kaiser Meyer- Olkin
KRA	Kenya Revenue Authority
NFI	Bentler-Bonnet Normed Fit Index
OECD	Organization for Economic Co-operation Development
OEM	Original Equipment Manufacturer

OLS	Ordinary Least Squares Regression
OSCT	Organizational Supply Chain Transparency
PCA	Principal Component Analysis
PWC	Price Water House Coopers
R&D	Research and Development
RBV	Resource Based View
RFID	Radio Frequency Identification
RoK	Republic of Kenya
ROS	Return on Sales
ROT	Resource Orchestration Theory
RTAK	Retail Traders Association of Kenya
SARS	Severe Acute Respiratory Syndrome
SC	Supply Chain
SCA	Supply Chain Agility
SCC	Supply Chain Configuration
SCI	Supply Chain Integration
SCM	Supply Chain Management
SCND	Supply Chain Network Design
SCRM	Supply Chain Risk Management
SCX	Supply Chain Ambidexterity
SEM	Structural Equation Modelling
SKU	Store Keeping Unit
SPSSS	Statistical Package for Social Sciences
SRES	Supply Chain Resilience

SSC	Sustainable Supply Chain
USA	United States of America
VIF	Variance Inflation Factor
VMI	Vendor Managed Inventory

DEFINITION OF TERMS

Dynamic Capabilities: Refers to a learned pattern of collective activity and strategic routines through which an organization can generate and modify operating practices to achieve a new resource configuration and achieve and sustain a competitive advantage' (Augier & Teece, 2009, p. 412).

Supply Chain Agility: Refers to the ability of an organization to adjust its operations either proactively or reactively, enabling the firm to modify its routines and adjust according to changing conditions such as disruptions helping the organization's response to environmental uncertainty in an accurate manner (Gligor & Holcomb, 2012)

Supply Chain Alignment: Refers to a property of the supply chain such that the interests of all of the organizations in the supply chain are aligned through free information exchange, clearly laying out the role of each constituent of the supply chain and through equitable sharing of risks, costs, and benefits (Dubey et al., 2018).

Supply Chain Analytics: SCA includes tools and techniques that harness data from various internal and external sources to produce breakthrough insights that can help supply chains reduce costs and risk while improving operational agility and service quality (Arya et al., 2017).

Supply Chain Configuration:	Refers to a set of supply chain units and links among these units defining the underlying supply chain structure and critical attributes of the supply chain network.' (Chandra & Grabis, 2016)
Supply Chain Innovation	Refers to a change (incremental or radical) within the supply chain network, supply chain technology, or supply chain processes (or combinations of these) that can take place in a company function, within a company, in an industry, or a supply chain in order to enhance new value creation for the stakeholder.' (Arlbjørn, de Haas, & Munksgaard, 2011, p. 8).
Supply Chain Resilience:	Refers to the ability of an organization to rebound after and involves preventing recognizable risks, meeting business objectives in the face of disruptions and achieving the required performance level after the occurrence of disruption, and enabling an organization to adapt swiftly to impulsive events by minimizing instabilities through dynamic capabilities that continuously anticipate and make adjustments to constant changes impairing the earning potential of the organization (Adobor & McMullen, 2018).

ABSTRACT

Retail chains are undoubtedly susceptible to a castellation of turbulences such as cash crunch, ineffective distribution flows downstream, perishability of merchandise, and inadequate capacities for storage areas, among other turbulences that, more often than not, precipitate non-resilience of these chains. For these reasons and others, the chains need to adapt to several situations by exhibiting readiness, response, and recovery capability, which brings about resilience in a retail chain. On the flip side, more empirical research on resilience in the retail sector needs to be done. It is against this brief outline that the study focused on providing granular insights into the relationship between dynamic supply chain capabilities and resilience in retail chains of stores in Kenya. Five specific objectives guided the study. The predictor variables under assessment in the study are dynamic SC agility capability, SC analytics capability, SC innovation capability, and SC alignment capability. The criterion variable under study was resilience in the retail sector. The study also adopted supply chain configuration as the moderator variable. Further, the researcher situated this study on Resource orchestration theory, supply chain network theory, and structural dynamics theory. A diagrammatic conceptual framework was drawn to contend the relationship of the variables under study. Operationalization of study variables was done. More so, an empirical review of study variables was exhaustively done, to the best ability of the researcher, precipitating a critique and identification of research gaps manifested by extant research. In research methodology, the study accentuated positivist epistemology and stance. Additionally, the study adopted an ex-post facto, cross-sectional survey research design. The study population was the retail chain of stores in Kenya, and the target population was listed retail chains in Nairobi City County. The study adopted two-stage sampling that yielded a sample size of 318 respondents. The primary data collection instrument for the study was a structured questionnaire. After seeking the relevant approvals and research permits, questionnaires were self-administered with the research assistants' help. The pilot study was conducted in Kiambu County as it exhibited homogeneous characteristics as the target population. Before data analysis, the psychometric properties of the data collection instruments were tested through reliability and validity. The study adhered to content validity, construct validity, and face validity. Both descriptive statistics and inferential statistics analyzed quantitative data. The hypotheses test was done using SEM. These analyses were done with the help of IBM SPSS software, IBM-AMOS version 22. Qualitative data analysis was done through content analysis. Given the high response rate, non-response bias was not an issue. Exploratory factor analysis was conducted to establish the interrelationships among set variables, and it also facilitated the reduction of a large number of factors to a more manageable number. Before conducting EFA, Kaiser-Meyer-Olkin (KMO), the test was conducted to test the suitability of data for factor analysis. The KMO values for the variables were all above 0.7, indicating sampling adequacy. KMO was supplemented by Bartlett's Test of Sampling adequacy, reaffirming the correlation matrix's factorability. Principle Component Analysis was used to extract factors. The study adopted the Varimax technique of orthogonal rotation, which resulted in a reduced number of factors. Confirmatory Factor Analysis was used to establish convergent validity and unidimensionality of constructs. CFA was performed separately for the variables

under study. The results indicated that the model was a good fit. The study conducted hypothesis testing that rejected the null hypothesis H01-H05. The study established that SCC needs to moderate the relationship between dynamic SC capabilities and resilience in the retail sector. The study concluded logically and recommended that retail chains focus more on flexibility and swiftness. It will enable them to exhibit ambidexterity ex-ante and ex-post disruptions. The study also suggested areas for further research.

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Brusset and Teller (2017) postulate that any supply chain should be able to surmount disruptions and unprecedented events. They also posit that any supply chain that possesses the capability to perform various activities relating to inbound logistics upstream of the supply chain, Original Equipment Manufacturer (OEM), and outbound logistics downstream of the supply chain to deliver goods and services under turbulent circumstances is deemed to be a resilient supply chain. Brusset and Teller (2017) underscore that a supply chain must develop capabilities to enhance resilience. Further, Brusset and Teller (2017) contended that such capabilities could take the form of lower-order, operational, and dynamic capabilities. More so, Brusset and Teller (2017) propounded that the dynamic capabilities approach enables practitioners in the supply chain to characterize supply chain capabilities that they wish to enhance across their supply chain.

On another spectrum, Su and Yang (2010) postulated that supply chain capabilities encompass Efficient Customer Response (ECR) that equips retail chains to collaborate through some systems such as Vendor Managed Inventories (VMI), Collaborative Planning, Forecasting, and Replenishment (CPFR), to bolster cooperative behavior among autonomous organizations to meet customers' needs. Brusset and Teller (2017) also postulated that supply chain integration capabilities enable firms to strategically collaborate with other firms in the supply chain to manage intra- and inter-firm management processes collaboratively. A firm can deliver maximum value to its clientele at minimum costs. Also, Brusset and Teller (2017) delineate that integration capability enables a firm to share information and reduce costs and risks of coordination by providing decision-makers with an opportunity to understand the focal areas that need to be addressed.

Building on dynamic theory (Valanciene & Gimzauskiene, 2009). suggested that supply chain dynamic capability is the ability of a supply chain, as a complex system, to adjust itself continuously. This capability equips a supply chain with the impetus to deal with environmental changes, swiftly adapt to market dynamics and volatilities, and deal with complex relationships in networked supply chain configurations. Beske et al. (2014) contended that supply chain dynamic capability is an abstract concept composed of several sub-capabilities: supply chain reconstruction, knowledge evaluation, co-evolvement, flexible supply chain control, alignment, and agility. Interesting to note that Beske et al. (2014) acknowledged that firm resilience is contingent upon dynamic capabilities, and there is a relationship between resilience and dynamic capabilities that is either superficial or latent.

The concept of dynamic capabilities dates back to the Sumerian competition anchored on innovations. The Sumerian competition believed that competitive advantage is achieved by creatively destroying the current resources and successfully reconfiguring them to seize new opportunities (Masteika & Čepinskis, 2015). Most researchers, key among them being Tecee, 1997 conceptualize dynamic capabilities as the process through which firms can reconfigure their existing resources to respond efficiently to changes in the organizational environment. Succinctly, Teece (1997) indicated that dynamic capabilities underline sensing, seizing, and reconfiguring.

Supply chains are more vulnerable to dynamic changes than casual markets. For this reason, there is dynamism in consumer behavior and the significant influence of diverse stakeholders on these supply chains. Dynamic supply chain capabilities are the novel approach that creates a nexus between the supply chain and the strategic management concept of dynamic capabilities. These dynamic supply chain capabilities are not limited to supply chain agility capability, supply chain analytics capability, supply chain innovation capability, and supply chain alignment capability (Masteika & Čepinskis, 2015). A supply chain can sense, seize and reconfigure its value chains through these capabilities to exhibit resilience ex-ante and ex-post disruptions. For these reasons, these capabilities are dynamic supply chain capabilities.

Retail involves selling mercantile goods and services to the end consumer (Knezevic et al., 2011). Retail businesses are categorized mainly based on the form of ownership, merchandise, and price. Also, the ownership-based classification comprises independent stores, chain stores, franchising, and leased department stores. The merchandise-based classification includes department stores, supermarkets, specialty stores, convenience stores, superstores, and retail services. Price-based classification comprises discount stores, factory outlets, category killers, off-price stores, warehouse clubs, and hypermarkets. Shopping centers are examples of place-based retailers. They all facilitate time utility, place utility, ownership utility, and shape utility (Hameli, 2018). Naik and Suresh (2018) demonstrate that the retail sector's success is pegged on a meticulous supply chain orchestration that encompasses product proliferation, providing customers and clients with reliable time, and placing utilities at a satisfactory customer service level.

Whereas resilience is a critical ingredient for the survival of the retail sector, the retail sector in Kenya could be more resilient owing to the turbulent economic environment and dynamics (Sandada, 2015). The retail landscape has witnessed remarkable adjustments and industry dynamics. The retail chains have revolutionized over time from open markets and workshops to a castellation of retail formats from outdoor market selling places to supermarkets to hypermarkets to chain stores to departmental stores to e-commerce platforms through e-tailing and or online shopping (Knezevic et al., 2011). Besides, the rapidly changing retail climate has precipitated some challenges. For example, the sector has experienced overcapacity resulting in fierce competition among industry players amidst a challenging economic time. Consumer demographics, lifestyles, and spending behavior are rapidly changing, and so are retail technologies (Hameli, 2018).

The retail sector requires a sophisticated supply chain configuration and a logistics network because its inherent nature is subject to various requirements, such as maintaining cold chain integrity and safeguarding the integrity of the commodities from pilferage, spoilage damage, and deterioration. Further, there is a need to account for the perishability of the product that influences storage conditions, transportation, order frequency temperature regulation, packaging, origin, and traceability (Shrivastava et al., 2009).

Technology is significantly changing the retail landscape. Both local and foreign retail chains are exploiting new opportunities, such as e-tailing presented by e-commerce platforms in tandem with rapid digitization and local geography consumption practices (De Kervenoael et al., 2016, cited in Lagorio & Pinto, 2020). It has resulted in cutthroat competition in the retail sector. The exploitation of digital innovations by traditional brick and motor stores has been partially attributed to the aging millennial and Generation Z. Such innovations include offering online shopping, home delivery, and click & collect services to allure the segment with these generation's customers. In fact, according to a report by (Capgemini Research Institute[CRI], 2020), about 40% of online shoppers consider home delivery capability as a must-have for online retailers, with 20% of online customers ready to switch retailers if home delivery service is not provided.

For firms to be averse to the susceptibilities of diverse vulnerabilities, firms are adopting some mechanisms to deal with the precipitating disruptions. These disruptions are difficult to predict, they have a small probability of occurrence, but when they occur, the impact is fatal. Such mechanisms include Business Continuity Planning (BCP) that endeavors to minimize the impact of unforeseen events through actions aimed at reducing the probability of a disruption taking place, coming up with measures aimed at reducing the impact of disruption once it occurs, or a combination of the two approaches (Zsidisin et al., 2005). Since supply chains and businesses are vulnerable to a castellation of disruptions, which can neither be avoided nor ignored, it is fundamental for supply chains to plan for them.

1.1.1 Global Perspective of Resilience in Retail Chain of Stores

World's leading retailers face challenges as they strive to expand and penetrate developing markets. First, the nationalist sentiments of Brexit and America have created uncertainties about new market entry. Local retailers' increasing sophistication and success have raised questions about what it takes to compete in such markets (Kearney, 2017) successfully. More so, retail technology and e-commerce advances have added another layer of complexity to the sector. Retailers are wallowing in the haze of how to enter a given market via e-commerce, the impact of e-commerce on brick and motor store footprints, and how to develop an omnichannel strategy to be at least resilient. The result is that many global retailers are re-evaluating their retail merchandise networks, formats, and logistics. Non-resilient chains are closing their premises while a few have exited the market, e.g., Marks & Spencer in China and Galeries Lafayette in Morocco. The resilient ones are leveraging innovations in e-commerce and mobile shopping. **Costco** and **Aldi's TMall,** Chai Cart, Tatkal, Easy Ship, and Seller Flex (Kearney, 2017).

The United Kingdom retail sector has approximately 319 125 retail outlets, both formal and informal. The sector accounted for £395 billion in 2017. The sector has been confronted by apocalyptic changes such as omnichannel retail management, internet retailing, changing consumer behavior, and dynamic retail environments. These changes have permeated non-resilience in part or whole in the UK's retail sector, which has seen an alarming exit of some retail businesses. For instance, about 11.2% of retail chains had closed down by the first half of 2017. A similar figure was recorded in 2016 (Center of Retail Research [CRR], 2018).

Similarly 2018, 28 retail companies with multiple retail stores exited the market, closing down 2 085 stores (CRR, 2018). It was the highest number of business closures compared with the years immediately following the 2008-2009 financial crisis and recession. Failure to keep abreast with the changing retail landscape is to blame for the closure. Traditional brick and motor stores that need to be more resilient to adapt to online retailing have experienced the brunt of the changing retail landscape by losing their market share. The growth of click-and-collect omnichannel retailing has made customers substitute physical shopping in brick and motor stores with online shopping (CRR, 2018). The last decade witnessed a downward spiral in the retail landscape. For instance, market share for the big four supermarkets, namely Tesco, Sainsbury & Morrison, dwindled. It was marked by shrinking groceries market share, decreased product portfolio, and decreased multi-channel retailing. The declining market share of the UK's largest retailer was compounded by a rise of "lower costs" and "no-frill" competitors such as Lidl and Aldi. Customer dynamics from "multi-buys" to more frequent smaller-value shopping have made stock proliferation by brick-and-mortar stores insignificant. According to a survey report by ARUP consulting group, it is expected that about 91% of the retail chains will experience some level of disruption due to the country's departure from the European Union. Only 50% of these firms have a contingency plan in place. More so, 70% of grocery stores expect disruption from adverse weather conditions. The report further indicates that 51% need to assess their firm resilience competitiveness based on technology, Innovation, and Research and Development R&D. Only 8% of the firms operate in a truly agile supply chain that can quickly respond to a disruption (ARUP, 2018).

Despite the organized Indian retail sector accounting for over 10% of the country's GDP and about 8% of its employment, it has struggled for various reasons. Pricewaterhouse Coopers [PWC], 2017 contends that about 85% of foreign retailers have not realized their original vision in the Indian market. The on-ground realities have hard-hit foreign retailers who ventured into the underpenetrated Indian market in contrast to the promised retail conditions. They have been compelled to cope with weak infrastructure, such as poor quality retail space, inaccessibility to capital for Foreign Direct Investment (FDI) and non-conglomerate Indian retailers, tight FDI regulations, and inferior retail talent; about 40% of the foreign retailers cited constraints in finding the right retail talent/ human capital with a turnover rate ranging between 25-40%. As a result, about 35% of foreign retailers have failed in value proposition in the Indian retail sector. At the height of struggles to balance between scale and profitability, the brick and motor stores have been faced with the unprecedented challenge of E-Commerce and omnichannel; therefore, they are not resilient enough to adjust to the prevailing harsh business operating environment in India as they do not have capabilities to shift online and be robust enough to withstand the harsh operating environment (PwC, 2016).

Although China had recorded a meteoritic growth in the retail sector, both formally and online, accounting for about 40% of e-commerce transactions globally, the overall retail growth is projected to significantly decline owing to economic wars with the United States of America (USA), increase in the cost of goods, low birth rate with an aging population and institutional issues such as competing with state-owned enterprises and decreasing consumer spend (Siebers, 2018). More so, the novel Severe Acute Respiratory Syndrome (SARS) pandemic has negatively affected brick-and-mortar retail chains, some of which are not resilient enough to be proactive and recover quickly from the shocks of the pandemic. According to research (Nielsen, 2020), about 10 000 informal groceries are yet to recover from the pandemic. There needs to be an indication that these firms adjusted their business strategies to reap the opportunities the post-pandemic era brought about in the foreseeable future.

1.1.2 Regional Perspective of Resilience of Retail Chain of Stores

About 70% of the firms in South Africa are in the retail sector. More so, between 70-80% of the businesses winding up due to non-resilience in the country are in the retail sector. Additionally, about 50% of new retail chains collapse within five years of establishment (Kativhu et al., 2018). One of the causes of non-resilience is fierce competition owing to little product differentiation and negligible switching costs. Some grocery retailers in fierce competition are Woolworth, Pick n Pay, Spar, and Checkers (Kearney, 2017).

Conversely, some retailers, such as H&M, are resilient enough to surmount the economic challenges to the extent of making sales worth US$ 76 million with about ten stores. It proposes to expand its stores in the coming years (Kearney, 2017). The emergence of malls in the country presents growth opportunities for the retail sector. Such malls include the Mall of Africa and Fourways Mall. Retailers are deploying pricing and assortment strategy to be resilient enough to operate in emerging malls (Kearney, 2017).

Although Nigeria has had a decade-long period of formal retail growth, the country is presently confronted by numerous macro factors that have influenced sluggish growth in the sector. Uncertainties hang in Nigeria's retail sector (Kearny, 2017). A report by Nielsen (2017) indicated that the retail sector had been negatively affected by the precipitating macro factors in the country, such as the 2016 recession, where the real GDP of the country shrunk to a low of 1.62%, the rapid depreciation of the naira, reduced disposable income that translated into a reduction in purchasing power of household (Nielsen, 2017). Formal retailers also need help coping with rising commodities and retail space prices while serving their clientele at competitive prices (Nielsen, 2017). AT Kearney's report in 2017 indicated that Nigeria had dropped by nine positions in the Global Retail Development Index as total national retail sales fell from YS$125 billion to US$ 109 billion. Formal retail is at the infant stage. Foreign retailers such as South Africa's Shoprite, SPAR, a Dutch retailer, and Addide, a local retailer, represent about 1% of retail sales in the country. Two foreign retailers, Truworths and Woolworths, have exit plans underway. According to (Kearney, 2017), such non-resilience is attributed to low oil prices and corruption, among others. Two trends are changing the retail landscape; the construction of shopping malls in Yantebura and Ikeja and the emergence of Nigeria as a top e-commerce destination in Africa. It is projected that by 2020, e-commerce companies with e-retailing will grow by double-digit; about 53% of Nigerians have access to the internet, and mobile shopping is on an upward spiral (Kearney, 2020).

There are infrastructural challenges in Côte d'Ivoire for retailers. Also, the country's political stability is fragile. The once stable country, dubbed Paris of Africa, has degenerated into civil strife. According to (Kearney, 2017), more than 50% of the country's retail transactions occur in informal markets. The formal market penetration by leading retail chains, Prosuma and Compagnie de Distribution de Côte d'Ivoire, is relatively low. Incumbent retailers have had to put up with the intense competition with Carrefour, which is on an expansion spree to open six more stores by 2020. On the other hand, Prousuma is exploring ways to bolster its number of outlets. Such resilience has been facilitated partly by the government's intervention, such as reducing business costs, business policy improvement, and structural reforms to achieve sustained growth of the economy (Kearney, 2020).

Enough challenges in Tanzania inhibit resilience in the formal retail sector; less than about 33% of its population is urbanized. About 70% of the country's population lives on less than US$ 2. Infrastructure and real estate are limited. Tanzania has only two major shopping malls, Mkuki Shopping Mall and Mlimani City. Such factors contribute to the negative growth of formal retail, which accounts for about 10% of the total retail sales in the country.

Nonetheless, some foreign retailers, such as an unnamed American supermarket, must adapt to the operating environment as it is in the early foothold of the Tanzanian market. It targets to open two more stores and serve between 15000-20000 customers daily in its Dar es Salaam store alone. However, foreign retail chains such as Nakumatt and Uchumi are shrinking their investments in the country due to their struggling parent companies in their home markets (Kearney, 2020).

Despite a conducive economic environment in Ethiopia, which is recording steady growth in its real GDP and a moderate increase in private consumption, the retail sector registered mild growth in 2019. Conservative consumer habits are limiting the potential growth of modern retail chains, and there is a latent growth of e-commerce. Foreign retailers are unwelcome in the highly regulated Ethiopian market (Euromonitor, 2020).

1.1.3 Kenyan Retail Sector

The wholesale and retail sector is the 5th most significant contributor to the country's GDP and ranks third most significant contributor to private-sector employment; the sector employs approximately 238 500 Kenyans (Cyntonn, 2018). More so, the sector has recorded a growth rate of 30% five years in a row from 2014-2018. The expansion is attributable to an array of factors, such as an increased rate of urbanization, a growing middle class with a dynamic lifestyle, and liberalization of trade that has precipitated cutthroat competition in the sector (Chesula & Nkobe, 2018). According to (Cytonn, 2018), Kenya has the fastest growing retail market, with an increment in the average value of shopper's basket by 67% to about 20$ (KES 2,016) recorded in 2011-2017. More so, the robust real estate industry has catapulted the expansion of the retail sector. Specific investments in the real estate industry, notably residential malls, and mixed-use developments, have positively influenced the growth of the retail sector in Kenya. Statistics indicate retail space increased by 41.6%, from 3.9 million square feet in 2016 to 5.6 million square feet in 2017. Additionally, Nielsen, a leading global information and measurement company, indicates the sector growth in formal retail by about 30% of Kenya's population shopping at informal retail establishments (Nielsen, 2018). The Kenyan retail sector has the second-highest market in Sub-Sahara after South Africa, with a formal retail penetration of 60% (Cytonn, 2018).

Founded in 1975, Uchumi is the oldest retail chain, followed by Nakumatt, established in 1987. The two retail chains owned flagship stores in Nairobi, Mombasa, and Kisumu, serving as crucial distributors for local consumer goods manufacturers. From the two large retail chains, relatively more minor retail chains like Tuskys, Naivas, and Ukwala served the average customer (Cytonn, 2018). The mid-'90s saw a sporadic growth in retail chains to over 300 (Kiruga, 2013, as cited in Chesula & Nkobe, 2018). Around this time, Uchumi spearheaded the hypermarket concept in Kenya. The retail chain landscape has been changing over time. The industry is currently well-represented by both local and international franchises. Notable industry players are Tuskys (58 outlets), Nakumatt (45 outlets), Naivas (39 outlets), Uchumi (25 outlets), Choppies (10 outlets), Eastmart (9 outlets), Chandarana Stores (8 outlets), Carrefour (4 outlets), Game Stores; Massmart (1 outlet). (Cytonn, 2018).

The sector operates under razor-thin margins of about 1.5%-3.8% making cost leadership strategy short-lived and unsustainable across the product portfolio (Business Daily, 2020). According to (Cytonn, 2018), Choppies, Shoprite, and Massmart have a net profit margin of 0.8%, 3.9%, and 1.4%, respectively. The low-profit margins are surmounted by leveraging economies of scale on buying and selling products (Cytonn, 2018).

For the longest time, players in the sector have been riding on ambition, abundant market opportunity, and investors' tolerance to expand—Uchumi Borrowed KES 3.6bn to double its footprint to 25 stores in Nairobi, Mombasa, and Kampala. Nakumatt also grew from 10 outlets in 2002 to 42 in 2013 and 64 in 2016. Likewise, Tuskys grew to 60 outlets, whereas Naivas grew to 40 outlets.

Nonetheless, the sector has been in turmoil. The rapid expansion with insignificant return on investment, which needs to be improved to meet the retail chains working capital, has led to the insolvency of some retail chains. A case in point is Uchumi, declared insolvent in 2006 and delisted from Nairobi Securities Exchange. Interventions to resuscitate the parastatal have had little impact up to date (Cytonn, 2018). Following the downward spiral was Nakumatt, which exited the retail market due to her financial woes. According to (Business Daily, 2020), Nakumatt was put under receivership when it became insolvent, with total liabilities of 35bn against total assets of 5.2 bn. More so, nearly the entire retail chains have been financially constrained. In this vein, a report by the state department of Trade (Republic of Kenya [RoK], 2017) indicates that the retail chain's cash flow constraints are manifested by over 40 billion debt, with two local retail chains accounting for two-thirds of the abovementioned debt. Similarly, Shoprite acquired funding of US$5.49M to facilitate footing in the Kenyan market. The amount is part of a scooping credit facility of US$764M, the retail chain recorded in 2019 (RoK, 2017).

In sum, players in the retail sector have exhibited notoriety for delaying supplier payments, issuing bouncing cheques, threats to delist and actual delisting of suppliers with no plausible reasons, and the unjust return of goods to suppliers, in part or whole. Following this notoriety, the government of Kenya, through the State Department of Trade, was constrained to conduct investigations on Kenya's retail sector prompt payment (RoK, 2017). Nearly all retail chains are indicative of the turmoil mentioned above.

1.2 Statement of the Problem

Globally, the retail chain of stores experienced growth from $ 3. 138.21 billion in 2022 to a steady 3, 373.9 billion in 2023 and at a CAGR of 7.5% despite the Russia-Ukrane war disrupting the positive trajectory of global economic recovery from the COVID-19 pandemic. In a plausible positive light, it is projected that retail chains are expected to experience a breathtaking growth of up to $4,346.14 billion at a CAGR of 6.5% (Research & Markets Survey, 2023). Consistent with the global trend, Africa's retail sector has expanded equally at a breathtaking pace. The African Consumer Retail Report indicates that although the retail sector is underdeveloped, international retailers strive to establish a footprint on the continent (KPMG, 2023).

Walmart has gambled into the African market through South Africa's Massmart in an economy precipitated by foreign exchange risk, fluid regulatory framework, and an elusive and volatile economy. Africa's middle class is the silver lining that has contributed about $ 1.1 trillion to African GDP. Nielsen (2020). Evidently, in light of the above retail landscape in Africa, it is clear that the retail sector in Africa is a roller coaster. Therefore, a question arises; how do the players in the retail sector navigate the retail distribution labyrinth?

The Kenyan perspective on the retail sector is that it is susceptible to unprecedented disruptions occasioned by unending sector-specific turmoil and disruptions (Chesula & Nkobe, 2018). The susceptibility is brought about by the operating nature of the retail chains in the sector, perishability of the items due to short product shelf life, razor-thin profit margins, and high competition. For these reasons and others, retail chains are not sufficiently resilient to adjust ex-and ex-post to disruptions, consistent with the postulations of (Vizinger & Zerovnik, 2018) that the nature of retail chains makes them sensitive, susceptible, and vulnerable to retail chain-specific disruptions and the domino effect is that they fail on the resilience litmus test to increase their reliability, flexibility, and convenience. It has permeated and precipitated non-resilience to either resist, adjust or recover from both ex-post and ex-ante disruptions by the sector players pushing some firms to insolvency and liquidation (Chesula & Nkobe, 2018).

Non-resilience in the retail chains is manifested through the shutdown of retail chains due to financial impropriety and absence of prudence in retail chain's financial management, poor strategic business decisions, poor operations management, poor corporate governance characterized by board-room wars and family feuds (Knight et al. [KFA], 2020). The reasons mentioned above justify, in part and or in whole, why Nakumatt Holdings shut down and was put under liquidation by the creditors, whom it owned a colossal sum of about 38bn. Uchumi, the one-time retail giant in Kenya and East Africa, is struggling to stay afloat and is always at the mercy of capital injections by the Government of Kenya. Tuskys supermarket is on the brink of collapse. Given the protracted courtroom battle of the Kenya Revenue Authority over tax disputes amounting to about 174 mn, Choppies is struggling to exit the Kenyan market (KRA, 2020). It comes barely four years after the Botswana headquartered retailer acquired Ukwala Supermarkets after the latter applied for liquidation, citing financial difficulties in Kenya's increasingly competitive retail landscape.

Indeed, Kenya Retail Sector Report 2020 (Cytonn, 2020) indicates that retail sector performance took a downward spiral, with average rental yields decreasing by 1.6% from 8.6% to 7.0 in 2018, and the downward spiral was entrenched in 2019 to 6.3%. It was attributed to reduced occupancy rates owing to retail shutdowns. In 2020, the Coronavirus pandemic exacerbated the retail sector's non-resilience, resulting in poor performance. This year, the average number of retail chains in Nairobi City County declined from 303 to 176 and was projected to decline further to 172 by 2023. (Cytonn, 2020).

Dark clouds linger over the sustainability of retail chains in Kenya due to their non-resilience. Still, the need for more resilience in retail chains is a nagging Achilles heel in the retail sector. Tusky's strategic Waterloo has been boardroom wars, poor management structure, and aggressive expansion. They are reasons for the dwindling performance of Tuskys in part, which is on its deathbed, clinging to a capital injection of 2bn from an undisclosed foreign retailer which will come in as its strategic partner. Like Uchumi and Nakumatt, Tuskys embarked on an expansion spree of their retail chains overstretching their financial muscle while the profit margins are razor thin. To exacerbate the matter, retail chains in Kenya cannot enable short-term resumption and long-term restoration after a disruption (Byadigera, 2019). This missing link partly explains why Tuskys and Shoprite have closed down some of their branches in Nairobi (RoK, 2020).

Supply chain configuration is on the cusp of supply chain dynamic capabilities and resilience in the retail sector. Past research has elucidated that applying dynamic capabilities in a supply chain management context is a strategic arsenal to make a supply chain resilient (Brusset & Teller, 2017). More so, extant literature has exemplified the moderating role of supply chain configuration on resilience; For instance, (Chandra, & Grabis, 2016) underscores the importance of configurable supply chains to enable retail outlets to adapt to their environment in the context of supply and demand fluctuations. It is against this brief outline that the study aims at developing and testing hypotheses on the relationship between dynamic supply chain capabilities and resilience in Kenyan Retail Chain of Stores.

1.3 Objectives of the Study

1.3.1 General Objective

To establish the relationship between dynamic supply chain capabilities and resilience of the Retail Chain of Stores in Kenya

1.3.2 Specific Objectives

1. To establish the relationship between SC agility capability and resilience of retail chain of stores in Kenya.
2. To examine the relationship between supply chain alignment capability and resilience of retail retail stores in Kenya.
3. To establish the relationship between SC analytic capability and resilience of retail chain of stores in Kenya.
4. To evaluate the relationship between SC innovation capability and resilience of retail chain of stores in Kenya.
5. To assess the moderating effect of SC configuration on the relationship between dynamic supply chain capabilities and resilience of the retail chain stores in Kenya.

1.4 Research Hypotheses

H_{01}: There is no statistically significant relationship between SC agility capability and the resilience of retail chain stores in Kenya.

H_{02}: There is no statistically significant relationship between SC alignment capability and the resilience of retail chain stores in Kenya.

H_{03}: There is no statistically significant relationship between SC analytic capability and resilience in the Retail Sector in Kenya.

H_{04}: There is no statistically significant relationship between dynamic SC innovation capability and resilience in the Retail Sector in Kenya.

H_{05}: Supply chain configuration does not significantly moderate the relationship between dynamic SC capabilities and resilience in the Retail Sector in Kenya.

1.5 Significance of the Study

This research was undertaken when the Kenyan retail sector faced a remarkable litany of transformations aimed at survival after substantive dark clouds of collapse. In this regard, the study aimed to establish the extent to which dynamic supply chain practices, as part of the transformations, relates to the resilience of the retail sector.

1.5.1 Retail Sector

This study sought to establish the nexus between SC dynamic capabilities and organizational resilience in the retail sector. Different players in the industry can adopt the findings of this study. It will help the different players, such as proprietors, chief executives, investors, various line managers, and knowledge workers, to understand the relationship between SC capabilities and resilience in the retail sector. The output of this research teased out the nuggets of knowledge on resilience strategies that need to be deployed to yield the resilience of the retail sector both in the short term and long term.

1.5.2 Researchers and/ Academicians

The study contributed to the two-fold limited body of knowledge on resilience and SC dynamic capabilities. The existing published research on SCRes is fragmented, with a relative disparity in the concept, identification of its constructs, and lack of clarity between the relationship of the constructs under study (Bhamra et al., 2011; Blackhurst et al., 2011; Jüttner & Maklan, 2011; Melnyk et al., 2014). This study aimed at addressing this gap. Additionally, the study helped in testing the hypothetical models and validating the extant working hypotheses on the nexus between SC dynamic capabilities and resilience of the retail sector as opined by

(Iranov, 2018) grounded by (Fahimnia, & Jabbarzadeh, 2016; Ramezankhani et al., 2018).

1.5.3 Stakeholders

The study offered actionable recommendations to diverse pockets of stakeholders such as the Retail Trade Association of Kenya (RETRAK), Association of Kenya Suppliers (AKS), and Kenya Association of Manufacturers (KAM) as the findings of this study can be inferred from other sectors of the economy, i.e., broader manufacturing sector where there is homogeneity.

1.5.4 Government and Policy Makers

The government, through the relevant agencies such as the Ministry of Trade and Foreign Affairs, State Department of Trade, and Kenya Investment Authority (KIA), among others, can leverage the findings as a basis for coming up with policy interventions in the retail and wholesale sector.

1.6 Scope of the Study

The unit of analysis was the retail sector. The sector was selected for the study because players record a significant upward trajectory on uptake of dynamic SC capabilities to at least adjust ex-post to the disruptions to gain resilience. Whereas the retail sector is expansive, cutting across clothing, textiles and apparel industries, foodstuff, beauty assortments, grocery, and footwear. However, our study was limited to the retail chain of stores. The study surveyed retail chains listed by the Retail Trade Association of Kenya, which is located in Nairobi City County. Nairobi City County was selected as retail chains in this county are experiencing relatively higher disruptions, leading to the closure of some of the retail chains (RETRAK, 2020). The Predictor variable was dynamic SC capabilities. Given the expansive scope of organizational capabilities, dynamic capabilities were exemplified in this research objectively, focusing on how well a firm adapts to changing business environment by building, integrating, and its competencies. Succinctly, given the problem at hand, the conceptualization of the study, and its operationalization, this research underscores the concept of dynamic capabilities as it is the only set of capabilities that can sense and shape the opportunities and threats, seize opportunities; and maintain competitiveness through enhancing, combining, protecting and when necessary reconfigure business enterprise assets (Tecee, 2009). The unit of observation was employees working in large retail chains in Nairobi City County because the retail sector is relatively wide, covering wholesale, large retail chains, and small retail chains. Supply chain configuration has been used as a moderating variable and is on the cusp of supply chain dynamic capabilities and retail chain resilience (Sahebjamnia et al., 2015; Sawalha et al., 2015). Further, the study demystified four predictor variables; SC agility capability, SC alignment capability, SC analytic capability, and SC innovative capability.

1.7 Limitations of the Study

One limitation of this study is that the respondents were not keen on filling the open-ended questions, which deprived the researchers of the opportunity to comprehensively analyze qualitative data, providing grounds to tease out new knowledge using grounded theory methodology. Hence, this study was limited to hypothesis testing. This study admits that no research is immune to non-response or partial response; nonetheless, this bottleneck was addressed by using tactics and ploys to invite study participants to respond to open-ended questions. These tactics included writing follow-up emails inviting respondents to respond to open-ended questions.

The recovery measurement was limited to Likert scale questions because the resumption of the retail chains after shutdowns was too little and statistically insufficient to conduct a trend series analysis on the recovery. This limitation was incurable with the limited data. It forms a basis of the areas for further study. Future researchers should consider conducting a qualitative study to establish the extent of recovery of these retail chains.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter outlines the theories underpinning the study, conceptual framework, empirical review of study variables, critique of existing literature, research gap, and chapter summary.

2.2 Theoretical Framework

Defee et al. (2010) propose that proper research should be based on a theory. This study is anchored on Supply Chain Resource Orchestration Theory, Supply Chain Network Theory, and Structural Dynamics Theory.

2.2.1 Supply Chain Resource Orchestration Theory

Proponents of this theory include (Gruber et al., 2010; Simon et al., 2007; 2011; Jenkins, 2017; Chadwick et al., 2015; Yao & Zhu 2012 as cited in Feizabadi, Maloni, & Gligor, 2019). The unit of analysis of this theory is the firm. Resource orchestration theory addresses some limitations of a firm's resource-based view by explicating how tangible and intangible resources can be deployed to precipitate synergistic effects. Chadwick et al. (2015) initially combined the resource management framework with asset orchestration theory to precipitate resource orchestration theory. Further, Resource Orchestration Theory predicts ex-ante the set of resource combination strategies that can best derive competitive advantage (Gruber et al., 2010; Chadwick et al., (2015). Essentially, SC Resource Orchestration Theory postulates that the "competitive advantage of a firm is brought about by a blend of resources, capabilities, and managerial acumen that ultimately results in superior firm performance. (Chadwick et al., 2015). In a more superficial sense, Resource Orchestration Theory alludes that a firm can realize the full potential of its strategic resource endowment when it can convert these resources into capabilities and effectively leverage the capabilities in the marketplace to create value for customers (Chadwick et al., 2015).

Additionally, SC Resource Orchestration Theory posits that Resource Orchestration Theory examines the specific resource management processes such as structuring, bundling, and leveraging in a supply chain context, i.e., supply chain resource orchestration. In so doing, a firm can develop informative and actionable middle-range theory (Jenkins, 2017). Resource Orchestration Theory is essential to understanding the deployment of a castellation of SC resources and capabilities.

Researchers have previously used resource orchestration theory to ground their studies. For instance, Feizabadi et al. (2019), in their seminal contribution to the extant literature on the "Triple A" framework, underscored the importance of orchestrating agility capability, alignment capability, and adaptability capability. Further, Feizabadi et al. (2019) accentuate that agility enables an SC to address short-term fluctuations or changes in demand and disruptions. Also, Feizabadi et al. (2019) opined that adaptability capability is facilitative in SC to support adjustments to long-term market shifts. Additionally, he suggested that alignment capability enables the creation of incentives that synchronizes individual objectives of channel participants to common goals that unite the entire SC to serve the end customer. Li and Jia (2018) observed that innovation capability enables a supply chain to keep abreast with market dynamics.

Undoubtedly, dynamic supply chain capabilities are crucial to the resilience of any entity and are premised on supply chain ROT. Just like Resource Orchestration Theory posits, large-scale retail chains unreservedly deploy their resources to tease out combinative problem-solving capabilities into use. Therefore, the study embodies ROT as a bundling and leveraging capability to enhance resilience in the retail chain. The above view is informed by the proposition that ROT explicates how a firm can create unique combinations of interconnected resources that differentiate a company in the marketplace (Feizabadi et al., 2019).

2.2.2 Supply Chain Network Theory

Supply chain Network Theory was postulated by Hearnshaw and Wilson (2013) as an extension of the Complex Adaptive Systems theory and the Relational Exchange View of a Network. Hearnshaw and Wilson (2013) accentuated that SC is a network comprising a set of nodes that are autonomous functional elements of a business unit that are independent of each other. As such, they can make their own independent choices. However, Hearnshaw and Wilson (2013) accentuated that although these firms in a supply chain are independent of the other, some "connections" exist among the different business entities. Owing to these "connections," exchange relationships exist across the different business entities in a supply chain and underlying contracts, if any. For this reason, Hearnshaw and Wilson (2013) contended that different connection types result in different SC network topologies based on different sets of firms.

Hearnshaw and Wilson (2013) opined that supply chains represent different business entities representing different tiers or echelons in SCs. For instance, Chandra and Grabis (2016) corroborate that a typical basic supply chain structure will horizontally comprise the supply tier as the most upstream tier, the manufacturing and distribution tier, and the customer tier as the most downstream tier. Consistent with the postulations of Hearnshaw and Wilson (2013). Chandra and Grabis (2016) further espoused that a SC, to a vertical extent, comprises numerous members spread across different echelons, each echelon consisting of at least one business unit, possessing diverse contemporary functional areas such as design, marketing, sales, production, inbound and outbound logistics.

The moderator variable, supply chain configuration, was premised on supply chain network theory for this research. Akin to a typical supply chain network, retail chains also have both vertical and horizontal configurations that, when well configured, are robust enough to enhance the application of dynamic capabilities that precipitate short and middle-term resilience and lead to competitive advantage. Precisely, a strategic supply chain configuration of a retail chain equips a retail chain with the impetus to undertake horizontal integration, thus enabling the firm's growth through internal expansion, such as diversification of product portfolio to appeal to a broader and more diverse customer base. Resilient retailers undertake vertical integration through mergers and acquisitions and, at times, hostile takeovers of their competitors in the industry. Vertical integration is done by acquiring the physical distribution channels, i.e., forward or backward integration, by gaining control over the upstream supply.

2.2.3 Structural Dynamics Theory

Proponents of structural dynamics theory are (Chopra, 2011; Clough & Penzien, 1993; Humear, 2012; Paz, 1990 as cited in Iranov, 2018). Tenants of structural dynamics theory relate to discrete and continuous systems subject to mechanical systems' response to dynamic loads; in engineering approaches, structural dynamics control deals with the coordination of complex networks, which, more often than not, is affected by internal and external networks.

Just like structural dynamics in engineering, supply chains are dynamic systems subject to structural and parametrical changes, and such dynamics are encountered daily in a supply chain (Iranov, 2018). More succinctly, (Iranov et al., 2017) delineates that supply chains equally represent complex coordinated networks that operate in uncertain environments and are therefore predisposed to different risks and disruptions (Chopra et al., 2007; Dolgui & Proth, 2010; Martal & Klbi, 2016; Simchi-Levi et al., 2015, as cited in Iranov, 2018).

Using control theory, some elements of SC resilience outcomes, such as stability, robustness, and adaptability, can be considered. Ivanov (2018) further accentuates that structural dynamics control theory contributes to supply chain management literature in the adaptive understanding of planning and control processes. In this light, Structural dynamics control theory can underpin the adaptive capability of retail resilience in the pre-, during, and post-disruption recovery stages of disruption. More so, Iranov (2018) posits that continuous dynamic models permeate supply chain practitioners and researchers to optimize supply chain performance indicators with dynamics that are difficult to express with contemporary supply chain performance indicators. Iranov (2018) also opines that the theory underpins process-level SC dynamics and changes in the SC environment; as such, they significantly contribute to Structural dynamics control theory.

The criterion variable under study is premised on structural dynamics theory. Retail chains are analogous to structural dynamics. They operate equally under complex, multi-tiered supply chain networks in highly uncertain environments like demand uncertainty. Consequently, they are exposed to risks and disruptions like the *"Forrester effect."* As a result, resilient retailers proactively create redundancies such as backup facilities, inventory, and capacity flexibility to adjust ex-ante to disruptions. Agility capabilities are also leveraged in the reactive control stage in retail chains to recover ex-post to disruptions.

2.2.4 Dynamic Capabilities (DC) Theory

The proponents of this theory are (Eisenhardt & Martin, 2000; Helfat et al., 2009; Teece et al., 1997 as cited in Bleady & Ibrahim, 2018). They postulate that dynamic capabilities are "the firm's ability to integrate, build and reconfigure internal and external competencies to address rapidly changing environments" (Tecee et al., 1997, p. 516). DC theory is an alternative theory and an extension of the resource-based view of the firm. It addresses the weaknesses exhibited by RVB (Galvin et al., 2014) and the inability of the RVB to deduce the development and redevelopment of resources and capabilities to address the rapidly changing environments. DCS also compensates RBV for a firm's shortcomings in expounding sustainable competitive advantage in a dynamic environment (Bleady et al., 2018).

DC theory argues that when the ecosystem in which the firm is embedded is unstable, it must continuously reinvent itself (Teece, 2007). Thus, the firm develops dynamic capabilities that lend it the mechanism to direct the firm's internal and external resources consistent with marketplace needs and imperatives (Eisenhardt & Martin, 2000; Helfat et al., 2009; Teece et al., 1997 as cited in Bleady et al., 2018).

DC is the reason behind a firm's ability to integrate, marshall, and reconfigure resources and capabilities to adapt rapidly to dynamic environments (Teece et al., 1997). Simply put, DCs processes enable reconfiguring strategies and resources to achieve sustained competitive advantage and superior performance in dynamic marketplaces (Bleady et al., 2018). Tecee (2007) grounds DCs theory on three dimensions which are sensing, seizing, and transforming; sensing to identify and assess an opportunity that manifests; seizing the opportunity through mobilizing resources to grab opportunities that manifest and capture value; and transformation, the continuous renewal, and reconfiguration of firm's tangible and intangible assets.

Despite the groundbreaking contributions of (Tecee et al., 1997; 2007) on DCs theory, intense criticism has been leveled against the theory. It suffers from accusations of tautology, incoherent use and interpretation of terminologies, deficiency from lack of consistency and congruence, ubiquity and failure to meet the threshold of a scientific theory (Thomas & Pollock, 1999, cited in Wang & Ahmed, 2007). For instance, the theory needs explicit models to measure the dynamic capabilities and their short-term and long-term effects on the performance of firms (Zott, 2003, cited in Bleady, Ali, & Ibrahim, 2018). More so, the theory does not describe how the dynamic capabilities operate (Schreyögg & Kliesch-Eberl, 2007, as cited in Bleady et al., 2018). Also, it lacks clarity about what constitutes its core concepts (Ambrosini & Bowman, 2009, cited in Bleady, Ali, & Ibrahim, 2018). Collective efforts from researchers are required to demonstrate concepts related to DCS theory and how to link them to empirical practices within organizations (Wang & Ahmed, 2007, cited in Bleady, Ali, & Ibrahim, 2018)

Nonetheless, DCs theory has gained momentous application as a theoretical underpinning in supply chain management literature from academicians and practitioners in equal measure (Colicchia & Strozzi, 2012). Supply chains are increasingly becoming susceptible to turbulent, risky, and dynamic markets, and global supply chains aggravate the susceptibility due to increased linkages and complexities. As such, proactive and reactive mitigation measures are pursued as remedial action. In retrospect, supply chain resilience emerges as a dynamic capability of a firm in pursuit of sustainability of the firm economic, social, and environmental sense, consistent with the triple-bottom-line objective of firms. For this research, dynamic capabilities are decomposed into agility, analytics, alignment, and innovative capability. These capabilities are reactive and reactive, enabling the SC to sense, seize and transform opportunities and threats accordingly to the extent that the SC is robust enough to adapt, resist and recover quickly from any given disruption. Past researchers (Hong et al., 2018) used DC theory to ground their study entitled Sustainable supply chain management practices, supply chain dynamic capabilities, and enterprise performance.

DCT underpins the predictor variables under study as they are dynamic capabilities. Consistent with the characteristics of dynamic capabilities by Tecee (2007), the concurrent application of the aforementioned dynamic capabilities undoubtedly enables retail chains to have the much-needed sensing, seizing, and reconfiguration capabilities. By applying supply chain analytics, a retail chain can sense disruptions and market opportunities; alignment and agility capabilities enable the retail chain to form winning collaborations with the channel participants to seize market opportunities. More so, innovation capability brings about perpetuity to the retail chains.

2.3 Conceptual Framework

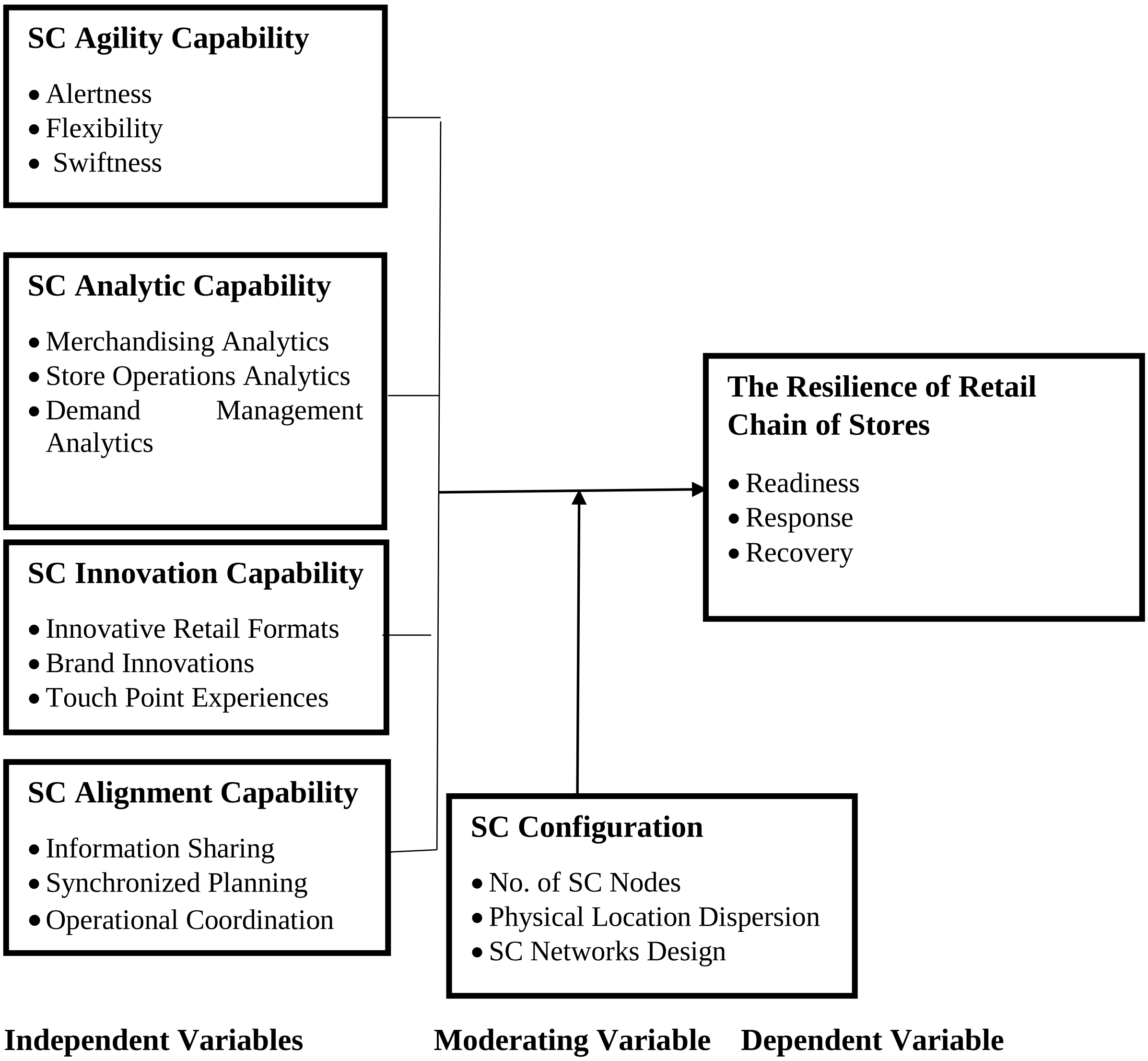

Figure 2.1: Conceptual Framework

A conceptual framework is a nerve center for empirical research. Ravitch and Riggan (2016, p. 32) indicate that a conceptual framework 'serves as a guide and ballast to research, functioning as an integrating ecosystem that helps researchers to intentionally bring all aspects of a study together through a process that explicates their connections, disjunctures, overlaps, tensions, and contexts shaping a research setting and the study of phenomena in that setting (Adom et al., 2018). In a similar lens, Maxwell (2005, p. 33) defines a conceptual framework as a system of concepts. Assumptions, expectations, beliefs, and theories that support and inform research.

Ravitch and Riggan (2016) contend that a conceptual framework makes a case for the significance and relevance of a given study. Through a conceptual framework, a researcher can situate a study in multiple contexts, including an overall methodological approach. A conceptual framework is multifaceted, enabling it to include the intersecting multiple components of the research and goes to the extent of deducing how these multiple intersecting components influence each other. The study adopted agility, analytics, innovation, and alignment capability as the predictor variables, SC configuration as the moderating variable, and resilience in the retail sector as the criterion variable.

2.3.1 Supply Chain Agility

Wilhelm and Sydow (2018) espoused that SC agility is the firm's ability to swiftly work with channel participants to respond to market dynamics. SC agility is a dynamic capability that firms should at least possess in response to disequilibrium in the business ecosystem. Precisely, agility enables a firm to mitigate SC disruptions and rapidly respond to dynamics in the marketplace and other uncertainties to exhibit resilience to achieve a superior competitive position. Do et al. (2021) demonstrated the conceptual evolution of SC Agility, alluding that SCA has evolved in fundamental aspects, namely pathways, criteria, scope, and objectives. Do et al., 2021 posit that early proponents of SCA propounded SCA through a lens that constrained the concept to the capability of providing swift or rather speedy responses to sudden demand fluctuations in the marketplaces to accrue a competitive edge. Emerging literature has, however, expanded the scope of agility further to encompass not only reactive measures but also proactive measures, as well as the cognitive capability to the dynamic capability to become alert and quickly or instead swiftly anticipate and detect not only the marketplace opportunities but also disruptions and disturbances in the marketplace. More so, Tse et al. (2016) propounded that speed/quickness are two criteria applied to measure responses to change. Additionally, Do et al. (2021) indicates that SCA addresses all and sundry concerning sudden changes in the supply chain, the scope of the changes ranging from internal to external, not necessarily constrained to the downstream supply chain. It is further noted that the changes within the scope of SCA, more often than not, are immediate, sudden, and spontaneous.

Flexibility is a concept that emerged from the need to mitigate the dire need to reduce the adverse effects of uncertainties, supply chain risks, disruptions, and turbulences for purposes of keeping abreast of market changes in the marketplace (Delic & Eyers, 2020). Flexibility in the SC accrues overriding benefits such as the ability to need and respond to market demand fluctuations. SC flexibility equips a firm with the capability to respond to changes in the business ecosystem (Liao, 2020). From the lens of Chirra *et al.* (2020), flexibility boosts agility in SC operations in the context of dynamic capability and contingency theory. Succinctly, Shekarian *et al.* (2020) note that agility denotes a firm's capability to maneuver in the face of disruption, which best manifests itself in flexible supply chains. In this research, we conceptualize flexibility as a precursor of SC Agility. SC flexibility is critical to non-resilient firms as it enables them to innovate new products, permits mass customization and adjustment of delivery dates, flexibility enables the firms to accept unplanned orders, synchronize existing capacities even negotiate with channel members to fulfill uncertain market requirements (Khanuja & Jain, 2021; Wang & Zhang, 2019).

Flexibility extends to the concept of supply chain flexibility which is classified into process flexibility in each firm and logistics flexibility. Relevant flexibility dimensions in the supply chain context were appraised by Wang and Zhang (2019), who contended the following taxonomy; volume flexibility, which refers to the ability to reduce/decrease production in response to customer demand within a minimum planning period. The second in the SC flexibility taxonomy is mix flexibility which refers to the ability to produce a wide range of product lines within the minimum planning period. The third one is new product flexibility which endeavors to introduce many new products and product varieties within the minimum planning period. The fourth element is access flexibility, which refers to meeting and exceeding customer requirements. In sum, flexibility is a coping mechanism that indemnifies an organization against internal and external uncertainties.

Much attention has been given to speed, quickness, and speed concerning agility in sports science (Sporiš et al., 2011). Given the ferocious market competition and ubiquitous changes in the marketplace, alongside unprecedented risks, SC agility is the emergent concept that bridges the gap between learning and speed necessary for organizational change. One of the agility inputs is speed, which also relates to swiftness (Appelbaum, 2017). Park (2017) posits that effectively dynamic firms tend to have a high propensity and acceleration in their environments. Further, the researcher links agility with speed and flexibility to achieve successful outcomes.

2.3.2 Supply Chain Analytic Capability

Supply chain analytics capability can be clustered into merchandising, store operations, and demand management analytics. Similarly, PWC (2016) categorizes the analytic framework into merchandising, marketing, channel, and store operations analytics. According to PWC (2016), merchandising analytics are used as leverage by retailers to stock the right merchandise on the right shelves (place) and at the right time. , merchandising analytics enables time and place utilities concerning retail merchandise management. Moreover, merchandising analytics encompasses assortment planning, demand forecasting, space allocation planogram analytics, location-based assortment, and product adjacency (PWC, 2016).

The second element of SC analytic capability is store operation analytics which is an all-inclusive function of the effectiveness of stores personnel, costs the firm absorbs concerning reducing pilferage from stores, managing inventory to the proper levels, and improving overall staff performance regarding footfalls and conversion rates by using video and sensor data to streamline store operations (PWC, 2016). The third element is demand management. It enables retailers to keep abreast with dynamic customer needs, thus ensuring loyalty. Demand management analytics gives retailers deeper customer insights, targeted interactions, and personalized and improved customer service. More so, demand analytics integrates the relevant customer's data from the point of sale terminal, customer relationship management database, and loyalty cards., with social media, weblog, and channel data to undertake sophisticated analytics and share data to help optimize marketing decisions. Retail chains leverage demand management analytics to deepen customer insights, optimize multichannel performance, improve marketing effectiveness, and enhance social media presence (PWC, 2016).

The conceptualizations of SC analytics extend to shaping the benefits accrued; the diverse elements of retail analytics enable street-to-store conversion and track the effectiveness of marketing campaigns on passers-by. Secondly, it facilitates generating in-store visitor traffic trends, including discovering the peak hours and optimizing staff operations during peak hours. Thirdly, SC analytics lets us know which merchandise engages the customers in-store and how different components translate to buying decisions. Fourth, it also facilitates real-time queue management, tracking, and tracing to enable taking immediate action to mitigate time lost in queues. It also enables the customer retention rate by determining the number of return customers and which product lines create the highest demand. It also enables the creation of customer data to determine a repeat customer base across stores and analyze which retail outlets are losing potential customers and why.

2.3.3 Supply Chain Innovation Capability

Innovative retail formats extend the application of the Internet of Things to optimize in-store layout. In-store layout optimization is brought about by using sensors whereby category managers can track the movements of customers and their behavior while inside the store. Gregory (2015), as cited in Vučenović (2018), notes that Hugo Boss leverages heat sensors to track and trace the in-store customer movement and places their premier products in high-traffic areas inside the retail chain. More so, Manyika et al. (2015) project that in-store layout optimization has the potential value of about 79$ billion to 158$ billion by 2025 and an increase by 5%in productivity. Another type of innovative retail format is automated checkouts. Bok (2016) notes that checkouts are one of the most intensive processes in the retailing process that can even lead to customer frustrations. Internet of Things (IoT) is leveraged to overhaul traditional checkout procedures by automatically scanning all the shopping in the shopping basket and charging the customer using barcode scanners combined with RFID technology.

Another innovation in the retail space is the application of IoT-based store mapping. It refers to using a combination of Indoor Positioning Systems to allow customers to locate the products and make them appear on the store's floor plan. It also extends to fitting RFID tags on the products to link them with the store mapping software. The software can show the shortest distance/ pathway to retrieve the product on the list. It saves customers time and enhances their customer experience. Another innovation is the application of IOT on on-shelf availability. On-shelf availability refers to 'product availability in designated locations when the shopper is looking for it (Varghеese et al., 2014). It is a paramount metric for SC innovations for retail outlets. Through the application of IOT, big data analytics and sensors are used to generate critical information about out-of-stock products, such information is sent to the concerned employees, notifying them to replenish stock or other mitigation measures such as recommending the customer to pick the goods from another store.

Retail chains have traditionally used cost as the primary criterion for costing. With the advent of technology, the retail landscape has significantly evolved to the extent of adopting more sophisticated pricing models that frequently update the prices from time to time based on demand and supply characteristics (Grewal et al., 2011). Such pricing models consider inter and intra-category optimization, market expansion, psychological pricing elements, optimization, product adjacency, and scalability. Dynamic pricing models permit retail chains to undertake price discrimination to a small extent, even to an individual shopper level. Notably, emergent technologies such as Radio Frequency Identification (RFID), wireless networks, and Global Positioning Systems enhance the appeal of dynamic pricing in the retail landscape (Grewal et al., 2011).

E-tailing is another form of innovative retail format where a couple of online retailers offer a limited number of products in different product lines to select consumers who must subscribe to the e-tailing site. Some sites only allow subscribers to be referred to the site by another subscriber. It creates a sense of exclusiveness. Extant literature has exhibited that customers value exclusive promotions over inclusive ones. More so, such e-tailing sites reward existing customers should they provide referrals to others (Grewal et al., 2011).

These invitations-only promotions significantly reduce the chance that other consumers will see the offer and create the perception that they will find such items at sharp discounts, often discounted at more than 50%. Other types of innovative promotions in retail formats are conditional promotions whereby the customer has to meet a given condition to be eligible to get a promotion. For instance, customers must shop for goods worth KES 1000 for a 5% discount. Others include volume-based pricing (Grewal et al., 2011).

Touchpoint refers to 'direct contact between the customer and the actual product or service or with the representation inflicted by the company's third party (Roto *et al.*, 2016). From this definition, Grewal et al. (2011) deduced that touch points between a company, its agent or representatives, and the customer can occur. Touchpoints with third parties occur through word of mouth, news, and product or service reviews. There exist different types of touchpoints. The first one is brand-owned touchpoints, whereby the interaction is between the company and the customer. The company or its agents trigger this type of touch point. Examples of brand-owned touchpoints include media, ads, product packaging, and pricing (Liljedahl, 2020). The second is partner-owned touch points, which refer to simultaneous interaction initiated and managed by a firm and its associates, such as marketing agents or retail partners (Liljedahl, 2020). The third type is customer owned touch point, which the customer initiates, and is neither under the control of the company nor its partners (Liljedahl, 2020). The fourth type of touchpoint is social touch point which refers to diverse external touchpoints created by other people around the customer and often affecting customer experiences. Such touchpoints are friends, family, and autonomous information sources available online (Liljedahl, 2020).

2.3.4 Supply Chain Alignment Capability

Simatupang and Sridharan (2004) indicate that information sharing refers to the actions relating to capturing and disseminating not only timely but also relevant information for the decision-makers to plan, execute and control supply chain operations. Further, decision synchronization refers to joint decision-making in planning and operational contexts. Gupta and Maranas (2003) observe that planning refers to a series of activities examining the demand for materials and the capacity to formulate plans and schedules to meet both the demand and company goals. Planning is categorized into strategic planning, tactical planning, and operational planning (Kaipia, 2007). Simatupang and Sridharan (2004) contended the different types of information that can be shared and their potential benefits. In their research output, they argued that sharing order status information improves the quality of customer service and reduces payment cycles and labor costs.

Additionally, it is noted that sharing sales data can significantly mitigate the risk of the bullwhip effect. More so, Huang et al. (2003) stratified information into six categories relating to product, process, resource, inventory, order, and planning. Product information is product structure; information relating to the process includes; material lead time, lead time variance, order transfer lead time, process cost, quality, shipment, and set-up cost. Information relating to inventory includes inventory level, holding costs, backlog costs, and service level. Information about resources includes capacity and capacity variance. Order information includes demand, demand variance, order batch size, order due date, and demand correlation. Information about planning includes demand forecasting, order scheduling forecasting models, and time fence (Huang et al., 2003). A significant attribute of information is timeliness. If the delayed transmission of information occasions a supply chain, the ripple effect exacerbates the effects of the upstream supply chain, specifically the producer. Additionally, another element of information is its completeness.

Thomé et al. (2014) argue that through Collaborative Planning, Forecasting, and Replenishment initiatives, organizations undertake synchronized planning in their supply chains by enhancing customer demand visibility and matching demand with supply, precipitating a synchronous flow of goods from production upstream of the supply chain to the point of final consumption in the downstream supply chain. Voluntary Inter-Industry Commerce Standard (VICS)demonstrates that operational coordination can be achieved by leveraging supply chain collaboration initiatives such as Electronic Data Interchange (EDI), Efficient Consumer Response Movement (ECR), Vendor Managed inventories (VMI), and Continous Replenishment (CR).

2.3.5 Supply Chain Configuration

Sabri *et al.* (2017) note that SCC is concerned with the firm's nodes, geographical locations, and the degree of dispersion of the outlets and how raw materials are supplied through examining supplier network design and the extent of information flow or communication across the SC and concern on distribution channel design, regarding how the final product reaches the final consumer and which types of links are existing between the nodes and money flow between the respective supply chain nodes. Sabri *et al.* (2017) synthesized different approaches to supply chain configuration and categorized these approaches based on product characteristics, functions, operations, and systems. The product characteristic approach proposes a customized SC configuration for products with different functions from the same product family, i.e., differentiating luxurious sports cars from the regular ones in the automobile industry. Hence the need to have different supply chain configurations with different functions from the same product family. Selldin and Olhager (2007) observed that companies that can match their product characteristics to supply chain configuration exhibit stellar performance compared to those that fail to do so.

The second category involves operations and practices performed by supply chain participants, which extends to the governance of the organizational links. Supply chain configuration deals with decisions such as supplier selection, assembling, production/processing/manufacturing facilities, and distribution channel design. The systems approach in supply chain configuration regards the main constituents or entities of configuration (such as supplier, manufacturer, and distributor), the size and location of these entities, their inter-relationships, corresponding information flows, the supply chain structure, and organizational structure. In this view, a supply chain is an interconnected business that collaboratively works together to achieve a synchronized and shared goal. An ideal supply chain configuration entails determining the demand, the type of products, and the type of supply chain priorities such as responsiveness, efficiency, reliability, and flexibility of the SC (Fisher, 1997, as cited in Sabri et al., 2017). Min and Zhou (2002); Chandra and Grabis (2007), as cited in Sabri et al. (2017), contend that the initial step in SC configuration is to identify the value-adding members within a given SC; this means that it should start by identifying the entities, their sizes, and their physical location. In their view, the second step is to determine the relationships and links between these entities, how they communicate (information flow), and how they manage their processes (organizational structure). Lastly, determine the operational variables (demand level and product features).

Sabri et al. (2017), in an extensive systematic literature review, observed several supply chain configurations based on distinctive industries or sectors. The first one is supply chain configuration for the food sector (Reiner & Trcka, 2004; Aramyan et al., 2007) as cited in the Sabri et al. (2017); electronics industry (Chiang et al., 2007); automotive industry (Pires & Neto, 2008) as cited in Sabri et al., (2017; luxury industry (Brun et al., 2008; Caniato et al., 2011) as cited in Sabri et al., (2017). Exploration of the global/local perspective in supply chain configuration (Meixell & Gargeya, 2005; Cagliano *et al.*, 2008; Caniato *et al.*, 2013) as cited in Sabri et al., (2017); Furthermore, humanitarian supply chain configuration is investigated as a case of a not-for-profit supply chain (Jahre et al., 2009; Costa et al., 2012) as cited in Sabri et al., (2017)

2.3.6 Resilience of Retail Chain of Stores

Supply chain resilience is the ability to resist and recover from such disruptions to exhibit operational capabilities after the occurrence of disruptions (Melnyk et al., 2014). In their view, they contend that SCRES consists of resistance capacity and recovery capacity. Resistance capacity enables the organization to minimize the impact of disruption by evading it in its entirety or at least minimizing the time between the initial occurrence of disruption and the Onset of recovery from that disruption, often referred to as containment.

Robustness is a dynamic property in resilient supply chains that allows a firm to maintain its functions against internal and external perturbations (Monostori, 2018). In SC contexts, there exists structural (static) and operational (dynamic) robustness. Operational robustness is the extent to which dynamic supply chain processes and activities are robust based on unchanged structures (Monostori, 2018). Different measures of operational robustness exist, such as delivery performance, throughput time and delivery lead time measures, percentage of late deliveries, and delivery tardiness. Throughput time refers to the average time to execute an order from the start of its production to its logical completion. Delivery lead time is the average time between placing an order and its subsequent shipment to the customer. The percentage rate of deliveries refers to the ratio of late deliveries to the total number of deliveries. Delivery tardiness refers to the average time the late deliveries lag behind their contractual delivery times, indicating the extent to which a customer has been inconvenienced (Monostori, 2018).

In the view of Vlajic et al. (2012), robustness is the ability to withstand and resist disruptions with no need to leverage adaptability in the SC configuration with plausible performance pre and post-disruptive events. Additionally, (Chowdhury *et al.*, 2016) opine that robustness is the ability to anticipate and manage risks by putting controls to prevent or minimize ensuing damages. Further ((Chowdhury et al., 2016) suggested that since the goal of any supply chain is to operate as a going concern by minimizing and mitigating disruptions, building robust supply chains is a prerequisite to resilience. Consistent with this view, the study profoundly observes that robustness is an antecedent of resilience.

Chowdhury et al. (2016) alluded that Readiness brings about dynamic control and adaptive management and that Readiness is imperative for establishing dynamic control on the supply chain. The study demonstrates that supply chains with high levels of Readiness have the flexibility of organizing to have alternative strategies to mitigate/reduce vulnerabilities. They note that SC readiness is paramount to surmount any disruptions and develop resilience. In their view, the sub-constructs relating to Readiness include disaster preparation, redundancy/backup capacity, and SC visibility. The study further conceptualizes supply chain response as the ability to respond quickly to a critical situation, and it is a critical ingredient of SC resilience. It contends the argument that the ability of an organization or a supply chain to respond to environmental forces swiftly, reconfigure resources and recover quickly from any vulnerability is an essential resilience capability (Chowdhury et al., 2016). Recovery is the ability of a supply chain to return to normalcy ex-post disruption. An ideal recovery constitutes a stabilization phase from which a steady performance can be pursued. A supply chain does not need to reacquire the original performance level. The recovery aspect is measured by assessing a few elements: time of disturbance, time of Onset, time of climax, the response at the climax, turning point, response at a turning point, time of recovery, and response at recovery. In other words, supply chain resilience constitutes turbulence avoidance, turbulence containment, stabilization, and return capability.

From crisis management literature, resilience in the supply chain context suggests that resilience includes robustness, response, and recovery. This trinity addresses all the aspects of supply chain resilience ex-ante and ex-post to disruptions. Readiness is the upfront capability that supply chains exhibit ex-ante to disruption. Readiness reduces the likelihood and the impact of disruption (Chowdhury & Quaddus, 2016). Readiness calls for practitioners to be preemptive for preparedness and mitigating susceptibility to supply chain disruption. Readiness is imperative for retail chains to establish dynamic control over their supply chain. It has been observed that the supply chains that demonstrate a high level of Readiness exhibit the flexibility of organizing alternative strategies to mitigate vulnerabilities across the supply chain. More so, through Readiness, organizations can identify, anticipate and guard against diverse, dynamic risks before the consequences of such risks (Chowdhury & Quaddus, 2016). Sensing capability is part of Readiness. Through this, organizations can overcome uncertainties.

Dimensions of recovery from a times series perspective include the time of disturbance, time of Onset, time of climax, the response at the climax, turning point, response at a turning point, time of recovery, and response at recovery. The time of disturbance is when the triggering event is initiated (Melnyketal et al., 2014). The time of Onset is when the system being studied feels the impact of the triggering event. The time of climax is when the system reaches its climax. Additionally, the response at the climax is the system response at the climax. The turning point is when the system begins to recover from the disturbance. Response at the turning point refers to the response at which the system transitions from being impacted by the disturbance to recovering. The time of recovery is when the system returns to a steady state. Response at recovery may differ from the pre-disturbance and response level (Melnyketal et al., 2014).

The response is aligned with Readiness, and the supply chain can return to equilibrium ex-post disruption. An organization can swiftly respond to critical situations, constituting a critical element of supply chain resilience. A lack of an expeditious response will occasion a loss in the supply chain (Chowdhury & Quaddus, 2016).

Kopanaki (2022) conducted a systematic literature review on extant literature concerning conceptualizations on SC resilience; the study observed that Wieland and Wallenburg (2013), as cited in Kopanaki (2022), indicated that metrics to measure SCRES are agility and robustness. Scholten et al. (2019), as cited in Kopanaki (2022), contended flexibility, velocity, robustness, and visibility as the SCRES elements. Chowdhury and Quaddus (2017), as cited in Kopanaki (2022), indicated that the three primary dimensions for measuring resilience are; proactive capability, reactive capability, and supply chain design quality. Ali et al. (2017), as cited, contended Readiness, responsiveness, and recovery of growth (pre-, during, and post-disruption). The study resonates with/adopts the metrics contended by Ali et al. (2017), as cited in Kopanaki (2022).

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

Research methodology situates a study illustrating how the researcher philosophically, epistemologically, methodology, and analytically defines the study. This chapter focuses on the research design that this study adopted, the study population, the sample and sampling frame, the sampling technique, the pilot study, the data collection instrument and data collection method used, and the statistical measurement model that was used to analyze data and test the hypothesis.

3.2 Research Philosophy

Saunders, Lewis, and Thornhill (2019, p. 107) observed that research philosophy 'relate to the development of knowledge and the nature of knowledge.' Research philosophy contends assumptions that underpin a researcher's research strategy and methods. This study adopted a positivist epistemology stance which bolsters the sense that the social world exists not only externally, but the properties of the social world should be measured objectively, and they should not be subject to the scope of interpretation (Bell et al., 2018; Easternby-Smith et al., 2018). Epistemology is concerned with acceptable knowledge in any given field of study.

The positivism paradigm postulates that a brief, in theory, precedes research and statistical justification of conclusions from empirically testable hypotheses (Schindler & Cooper, 2014). Koul (2008) contends that the positivist paradigm aims to unravel the truth by empirically evaluating the study phenomena; the quality standards in this paradigm are, therefore, valid and reliable. Sekeran and Bougie (2010) contended that positivism helps test speculations and evaluates possible relationships between several variables. Additionally, the positivism paradigm employed was a survey research strategy. According to (Dillman et al., 2014), It is appropriate for gathering rich empirical data and is considered a deductive approach.

3.3 Research Design

Kothari (2008, p. 31) argued that research design refers to 'the arrangement of conditions for collection and analysis of data in a manner that aims to combine relevance to research purpose with economy in procedure.' The study adopted an ex-post facto, cross-sectional survey research design with a deductive approach. An ex-post facto research design because the researcher had no control group, and the study sample was not randomized. Again, the researcher had no baseline, which is often used in the absence of a control group in the case of quasi-experiments (Schindler & Cooper, 2014). The study was cross-sectional because the study was conducted only once and revealed a snapshot of one point in time (Schindler & Cooper, 2014; Saunders, 2019). It was a deductive study since it espoused the causal relationships between study variables and permitted the testing contended relational hypotheses (Saunders et al., 2019, p. 125). A survey research design was employed because data collected from a survey strategy 'suggests possible reasons for particular relationships between variables and has the propensity to tease out models of the emerging relationships. Secondly, the survey strategy enables the researcher to collect quantitative data and analyze it quantitatively using both descriptive and inferential statistics. Thirdly, data collected through a survey strategy tends to exhibit external validity.

3.4 Population

Sekaran and Bougie (2005 p. 282) explicated that a population 'refers to the entire group of people, events or things of interest that the researcher wishes to investigate and make inference based on sample statistics.' The population for this study was a retail chain of stores in Kenya. The sector was selected for the study due to non-resilience among retail players. They are recording a significant upward trajectory in engagement on SC dynamic capabilities to at least adjust ex-post to the disruptions to gain resilience.

3.4.1 Target Population

Kombo and Tromp (2009) postulated that a target population is a group of individuals, objects, or items from which a sample for measurement is derived. The target population for this study was retail chain stores listed by the Retail Trade Association of Kenya (2020) in Nairobi City County. It was informed by the fact that given the cosmopolitan nature of Nairobi City County, retail chains in this county are experiencing relatively higher disruptions, leading to the closure of some of the retail chains while adjusting ex-post to the disruptions by leveraging dynamic capabilities to be resilient to at-least maintain their market-share (RETRAK, 2020).

3.5 Sampling Frame

A sampling frame is a complete list of all the cases in the population from which a probability sample is drawn' (Saunders et al., 2019). For this study, a sampling frame was obtained from the Retail Trader Association of Kenya (RTAK, 2019). The sampling frame constituted ten listed retail chains with various branches across Nairobi City County. Retail Trade Association is a representative body of member retailers in the more significant retail sector with a cardinal objective of providing retailers with a central representative body in matters about the advocacy of their agenda and the concerns about retail trade to third parties such as government and its agencies for their benefit (RTAK, 2022).

Table 3.1: Sampling Frame

S/No.	Name of Retailer	Category	Current No of Branches (As of the Year 2019)
1.	Naivas	Local	32
2.	Quicksmart	Local	27
3.	Chandarana FoodPlus	International	16
4.	Carrefour	International	11
5.	Choppies	International	3
6.	Cleanshelf	Local	5
7.	Tuskys	Local	5
8.	Uchumi	Local	3
9	Game Stores	International	2
10.	Shoprite	International	2
	Total		106

3.6 Sample Size and Sampling Technique

Saunders et al. (2009) denote that a sample is a subset of the entire population. Cooper and Schindler (2009) indicate that the rationale for sampling is that by selecting some elements in a population, the researcher can conclude the entire population. The study adopted two-stage sampling. Two-stage sampling is a probabilistic sampling technique. The first stage comprised conducting a census of the ten listed retail chains (RTAK, 2019) with multiple retail outlets in Nairobi City County. In the second stage, the study purposively sampled three respondents in each retail outlet who were in charge of category management, demand planning, and logistics management. It resulted in a sample size of 318 respondents.

Table 3.2: Sample size

S/No.	Name of Retailer	Category	Current No of Branches (As of the Year 2020)	Formula	Sample Size
1	Naivas	Local	29	32*3	96
2	Quicksmart	Local	28	27*3	81
3	Chandarana FoodPlus	International	16	16*3	48
4	Carrefour	International	10	11*3	33
5	Choppies	International	5	3*3	09
6	Cleanshelf	Local	4	5*3	15
7	Tuskys	Local	3	5*3	15
8	Uchumi	Local	3	3*3	09
9	Game Stores	International	2	2*3	06
10	Shoprite	International	2	2*3	06
	Total		**102**		**318**

3.7 Data Collection Instrument

Primary data was collected using a questionnaire. According to Mugenda and Mugenda (2003), a questionnaire is a data collection tool that collects data over a large sample to translate the research objectives into specific questions and answers, thereby providing data for hypothesis testing. Sekaran and Bougie (2005) contend that questionnaires 'have the advantage of obtaining data more efficiently, concerning time, energy and cost.'

The questionnaire was semi-structured and contained both open and closed questions. Additionally, it contained category questions, ranking questions, rating questions, quantity questions, and matrix questions. The questionnaire was developed around the study constructs. Moreso, the measurement scales were crafted in strict adherence to the procedure Pallant (2013) suggested for developing measures. The questionnaire had five-point Likert scale questions, key measures to establish relationships between predictor and criterion variables.

3.8 Data Collection Procedure

Kombo and Tromp (2009) postulate that data collection involves gathering information to serve or prove some salient facts. The researcher first sought a *bona fide* letter from the Department of Procurement and Logistics. The researcher after that sought a research permit from National Commission for Science, Technology, and Innovation (NACOSTI) after paying the requisite fees for the research permit.

Since the dynamic supply chain capability practices and their metrics were objectively determined and not inferred subjectively through social construction (Easterby-Smith et al., 2018), a mixed-mode data collection approach was employed as suggested by (Dillman et al., 2018). In this regard, the study adopted an internet-based survey and hand-delivered it to the respondents. It was meant to mitigate any prejudice that often arises using a single method. The approach is meant to improve data quality beyond a single survey method while eliminating bias (Frankfort-Nachmias, 2007).

3.9 Pilot Test

Schindler and Cooper (2014, p.662) explicate that a pilot test 'is a trial collection of data to detect weakness in design and instrumentation and provide proxy data for the selection of probability sample, often referred to as pretesting. Tayie (2005) contends that samples of 25-50 are appropriate to pretest a data collection instrument. For this study, a pilot study was undertaken in Kiambu County. The study pilot tested 10% of the sample size, which comprised 31 respondents from 10 clusters of retail chains listed by the Retail Trade Association of Kenya. The researcher informs that Kiambu County is also a cosmopolitan county with homogeneous characteristics as the target population under study.

3.9.1 Validity of the Research Instrument

Saunders et al. (2019, p. 602) propounded that validity refers to 'the extent to which data collection method(s) accurately measures what they were intended to measure and the extent to which research findings are really about what they profess to be about.' Further, Saunders et al. (2019, p. 602) posit that there are different types of validity, such as construct, criterion, ecological, face, internal, measurement, external, and predictive.

The research tool was developed with supervisors to ensure content validity. Face validity was achieved by ensuring that the data collection instrument was subjected to expert analysis and opinion from at least external experts who checked the representativeness of the questionnaire both extensively and intensively. Construct validity was achieved by ensuring that the questions in the questionnaire were restricted to the conceptualization of the study variables and that each metric of the variables fell within the same construct. Bartlett's test of Sphericity and Kaiser Meyer Olkin Measure of Sampling adequacy was conducted to establish the construct validity of all the variables.

3.9.2 Reliability of the Research Instrument

The study adopted the internal consistency method to test the reliability of the questionnaire. Internal consistency of the questionnaire was gauged using Cronbanch's alpha (α) statistic against a cutoff point of 0.7 as recommended by (Cronbach, 1951; Nunnaly, 1978). Kenneth and Bordens (2010), as cited by Muli and Bwisa (2017), delineate that the reliability of any given scale indicates how free such a scale is from a random error.

3.10 Data Processing and Analysis

With the help of statistical software, Statistical Package for Social Sciences version 23, quantitative data was coded, entered, and processed on a case-by-case basis to rectify illogical, inconsistent, and illegal data and omissions from respondents. For ease of analysis, the coded data was transformed as it is necessary to transform data when several questions are used to measure a single concept (Sekaran & Bougie, 2005, pp. 330-331). Quantitative data was analyzed by use of both descriptive statistics and inferential statistics. Measures of central tendencies and dispersion did a descriptive analysis of variables. Inferential data analysis was done through Exploratory Factor Analysis, Confirmatory Factor Analysis, and an assessment of model fit to establish relationships between observed and latent constructs. Data was then exported into SPSS Analysis of Moment Structures (AMOS) for analysis. SPSS AMOS is convenient for performing structural equation modeling adopted in this study. Testing of the hypothesis was also done using Structural Equation Modeling. To a more considerable extent, the substance of SEM lies in the ease with which it allows non-specialists to solve estimation and hypothesis testing problems that were once considered a preserve of statisticians (Bhattacharyya, 2011). SEM is a multivariate analysis technique that subsumes standard methods, including regression, factor analysis, simultaneous equations, and analysis of variance. The most potent aspect of SEM is the ability to correct measurement errors. SEM is also quite flexible. AMOS software makes SEM easy. This study also used AMOS to construct a conceptual model linking the variables under study.

Qualitative data was analyzed using content analysis. Content analysis was conducted by classifying the qualitative data into categories and then analyzing the categories using both conceptual and relational analysis. The conceptual analysis enabled the researcher to establish the existence and frequency of concepts, i.e., words, themes, or characters and also enabled categorizing data into manageable content categories. On the other hand, relational analysis is built on conceptual analysis by evaluating the relationships among concepts in a text. The conceptual and relational analysis results were used to make inferences about the study phenomenon (Sekaran & Bougie, 2005, p. 406).

3.11 Confirmatory Measurement Model

In order to proceed with SEM, this study conducted confirmatory factor analysis (CFA) to evaluate the measurement model of multiple criteria, such as internal reliability, convergent validity, and discriminant validity. Before CFA, Exploratory Factor Analysis was conducted and comprised of computation of factor loading matrix, commonalities, and Principle Component Analysis (PCA).

3.11.1 Explanatory Factor Analysis

Tabachnick and Fidell (2013) opined that EFA is used when the researcher has a large set of variables that he/she wishes to express simplistically or has no *priori* ideas about which variables will cluster together. As a rule of thumb. EFA is used at the early stages of research in order to identify the variables that cluster together (Bordens & Abbot, 2014). EFA also provides intuition about the number of factors that cluster together (Hair et al., 2010). The goal of factor analysis is to identify factors based on data and maximize the variance explained (Sur, 2006).

Before EFA, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett’s Test of Sphericity were conducted to assess the data's factorability or suitability for structure detection. High KMO values close to 1 indicate that factor analysis is helpful with the data. Bartlett's Test of Sphericity was used to test the hypothesis that the correlation matrix is an identity matrix, indicating that the variables are unrelated and, therefore, unsuitable for structural detection. Small values ($p < .05$) of significance level indicate that factor analysis is helpful with one's data and hence suitable for structural detection.

3.11.2 Pattern Matrix

Rummel (1970) asserts that a pattern matrix contains the coefficients or "loadings" that express the items in terms of factors. As a rule, the more factors, the lower the pattern coefficients since more contributions to the variance will be explained. Rummel (1970) further accentuates that pattern matrix ladings are zero when a variable is not involved and close to 1.0 when a variable is almost perfectly related to a given factor pattern.

3.11.3 Communality

Field (2009) opines that communality values measure each observed variable the extracted factor can explain. Pallant (2010) opines that a low value for Communality, i.e., a value less than 0.3, could indicate that the variable does not fit well with other variables in its component and is undesirable. Communality values greater than 0.7 are acceptable as they indicate that the variables fit well with other variables in their factor.

3.11.4 Principal Component Analysis

Tabachnick and Fidell (2013) posit that the goal of Principal Components Analysis (PCA) is to extract maximum variance from the data set with each component with the threshold being eigenvalue greater or equal to 1.0 (Hair et al., 2010). The fewer the variables explaining more of the variability in the original variables, the better it is in ensuring that there is no redundant information (Hair et al., 2010). Principal Component Analysis (PCA) was employed to identify the number of underlying factors and the extent to which variables load onto each other (Abdi et al., 2010).

3.11.5 Confirmatory Factor Analysis (CFA)

CFA is a statistical technique used to verify the factor structure of a set of observed variables. The study adopted CFA to test the hypothesis that there is a relationship between observed variables and their underlying latent constructs. Additionally, for this study, confirmatory factor analysis was used to evaluate the measurement model on multiple criteria, structural equation modeling to fit a theoretical model

3.11.6 Chi-Square Goodness of Fit Test

The chi-square goodness of fit test was used to establish whether the model adequately fits the data. Different fit statistical tests were conducted to assess whether overall models were acceptable, and when found acceptable, the study established whether specific paths were significant (Hu & Bentler, 1999). The chi-square index's acceptance criterion ranges from less than 2 to less than 5 (Marsh et al., 2011).

3.11.7 Convergent Validity

Bahl and Wali (2014) suggested that convergent validity is a component of construct validity. It refers to the extent to which a set of variables converge in measuring the concept of the construct. It is often confirmed using item reliability, composite reliability, and Average Variance Extracted (AVE) (Hair et al., 2010). When all items are crucial in measuring their constructs, composite reliability values are at least 0.7, and AVE values are at least 0.5. It confirms the presence of convergent validity.

3.11.8 Discriminant Validity

Discriminant validity shows that measures that should not be related are, in reality, unrelated. Factor loadings under 0.7 indicate discriminant validity (Hair et al., 2010).

3.12 Operationalization of Study Variables

Table 3.3: Operationalization of Study Variable

Type of Variable	Variable	Indicator	Scale
Dependent	The Resilience of Retail Chain of Stores	• Readiness • Response • Recovery	Ordinal
Independent	Agility Capability	• Alertness • Flexibility • Swift	Ordinal
	Analytic Capability	• Merchandising Analytics • Prescriptive Analytics • Store Operations Analytics • Demand Mgt Analytics	Ordinal
	Innovation Capability	• Innovative Retail Formats • Brand Innovations • Category Management	Ordinal
	Alignment Capability	• Information Sharing • Synchronized Planning • Operational Coordination	Ordinal
Moderating	SC Configuration	• No. of SC Nodes • Physical Location Dispersion • SC Network Design	Ordinal

CHAPTER FOUR

RESEARCH FINDINGS AND DISCUSSION

4.1 Introduction

This chapter provides a detailed analysis of the study's results and the findings. Qualitative analysis was done for open-ended questions, and quantitative analysis was done for closed-ended questions. Cognizant of the need for building an excellent quantitative model, an array of steps were undertaken, and the analyses were conducted using a two-phase process that constituted the confirmatory measurement model and a confirmatory structural model.

4.2.1 Response Rate

Lehman (1974) contended that response rate is the proportion of observation units eligible to participate in a survey from which a complete and usable set of data is collected. It is numerically expressed as

Response rate = C/E

Where

C= the number of completed questionnaires

E= the number of eligible sample members

Three hundred eighteen questionnaires were populated and distributed to respondents, and 253 318 were filled and returned. It represented a response rate of 79.56%. Mugenda and Mugenda (2003) posited that a 50% response rate is adequate for data analysis, a response rate between 60-69 is considered good, and a response rate above 70% is excellent. Consistent with the supposition of Mugenda and Mugenda (2003), the response rate of 79.56% was excellent and was achieved by the researcher making persuasions to respondents and briefing the research assistants. Table 4.1 below illustrates the response rate as per retail chain.

Notably, the researcher hand-delivered 202 questionnaires to the respondents. Out of these, 169 questionnaires were filled and returned by the respondents indicating a response rate of 83.67%. Additionally, 116 questionnaires were internet-based surveys, of which 84 respondents responded, marking a response rate of 72.41%. The response rates in both cases were not only ideal but plausible.

Table 4.1 below depicts data from 253 respondents from 10 retail chains with multiple retail outlets within Nairobi County. Most of the respondents who participated in the study were drawn from Naivas Limited (29.2%), Quickmart Supermarkets (27.3%), Chandarana Food Plus (9.9%), Carrefour (8.7%), Cleanshelf (5.1%), Tuskys (4.0%), Game Stores (2.4%) Uchumi (5.5%), Choppies (6.3%), Shoprite (1.6%).

Table 4.1: Trading name of retail chains

Name of retail chain	Frequency	Percent
Naivas	74	29.2
Quicksmart	69	27.3
Chandarana FoodPlus	25	9.9
Carrefour	22	8.7
Cleanshelf	13	5.1
Tuskys	10	4.0
Game Stores	6	2.4
Uchumi	14	5.5
Choppies	16	6.3
Shoprite	4	1.6

N 253

4.2.2 Non-Response Bias

The study compared the early and late responses as a proxy for non-response using the approach suggested by (Armstrong & Overton, 1977). The early responses (n=

84) were completed before a follow-up was made through email reminders and telephone calls. It was grouped as the early wave. The respondents (n = 169) who filled out the questionnaire after the reminder formed the late wave group. An independent-sample t-test was conducted. The test compared the scores for early and late waves. The results indicated that there was no significant difference between the mean values of both the early wave and the late wave. It is based on accepting the null hypothesis that no statistically significant difference exists between respondents and non-respondents. Additionally, Levene's t-test indicates that non-response bias was non-existent, as presented in tables 4.2-4.3 below.

Table 4.2: Non-Response Bias

Constructs	**Wave of Response**	**N**	**Mean**	**Std. Deviation**	**Std. Error Mean**
Agility	Early Responses	84	4.2143	.48592	.05302
	Late Responses	169	4.3125	.64336	.04949
Analytics Capability	Early Responses	84	4.2296	.59505	.06493
	Late Responses	169	4.2585	.66434	.05110
Innovations Capability	Early Responses	84	4.2143	.48592	.05302
	Late Responses	169	4.3583	.75726	.05825
Alignment Capability	Early Responses	84	4.2143	.48592	.05302
	Late Responses	169	4.2438	.61383	.04722
Supply Chain Configuration	Early Responses	84	4.2143	.48592	.05302
	Late Responses	169	4.3582	1.40999	.10846
Resilience	Early Responses	84	4.2143	.48592	.05302
	Late Responses	169	4.1935	.46485	.03576

Table 4.3: Levene's t-test

Independent Samples Test

Construct(s)		**Levene's Test for Equality of Variances**		**t-test for Equality of Means**				
		F	**Sig.**	**t**	**df**	**Sig. (2-tailed)**	**Mean Difference**	**Std. Error Difference**
Agility	Equal variances assumed	.129	.720	-1.234	251	.218	-.09818	.07955
	Equal variances are not assumed.			-1.354	211.369	.177	-.09818	.07253
Analytics Capability	Equal variances assumed	.110	.741	-.336	251	.737	-.02885	.08574
	Equal variances not assumed			-.349	182.998	.727	-.02885	.08262
Innovations Capability	Equal variances assumed	.361	.548	-1.587	251	.114	-.14395	.09073
	Equal variances are not assumed.			-1.828	235.086	.069	-.14395	.07877
Alignment Capability	Equal variances assumed	.130	.718	-.385	251	.701	-.02950	.07672
	Equal variances not assumed			-.416	203.598	.678	-.02950	.07100
Supply Chain Configuration	Equal variances assumed	2.061	.152	-.908	251	.365	-.14383	.15845
	Equal variances are not assumed.			-1.191	231.164	.235	-.14383	.12073
Resilience	Equal variances assumed	.346	.557	.331	251	.741	.02087	.06300
	Equal variances not assumed			.326	159.390	.745	.02087	.06395

4.2.3 Psychometric Properties

a. Reliability Test Results

Carmines and Zeller (1979); Moser and Kalton (1989) contend that reliability is the extent to which a measurement of a phenomenon provides both stable and consistent results. A scale is said to have high internal consistency reliability if items of the scale 'hang together' and measure the same construct. Where there are different types of reliability, the study adopted internal consistency reliability and used the Cronbach Alpha coefficient to measure the internal consistency of the data collection instrument. Whereas there is no absolute rule for internal consistencies, most scholars conform to the supposition that a minimum internal consistency α coefficient of .70 is acceptable.

The overall results of the reliability tests for the study variables are depicted in Table 4.4 below.

Table 4.4: Reliability of Study Variables

Construct(s)	Cronbach α-Value	No. of Items
SC Agility Capability	.749	15
SC Analytic Capability	.703	14
SC Innovation Capability	.700	9
SC Alignment Capability	.714	11
SC Configuration	.714	5
Resilience	.803	16

N=253

The Cronbach's α-value for SC agility capability was 0.749. Fifteen items were aggregated, and their average was taken as an SC agility capability construct. For this variable, no item was dropped. The construct on SC analytic capability exhibited a Cronbach α-value of 0.703 in which 14 items were aggregated to give the α-value as mentioned above, having deleted items (ALY3, ALY5, and ALY6). The Cronbach α-value for SC innovation capability was 0.700 and comprised an average of 9 items having deleted items (SCI1, SCI2, SCI6, SCI10, SCI 12, and SCI13). Additionally, the Cronbach α-value for SC alignment capability was 0.714 after aggregating 11 items, having deleted item (SCAL4). The Cronbach α-value for SC Configuration was 0.726 after averaging the aggregation of 2 items, having deleted items (SCC1, SCC3, and SCC5). The Cronbach α-value for Resilience was 0.803, achieved by aggregating 16 items. In this case, no item was deleted.

4.3 Pilot Study Results

A pilot study was conducted in Kiambu County, where 43 respondents were involved to pre-test the data collection instrument. From the pilot test, the following is the aggregate of reliability statistics.

Table 4.5: Reliability of Data Collection Instrument

S/No.	Objectives(s)	No. of Items	Cronbach Alpha
1.	Supply Chain Agility Capability	15	.865
2.	Supply Chain Analytics Capability	15	.762
3.	Supply Chain Innovation Capability	15	.717
4.	Supply Chain Alignment Capability	15	.762
5.	Supply Chain Configuration	9	.811

Streiner (2003) accentuated that the Cronbach alpha coefficient is a value ranging from 0-1 and that a high Cronbach alpha value suggests a high level of internal consistency among items. However, Streiner (2003) suggests that a Cronbach's alpha of >.98 indicates a high degree of internal consistency to an extent where researchers should suspect that the case items are redundant, testing the same construct repeatedly. For purposes of this study, although Cronbach's alpha values for each case item were high (>.70<.92), they were not too high to warrant the suspicion of the redundancy of the study constructs. As such, this study conclusively posits that the constructs exhibited an acceptable high degree of internal consistency. Therefore, the study concluded that the data collection instrument was reliable.

Table 4.6: Form of ownership of the retail chain

Form of Ownership	Frequency	Percent
Locally owned	228	90.1
Foreign Owned	25	9.9
Total	**253**	**100.0**

4.4 Demographic Information

4.4.1 Form of Ownership

Table 4.6 above depicts the form of ownership of the retail chains. 90.1% of the respondents indicated that the retail chains they are employed in are locally owned, and 9.9% indicated that they are foreign-owned. It indicates that foreign players' penetration of the Kenyan retail sector is challenging. It can be attributed to the government allowing a free market to its citizens and substantially limiting foreign entrants by setting high barriers for foreign players, making it difficult for them to contest.

4.4.2 years in operation

Table 4.7: Number of years that the retail chain has been in operation

No of Years	Frequency	Percent	Cumulative Percent
Less than five years	21	8.3	8.3
Between 5-10 years	20	7.9	16.2
Between 11-15 years	9	3.6	19.8
Between 16-20 years	50	19.8	39.5
More than 20 years	153	60.5	100.0
Total	**253**	**100.0**	

Table 4.7 above indicates the years that the respondents' retail chains have been operating. 8.3% of the respondents indicated that their retail chains have operated for less than five years. 7.9% of the respondents indicated that the retail chains that they work in have been in operation for a period ranging between 5-10 years. 3.6% of the respondents indicated that their retail chains have been in operation for a period ranging between 11-15 years, while 19.8% indicated that their retail chains have been in operation for a period ranging between 16-20 years. 60.5% of the respondents indicated that the retail chains they work in have operated for over 20 years.

4.4.3 Respondents' Department

Table 4.8: Respondents' Department

Department	Frequency	Percent
Category Management	99	39.1
Demand Planner	57	22.5
Logistics	97	38.3
Total	253	100

N=253

The respondents indicated their respective departments, as depicted in Table 4.8 above. 39.1% of the respondents indicated that they undertake category management functions. In comparison, 22.5% indicated they serve in the demand planning department, while 38.3% indicated they work as logisticians. Going by the above stratification of the respondents by their respective departments, it is evident that the study selected the suitable observation unit to achieve the study objectives.

4.4.4 Work Experience

Table 4.9: Period of service in the retail chain

Work Experience	**Frequency**	**Percent**	**Cumulative Percent**
Less than five years	110	43.5	43.5
Between 5-10 years	98	38.7	82.2
Between 11-15 years	33	13.0	95.3
Over 15 years	12	4.7	100.0
Total	**253**	**100.0**	

Respondents were asked to indicate the number of years they have worked in their respective retail chains, as depicted in Table 4.9 above. 43.5% of the respondents indicated that they have worked for less than five years. 38.7% of the respondents indicated that they have worked for a period between 5-10 years, while 13.0% of the respondents indicated that they have worked for a period between 11-15 years. Only a meager 4.7% of the respondents indicated they have worked for over 15 years in their retail chains. The statistics that most respondents (43.5%) have worked in their respective retail chains for less than five years indicate high employee turnover. Nonetheless, since a cumulative 51% of the respondents have worked for a period between 5-15 years indicates that the information they provide is reliable as they have stayed in the organization long enough to make some independent observations about the research questions under study.

4.4.5 Highest Level of Qualification

Table 4.10: Indicate your highest level of education

Level of Education	**Frequency**	**Percent**
Diploma	104	41.1
Undergraduate degree	86	34.0
Postgraduate degree	26	10.3
Professional Certifications	37	14.6
Total	253	100

The study participants were also asked to indicate their highest academic qualifications. 41.1% of the respondents indicated that they possess diploma qualifications, 34% indicated that they possess undergraduate degrees, and 10.3% indicated that they possess postgraduate qualifications. 14.6% of the respondents indicated that they possess professional certifications. It indicates the respondents had the requisite skills and competencies to undertake tasks in different organizational capacities. It also shows that they were qualified enough to respond to the research questions administered to them.

4.5 Descriptive Statistics

4.5.1 SC Agility Capability

Respondents were asked about various aspects of agility capability; their responses are presented in Table 4.11 below:

Table 4.11: Descriptive results on agility capability

S/No	Statements	Mean	Std. Deviation
SCAC1	We promptly detect changes in the business environment	4.5968	.63894
SCAC2	We promptly identify and seize business opportunities in the business environment	4.3439	.78448
SCAC3	We promptly sense threats in the business environment	4.3241	.67089
SCAC4	We promptly detect stock re-order levels	4.6047	.67399
SCAC5	We promptly sense shopper's reactions to new merchandise	4.0514	1.03956
SCAC6	We are flexible enough to ensure there is on-shelf product availability.	4.6443	.69575
SCAC7	We are flexible enough to handle shoppers' reactions to new merchandise.	4.2174	.85691
SCAC8	We are flexible enough to undertake last-minute promotions to meet quarterly sales goals	4.0553	1.18057
SCAC9	We are flexible enough to react promptly to customer orders, tastes, and preferences changes.	4.3360	.76231
SCAC10	We quickly implement decisions regarding increasing short-term capacity as needed	4.2134	.72505
SCAC11	We quickly provide various inbound logistics options, e.g., transportation, warehousing, and stock inventory.	4.2569	.82207
SCAC12	We quickly adjust our merchandise to meet customer's needs	4.5810	.54039
SCAC13	We quickly undertake order processing	4.5020	.62757
SCAC14	We quickly undertake to retail an assortment of supplies	4.4308	.78184
SCAC15	We differentiate our SKU	4.0593	1.04675

Cronbach Alpha value = .749 with 15 items; N=253; $\bar{X}$= 4.34782

To establish the relationship between agility capability and Resilience in large retail chains in Kenya. The study operationalized SC agility capability in three ways alertness, flexibility, and swiftness. In obtaining this information from the respondents, five-point Likert scale statement questions were structured, for which the responses are presented in the table above.

As indicated in the table above, on alertness, an ($\bar{x}$ = 4.5968, SD = .63894), most respondents strongly agreed that they promptly detect changes in the business environment. Also, most respondents agreed that they promptly identify and seize business opportunities in the business environment as indicated by an ($\bar{x}$ = 4.3439, SD = .78448). Most respondents agreed that they promptly sense threats in the business environment as indicated by an ($\bar{x}$ = 4.3241, SD = .67089). Study participants strongly agreed that they promptly detect stock re-order levels as indicated by an ($\bar{x}$ = 4.6047, SD = .67399). Respondents agreed that they promptly sense shopper's reaction to new merchandise ($\bar{x}$ = 4.0514, SD = 1.03956). Additionally, respondents strongly agreed that they are flexible enough to ensure on-shelf product availability, as indicated by an ($\bar{x}$ = 4.6443, SD = . 69575). Respondents agreed they are flexible enough to handle shoppers' reactions to new merchandise as indicated by an ($\bar{x}$ = 4.2174, SD = .85691). More so, respondents agreed that they are flexible enough to undertake last-minute promotions to meet quarterly sales goals ($\bar{x}$ = 4.0553, SD = 1.18057). Respondents agreed they are flexible enough to react timely to changes in customers' orders, tastes, and preferences ($\bar{x}$ = 4.3360, SD = 76231). Further, on swiftness, respondents agreed they quickly implement decisions regarding increasing short-term capacity as needed ($\bar{x}$ = 4.2134, SD = .72505). Study participants agreed that they quickly provide various inbound logistics options, e.g., transportation, warehousing, and stock inventory ($\bar{x}$ = 4.2569, SD = .82207). Additionally, respondents strongly agreed that they quickly adjust their merchandise to meet customers' needs ($\bar{x}$ = 4.5810, SD = .54039). Study participants further agreed that they quickly undertake order processing ($\bar{x}$ = 4.5020, SD = .78184). Respondents also agreed that they quickly undertake retailing of an assortment of supplies ($\bar{x}$ = 4.4308, SD = 1.04675). Respondents also agreed that they differentiate their SKUs ($\bar{x}$ = 4.0593, SD = 1.04675).

Qualitative data was analyzed using content analysis, and the following themes emerged; agility is the ability to change direction quickly, the ability to speed/accelerate operations, the ability to scan the retail environment and anticipate the changes in the operating environment, and it also entails the ability to empower the customer. The respondents also intimated that integrating processes qualifies as agility capability. Respondents indicated that considering information lead-time is an objective metric to measure the agility of the retail chain in order processing. And that agility can either be reactive or proactive.

To a large extent, the pattern of these findings is consistent with extant literature about agility. Concisely, this study is in agreement with Gligor et al. (2013), who conducted a multidisciplinary literature review to conceptualize supply chain agility and established that SC agility is comprised of five distinct dimensions that are alertness, accessibility, decisiveness, swiftness, and flexibility. Further, these findings are consistent with Kumar and Suresh (2021), who conducted an agility assessment in a retail store environment using multi-grade fuzzy and established that retail chains are agile; they possess the dynamic capability to anticipate changes in the marketplace and proactively restructure their interior environment.

4.5.2 SC Analytics Capability

Respondents were asked about various aspects of SC analytics capability; their responses are presented in Table 4.12 below:

Table 4.12: Descriptive on SC Analytics Capability

S/No.	Statements	Mean	Std. Deviation
ANLYC1	We use retail analytics to improve product placement.	4.4506	.56566
ANLYC2	We use retail analytics to increase cross-selling opportunities	4.0435	.86950
ANLYC3	We use retail analytics in space allocation	4.1304	.67464
ANLYC4	We use retail analytics to optimize inventory levels	4.4980	.69934
ANLYC5	We use retail analytics to decrease inventory shrink	4.1028	1.03764
ANLYC6	We have adopted sensors to restock shelves automatically	4.0395	1.04199
ANLYC7	We use location analytics to map how customers move through a store	4.4980	.86200
ANLYC8	We use a combination of IT tools to track which sections of the store receive the most traffic	4.3033	.68360
ANLYC9	We use retail analytics to make personalized recommendations and offers	4.0277	.98159
ANLYC10	We use retail analytics to undertake sales forecasting	4.2648	.95381
ANLYC11	We use retail analytics to optimize the price of our merchandise	4.4901	.65836
ANLYC12	We use retail analytics to develop better pricing strategies	4.1542	.77916
ANLYC13	We use retail analytics to optimize multichannel performance	4.0000	.75593
ANLYC14	We use retail analytics to enhance our social media presence	4.3043	.88094

Cronbach α= .703 with 15 1tems; N= 253; $\bar{X}$= 4.2362

To establish the relationship between SC analytics capability and Resilience in large retail chains in Kenya. The study operationalized SC analytics capability in three ways merchandising analytics, store operations analytics, and demand management analytics. In obtaining this information from the respondents, five-point Likert scale statement questions were structured for which the responses are presented in the table above. On merchandising analytics, study participants agreed that they use retail analytics to improve product placement ($\bar{x}$ = 4.4506, SD = .56566). Respondents further agreed that they retail analytics to increase cross-selling opportunities ($\bar{x}$ = 4.0435, SD = .86950). Study participants also agreed that they use retail analytics in space allocation as indicated by an ($\bar{x}$ = 4.1304, SD = .67464). On store operations analytics, respondents agreed that they use retail analytics to optimize inventory levels ($\bar{x}$ = 4.4980, SD = .69934). Further, respondents agreed that they use retail analytics to decrease inventory shrink ($\bar{x}$ = 4.1028, SD = 1.03764). Respondents also agreed that they adopted sensors to automatically restock shelves ($\bar{x}$ = 4.0395, SD = 1.04199). We use location analytics to map how customers move through a store ($\bar{x}$ = 4.4980, SD = .86200). Respondents agreed that they use a combination of IT tools to track which store sections receive the most traffic ($\bar{x}$ = 4.3033, SD = .68360). Respondents agreed they use retail analytics to make personalized recommendations and offers ($\bar{x}$ = 4.0277, SD = .98159). On-demand management, the study participants also agreed that they use retail analytics to forecast sales ($\bar{x}$ = 4.2648, SD = .95381). The respondents also agreed that they use retail analytics to optimize the price of our merchandise ($\bar{x}$ = 4.4901, SD = .65836). Respondents agreed to use retail analytics to develop better pricing strategies ($\bar{x}$ = 4.1542, SD = .77916). The respondents further agreed that they use retail analytics to optimize multichannel performance ($\bar{x}$ = 4.0000, SD =. 75593). The respondents also agreed that they use retail analytics to enhance our social media presence ($\bar{x}$ = 3.9921, SD = .88094).

Qualitative data was analyzed using content analysis, and the following themes emerged; Respondents indicated that they are investing in applying self-service analytics, cloud analytics, and predictive modeling to supplement retail analytics. They outlined the shortcomings of analytics that clustered into; privacy, security, and intellectual property constraints. They contended that there is a need to be stringent with the umbrella of BDA. Respondents indicated that they also leverage the use of robotics, and virtual reality, among others.

These findings are in tandem with Mostaghel et al. (2022), who established that the retail industry had adopted diverse digital technologies such as the Internet of Things (IoT), Virtual Reality (VR), and Augmented Reality. Further, Mostaghel et al. (2022) established that digitization enables retail business model innovation, leading to value creation culminating in value delivery and capture.

The descriptive findings of this study converge with the descriptive findings of Chandramana (2017), who concluded that merchandising analytics enables retail chains to successfully undertake assortment planning, space allocation, and product adjacency. The findings above align with the findings of Chandramana (2017), who also established that supply chain analytics enables retail chains to manage their logistics, inventory forecast demand better and improve supply chain performance. The study also established that marketing analytics enables retail chains to undertake in-store promotions, pricing, personalization, and campaigns. Further, Chandramana (2017) established that store operations analytics brings about workforce effectiveness, reduces shrinkages, and bolsters store performance. In sum, these findings are similar to the findings discussed above.

4.5.3 SC Innovation Capability

Respondents were asked about various aspects of SC innovation capability; their responses are presented in Table 4.13 below:

Table 4.13: Descriptive on SC Innovation Capability

S/No.	Statements	Mean	Std. Deviation
SCIC1	We use open flagship stores in either downtown and or high-traffic areas	3.9921	.94698
SCIC2	We use open flagship stores in either downtown and or high-traffic areas	3.8656	.87612
SCIC3	We have a wide assortment of products and a specific in-store layout	4.3478	.76995
SCIC4	We have pronounced private labels in some of the categories of our merchandise, such as milk and personal care products	4.3913	.70784
SCIC5	We make continuous and significant improvements to current retail formats	4.2372	.84462
SCIC6	We innovatively stimulate shoppers' demand for products	4.4071	.61421
SCIC7	We undertake retail advertising to create positive touchpoint experiences for our shoppers in the interest of parsimony	4.5257	.77430
SCIC8	We undertake word-of-mouth communication through social media platforms to create positive touchpoint experiences for our shoppers	4.3874	.64254
SCIC9	We leverage earned media, such as editorial and news coverage	4.3953	.63769

Cronbach Alpha = .700; N=253; $\bar{X}$= 4.2833

To establish the relationship between innovation capability and Resilience in large retail chains in Kenya. The study operationalized SC innovation capability in three ways; innovative retail formats, brand innovations, and touchpoint experiences. Five-point Likert scale statement questions were structured to obtain this information from the respondents, for which the responses are presented in Table 4.11 above.

As indicated in the table above, on innovative retail formats, respondents were neutral about using open flagship stores in either downtown and or high-traffic areas ($\bar{x}$ =3.9921, SD = .94698). Further, respondents were neutral on the statement if they use open flagship stores in either downtown or high-traffic areas ($\bar{x}$ = 3.8656, SD = .87612). Study participants agreed they have a wide assortment of products and a specific in-store layout ($\bar{x}$ = 4.3478, SD = .76995). Additionally, respondents agreed that they had pronounced private labels in some of our merchandise categories, such as milk and personal care products ($\bar{x}$ = 4.3913, SD = .70784). It is in line with Reinartz et al. (2011), who established that retail chains engage in product design and private labels for customization and personalization to solve customer-based challenges. The respondents agreed that they make continuous and significant improvements to current retail formats ($\bar{x}$ = 4.2372, SD = .84462). Further, the study participants agreed they innovatively stimulate shoppers' product demand ($\bar{x}$ = 4.4071, SD = .61421). Additionally, the respondents agreed that they undertake retail advertising to create positive touch point experiences for our shoppers in the interest of parsimony ($\bar{x}$ = 4.5257, SD = .77430). The above finding agrees with Reinartz et al. (2011), who established that retail chains develop new shopping experiences for both in-store and online shoppers. Also, the respondents agreed that they undertake word-of-mouth communication through social media platforms to create positive touch point experiences for our shoppers ($\bar{x}$ = 4.3874, SD = .64254). The study participants also agreed they leverage earned media such as editorial and news coverage ($\bar{x}$ = 4.3953, SD = .63769). These findings resonate with De Oliveira et al. (2020), who established that retail chains increasingly leverage social media as innovation channels as an antecedent to multichannel retail strategy.

Qualitative data was analyzed using content analysis, and the following themes emerged; the respondents indicated that there had been some trends in retail innovations, such as the emergence of social commerce, where most customers have been buying goods online via smartphones, tablets, and iPhones. And this trend took an upward trajectory when the Covid-19 pandemic hit the world, and the resulting cessation of movement and lockdowns ensued. They also indicated that influencer marketing is another trend that has emerged recently as a retail marketing strategy and that Augmented Reality is the future of retail chains to bridge the gap between online and brick and motor stores. These findings are consistent with Reinartz et al. (2011), who established that retail chains develop new shopping experiences for both in-store and online shoppers.

4.5.4 SC Alignment Capability

Respondents were asked about various aspects of SC alignment capability; their responses are presented in Table 4.14 below:

Table 4.14: Descriptive on SC Alignment Capability

S/No.	Statements	Mean	Std. Deviation
SCAL1	We share information about our sales and demand forecasts with our channel participants in the supply chain	4.3241	.94159
SCAL2	We leverage independent demand from Electronic Points of Sale (EPOS) to meet customers' expectations	4.3913	.67923
SCAL3	We use Vendor Managed Inventories to share our retail chain's inventory status with suppliers upstream	4.4862	.73787
SCAL4	We treat product categories as strategic business units to plan and achieve sales and profit targets and satisfy customers' needs and preferences.	4.217	.8932
SCAL5	We jointly develop category-based plans internally in our retail chains	4.1937	.78556
SCAL6	We jointly develop strategic plans externally with suppliers to measure financial performance at the category level	4.0711	.84214
SCAL7	We integrate procurement, pricing, and merchandising of all brands in a category	4.5534	.63786
SCAL8	We provide various inbound logistics options to facilitate the delivery of inbound goods.	4.4150	.69414
SCAL9	We adjust inventory, packaging, warehousing, and transportation of goods downstream to meet customer's needs	4.3755	.88040
SCAL10	We exhibit demand flexibility regarding order processing,	4.2609	.82804
SCAL11	We exhibit purchasing flexibility through retailing of an assortment of supplies and differentiation of SKUs	4.3360	.80288

Cronbach Alpha = .714 with 11 items; N=253; $\bar{X}$= 4.3295

To establish the relationship between SC alignment capability and Resilience in large retail chains in Kenya. The study operationalized SC alignment capability: information sharing, synchronized planning, and coordination. In obtaining this information from the respondents, five-point Likert scale statement questions were structured for which the responses are presented in the table above.

As indicated in Table 4.14 above, on information sharing, most respondents agreed that they share information about our sales and demand forecasts with channel participants in the supply chain, an ($\bar{x}$ = 4.3241, SD = .94159). The respondents further agreed that they leverage independent Electronic Points of Sale (EPOS) demand to meet customers' expectations ($\bar{x}$ = 4.3913, SD = .67923). Furthermore, study participants agreed that they use Vendor Managed Inventories to share our retail chain's inventory status with upstream suppliers ($\bar{x}$ = 4.4862, SD = .73787). Respondents also agreed that they treat product categories as strategic business units to plan and achieve sales and profit targets and satisfy customers' needs and preferences ($\bar{x}$ = 4.217, SD = .8932). Most respondents also agreed they jointly develop category-based plans internally in their retail chains ($\bar{x}$ = 4.1937, SD = .78556). Further, most respondents agreed that they jointly develop strategic plans externally with suppliers to measure financial performance at the category level ($\bar{x}$ = 4.0711, SD = .84214). Most respondents strongly agreed that they integrate all brands' procurement, pricing, and merchandising in a category ($\bar{x}$ = 4.5534, SD = .63786). Most respondents also agreed that they provide a variety of inbound logistics options to facilitate the delivery of inbound goods. ($\bar{x}$ = 4.4150, SD = .69414). Additionally, most respondents agreed that they adjust inventory, packaging, warehousing, and transportation of goods downstream to meet customers' needs ($\bar{x}$ = 4.3755, SD = .88040). Moreover, most respondents agreed that they exhibit demand flexibility regarding order processing ($\bar{x}$ = 4.2609, SD = .82804). Most respondents also agreed that they exhibit purchasing flexibility through retailing an assortment of supplies and differentiation of SKUs ($\bar{x}$ = 4.3360, SD = .80288).

Respondents were further required to provide their insights on alignment capability. A respondent indicated that aligning the retail chain to the customer's needs is increasingly becoming a critical competitive advantage; given the diverse nature of customers, they are becoming increasingly inscrutable, harder to find, and harder to please. Respondents indicated that investing in IT tools to enhance alignment by sharing information, resources, and capabilities is fundamental. Study participants indicated that collaborations with stakeholders strengthen customer engagement and build better brand equity.

The findings above resonate with Patrucco and Kähkönen (2021), who contends that alignment capability can be enhanced by encouraging extensive information sharing among channel participants, allocating clear responsibilities to channel participants and or partners, and enhancing the transparent definition of how costs and benefits are shared between supply chain partners.

4.5.5 SC Configuration

Respondents were asked about various aspects of SC configuration; their responses are presented in Table 4.15 below:

Table 4.15: Descriptive of SC Configuration

S/No.	Statements	N	Mean	Std. Deviation
SCC1	The more the number of channel participants, the higher the order fulfillment rate	253	4.379	.53294
SCC2	Less dispersed physical location translates to increased supply chain costs	253	4.288	.70693
SCC3	Globalization increases uncertainties, which causes supply chain disruptions.	253	4.156	.45678
SCC4	The higher the number of nodes, the less the lead-times	253	4.087	.78567

Cronbach Alpha = .726 with 4 items, N=253; $\bar{X}$= 4.2275

To establish if SC configuration moderates the relationship between dynamic supply chain capabilities and Resilience in large retail chains in Kenya. The study operationalized SCC in three ways; no. of SC nodes, physical location dispersion, and SC network design. In obtaining this information from the respondents, five-point Likert scale statement questions were structured, for which the responses are presented in Table 4.15 above. Most respondents agreed that the more channel participants, the higher the order fulfillment rate ($\overline{x}$ = 4.3794, SD = .53294). Most respondents also agreed that Less dispersed physical location translates to increased supply chain costs ($\overline{x}$ = 4.2885, SD = .70693). Further, the respondents agreed that globalization increases the uncertainties, which cause supply chain disruptions ($\overline{x}$ = 4.156, SD = .45678) and that the higher the number of nodes, the less the lead times ($\overline{x}$ = 4.087, SD = .78567).

These findings resonate with Sabri et al. (2017), who established six individual SC configuration settings and expounded on the motive behind different SC configuration decisions. These findings are consistent with Sabri et al. (2017), who conceptualized the relationship between six individual configuration settings and performance outcomes to obtain the optimal fit between supply chain configuration and performance.

4.5.6 Resilience in the Retail Sector

Respondents were asked about various aspects of Resilience in the retail sector; their responses are presented in Table 4.16 below:

Table 4.16: Descriptive Resilience of Retail Chain of Stores

S/No	Statements	Mean	Std. Deviation
Res 1	We anticipate and mitigate the impact of disruptions by using safety stocks to buffer unexpected demand	4.5573	.57189
Res 2	Our retail chain is robust enough to maintain a desired level of control over structure and function ex-ante to disruption.	4.1779	.79432
Res 3	We have pre-defined contingency plans to decrease response time	4.0909	.97775
Res 4	We have redundancy capacities that are used as "shock absorbers" in the event of the occurrence of short-term disruptions	4.0395	.77050
Res 5	We are robust enough to deal with financial outcomes of potential supply chain disruptions	4.1858	.81715
Res 6	We speedily respond to an influx in demand by reducing the probability of stockouts and lost sales in our retail chain	4.3004	.59485
Res 7	We are speedily responsive to maintain a desired level of control over structure and function ex-post to disruption	4.3597	.52049
Res 8	We speedily deploy our pre-defined contingency plans to decrease response time	4.0000	.93859
Res 9	We speedily unleash redundancy capacities such as multiple suppliers, and slack resources in our retail chain	4.0870	.77174
Res 10	We speedily deal with financial outcomes of potential supply chain disruptions in our retail chain	3.9209	1.00083
Res 11	We can rebuild and or reconstruct our retail chain after the disruption	4.0791	.86927
Res 12	We can quickly return the retail supply chain to its original state after being disrupted	4.0474	.92030
Res 13	We can move our retail chain to a new or more desirable state after being disrupted	4.2648	.71062
Res 14	We possess the knowledge management capability to learn from feedback from a disruption to develop better plans and solutions for future ones	4.3913	1.97430
Res 15	We maintain a strong market position characterized by financial strength, market share, and loss absorption allowing more investment in the Resilience of the retail chain	4.3004	.91541
Res 16	Our contingency planning capability enhances our retail chain’s ability to recover through situational analysis	4.5285	.69194

Cronbach Alpha = .803 with 16 items. N=253; $\bar{X}$= 4.2082

The study operationalized the criterion variable into; readiness, response, and recovery. Five-point Likert scale statement questions were structured to obtain this information from the respondents, for which the responses are presented in Table 4.14 above. On readiness, most respondents strongly agreed that they anticipate and mitigate the impact of disruptions by using safety stocks to buffer unexpected demand ($\bar{x}$ = 4.5573, SD = .57189). Further, the majority of the respondents agreed that their retail chain is robust enough to maintain a desired level of control over structure and function ex-ante to disruption ($\bar{x}$ = 4.1779, SD = .79432). Additionally, respondents agreed that they have pre-defined contingency plans to decrease response time ($\bar{x}$ = 4.0909, SD = .97775). Also, most respondents agreed that they have redundancy capacities that are used as "shock absorbers" in the event of short-term disruptions ($\bar{x}$ = 4.0395, SD = .77050). Respondents also indicated that they are robust enough to deal with financial outcomes of potential supply chain disruptions ($\bar{x}$ = 4.1858, SD = .81715). On responsiveness, the majority of the respondents indicated that they speedily respond to an influx in demand by reducing the probability of stockouts and lost sales in our retail chain ($\bar{x}$ = 4.3004, SD = .59485). Most respondents agreed that they are speedily responsive to maintain a desired level of control over structure and function ex-post to disruption ($\bar{x}$ = 4.3597, SD = .52049). Most study participants also agreed that they speedily deployed our pre-defined contingency plans to decrease response time ($\bar{x}$ = 4.0000, SD = .93859). Most respondents also agreed that they speedily unleash redundancy capacities such as multiple suppliers and slack resources in our retail chain ($\bar{x}$ = 4.0870, SD = .77174). Additionally, most respondents were neutral on the statement that they speedily deal with financial outcomes of potential supply chain disruptions in our retail chain ($\bar{x}$ = 3.9209, SD = 1.00083). On recovery, most respondents agreed that they could rebuild and reconstruct our retail chain after disruption ($\bar{x}$ = 4.0791, SD = .86927). More so, most respondents agreed that they could quickly return the retail supply chain to its original state after being disrupted ($\bar{x}$ = 4.0474, SD = .92030). Most respondents agreed they could move our retail chain to a new or more desirable state after disruption ($\bar{x}$ = 4.2648, SD = .71062). Most respondents agreed that they possess the knowledge management capability to learn from feedback from a disruption to develop better plans and solutions for future ones ($\bar{x}$ = 4.3913, SD =

1.97430). Respondents agreed that they maintain a strong market position characterized by financial strength, market share, and loss absorption allowing more investment in the Resilience of the retail chain ($\bar{x}$ = 4.3004, SD = .91541). Moreover, respondents agreed that their contingency planning capability enhances our retail chain's ability to recover through situational analysis ($\bar{x}$ = 4.3004, SD = .91541).

Qualitative data was analyzed using content analysis, and the following themes emerged*;* Respondents indicated that the COVID-19 pandemic had been the biggest disruptor in the retail landscape. At its onset, stores closed down; panic buying resulted in a bullwhip effect. It was further noted that some categories fared better than others during the pandemic, hence transforming the retail landscape. For instance, essential segments saw about 20% growth in sales, while non-essential segments, such as footwear apparel, were a nearly 15% decrease in sales. Additionally, when the pandemic persisted, the omnichannel experience was redefined; most shoppers moved online. However, they kept the brick and motor stores.

The findings of these studies resoundingly converge with the findings of Shishodia, Sharma, Rajesh, & Munim (2023). who propounded that retail Resilience can be demystified into four dimensions; the first dimension is the resistance phase, which constitutes the degree of sensitivity or gravity of the retort of a retail center to any shocks or disturbances indicated by the scale of decline in sales and turnover, among other financial indicators. The second dimension is the reorientation phase, characterized by adapting a retail center in response to any shocks indicated by changes to marketing models and such. The third phase is the recovery phase, in which a retail chain speedily recovers from any shocks or disturbances indicated by the extent of return to the previous growth path before the disturbance. The fourth phase is the renewal phase, in which the retail chain renews its growth path and resumes its previous track or hysteric shift to recent growth trends.

4.6 Inferential Statistics

a) Common Method Variance (CMV)

CMV is a systematic error variance shared among variables measured using the same source or method. CMV threats the validity of associations among constructs and creates a systematic bias in a study by either inflating or deflating the correlations (Reio, 2010); Accordingly, Podsakoff et al. (2003) contend that depending on whether CMB inflates or deflates the relationship; it affects the hypothesis testing, leads to type I or II errors, leads to incorrect views about the amount of variance attributed to a criterion by predictor variable and embellish or reduce discriminant validity of the scale. Additionally, (Podsakoff et al., 2003) note that CMV leads to false internal consistency. On average, such extant research has shown that variance explained in the criterion variable is about 35% when CMV was present but only 11% in the absence of CMV.

In this light, to ensure the validity and consistency of the research findings, the study controlled the Common Method Bias using procedural remedies. Since it was impossible to eliminate all the impact of Common Method Bias through procedural remedies, the study also applied statistical remedies to control CMV's impact on research findings herein.

The Common Marker Variable Technique was applied to estimate the Common Method Variance. The common variance in this technique is the square of all the common factors of each path before standardization. Additionally, the common heuristic is to set the threshold to 50%. Rindfleisch, Malter, Ganesan and Moorman (2008) postulate a threshold of up to 0.21 for the t-statistic value for CMV. The study adopted the CFA marker technique that produced a t-statistic of 0.01, as the figure below indicates. Conclusively, CMV was not a concern in this study as the test statistic was less than the recommended test statistic of up to 0.21. Podsakoff, MacKenzie, Lee & Podsakoff (2003), in their study on Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies, also tested for standard method variance and got a t-statistic of < .21.

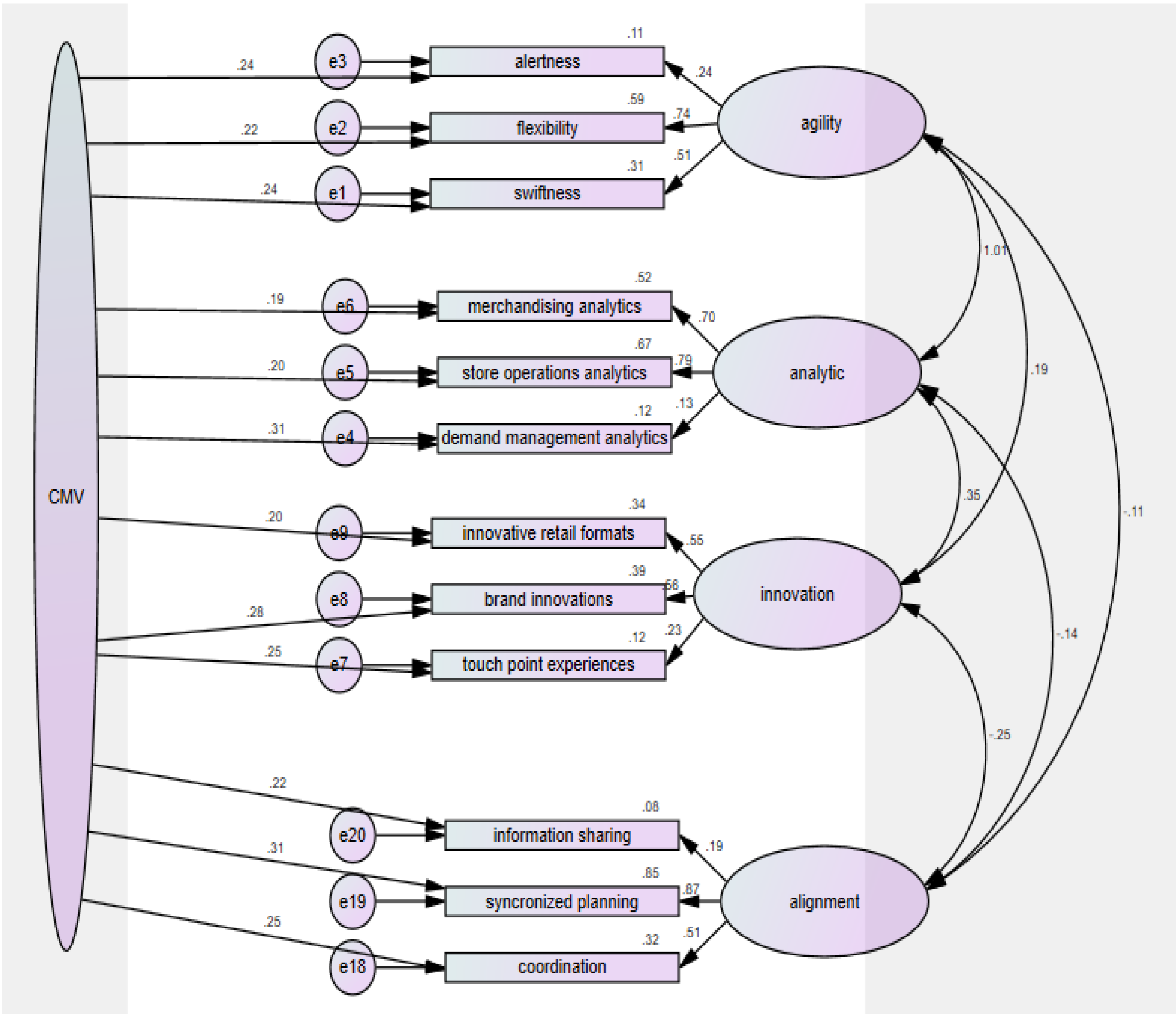

Figure 4.1: Common Method Variance

4.6 Confirmatory Measurement Model

The first step in the analysis encompasses Confirmatory Factor Analysis (CFA) which evaluates the measurement model of an array of criteria such as internal reliability, convergent validity, and discriminant validity. Before conducting CFA, Exploratory Factor Analysis (EFA) was conducted. The key steps included the computation of the factor loading matrix, commonalities, and Principal Component Analysis (PCA).

4.6.1 Exploratory Factor Analysis

Tabachnick and Fidell (2014) opined that Exploratory Factor Analysis (EFA) is used when you have a large set of variables you want to describe in more straightforward terms, and these variables you have no a priori ideas about which variables will cluster together. It could narrow down a large sample of data into smaller ones. In other words, it helps the researcher determine the belongings of the variables (Emory & Cooper, 1991). Ali and Chin-Hong (2015), in their study on factors affecting intention to use Islamic personal financing in Pakistan: Evidence from the modified TRA model used (EFA).

Tabachnick and Fidell (2014) suggested that EFA is used in the preliminary stages of the research to collect data to establish interrelationships among study variables. More so, they posit that EFA is used to reduce a large number of related variables to a manageable number before they are used in SEM. Before conducting an EFA, the suitability of data for factor analysis was established. Upon assessing the correlation matrix for all the variables under study, all the correlation matrices revealed the presence of coefficient values above the recommended cut-off value of 0.6 (Kaiser, 1974), and Batlett's Test of Sphericity (Bartlett, 1954) reached statistical significance value of 0.0000. It reaffirms the factorability of the correlation matrix as indicated in KMO and Bartlett's Test of Sphericity tables below.

Table 4.17: KMO and Bartlett's Test of Sphericity

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		**.865**
Bartlett's Test of Sphericity	Approx. Chi-Square	766.751
	df	105
	Sig.	**.000**

Prior to conducting EFA, Bartlett's Test of Sphericity was conducted. It is an objective test of the factorability of the correlation matrix. It statistically tests the hypothesis that a "correlation matrix is an identity matrix"; hence it was generated by random data. As a rule of thumb, this test should produce a statistically significant Chi-square value (p-value $\leq$ .05) to justify the application of EFA (Watkins, 2018). Indicating that the variables are unrelated and hence suitable for structure detection. A p-value < .05 indicates that factor analysis is helpful with one's data. Since large samples make Bartlett's Test of Sphericity sensitive to even trivial deviations from randomness, (Watkins, 2018) recommends that its results should be supplemented with a measure of sampling adequacy. Given this reality, the Kaiser-Meyer-Olkin [KMO] (Kaiser, 1974) measure of sampling adequacy was conducted. KMO values ranged from 0.00 to 1.00 and can be computed for the total correlation matrix and each measured variable. Kaiser (1974) described KMO values in the .90s as marvelous, in the .80s meritorious, in the .70s middling, in the .60s mediocre, in the .50s miserable, and below the .50s unacceptable. Results of Bartlett's test of sphericity (Bartlett, 1954) indicated that the correlation matrix was not random, $\chi 2$ (253) = 766.751, $p < .001$, and the KMO statistic (Kaiser, 1974) was .865, well above the minimum standard for conducting factor analysis. Therefore, it was determined that the correlation matrix was appropriate for factor analysis and hence suitable for structure detection.

a) Principle Component Analysis (PCA)

Principle Component Analysis was The factor extraction method used to perform Exploratory Factor Analysis. Varimax technique of orthogonal Rotation (Fullerton et al., 2014) was applied, resulting in 24 factors with eigenvalues greater than 1, explaining the respective variances (Hair et al., 2014). Notably, components with factor loadings less than 0.70 were removed, and the minimum cut-off point is 0.50, consistent with (Marshall et al., 1996).

To validate the construct validity of the items, PCA was applied. A total number of 82 items were loaded. These factors were split into five: Supply Chain Agility, Supply Chain Analytics, Supply Chain Innovations, Supply Chain Alignment, and Resilience in the retail sector. The initial 82 items were reduced to 24 items. Factor loadings for all the retained items were above 0.7, which satisfied the minimum criteria of 0.30 (Hair et al., 2010). Table 4.14 below indicates the results of the factor analysis. Akinwuni (2009) used a factor-loading matrix to check the validity of constructs. The pattern matrix coefficients for this study ranged between 0.741-0.998, indicating that the variables are almost perfectly related to a factor pattern.

At this juncture, the moderator variable, SC configuration, was expunged because its items failed to satisfy the minimum criteria indicating that they were not perfectly related; hence, it was unsuitable for structural detection.

In sum, the examination of factor items in the table below indicates components of both predictor and criterion variables. For instance, component 1represesets agility capability (SCA) that initially had 16 factors but was crystalized to 5 factors after PCA. Component 2 represents an analytic capability that initially had 17 factors crystalized into five factors after PCA. Component 3 represents innovation capability that initially had 16 factors crystallized into four factors after PCA. Component 4 represents alignment capability that initially had 15 factors crystallized into four factors after PCA. Component 6 represents resilience, the criterion variable that initially had 15 factors crystalized into six factors after PCA. Component 5 had the moderator variable, and after PCA, the study concluded that the moderator was not fit for structural detection.

Table 4.18: Component Matrix

	Indicators/variables	SC Agility Capability	SC Analytics Capability	SC Innovation Capability	SC Alignment Capability	Retail Sector Resilience
SCAC2	We promptly identify and seize business opportunities in the business environment	.860				
SCAC4	We promptly detect stock re-order levels	.809				
SCAC5	We promptly sense shopper's reactions to new merchandise	.858				
SCAC7	We are flexible enough to react timely to changes in customers' orders, tastes, and preferences	.819				
SCA14	We quickly undertake to retail an assortment of supplies	.858				
ANALY01	We use retail analytics to increase cross-selling opportunities.		.932			
ANALY12	We use retail analytics to provide our customers with personalized recommendations.		.875			
ANALY05	We use retail analytics in product adjacency.		.941			
ANALY10	We use location analytics to map how customers move through a store.		.887			
ANALY13	We use retail analytics to undertake sales forecasting.		.941			
INNOV01	We use new retail formats to keep abreast of market dynamics and constraints.			.839		
INNOV07	We have pronounced private labels in some merchandise categories, such as milk and personal care products.			.757		
INNOV10	We leverage brand innovations to meet shoppers' needs, tastes, and preferences.			.998		
INNOV16	We influence shoppers' post-touch effect in a manner that remains in their episodic memory after that.			.998		
ALIGN01	We share information about our sales and demand forecasts with our channel participants in the supply chain.				.756	
ALIGN11	We integrate procurement, pricing, and merchandising of all brands in a category.				.792	
ALIGN07	We use Vendor Managed Inventories to share our retail chain's inventory status with suppliers upstream.				.941	
ALIGN09	We jointly develop category-based plans internally in our retail chains				.941	
RES02	Our retail chain is robust enough to maintain a desired level of control over structure and function ex-ante to disruption.					.818
RES06	We speedily respond to an influx in demand by reducing the probability of stockouts and lost sales in our retail chain.					.796
RES07	We are speedily responsive to maintain a desired control over structure and function ex-post to disruption.					.753
RES11	We can quickly return the retail supply chain to its original state after a disruption.					.989
RES08	We speedily deploy our pre-defined contingency plans to decrease response time.					.894
RES12	We can move our retail chain to a new or more desirable state after being disrupted					.989

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 7 iterations.

4.6.3 Construct Validity for Supply Chain Agility Capability

Table 4.19: Construct Validity for Supply Chain Agility Capability

Construct(s)	Cronbach α-Value	No. of Items	Acceptability
SC Agility Capability	.749	15	Accepted

The variable on SC agility capability was measured using a 5-point Likert scale ranging from 1-Strongly Disagree, 2-Disagree, 3- Undecided, 4- Agree, 5-Strongly Agree. The Cronbach α value of this construct was 0.749 for 15 items, above the cut-off point of 0.7 as suggested by (Cronbach, 1959; Nunnally, 1978). A pretest of the data collection instrument was conducted among 45 study participants.

4.6.4 Construct Validity for Supply Chain Agility Capability

Table 4.20: Descriptive on Construct Validity for Supply Chain Agility Capability

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.723
Bartlett's Test of Sphericity	Approx. Chi-Square	766.751
	df	105
	Sig.	.000

Bartlett's Test of Sphericity was conducted to test the factorability of the correlation matrix. It statistically tests the hypothesis that a "correlation matrix is an identity matrix"; hence it was generated by random data. As a rule of thumb, this test should produce a statistically significant Chi-square value (p-value $\leq$ .05) to justify the application of EFA (Watkins, 2018). Indicating that the variables are unrelated and hence suitable for structure detection. A p-value < .05 indicates that factor analysis is helpful with one's data. Since large samples make Bartlett's Test of Sphericity sensitive to even trivial deviations from randomness, (Watkins, 2018) recommends that its results should be supplemented with a measure of sampling adequacy. Given this reality, the Kaiser-Meyer-Olkin [KMO]; (Kaiser, 1974) measure of sampling adequacy was conducted. KMO values ranged from 0.00 to 1.00 and can be computed for the total correlation matrix and each measured variable. Kaiser (1974) described KMO values in the .90s as marvelous, in the .80s meritorious, in the .70s middling, in the .60s mediocre, in the .50s miserable, and below the .50s unacceptable. Results of Bartlett's test of sphericity (Bartlett, 1954) indicated that the correlation matrix was not random, χ^2 (253) = 766.751, $p < .001$, and the KMO statistic (Kaiser, 1974) was .723, well above the minimum standard for conducting factor analysis. Williams, Brown, and Onsman (2013); Tabachnick and Fidell (2014) argued that the sampling adequacy threshold should be more than 0.5. Therefore, it was determined that the correlation matrix was appropriate for factor analysis and hence suitable for structure detection.

4.6.5 Communalities

Table 4.21: Communalities for Supply Chain Agility Capability

SCAC	Statements	Initial	Extraction
SCAC1	We promptly detect changes in the business environment	1.000	.462
SCAC2	We promptly identify and seize business opportunities in the business environment.	1.000	.781
SCAC3	We promptly sense threats in the business environment	1.000	.608
SCAC4	We promptly detect stock re-order levels	1.000	.796
SCAC5	We promptly sense shopper's reactions to new merchandise	1.000	.762
SCAC6	We are flexible enough to ensure there is on-shelf product availability	1.000	.578
SCAC7	We are flexible enough to react timely to changes in customers' orders, tastes, and preferences	1.000	.642
SCAC8	We are flexible enough to undertake last-minute promotions to meet quarterly sales goals	1.000	.496
SCAC9	We are flexible enough to react timely to changes in customers' orders, tastes, and preferences	1.000	.798
SCAC10	We quickly implement decisions regarding increasing short-term capacity as needed	1.000	.474
SCAC11	We quickly provide a variety of inbound logistics options, e.g., transportation, warehousing, and stock inventory	1.000	.347
SCAC12	We quickly adjust our merchandise to meet customer’s needs	1.000	.539
SCAC13	We quickly undertake order processing	1.000	.501
SCAC14	We quickly undertake to retail an assortment of supplies	1.000	.625
SCAC15	We differentiate our SKUs	1.000	.748
	Extraction Method: Principal Component Analysis.		

Field (2009) contended that communality values measure each variable's degree of variability that the extracted factors can explain. Factor extraction was used to determine the least number of factors that best represent the set variables' interrelations. The conventional factor extraction method is Principle Component Analysis, but others include image factoring, maximum likelihood factoring, alpha factoring, unweighted least squares, and generalized least squares. The rule of thumb is that only variables with loadings > .32 are interpreted (Pallat, 2010). Additionally, the greater the loading, the more the variable is considered a pure measure of the factor. Generally, (Tabachnick & Fidell, 2014), loadings over .71 (50% overlapping variance) are considered excellent, 0.63 (40% overlapping variance) are considered very good, 0.55 (30% overlapping variance) as good, 0.45 (20% overlapping variance) as fair and 0.32 (10% overlapping variance) as poor. Principle component analysis works on the initial assumption that all variance is common; therefore, the communalities are all one before extraction. The commonalities in the column labeled ***extraction*** reflect the common variance in the data structure. Small values indicate variables that do not fit with the factor solution and should be candidates for dropping from the analysis. Table 4.18 above shows the variables before and after extraction. For purposes of this study, the threshold was set above 0.6. The study retained SCAC2, SCAC4, SCAC5, SCAC7 and SCAC14. The extraction communalities were greater than 0.5, as shown in and are acceptable, indicating that the variables fitted well with other variables in their factor (Pallant, 2010).

Table 4.22: Total Variance Explained for SC Agility

Total Variance Explained

Component	**Initial Eigenvalues**			**Extraction Sums of Squared Loadings**			**Rotation Sums of Squared Loadings**
	Total	**% of variance**	**Cumulative %**	**Total**	**% of variance**	**Cumulative %**	**Total**
1	3.020	20.135	20.135	3.020	20.135	20.135	2.256
2	1.694	11.294	31.429	1.694	11.294	31.429	1.663
3	1.381	9.207	40.636	1.381	9.207	40.636	1.901
4	1.195	7.970	48.606	1.195	7.970	48.606	1.700
5	1.067	7.115	55.720	1.067	7.115	55.720	1.566
6	.998	6.655	62.375				
7	.887	5.911	68.286				
8	.819	5.460	73.745				
9	.811	5.405	79.150				
10	.670	4.466	83.617				
11	.612	4.077	87.694				
12	.559	3.730	91.424				
13	.525	3.503	94.927				
14	.477	3.180	98.107				
15	.284	1.893	100.000				

Extraction Method: Principal Component Analysis.
a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.

More so, the number of factors to be retained is decided using Kaiser's criterion/Eigenvalue, with factors of Eigenvalue of 1.0 or more retained for further investigation (Kaiser, 1960; Field, 2000). The principal components analysis was conducted, and five factors with eigenvalues greater than 1.0 were extracted. These factors (1, 2, 3, 4, & 5) accounted for 20.135%, 11.294%, 9.207%, 7.970%, and 7.115% of the variance, respectively, and cumulatively accounted for 55.720 of the variance, as shown in table 4.22 above.

Table 4.23: Construct Validity for Supply Chain Analytics Capability

Construct(s)	Cronbach α-Value	No. of Items	Acceptability
SC Analytics Capability	.703	14	Accepted

The variable on SC agility capability was measured using a 5-point Likert scale ranging from 1-Strongly Disagree, 2-Disagree, 3- Undecided, 4- Agree, 5-Strongly Agree. The Cronbach α value of this construct was 0.749 for 15 items, above the cut-off point of 0.7 as suggested by (Cronbach, 1959; Nunnally, 1978). A pretest of the data collection instrument was conducted among 45 study participants.

Table 4.24: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		**.720**
Bartlett's Test of Sphericity	Approx. Chi-Square	1004.301
	df	91
	Sig.	.000

KMO results and Bartlett's test results for supply chain analytics capability.

Bartlett's Test of Sphericity for SC analytics capability was conducted to test the factorability of the correlation matrix. The Chi-square value was statistically significant; $\chi 2$ (253) = 1004.301, p = .000. As a rule of thumb, this test should produce a statistically significant Chi-square value (p-value $\leq$ .05) to justify the application of EFA (Watkins, 2018). Since the sample size was large, Bartlett's sphericity test was supplemented by sampling adequacy. The Kaiser-Meyer-Olkin; KMO (Kaiser, 1974) measure of sampling adequacy was conducted. KMO values ranged from 0.00 to 1.00 and can be computed for the total correlation matrix and each measured variable. Kaiser (1974) described KMO values in the .90s as marvelous, in the .80s meritorious, in the .70s middling, in the .60s mediocre, in the .50s miserable, and below the .50s unacceptable. Results of Bartlett's test of sphericity (Bartlett, 1974) indicated that the correlation matrix was not random, $\chi 2$ (253) = 1004.301, $p < .001$, and the KMO statistic (Kaiser, 1974) was .720, well above the minimum standard for conducting factor analysis. Tabachnick and Fidell, (2014). The sampling adequacy threshold should be more than 0.5. Therefore, it was determined that the correlation matrix was appropriate for factor analysis and hence suitable for structure detection.

Table 4.25: Descriptive Communalities for Supply Chain Analytic Capability

Communalities

ANLYC	Statements	Initial	Extraction
ANLYC1	We use retail analytics to increase cross-selling opportunities	1.000	.894
ANLYC2	We use retail analytics to improve product placement	1.000	.670
ANLYC3	We use retail analytics in assortment planning to enable assortment optimization	1.000	.552
ANLYC5	We use retail analytics in product adjacency	1.000	.897
ANLYC6	We have adopted sensors to restock shelves automatically	1.000	.560
ANLYC7	We use retail analytics in space allocation	1.000	.468
ANLYC8	We use retail analytics to decrease inventory shrink	1.000	.573
ANLYC9	We have adopted sensors to restock shelves automatically	1.000	.512
ANLYC10	We use location analytics to map how customers move through a store	1.000	.923
ANLYC11	We use a combination of IT tools to track which sections of the store receive the most traffic	1.000	.310
ANLYC12	We use retail analytics to make personalized recommendations and offers	1.000	.323
ANLYC13	We use retail analytics to undertake sales forecasting	1.000	.933
ANLYC14	We use retail analytics to optimize the price of our merchandise	1.000	.590

Extraction Method: Principal Component Analysis.

Principle component analysis works on the initial assumption that all variance is common; therefore, the communalities are all one before extraction. The commonalities in the column labeled ***extraction*** reflect the common variance in the data structure. Small values indicate variables that do not fit with the factor solution and should be candidates for dropping from the analysis. Table 4.24 above shows the variables before and after extraction. For purposes of this study, the threshold was set above 0.6. The study retained ANLY1, ANLYC5, ANLYC10, and ANLYC13. The extraction communalities were greater than 0.5, as shown, and are acceptable, indicating that the variables fitted well with other variables in their factor (Pallant, 2010).

Table 4.26: Descriptive on Total Variance Explained for Analytics Capability

Component	**Initial Eigenvalues**			**Extraction Sums of Squared Loadings**			**Rotation Sums of Squared Loadings**
	Total	**% of variance**	**Cumulative %**	**Total**	**% of variance**	**Cumulative %**	**Total**
1	3.177	22.691	22.691	3.177	22.691	22.691	2.680
2	1.646	11.760	34.451	1.646	11.760	34.451	2.178
3	1.328	9.484	43.936	1.328	9.484	43.936	1.706
4	1.269	9.067	53.003	1.269	9.067	53.003	1.300
5	1.042	7.440	60.443	1.042	7.440	60.443	1.270
6	.955	6.820	67.263				
7	.840	5.999	73.262				
8	.796	5.686	78.948				
9	.736	5.255	84.203				
10	.593	4.237	88.440				
11	.532	3.798	92.238				
12	.498	3.559	95.797				
13	.457	3.267	99.064				
14	.131	.936	100.000				

Extraction Method: Principal Component Analysis.
a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.

Additionally, the number of factors to be retained is decided using Kaiser's criterion/Eigenvalue, with factors of Eigenvalue of 1.0 or more retained for further investigation (Field. 2000; Kaiser, 1960). The principal components analysis was conducted, and five factors with Eigen values greater than 1.0 were extracted. These factors (1, 2, 3, 4, & 5) accounted for 22.691%, 11.760%, 9.484%, 9.067%, and 7.440% of the variance, respectively, and cumulatively accounted for 60.443 of the variance, as shown in Table 4.26 above.

Table 4.27: Construct Validity for Supply Chain Innovation Capability

Construct(s)	Cronbach α-Value	No. of Items	Acceptability
SC Innovation Capability	.700	9	Accepted

The variable on SC innovation capability was measured using a 5-point Likert scale ranging from 1-Strongly Disagree, 2-Disagree, 3- Undecided, 4- Agree and 5-Strongly Agree. The Cronbach α value of this construct was 0.700 for nine items, and it was above the cut-off point of 0.7 as suggested by (Cronbach, 1959; Nunnally, 1978).

Table 4.28: KMO and Bartlett's Test

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		**.786**
Bartlett's Test of Sphericity	Approx. Chi-Square	1234.982
	df	91
	Sig.	.000

Bartlett's Test of Sphericity for SC innovations capability was conducted to test the factorability of the correlation matrix. The Chi-square value was statistically significant; $\chi2$ (253) = 1234.982, p = .000. As a rule of thumb, this test should produce a statistically significant Chi-square value (p-value $\leq$ .05) to justify the application of EFA (Watkins, 2018). Since the sample size was large, Bartlett's sphericity test was supplemented by sampling adequacy. The Kaiser-Meyer-Olkin;

KMO (Kaiser, 1974) measure of sampling adequacy was conducted. KMO values ranged from 0.00 to 1.00 and can be computed for the total correlation matrix and each measured variable. Kaiser (1974) described KMO values in the .90s as marvelous, in the .80s meritorious, in the .70s middling, in the .60s mediocre, in the .50s miserable, and below the .50s unacceptable. Results of Bartlett's test of sphericity (Bartlett, 1954) indicated that the correlation matrix was not random, $\chi2$ (253) = 1234.982, $p < .001$, and the KMO statistic (Kaiser, 1974) was .786, well above the minimum standard for conducting factor analysis. Tabachnick and Fidell (2014); Williams et al., 2013; postulated that the sampling adequacy threshold should be more than 0.5. Therefore, it was determined that the correlation matrix was appropriate for factor analysis and hence suitable for structure detection.

Table 4.29: Communalities for Supply Chain Innovations Capability

Communalities

SCENIC	Statements	Initial	Extraction
SCI1	We use new retail formats to keep abreast with market dynamics and constraints	1.000	.982
SCI5	We leverage brand innovations to meet shoppers' needs, tastes, and preferences	1.000	.777
SCI7	We have pronounced private labels in some merchandise categories, such as milk and personal care products.	1.000	.849
SCI8	We make continuous and significant improvements to current retail formats	1.000	.428
SCI10	We innovatively stimulate shoppers' demand for products	1.000	.590
SCI11	We undertake retail advertising to create positive touch-point experiences for our shoppers in the interest of parsimony	1.000	.571
SCI14	We undertake word-of-mouth communication through social media platforms to create positive touch-point experiences for our shoppers	1.000	.474
SCI15	We influence shoppers' post-touch effect in a manner that remains in their episodic memory after that	1.000	.982

Extraction Method: Principal Component Analysis.

Principle component analysis works on the initial assumption that all variance is expected; therefore, the communalities are all one before extraction. The commonalities in the column labeled ***extraction*** reflect the expected variance in the data structure. Small values indicate variables that do not fit with the factor solution and should be candidates for dropping from the analysis. Table 4.26 above shows the variables before and after extraction. For purposes of this study, the threshold was set above 0.7. The study retained SCI1. SCI5, SCI 7, SCI15The extraction communalities were more significant than 0.5, as shown, and are acceptable, indicating that the variables fitted well with other variables in their factor (Pallant, 2010) apart from SCI8 and SCI14.

Table 4.30: Total Variance Explained for Innovation Capability

Total Variance Explained

Component	**Initial Eigenvalues**			**Extraction Sums of Squared Loadings**			**Rotation Sums of Squared Loadings**
	Total	**% of variance**	**Cumulative %**	**Total**	**% of variance**	**Cumulative %**	**Total**
1	2.681	29.789	29.789	2.681	29.789	29.789	2.495
2	1.995	22.168	51.956	1.995	22.168	51.956	2.158
3	1.243	13.806	65.762	1.243	13.806	65.762	1.556
4	.773	8.583	74.346				
5	.750	8.329	82.674				
6	.655	7.273	89.947				
7	.486	5.401	95.348				
8	.419	4.652	100.000				
9	-1.000E-013	-1.002E-013	100.000				

Extraction Method: Principal Component Analysis.

a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.

Moreover, the number of factors to be retained is decided using Kaiser's criterion/Eigenvalue, with factors of Eigenvalue of 1.0 or more retained for further investigation (Field, 2000; Kaiser, 1960). The principal components analysis was conducted, and three factors with Eigen values greater than 1.0 were extracted. These factors (1, 2 & 3) accounted for 29.789%, 22.168%, and 13.806% of the variance, respectively, and cumulatively accounted for 65.762, as shown in Table 4.30 above.

Table 4.31: Descriptive on Construct Validity for Supply Chain Alignment Capability

Construct(s)	**Cronbach α-Value**	**No. of Items**	**Acceptability**
SC Alignment Capability	.714	11	Accepted

The variable on SC alignment capability was measured using a 5-point Likert scale ranging from 1-Strongly Disagree, 2-Disagree, 3- Undecided, 4- Agree, 5-Strongly Agree. The Cronbach α value of this construct was 0.700 for nine items, and it was above the cut-off point of 0.7 as suggested by (Cronbach, 1959; Nunnally, 1978).

Table 4.32: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		**.775**
Bartlett's Test of Sphericity	Approx. Chi-Square	736.918
	df	55
	Sig.	.000

Bartlett's Test of Sphericity for SC alignment capability was conducted to test the factorability of the correlation matrix. The Chi-square value was statistically significant; $\chi 2$ (253) = 736.918, p = .000. As a rule of thumb, this test should produce a statistically significant Chi-square value (p-value $\leq$ .05) to justify the application of

EFA (Watkins, 2018). Since the sample size was large, Bartlett's sphericity test was supplemented by sampling adequacy. The Kaiser-Meyer-Olkin; KMO (Kaiser, 1974) measure of sampling adequacy was conducted. KMO values ranged from 0.00 to 1.00 and can be computed for the total correlation matrix and each measured variable. Kaiser (1974) described KMO values in the .90s as marvelous, in the .80s meritorious, in the .70s middling, in the .60s mediocre, in the .50s miserable, and below the .50s unacceptable. Results of Bartlett's test of sphericity (Bartlett, 1954) indicated that the correlation matrix was not random, $\chi 2$ (253) = 736.918, $p < .001$, and the KMO statistic (Kaiser, 1974) was .775, well above the minimum standard for conducting factor analysis. Tabachnick and Fidell (2014); Williams et al., 2013; postulated that the sampling adequacy threshold should be more than 0.5. Therefore, it was determined that the correlation matrix was appropriate for factor analysis and hence suitable for structure detection.

Table 4.33: Construct Communalities for Supply Chain Alignment Capability

Communalities

SCAL	**Statements**	**Initial**	**Extraction**
SCAL1	We share information about our sales and demand forecasts with our channel participants in the supply chain	1.000	.759
SCAL3	We leverage independent demand from Electronic Points of Sale (EPOS) to meet customers' expectations	1.000	.679
SCAL7	We use Vendor Managed Inventories to share our retail chain’s inventory status with suppliers upstream	1.000	.746
SCAL8	We treat product categories as strategic business units to plan and achieve sales and profit targets and satisfy customers' needs and preferences.	1.000	.449
SCAL9	We jointly develop category-based plans internally in our retail chains	1.000	.762
SCAL10	We jointly develop strategic plans externally with suppliers to measure financial performance at the category level	1.000	.410
SCAL11	We integrate procurement, pricing, and merchandising of all brands in a category	1.000	.784
SCAL12	We provide various inbound logistics options to facilitate the delivery of inbound goods.	1.000	.387
SCAL13	We adjust inventory, packaging, warehousing, and transportation of goods downstream to meet customer's needs	1.000	.513
SCAL14	We exhibit demand flexibility regarding order processing,	1.000	.583
SCAL15	We exhibit purchasing flexibility through retailing of an assortment of supplies and differentiation of SKUs	1.000	.258

Extraction Method: Principal Component Analysis.

Principle component analysis works on the initial assumption that all variance is common; therefore, the communalities are all one before extraction. The commonalities in the column labeled ***extraction*** reflect the common variance in the data structure. Small values indicate variables that do not fit with the factor solution and should be candidates for dropping from the analysis. Table 4.22 above shows the variables before and after extraction. For purposes of this study, the threshold was set above 0.7. The study retained SCAL1, SCAL7, SCAL9, and SCAL11. The extraction communalities were greater than 0.5, as shown, and are acceptable, indicating that the variables fitted well with other variables in their factor apart from SCI1 and SCI12. (Pallant, 2010)

Table 4.34: Total Variance Explained FOR SC Alignment

Total Variance Explained

Component	**Initial Eigenvalues**			**Extraction Sums of Squared Loadings**			**Rotation Sums of Squared Loadings**
	Total	**% of variance**	**Cumulative %**	**Total**	**% of variance**	**Cumulative %**	**Total**
1	2.612	23.742	23.742	2.612	23.742	23.742	2.143
2	2.147	19.516	43.259	2.147	19.516	43.259	2.355
3	1.271	11.554	54.813	1.271	11.554	54.813	1.929
4	.948	8.615	63.427				
5	.869	7.900	71.327				
6	.733	6.664	77.991				
7	.652	5.929	83.919				
8	.593	5.389	89.308				
9	.462	4.202	93.510				
10	.406	3.695	97.206				
11	.307	2.794	100.000				

Extraction Method: Principal Component Analysis.

a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.

Moreover, the number of factors to be retained is decided using Kaiser's criterion/Eigenvalue, with factors of Eigenvalue of 1.0 or more retained for further investigation (Field, 2000; Kaiser, 1960). The principal components analysis was conducted, and three factors with Eigen values greater than 1.0 were extracted. These factors (1, 2 & 3) accounted for 23.742%, 19.516%, and 11.554% of the variance, respectively, cumulatively accounted for 54.813 of the variance, as shown in Table 4.34 above.

Table 4.35: Construct Validity for Resilience in the Retail Sector

Construct(s)	**Cronbach α-Value**	**No. of Items**	**Acceptability**
SC Alignment Capability	.803	16	Accepted

The variable on resilience in the retail sector was measured using a 5-point Likert scale ranging from 1-Strongly Disagree, 2-Disagree, 3- Undecided, 4- Agree, 5- Strongly Agree. The Cronbach α value of this construct was 0.803 for 16 items, and it was above the cut-off point of 0.7 as suggested by (Nunnally, 1978). A pretest of the data collection instrument was conducted among 45 study participants.

Table 4.36 KMO and Bartlett's Test

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		**.703**
Bartlett's Test of Sphericity	Approx. Chi-Square	698.964
	df	120
	Sig.	.000

Bartlett's Test of Sphericity for SC alignment capability was conducted to test the factorability of the correlation matrix. The Chi-square value was statistically significant; $\chi 2$ (253) = 698.964, p = .000. As a rule of thumb, this test should produce a statistically significant Chi-square value (p-value $\leq$ .05) to justify the application of EFA (Watkins, 2018). Since the sample size was large, Bartlett's test of sphericity was supplemented by a measure of sampling adequacy. The Kaiser-Meyer-Olkin; KMO (Kaiser, 1974) measure of sampling adequacy was conducted. KMO values ranged from 0.00 to 1.00 and can be computed for the total correlation matrix and each measured variable. Kaiser (1974) described KMO values in the .90s as marvelous, in the .80s meritorious, in the .70s middling, in the .60s mediocre, in the .50s miserable, and below the .50s unacceptable. Results of Bartlett's test of sphericity (Bartlett, 1954) indicated that the correlation matrix was not random, $\chi 2$ (253) = 736.918, $p < .001$, and the KMO statistic (Kaiser, 1974) was .703, well above the minimum standard for conducting factor analysis. Tabachnick and Fidell (2014); Williams et al. 2013; contended that the sampling adequacy threshold should be more than 0.5. Therefore, it was determined that the correlation matrix was appropriate for factor analysis and hence suitable for structure detection.

Table 4.37: Communalities for Resilience in the Retail Sector

Communalities

RES	Statements	Initial	Extraction
RES1	We anticipate and mitigate the impact of disruptions by using safety stocks to buffer unexpected demand	1.000	.501
RES2	Our retail chain is robust enough to maintain a desired level of control over structure and function ex-ante to disruption.	1.000	.836
RES3	We have pre-defined contingency plans to decrease response time	1.000	.634
RES4	We have redundancy capacities that are used as "shock absorbers" in the event of the occurrence of short-term disruptions	1.000	.565
RES5	We are robust enough to deal with financial outcomes of potential supply chain disruptions	1.000	.617
RES6	We speedily respond to an influx in demand by reducing the probability of stockouts and lost sales in our retail chain	1.000	.810
RES7	We are speedily responsive to maintain a desired level of control over structure and function ex-post to disruption	1.000	.763
RES8	We speedily deploy our pre-defined contingency plans to decrease response time	1.000	.877
RES9	We speedily unleash redundancy capacities such as multiple suppliers, and slack resources in our retail chain	1.000	.478
RES10	We speedily deal with financial outcomes of potential supply chain disruptions in our retail chain	1.000	.612
RES11	We can rebuild and or reconstruct our retail chain after the disruption	1.000	.789
RES12	We can quickly return the retail supply chain to its original state after being disrupted	1.000	.920
RES13	We can move our retail chain to a new or more desirable state after being disrupted	1.000	.628
RES14	We possess the knowledge management capability to learn from feedback from a disruption to develop better plans and solutions for future ones	1.000	.660
RES15	We maintain a strong market position characterized by financial strength, market share, and loss absorption allowing more investment in the resilience of the retail chain	1.000	.628
RES16	Our contingency planning capability enhances our retail chain’s ability to recover through situational analysis	1.000	.637

Extraction Method: Principal Component Analysis.

Principle component analysis works on the initial assumption that all variance is common; therefore, the communalities are all one before extraction. The commonalities in the column labeled ***extraction*** reflect the common variance in the data structure. Small values indicate variables that do not fit with the factor solution and should be candidates for dropping from the analysis. Table 4.26 above shows the variables before and after extraction. For purposes of this study, the threshold was set above 0.6. The study retained RES2, RES 6, RES 7, RES 8, RES 11, and RES 12. The extraction communalities were more significant than 0.5, as shown, and are acceptable, indicating that the variables fitted well with other variables in their factor (Pallant, 2010).

Table 4.38: Descriptive on Total Variance Explained

Total Variance Explained

Component	**Initial Eigenvalues**			**Extraction Sums of Squared Loadings**		
	Total	**% of variance**	**Cumulative %**	**Total**	**% of variance**	**Cumulative %**
1	2.989	18.682	18.682	2.989	18.682	18.682
2	1.805	11.281	29.963	1.805	11.281	29.963
3	1.350	8.435	38.398	1.350	8.435	38.398
4	1.157	7.233	45.630	1.157	7.233	45.630
5	1.129	7.055	52.685	1.129	7.055	52.685
6	1.025	6.407	59.092	1.025	6.407	59.092
7	.908	5.675	64.767			
8	.848	5.299	70.066			
9	.761	4.758	74.824			
10	.701	4.380	79.205			
11	.679	4.244	83.449			
12	.646	4.038	87.487			
13	.583	3.647	91.133			
14	.532	3.326	94.459			
15	.458	2.864	97.323			
16	.428	2.677	100.000			

Extraction Method: Principal Component Analysis.

Moreover, the number of factors to be retained is decided using Kaiser's criterion/Eigenvalue, with factors of Eigenvalue of 1.0 or more retained for further investigation (Field, 2000; Kaiser, 1960). The principal components analysis was conducted, and three factors with Eigen values greater than 1.0 were extracted. These factors (1, 2, 3, 4, 5 & 6) accounted for 18.682%, 11.218%, and 8.435%, 7.233%, 7.055%, and 6.407% of the variance, respectively, and cumulatively accounted for 59.092% of the variance as shown in table 4.38 above.

4.7 Confirmatory Factor Analysis (CFA)

The study employed Confirmatory Factor Analysis (CFA) to test whether a relationship exists between observed variables and the underlying latent constructs (Hair et al., 2010). In the CFA model, 12 items were loaded to best fit the sample data between the observed and unobserved variables (Byrne, 2013). These items for the study variables were assessed using CFA based on EFA results to evaluate each variable's dimensionality and test the model fit of the factors of the study variables (Anderson & Gerbing, 1988). Each observed variable was assigned to one and only one latent variable, as shown in Figure 4.2, which confirmed that a relationship exists between the observed and latent variables, as evident in the correlations shown in the figure below.

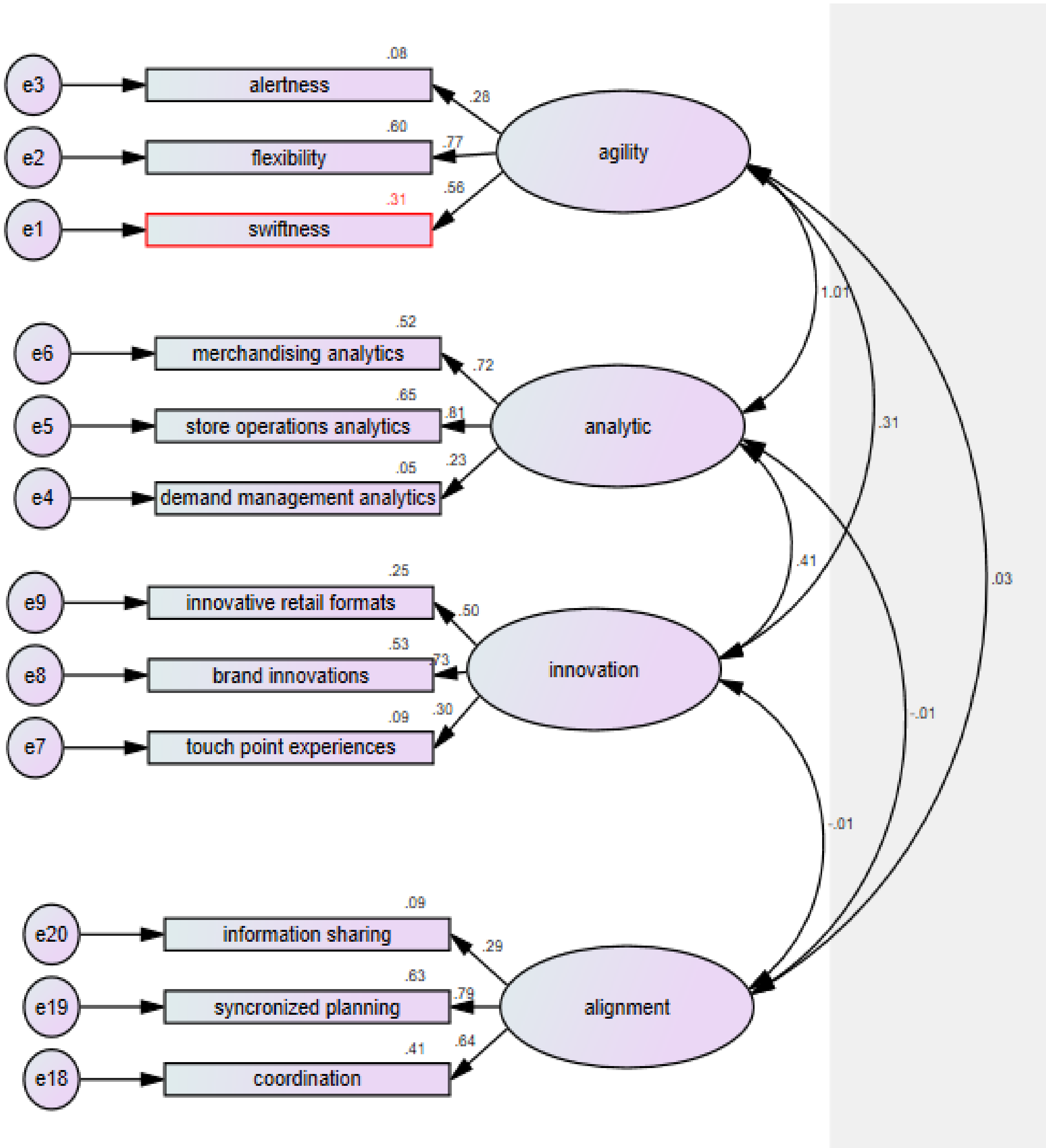

Figure 4.2: Confirmatory Factor Analysis

4.7.1 Test for Psychometric Properties

a) Reliability

Additionally, CFA was conducted to assess the construct validity in the measurement model on various criteria such as convergent validity, discriminant validity, and internal reliability. Bahl and Wali (2014) postulate that both convergent and discriminant validity are subcomponents of construct validity. In their study on

Housing Bubble Debate, Bryant and Kohn (2013) used CFA to measure both convergent and divergent validity.

Prior to data analysis, reliability, and validity tests were conducted. The study adopted the internal consistency method and used Cronbach's alpha coefficient as the test statistic to assess reliability. The Cronbach α coefficient for all the variables was above the recommended cut-off point of 0.70. It suggests robust internal consistency and reliability. Further, CFA was used to determine both convergent validity and the unidimensionality of constructs. CFA was conducted separately for all predictor and criterion variables. The results indicate a good model fit for the variables under study. Agility capability had a Normed Fit Index ($\varkappa^2$/df) value of 0.995, a Root Mean Square Error of Approximation (RMSEA) value of 0.04, a Goodness of Fit Index (GFI) value of 0.917 and a Comparative Fit Index value of 0.902. Agility capability had a Normed Fit Index ($\varkappa^2$/df) value of 0.995, a Root Mean Square Error of Approximation (RMSEA) value of 0.04, a Goodness of Fit Index (GFI) value of 0.917 and a Comparative Fit Index value of 0.902. Analytic capability had a Normed Fit Index ($\varkappa^2$/df) value of 0.941, a Root Mean Square Error of Approximation (RMSEA) value of 0.06, a Goodness of Fit Index (GFI) value of 0.977 and a Comparative Fit Index value of 0.955. Innovation capability had a Normed Fit Index ($\varkappa^2$/df) value of 0.902, a Root Mean Square Error of Approximation (RMSEA) value of 0.054, a Goodness of Fit Index (GFI) value of 0.989 and a Comparative Fit Index value of 0.951. Alignment capability had a Normed Fit Index ($\varkappa^2$/df) value of 0.984, a Root Mean Square Error of Approximation (RMSEA) value of 0.00, a Goodness of Fit Index (GFI) value of 0.995 and a Comparative Fit Index value of 1.00. These fit indices exceeded the minimum cut-off value of 0.9 (Koufteros, 2009).

a. Convergent and Divergent Validity

Table 4.39: Total Variance Explained Convergent Validity

Constructs	Composite reliability	Average variance Extracted (AVE)
SCA Capability	0.958	0.792
SC Analytics Capability	0.980	0.908
SC Innovations Capability	0.991	0.959
SC Alignment Capability	0.957	0.787
Resilience	0.967	0.830

In the case of convergent validity, the factor loadings should be at least 0.5 (Hair et al., 2010). In this study, the average loadings are more than 0.7, indicating high enough to converge, as shown in the table above. Composite Reliability (CR) suggests a cut-off value of 0.6 or higher for acceptability, indicating the measurement model's internal consistency (Hair et al., 2010; Kline, 2005). As shown in the table, the CR value of all items was above 0.900, evident in the high internal reliability of the data. Conclusively, the internal validity of the data was met. Fauziah, Taib, Ramayah, & Abdul (2008) used convergent validity in their study on Factors Influencing the Intention to use Diminishing Partnership Home Financing in the Middle East to measure the extent to which the underlying latent construct correlated to the observed variables that were designed to measure the same construct.

Discriminant validity establishes that the measures should not be related and are, in reality, not related (Hair et al., 2010). The study compared the square root of the construct's average variance extracted with the correlation of the constructs to establish discriminant validity as suggested by (Fornell & Larcker, 1981). The construct's correlation was less than the square root of the average variance extracted for individual constructs. In this regard, there is support for discriminant validity. The table below demonstrates discriminant validity. In their study on Social Networks and the Success of Market Intermediaries: Evidence from the US Residential Real Estate Industry, Crowston et al. (2015) used discriminant validity to show that measures that should not be related are, in reality, unrelated.

Table 4.40: Descriptive on Discriminant Validity

Construct(s)	CR	AVE	SCA	SCALY	SCI	SCALING
SCA	.958	.792	**.891**			
SCALY	.980	.908	.231**	**.953**		
SCI	.991	.959	.543**	.314**	**.979**	
SCALIG	.957	.787	.455**	.354**	.557**	**.887**

Scale reliability was established by computing Cronbach's Alpha reliability coefficient for every construct. The Cronbach Alpha statistic for each construct was greater than the recommended cut-off point of 0.7 to infer the internal consistency of the items as recommended (Devilish, 2003; Nunnally & Bernstein, 1994). Valentini, Ippoliti, and Fontanella (2013) assessed the reliability and validity of the measurement model by evaluating internal consistency, convergent validity, and discriminant validity in their study on Modeling US Housing Prices by Spatial Dynamic Structural Equation Models.

The second step involved answering the study objectives, where Analysis of Moment Structures software was used for Confirmatory Factor Analysis, measurement model, and structural equation modeling. Schumacker and Lomax (2004) demonstrated that SEM is a general, linear, cross-sectional statistical modeling technique. On another lens, SEM is more of a confirmatory technique than exploratory, and AMOS can be used to perform CFA. Similarly, Jackson et al. (2009) also postulated that path analysis, factor analysis, and regressions are all special cases of SEM. In this study, SEM was used to test the hypothesis and to fit the theoretical model. Kohn and Bryant (2010) on factors leading to the US housing bubble: A structural equation modeling approach used SEM to test the research hypothesis and fit theoretical and statistical models.

For this study, each model variable was tested for normality and outliers on variable aspects using Exploratory Data Analysis (EDA) to understand the structure of variables before further data analyses were undertaken. It enabled the researcher to apply appropriate analytical data analysis techniques to avoid crucial violations of key assumptions in consequent modeling processes. It was followed by testing the model fit. In SEM, the fit indices establish whether the model is acceptable, and if acceptable, the researcher then establishes if the specific paths are significant (Moss, 2009).

The study adopted two commonly used fit indices: absolute fit indices and incremental fit indices (Hair et al., 2010). For the case of absolute fit indices, this study applied the Goodness-of-Fit Index (GFI), Adjusted Goodness-of-Fit (AGFI), and Root-Mean-Square Error of Approximation (RMSEA). On the other hand, for Incremental Fit Indices, Comparative Fit Index (CFI) and Normed Fit Index (NFI) were used. Wei and Wang (2010) used absolute and incremental fit indices for assessing model fit in their study on the Dynamic Model: House Price Returns, Mortgage rates, and Mortgage Default rates to estimate the dynamic relations among house price returns, mortgage default rates, and mortgage rates.

As depicted in Table 4.26, NFI was a good fit. Kline (2005) posited that the acceptable value of NFI in order to make it a good fit is NFI > 0.90. Similarly, including GFI is also important to expound on the model fit. Kline (2005) propounded that GFI = 1.0 indicates a perfect model fit, a GFI > 0.90 indicates a good fit, and that values close to zero indicate a very poor fit. Nonetheless, it is possible to have the values of GFI greater than 1.0 with just-identified models and over-identified models with almost perfect fit. Negative values occur when the sample size is small, or the model fit is extremely poor. In resonance with the postulations (Kline, 2005), the study's findings reported GFI > 0.90. It explains that the model(s) were within the acceptable range.

The rule of thumb for CFI and other incremental fit indices is that a value greater than roughly 0.90 indicates a reasonably good fit of the researcher's model (Hu &

Bentler, 1999). The study's CFIs exceed 0.90, which leads to the conclusion that the study had a good fit for CFI. In summary, all the model fit measures of the measurement model achieved the minimum threshold level. Hence the measurement model achieved the minimum was appropriate. Bryant and Kohn (2013), in their study entitled A Housing Bubble Debate Resolved, tested their research model using the goodness-of-fit test indicators, which revealed that the values were within the range of recommended levels.

Table 4.41: Results of Confirmatory Factor Analysis

Item	**Scale Items**	**Standardized Item/Factor Loadings**	**R^2**
Agility Capability	Alertness	.28	.08
	Flexibility	.77	.60
	Swiftness	.56	.31
Analytic Capability	Merchandising analytics	.72	.52
	Store operations analytics	.81	.65
	Demand management analytics	.23	.05
Innovation Capability	Innovative Retail Formats	.50	.25
	Brand Innovations	.73	.53
	TouchPoint experiences	.30	.09
Alignment Capability	Information Sharing	.29	.09
	Synchronized Planning	.64	.41

4.7.1 Testing of Outliers of the Study Variables

The study had both predictor and criterion variables whose constructs were on a continuous scale. In this regard, outliers were tested univariately on both sets of variables. The outliers from the data set were dropped. (Hair et al. (2010), Kline (2005) suggested that outliers should be dropped, and further (Abbott & McKinney, 2013) contended that outliers distort the true relationship between variables by either building a correlation that is non-existent or suppressing a correlation that truly exists. Consequently, multivariate testing of outliers on the dependent variable using Mahalanobis d-squared produced reasonable box plots affirming that all constructs are symmetrical and with no outliers identified.

4.7.2 Normality Test of the Study Variables

The study adopted Kolmogorov-Smirnov and Shapiro-Wilk goodness of fit tests to assess normality. Thode (2002) averred that Kolmogorov-Smirnov is used for large samples while the Shapiro-Wilk test is used for small samples. The p-values of the test results were > .05, as shown in Table 4.41 below. It implies that the assumption of normality was satisfied.

Table 4.42: Tests of Normality

Tests of Normality

	Kolmogorov-Smirnov[a]			**Shapiro-Wilk**		
	Statistic	**df**	**Sig.**	**Statistic**	**df**	**Sig.**
SC Resilience	.112	252	.068	.965	252	.059
Agility	.101	252	.075	.962	252	.050
Analytic	.100	252	.078	.958	252	.079
Innovation	.100	252	.081	.961	252	.057
Alignment	.099	252	.089	.960	252	.065
Configuration	.102	252	.068	.963	252	.089

a. Lilliefors Significance Correction

The Kolmogorov-Smirnov goodness of fit test was corroborated with graphical analysis, which indicated the line representing the actual data distribution followed the diagonal in the typical Q-Q plots, as shown in figures 4.3- below, validating a normal distribution (Hair et al., 2006). Pallant (2007) suggests that in a typical probability plot, the Q-Q plot, the observed value for each score is plotted against the expected value from a normal distribution, where a sensible straight line suggests a normal distribution. If points in a Q-Q plot deviate from the straight line, we can cast aspersions to the assumption of normality, alluding to its violation.

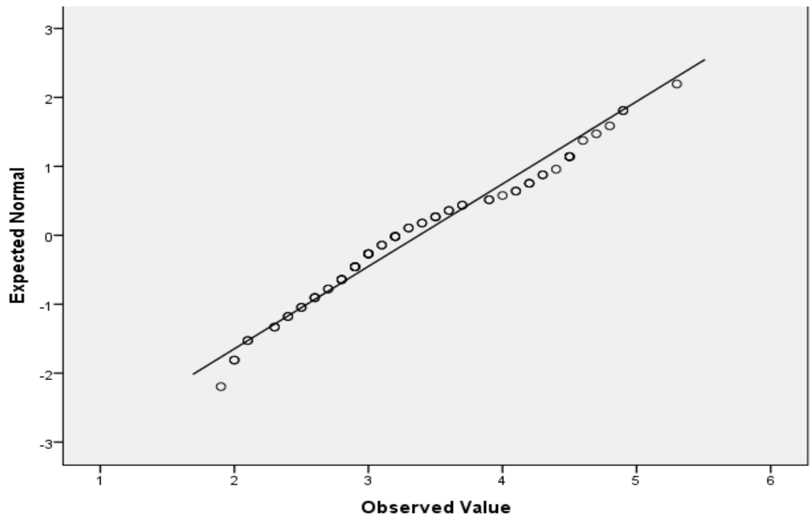

Figure 4.3: Normal Q-Q Plot of Supply Chain Resilience

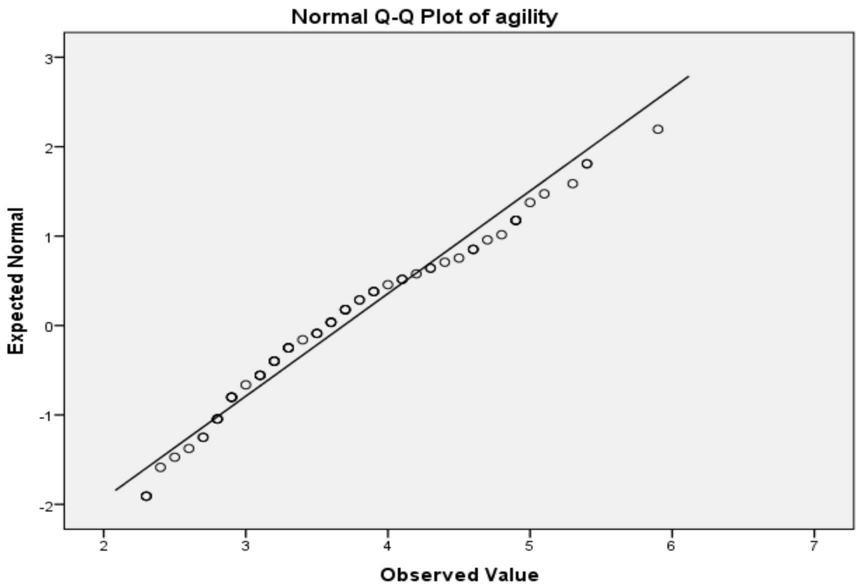

Figure 4.4: Normal Q-Q Plot of SC Agility Capability

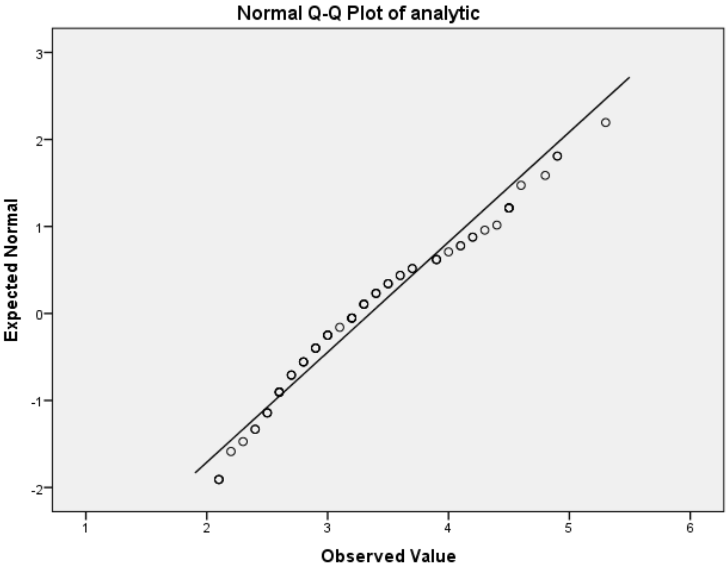

Figure 4.5: Normal Q-Q Plot of SC Analytics Capability

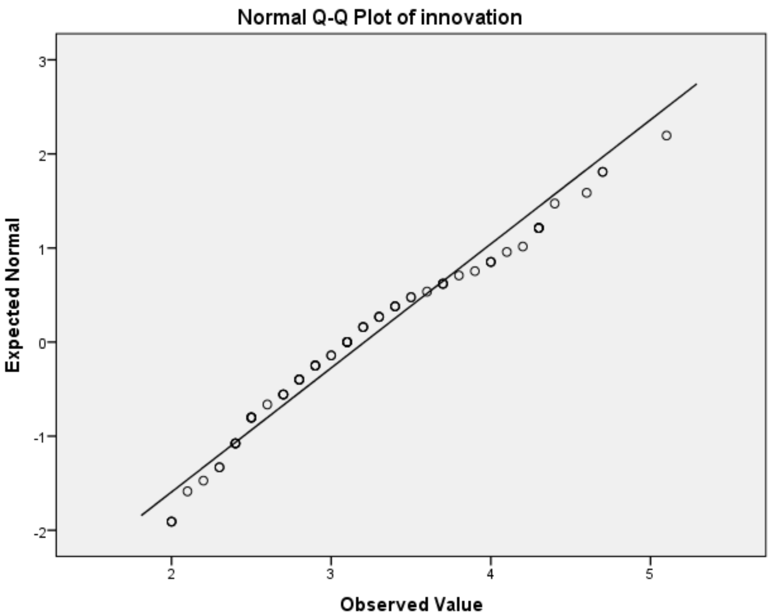

Figure 4.6: Normal Q-Q Plot of SC Innovation Capability

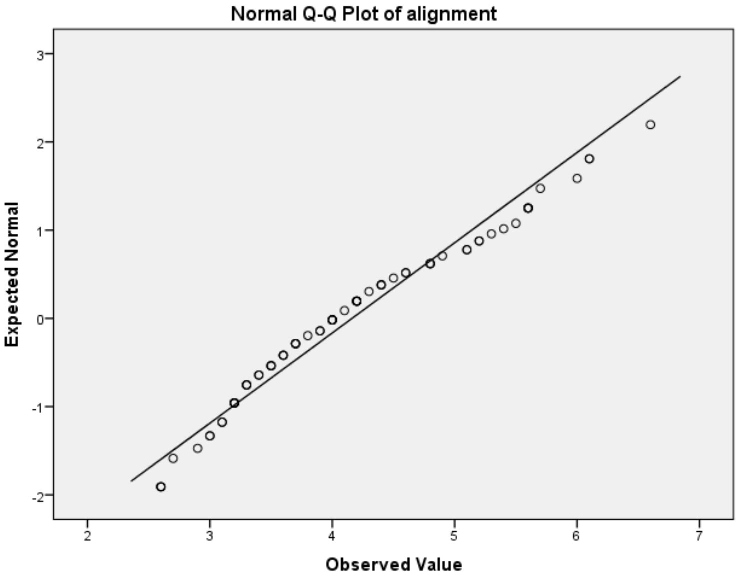

Figure 4.7: Normal Q-Q Plot of SC alignment Capability

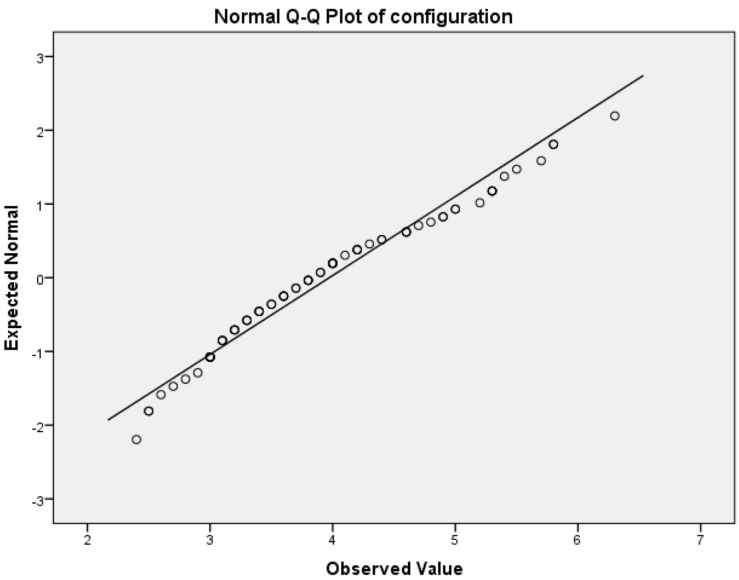

Figure 4.8: Normal Q-Q Plot of SC Configuration Capability

4.9 Assessing the Fit of the Structural Equation Model

The study further determined if the model fit structural equation modeling. According to (Hair, 2014), the cardinal factor of a good model is the fit among the covariance matrix. The draconian rule of thumb, however directly related to the X2 value, states that a good fitting model is the one whose ratio of X2 to the degree of freedom is less than 2. The following fit indices were assessed (Hair et al., 2014; Tabachnick & Fidell, 2014). The normed fit index (NFI) compares the X2 value of the estimated model to the X2 value of the independent model. The non-normed fit index (NNFI) is an adjustment to the NFI integrating the degree of freedom in the model. The incremental fit index (IFI) addresses the problem of the large variability in the NNFI, and the comparative fit index (CFI) assesses fit relative to other models. Other fit indexes include the Root Mean Square Error of Approximation (RMSEA), the goodness-of-fit index (GFI), and many others (Hair et al., 2014; Tabachnick & Fidell, 2014). The suggested CFI, IFI, and TLI values must be above 0.90 or close to 1.00 (Byrne, 2016). Whereas RMSEA values for a good model should be less than or equal to 0.06 (Hu & Bentler, 1999), in this study, the assessment of model fit shows a normed chi-square (chi-square/degree of freedom) value that indicates that the model provides a good model fit. The components also give a good structure to continue the structural equation modeling.

Table 4.43: Confirmatory factor analysis model fits of SC agility Capability

Model	CMIN	GFI	AGFI	NFI Delta1	TLI rho2	CFI	RMSEA
Default model	62.330	.917	.690	.995	.904	.902	.041
Saturated model	.000	1.000		1.000		1.000	
Independence model	303.982	.681	.521	.000	.000	.000	.342

For SC agility capability, the assessment of model fit shows a normed chi-square (chi-square/degree of freedom) values of (X2 = 62.330, P < 0.05); CFI value of 0.902; TLI value of 0.904; CFI value of 0.902 and RMSEA value of 0.041. It indicates that the model provides a good model fit. The components also give an excellent structure to continue the structural equation modeling.

Table 4.44: Confirmatory factor analysis model fits of SC Analytics Capability

Model	**CMIN**	**GFI**	**AGFI**	**NFI Delta1**	**TLI rho2**	**CFI**	**RMSEA**
Default model	15.256	.977	.913	.941	.987	.955	.06
Saturated model	.000	1.000		1.000		1.000	
Independence model	259.419	.702	.552	.000	.000	.000	.315

For SC analytics capability, the assessment of model fit shows a normed chi-square (chi-square/degree of freedom) values of (X2 = 15.256, P < 0.05); CFI value of 0.955; TLI value of 0.987; CFI value and RMSEA value of 0.041. It indicates that the model provides a good model fit. The components also give an excellent structure to continue the structural equation modeling.

Table 4.45: Confirmatory factor analysis model fits of SC Innovation Capability

Model	**CMIN**	**GFI**	**AGFI**	**NFI Delta1**	**TLI rho2**	**CFI**	**RMSEA**
Default model	6.953	.989	.959	.902	.978	.951	.054
Saturated model	.000	1.000		1.000		1.000	
Independence model	70.754	.898	.848	.000	.000	.000	.155

For SC innovation capability, the assessment of model fit shows a normed chi-square (chi-square/degree of freedom) values of (X2 = 6.953, P < 0.05); CFI value of 0.951; TLI value of 0.978; CFI value and RMSEA value of 0.054. It indicates that the model provides a good model fit. The components also give an excellent structure to continue the structural equation modeling.

Table 4.46: Confirmatory factor analysis model fits of SC Alignment Capability

Model	CMIN	GFI	AGFI	NFI Delta1	TLI rho2	CFI	RMSEA
Default model	3.421	.995	.980	.984	1.074	1.000	.000
Saturated model	.000	1.000		1.000		1.000	
Independence model	29.602	.955	.932	.000	.000	.000	.088

For SC alignment capability, the assessment of model fit shows a normed chi-square (chi-square/degree of freedom) values of (X2 = 3.421, P < 0.05); CFI value of 1.00; TLI value of 1.074; and RMSEA value of 0.000. It indicates that the model provides a good model fit. The components also give a good structure in which to continue the structural equation modeling.

Table 4.47: Confirmatory factor analysis model fits of resilience

Model	CMIN	GFI	AGFI	NFI Delta1	TLI rho2	CFI	RMSEA
Default model	2.678	.962	.936	.963	1.011	1.000	.000
Saturated model	.000	1.000		1.000		1.000	
Independence model	22.567	.932	.983	.000	.000	.000	.088

For resilience, the assessment of model fit shows a normed chi-square (chi-square/degree of freedom) values of (X2 = 2.678, P < 0.05); CFI value of 1.00; TLI value of 1.011; CFI value of 1.00 and RMSEA value of 0.000. It indicates that the model provides a good model fit. The components also give an excellent structure to continue the structural equation modeling.

4.9 Hypothesis Testing

Despite establishing support for hypothesized model, post hoc modifications were undertaken to contend a better fitting model. Based on theoretical significance, covariances were estimated. The model was improved with the addition of paths. Assessment of the model fit indicates a normed chi-square (chi-square/df) value of ($\varkappa^2$= 2.326, p<0.001), CFI value of 0.947, TLI value of 0.929; TLI value of 0.954; IFI value of 0.929 and RMSEA value of 0.043, all these fit indices indicates a good fit.

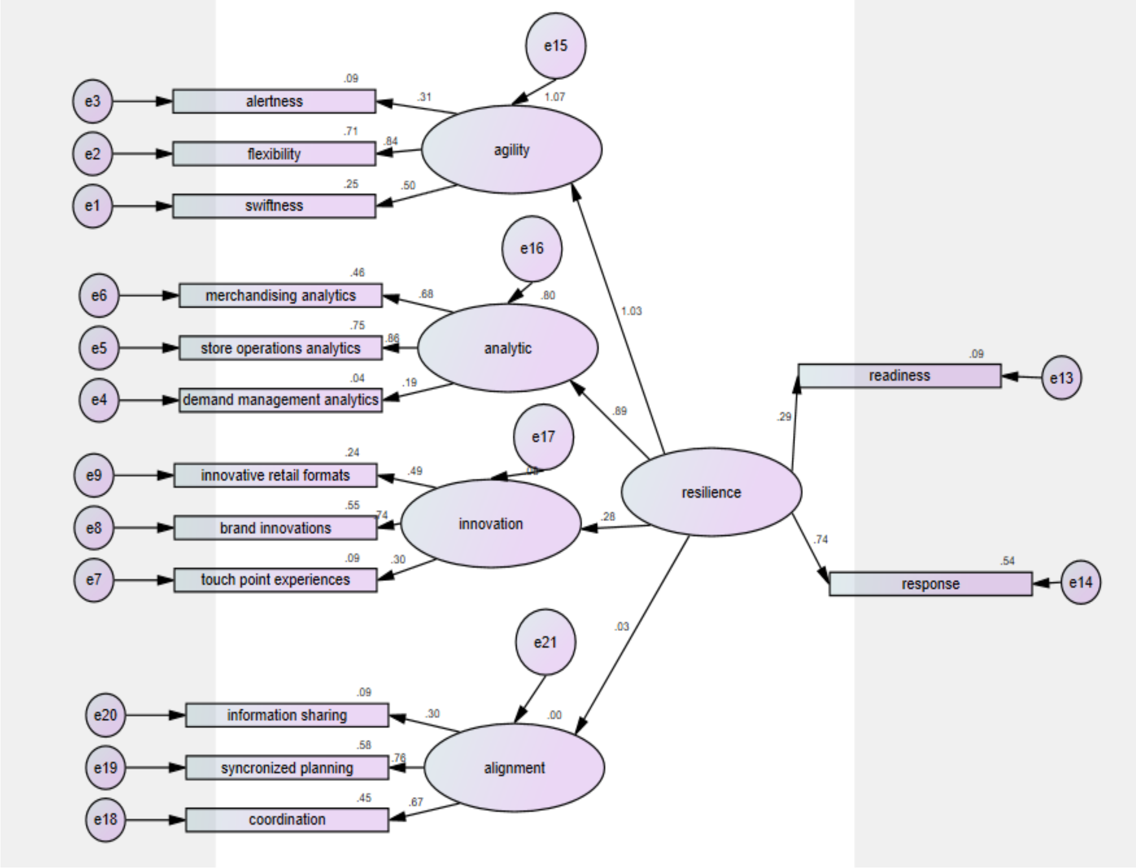

Figure 4.9: SEM Model without Moderator

Table 4.48: Hypothesis Test Results

			β	SE.	CR.	P
agility	<---	resilience	1.766	.444	3.975	***
analytic	<---	resilience	.447	.187	2.383	.017
innovation	<---	resilience	.280	.129	2.173	.030
alignment	<---	resilience	.062	.180	.342	.032

H_{01}: There is no statistically significant relationship between SC agility capability and resilience in the Retail Sector in Kenya.

The study established a statistically significant positive relationship between supply chain agility capability and resilience in the retail sector (β = 1.766, p = 0.000). Hence, the study rejected the null hypothesis. These results corroborate the findings of Gilgor et al. (2015), who contended the hypothesis that there is a direct positive relationship between firm SC agility and performance outcomes. More so, the results of the study further converge with the findings of Ahmed et al. (2019), which used the Partial Least Square Method and Structural Equation Modeling and found that flexibility, responsiveness, learning orientation, swiftness, and visibility were statistically significant and they are positively correlated with SC agility. Additionally, the study findings agree with Baah et al. (2021), which established a statistically significant positive relationship between supply chain agility and performance. (β= 0.158***, T= 2.641). The statistically significant positive relationship between agility and resilience and performance outcome is attributed to the ability of agile firms to respond swiftly to customer needs and market volatilities.

H_{02}: There is no statistically significant relationship between analytic capability and resilience in the Retail Sector in Kenya.

The study established a statistically significant positive relationship between analytic capability and resilience in the retail sector (β = 0.447, p = 0.017). Hence, the study rejected the null hypothesis.

These findings corroborate with those of Wamba et al. (2017), who examined the impact of big data analytics capability on a firm and established a nexus between BDA capability and firm performance. The study established that big data analytics, directly and indirectly, impacts firm performance. More so, these findings are consistent with Suning et al. (2018), who averred the hypothesis that SC analytics can be stratified into categories that support sourcing/procurement, analytics that supports decision-making, and analytics that supports delivery functions. Additionally, these findings reaffirm the suppositions of Borade et al. (2013) that SC analytics enables inventory optimization, which is a prerequisite in a multi-echelon environment. These findings also agree with Chandramana (2017), who contended retail analytic framework, merchandising analytics, marketing analytics, supply chain analytics, and store operations analytics. In this regard, retail analytics brings the benefit of creating customer profiles, optimizing price, customer loyalty, and predicting demand. Manage inventory and detect fraud and pilferage in stores.

H_{03}: There is no statistically significant relationship between dynamic innovation capability and resilience in the Retail Sector in Kenya.

The study established a statistically significant positive relationship between innovation capability and resilience in the retail sector ($\beta = 0.287$, $p = 0.030$). Hence, the study rejected the null hypothesis.

These results are consistent with the findings of Moktadir et al. (2019), who assessed value-satisfaction-loyalty relationships in retailing by establishing the influence of image and innovation and hypothesizing value as a multi-dimensional construct. The study accepted the hypothesis that perceived retail innovation has a statistically significant positive impact on excellence value. Perceived retail innovation has a statistically insignificant positive impact on efficiency value. Perceived retail innovation has a positive impact on entertainment value. Perceived retail innovation has a positive impact on aesthetic value.

The study further corroborates with the suppositions of Iddris (2016), who contended that the dimensions of innovation capability are knowledge management, organizational culture, organizational learning, leadership, collaboration, creativity, idea management, and innovation management. Wong and Ngai (2019) conducted a critical review of supply chain innovation research published from 1999 to 2016 in diverse peer-reviewed journals, which adapted Gregor's (2006) framework to classify theories on SC innovations, further categorizing SC innovations by supply chain innovation research. Also, the study is in tandem with the findings of Gölgeci and Ponomarov (2015), who contended that innovative firms are less resistant to change, open to creating and leveraging niches, and, more often than not, exhibit higher capability and tendency to adopt, adapt and execute as well as effectively leverage new ideas. As such, firm innovativeness can be linked with various other dynamic capabilities, including resilience.

H_{04}: There is no statistically significant relationship between alignment capability and resilience in the Retail Sector in Kenya.

The study established a statistically significant positive relationship between alignment capability and resilience in the retail sector ($\beta = 0.062$, $p = 0.032$). Consequently, the study rejected the null hypothesis. These findings are inconsistent with Skipworth et al. (2015), which established that shareholder alignment is not positively related to business performance. It is because data from the two models did not support the H1 proposition. Nonetheless, the study corroborates with H_2, in which customer alignment was found to have a positive relationship with business performance. More so, there was a bi-directional connection between shareholder and customer alignment. The study also agrees with H_{3a} and H_{3b} as the data revealed a positive relationship between organizational structure and shareholder alignment, an enabler of shareholder and customer alignment. Additionally, the study is consistent with Skipworth et al. (2015) finding that customer relational behavior, internal relational behavior, information sharing, organization structure, business performance measurement system, and top management support, shareholder alignment, customer alignment are some of the constituents of SC alignment and enablers of resilience.

H_{05}: Supply chain configuration does not moderate the relationship between dynamic supply chain capabilities and resilience in the Retail Sector in Kenya.

The overall model predicted that SCC negatively moderated the relationship between dynamic supply chain capabilities and resilience in the retail sector (β = -8.750, p = .0000).

H_{05a}: The study established that SCC has a negative moderating effect on the relationship between SC agility capability and resilience in the retail sector (β = -.035, p = .0000).

H_{05b}: The study established that SCC negatively moderates the relationship between SC analytic capability and resilience in the retail sector (β = -.110, p = .0000).

H_{05c}: The study established that SCC has a significant positive moderating effect on the relationship between SC innovation capability and resilience in the retail sector (β = .004, p = .0000).

H_{05d}: The study established that SCC has no moderating effect on the relationship between SC alignment capability and resilience in the retail sector (β = .000, p = .0000).

These hypotheses' findings differ from Abdinnour's (2019), who empirically established how supply chain and product architecture decisions influence organizational competitiveness and resilience.

Data on dependent variables also corroborates with the extant research on resilience. For instance, it is in tandem with Melnyk et al. (2014), who postulated that resilient supply chains can be resistant in a way that it can delay a disruptive event and even reduce the impact of the disruption if it occurs. It is also consistent with Milynk et al. (2014), who postulated that a resilient supply chain is robustly malleable to surmount and withstand disruptions within acceptable degradation parameters and is smoothly effective in recovering within a reasonable time, composite costs, and risks. These postulations are consistent with the explications of Tukamuhabwa et al. (2015). The study also agrees with Han et al. (2020), who conceptualized the dimensions of SCRES as readiness, response, and recovery.

Further, this study reaffirms extant literature, which espouses that readiness is the dynamic capability of SC to recognize, anticipate and prevent risks and disruptions before the occurrence of any damage (Chowdhury & Quaddus, 2016). It also affirms that response is the dynamic capability of SC to swiftly to critical situations (Chowdhury & Quaddus, 2016). It is also in agreement with Holsten et al. (2015). That recovery is the aftershock of an event to restore and return to normal operations and is most related to recovery time. Additionally, the study converges with the empirical stances of Han et al. (2020), who espoused the 11 capabilities that are constituents of SCRES. Four of these capabilities, namely, situation awareness, visibility, security, and redundancy, are capabilities for the readiness dimension. The other four, agility, flexibility, collaboration, and leadership, are in the response dimension of SCRES, while the other three, knowledge management, contingency planning, and market position, are in the recovery dimension.

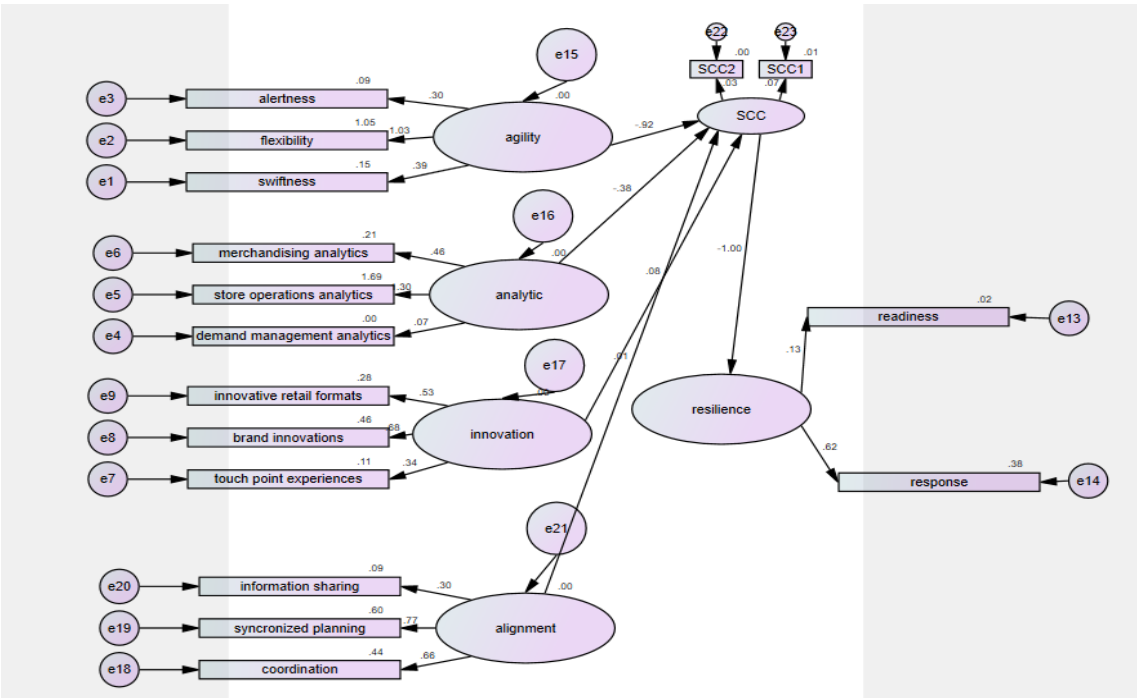

Figure 4.10: Overall Model

4.10 Model Summary

4.10.1 Model Summary without Moderator

Table 4.49: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.937[a]	.878	.876	.16564

a. Predictors: (Constant), x4, χ2, x1, x3

R^2, taken as a set, the predictors; X1: Agility capability, X2: Analytics capability, X3: Innovation capability, and X4 Alignment capability account for 87.8% of the variance of the criterion variable; resilience in the retail sector.

4.10.2 Model Summary with Moderator

Table 4.50: Model Summary

R	R Square	Adjusted R Square	Std. Error of the Estimate
.890[a]	.792	.789	.21638

a. Predictors: (Constant), x4z, χ2z, x1z, x3z

R^2, taken as a set, the predictors; X1Z: Agility capability, X2Z: Analytics capability, X3Z: Innovation capability, and X4Z Alignment capability accounts for 79.2% of the variance of the criterion variable; resilience in the retail sector.

4.10.3 Combined Model Summary

Table 4.51: Model Summary

Model	**R**	**R square**	**Adjusted R Square**	**significance**
Without Moderator	.937[a]	.878	.876	.000
With Moderator	.890[a]	.792	.789	.070

Table 4.52: ANOVA[a] Table without Moderator

Model		**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
1	Regression	44.314	4	11.078	236.611	.000[b]
	Residual	11.612	248	.047		
	Total	55.925	252			

a. Dependent Variable: y

b. Predictors: (Constant), x4, χ2, x1, x3

Table 4.53: ANOVA[a] Table with Moderator

Model		**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
1	Regression	49.103	4	12.278	438.500	.000[b]
	Residual	6.822	248	.028		
	Total	55.925	252			

a. Dependent Variable: y

b. Predictors: (Constant), x4z, χ2z, x1z, x3z

The overall model without the moderator was significant (p= .000 less than .05). The overall model with the moderator was also significant (p= .000 less than .05). However, the model with the moderating variable had a decreasing effect from .878 to .792. Therefore the R^2 change was negative.

4.10.4 Optimal Model

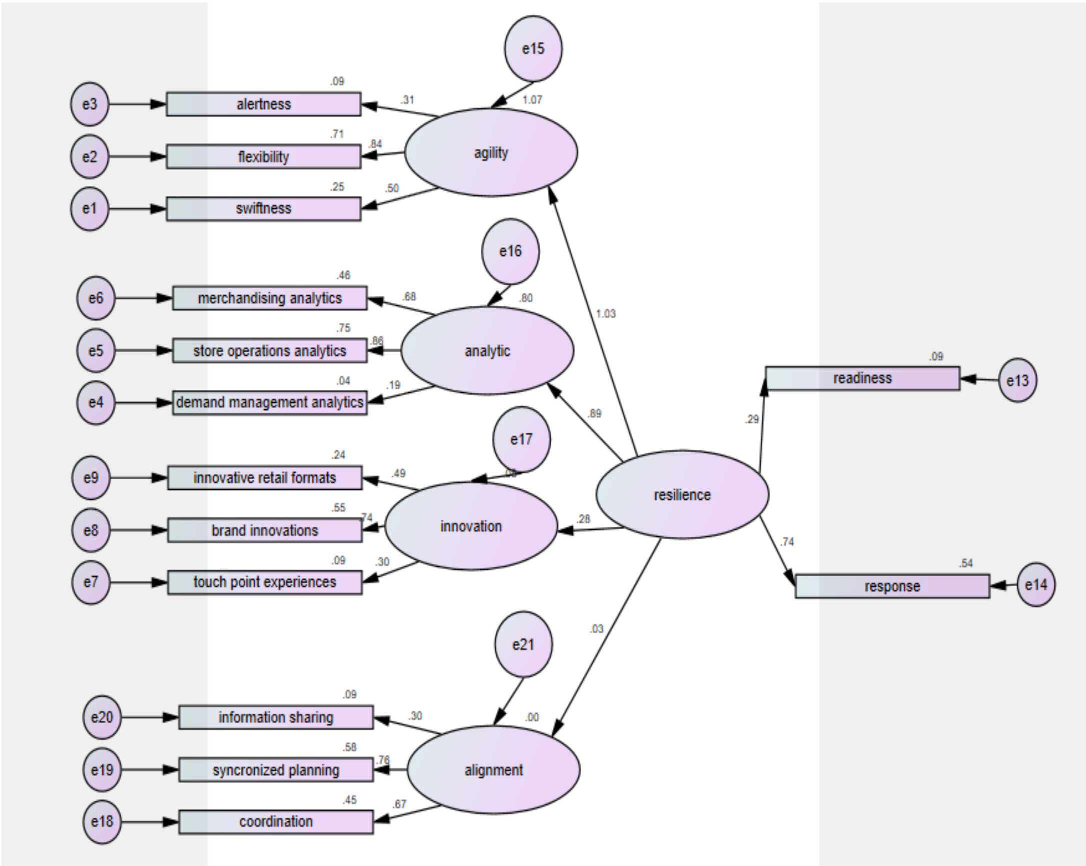

Figure 4.11: Optimal Model

CHAPTER FIVE

SUMMARY, CONCLUSION, AND RECOMMENDATIONS

5.1 Introduction

The section here is the last chapter of the thesis that endeavored to summarize the information obtained from the study participants on the relationship between dynamic supply chain capabilities and resilience in the retail sector in Kenya. Succinctly, the summary captured the key findings, which were based on the study objectives. More so, conclusions were drawn from the summary of the study, and so were the recommendations as they were drawn from the conclusions. Notably, summary, conclusions, and recommendations were drawn variables.

5.2 Summary

The summary of the findings of this study was presented as per the objectives.

5.2.1 Relationship between supply chain agility capability and resilience in the retail sector

From the descriptive statistics, the study established that retail chains were prompt in detecting changes in the business environment, seizing business opportunities, and sensing threats in the market environment. They possessed the dynamic capability to detect stock reorder levels. They, too, can sense shoppers' reactions to new merchandise. Concerning flexibility, retail chains were flexible enough to ensure on-shelf product availability, to undertake promotion to push sales to meet quarterly sales targets, and that they were also flexible to be swift enough to meet changes in customers' orders, tastes, and preferences. On quickness, the study established that retail chains quickly make and implement decisions regarding short-term capacity requirements, quickly adjust their merchandise to meet the diverse needs of their clientele, they quickly process customers' orders, and there are quick enough to provide the customers with an assortment of products and differentiate their SKUs.

The hypothesized model on the relationship between agility capability and resilience in the retail sector was acceptable and fit. The study rejected the null hypothesis that no statistically significant relationship exists between SC agility capability and the resilience Of Retail Chains of Stores in Kenya.

5.2.2 Relationship between supply chain analytics capability and resilience in the retail sector

Additionally, from the descriptive statistics, the study adduces that retail chains leveraged retail analytics to improve product placement, to increase cross-selling opportunities among their product portfolio. They, too, use retail analytics in merchandise space allocation to optimize inventory levels, by and large, decreasing inventory shrinks. They also use retail analytics to restock shelve merchandise automatically. Retail chains use analytics, specifically location analytics, to map in-store customer movements. Retail analytics indicates which sections of the retail chains receive the most traffic. It is also used to make personalized recommendations to customers; Further, analytics are used in retail chain sales/demand forecasting, in price optimization, and leveraged to determine merchandise pricing strategies and optimization of multichannel performance as well as enhancing social media presence. Additionally, based on the study statistics, the study rejected the null hypothesis that there is no statistically significant relationship between analytic capability and resilience of Retail Chain of Stores in Kenya.

5.2.3 Relationship between supply chain innovation capability and resilience in the retail sector

On the third research objective, the study established that retail chains use relative innovation strategies, such as opening flagship retail outlets in downtown or high-traffic areas to increase their markets-hare and sales. It also established that they have many products and innovative store layouts. Such is ideal as it deters customers from switching from one retail chain to another, increasing loyalty to the specific retail chain. More so, the study established that retail chains can use private labels in some of their merchandise categories. Private labels are pronounced in fast-moving consumer goods. The study also established that retail chains continuously develop innovative retail formats and innovatively stimulate shoppers' demand for products. They also leverage innovation to create positive customer touch-point experiences while safeguarding parsimony. The study also rejected the null hypothesis that there is no statistically significant relationship between dynamic innovation capability and resilience in the Retail Sector in Kenya.

5.2.4 Relationship between supply chain alignment capability and resilience in the retail sector

The descriptive statistics on supply chain innovation capability established that there is information asymmetry among the participants of the retail supply chain. The asymmetry is a result of information sharing across all echelons of the SC. Also, retail chains leverage the information obtained from EPOS to meet customers' needs. Additionally, retail chains use VMIs to share and align themselves with their suppliers upstream. Additionally, they jointly develop category-based and strategic plans internally and externally with other channel member participants. They also integrate various activities relating to merchandise management across the retail service chain. The study also rejected the null hypothesis that there is no statistically significant relationship between SC alignment capability and the resilience of Retail Chain of Stores in Kenya.

5.2.5 Moderating effect of supply chain configuration on the relationship between supply chain dynamic capabilities and resilience in the retail sector

The study sought to determine the moderating effect of supply chain configuration on the relationship between supply chain dynamic capabilities and resilience in the retail sector. Feedback from the study participants indicated that an increase in channel participants leads to a decrease in the order fulfillment rate. The study further established that total supply chain costs increase when the spatial distance between one retail chain to another is longer. And Globalization increases the uncertainties, which cause supply chain disruptions, and the higher the number of nodes, the less the lead times.

The study established that SCC negatively moderates the relationship between SC dynamic capabilities and resilience in the retail sector. Hence the study rejected the null hypothesis H05: Supply chain configuration does not moderate the relationship between dynamic supply chain capabilities and resilience of the Retail Chain of Stores in Kenya.

5.2.6 Relationship between supply chain dynamic capabilities and resilience in the retail sector

Going by the data obtained from the field, the study established that retail chains maintain the robustness of their chains by mitigating the impact of retail disruptions through safety stocks to buffer unexpected demand. The study also established that the retail chains are robust enough to maintain a desired level of control over structure and function ex-ante to disruption. Additionally, the retail chains have pre-defined contingency plans to decrease response time. They, too, have redundant capacities that they use in case of short-term disruptions. Further, they are robust enough to deal with the financial outcomes of potential supply chain disruptions. They can unleash redundant capacities such as multiple suppliers and slack resources in the retail chain. Retail chains can rebuild and reconstruct their retail chains. They, too, can quickly return the supply chain to its original state after a disruption.

Additionally, they can move their retail chains to a new or more desirable state after a disruption. They, too, have knowledge management capabilities to learn from feedback from disruption and develop better plans in the future. Additionally, resilience enables retail chains to maintain a strong market position. They have contingency plans that enable them to recover through situational analysis.

5.3 Conclusion

Academicians, practitioners, and quasi-governmental organizations have consistently endeavored to demystify why some players in the retail industry exhibit stellar performance whilst other players with the same operating environment remain in the doldrums. The study delved to unravel this mystery. The rigorous and vigorous empirical analysis of the nexus between dynamic supply chain capabilities and resilience in the retail sector in Nairobi City reaffirmed how SC dynamic capabilities, directly and indirectly, relate to retail resilience.

5.3.1 Supply Chain Agility Capability

From the findings, flexibility and swiftness contribute most to agility capability. From the hypotheses testing, the study reaffirms a relationship between supply chain agility capability and retail resilience. Agility capability is an intentional effort in organizations such as retail chains geared towards making the organization agile and flexible. Through agility, firms can easily adapt to emerging market trends and thwart existing turbulences, effectively precipitating resilience. Given that the retail landscape is changing from the traditional brick motor to e-tailing due to the high uptake of e-commerce, agility in these retail chains is inevitable. Through agility, retail chains can reconfigure their current structures identify market gaps, and seize marketplace opportunities.

5.3.2 Supply Chain Analytics Capability

Stores operations analytics and merchandising analytics contribute most to supply chain analytics. From the hypotheses testing, the study reaffirms a relationship between supply chain analytics capability and retail resilience. Supply chain analytics capability can bolster end-to-end supply chain visibility. Through SC analytics, a firm achieves resilience. The study has espoused a positive correlation between supply chain analytics capability and resilience. However, to reap the full benefits of analytics, firms should ensure full process integration across their supply chain, upstream and downstream, and end-to-end information synchronization/sharing. More so, the employees need to be competent in analytic skills.

5.3.3 Supply Chain Innovation Capability

Brand innovations and innovative retail formats contribute most to innovation capability. From the hypotheses testing, the study reaffirms a relationship between supply chain innovation capability and retail resilience. Continuous knowledge-seeking teases creativity and innovation. Through such innovations, organizations can meet the needs of their customers and surmount turbulences in the marketplace.

5.3.4 Supply Chain Alignment Capability

Synchronized planning and coordination contribute most to alignment capability. From the hypotheses testing, the study reaffirms a relationship between supply chain alignment capability and retail resilience. Through the Structural Equation Modelling approach, the study has demonstrated that supply chain alignment is achieved through information sharing, synchronized planning, and operational coordination. To this end, retail chains should share sales and demand forecast data with the channel participants upstream. They should ensure end-to-end visibility of retail chain activities and processes. Equally, they should invest in CPFR and VMI.

5.3.5 Supply Chain Configuration

From the hypotheses testing, the study reaffirms that SCC moderates the relationship between dynamic supply chain capability and retail resilience. Interestingly, the study negates the diverse conventional empirical stances that supply chain configuration positively moderates the relationship between dynamic SC practices and resilience in the retail sector. Notably, SC configuration negatively moderates the relationship between dynamic supply chain capabilities and the resilience of the Retail Chain of Stores in Kenya.

5.3.6 Resilience in the Retail Sector

The results of this study postulate and advance the knowledge of dynamic SC practices and resilience in the retail sector. It provides sufficient evidence of the facts postulated and contended herein and the nexuses. Notably, the structural model was a good fit even before post-ad-hoc modifications. Succinctly, the study adopts the dynamic capability view to demonstrate that supply chain practices are direct sources of resilience in the retail sector. Still, their impact is significantly reduced when moderated by supply chain configuration. It alludes that wholesomely, supply chain practices are necessary conditions and antecedents for maximizing resilience in the retail sector.

5.4 Recommendations

The study contends the following recommendations:

5.4.1 Relationship between agility capability and resilience in the Retail Sector in Kenya.

Given the research findings on the relationship between agility capability and resilience in the retail sector, the study recommends that retail chains focus more on flexibility and swiftness. It will enable them to exhibit ambidexterity ex-ante and ex-post disruptions. It will equip retail chains with the capability to identify and seize business opportunities and give a timely response to marketplace dynamics.

5.4.2 Relationship between analytic capability and resilience in the Retail Sector in Kenya.

Retail chains should leverage analytic capability, precise merchandising capability, and store operations analytics. In so doing, they can increase cross-selling opportunities, make personalized recommendations to customers based on past purchase behavior, make more pronounced and accurate demand forecasts, and eliminate the bullwhip effect.

5.4.3 Relationship between innovation capability and resilience in the Retail Sector in Kenya.

Retail chains should continuously be innovative in all facets of retail management. Based on the analyzed data, these retail chains should focus on innovative retail formats and brand innovations. It can be achieved through multiple ways, such as investing in private labels, especially in fast-moving consumer goods category and common user items; coming up with new retail formats that are consistent with the customer and marketplace dynamics; engaging in brand innovations to have a pronounced brand identity that their clientele can associate with. Despite touch point experiences contributing little to retail innovation, based on our data, we still recommend that retail chains revamp their different touch points as they significantly contribute to customer experiences by making the experiences episodic and memorable to the customer.

5.4.4 Relationship between alignment capability and resilience in the Retail Sector in Kenya.

Based on the data collected, the study recommends that retail chains engage in synchronized planning and coordination among the channel participants. In this regard, retail chains should integrate their processes. Intra-organizational integration between different retail outlets and inter-organizational integration with the strategic channel participants, such as suppliers of strategic supplies and customers, is vital for seamless supply chain flows. More so, the management of retail chains should have a strategic approach to category planning and, by extension, category management.

5.4.5 Moderating effect of supply chain configuration on the relationship between dynamic SC capabilities and resilience in the Retail Sector in Kenya.

From the analyzed data, the moderating effect of SCC reduced the relationship between dynamic SC capabilities and resilience in the retail sector. In this regard, the study makes some substantive recommendations; that retail chains should reevaluate their suppliers upstream and engage in objective supplier base reduction and rationalization in reconfiguring. The study recommends that retail chains foster strategic partnerships with strategic suppliers to eliminate upstream node barriers, leverage economies of scale, and eliminate superficial costs brought by extra SC nodes, which absorb their profit margins.

Despite the study findings showing a positive correlation between physical dispersion and supply chain costs, from a network perspective, the more dispersed a network is, the more fragmented the network becomes. Reasonably, given external factors beyond the scope of this study, the retail chains should refrain from engaging in an expansion spree but rather form physical clusters in high-traffic and densely populated areas such as in metropolitan counties and downtowns.

5.4.6 Policy Recommendations

The government of Kenya should closely scrutinize the retail chains in Kenya in a bid to enhance their resilience. It should adopt a national retail policy and a bureau to introduce regulations to at least police the retail sector. It is because self-regulation could be more fruitful given the trend analysis of the performance of most of the retail chains, save for a few. RETRAK should develop a code of conduct for retailers consistent with industry best practices.

5.5 Areas for Further Research

The study expressly reaffirms the axiomatic recognition of dynamic supply chain capabilities in retail logistics. Precisely, the study provides a novel yet dimensional contribution to the extant literature on the subject matter aforementioned using a theory-driven approach through Structural Equation Modelling to provide empirically evaluated practical insights into retail resilience using dynamic capabilities.

The study admits it wasn't exhaustive or immune to systematic and procedural biases. In this regard, future researchers should undertake further studies to establish the influence of supply chain configurations on the resilience of retail chains. Succinctly, having established that SCC has a negative moderating effect on the relationship between dynamic SC capabilities and resilience, qualitative researchers should conduct further studies to corroborate the findings herein. Further, it is the most considered view of this research that qualitative researchers should investigate this phenomenon of why SCC has a negative moderating contribution using a grounded theory approach. More so, a post-COVID evaluation of the retail chain's resumption to normalcy is timely.

The study admits and is conscious that supply chain practices are multi-dimensional constructs. However, the scope of the study was limited to four key first-order constructs of dynamic supply chain capabilities, agility, analytics, innovation, and alignment. In the future, researchers can endeavor to explore how other dimensions of dynamic SC capabilities contribute to resilience.

Future researchers should conduct further research on recovery and the measurement dimension of resilience using longitudinal data. The findings of such a study will provide managers with a latitude from which they can make decisions about recovery capability and mitigate decisional uncertainties during response and recovery. Additionally, future researchers should research supply chain analytics to better comprehend the necessary antecedents for value creation by adopting big data analytics.

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APPENDICES

Appendix I: Introductory Letter

Jomo Kenyatta University of Agriculture and Technology
P. O. Box 62000-00200,
NAIROBI
Mobile: 072978107
26th July 2021

Dear Respondent,

This questionnaire is part of a research thesis to establish the relationship between dynamic supply chain capabilities and resilience in the Retail Sector in Kenya. Your responses are important in enabling the researcher to obtain insights into resilience in the sector. The questionnaire should take you about five minutes to complete. Please answer the questions in the spaces provided. If you wish to add further comments, please feel free to do so. The information provided will be treated in the strictness confidence.

The answers from your questionnaire and others will be used as the main data set for my thesis, leading to an award of Doctor of Philosophy (Supply Chain Management) from Jomo Kenyatta University of Agriculture and Technology.

The nature of this research will require the researcher to triangulate your responses with a face-to-face, in-depth interview in near equivalent conditions to ensure that the data collected is reliable, vigorous, and robust.

The researcher hopes that you will find completing the questionnaire enjoyable.

Yours Faithfully,

Desmond Mwangi Wairimu
HD423-2011/2018

Appendix II: Questionnaire

This questionnaire establish**es** the relationship between dynamic supply chain capabilities and resilience in the Retail Se ctor in Large Retail Chains in Nairobi City County. The constructs under study are SC agility capability, SC alignment capability, SC analytics capability, SC innovation capability, SC configuration, and resilience in large retail chains.

Note that:

- All responses will be treated in the strictness confidence
- A copy of the study findings will be availed to your organization.

PART A: ORGANIZATIONAL DATA

Please provide the following information regarding your organization.

1. Indicate the name of your retail chain ………
2. Branch name……………………………………....
3. (a) Indicate the form of ownership of the retail chain (Tick one)
    a. Locally owned by a sole proprietor [ ] Yes [ ] No
    b. Locally owned through a partnership [ ] Yes [ ] No
    c. Locally owned by a limited company [ ] Yes [ ] No
    d. Foreign-owned company [ ] Yes [ ] No
    e. Foreign and locally owned [ ] Yes [ ] No
    f. Other [ ]

    (b) If ticked (f) in question 4 (a), please specify…………………………………….....

4. Indicate the number of years that your retail chain has been in operation. [Tick one]
   a. Five years or less [ ]
   b. 6 to 10 years [ ]
   c. 11 to 15 years [ ]
   d. 16 to 20 years [ ]
   e. More than 20 years [ ]
   f. Other [ ]

   (b) If ticked (f) in question 3 (a), please specify…………………………………….....

PART B: DEMOGRAPHIC INFORMATION

5. Indicate the department in which you work. [Tick one]
   a. Management level [ ]
   b. Customer Service [ ]
   c. Demand Planning [ ]
   d. Supervisory [ ]
   e. Procurement [ ]
   f. Floor Operative [ ]
   g. Any other [ ]

   (b) If ticked (h) in question 5 (a), please specify…………………………………….....

6. Indicate for how long you have been working in the retail chain.
   a. Less than five years [ ]
   b. 5-10 years [ ]
   c. 10-15 years [ ]
   d. Over 15 years [ ]

7. Indicate your highest level of education
   a. Diploma [ ]
   b. Undergraduate Degree [ ]

c. Post Graduate Degree [ ]
d. Over 15 years [ ]
e. Other [ ]

(b) If ticked (e) in question 7 (a), please specify………………………....

PART C: SUPPLY CHAIN AGILITY CAPABILITY

To what extent do you agree with the following supply chain agility capability statements?

Where SA= Strongly Agree, A=Agree, UD= Undecided, D =Disagree, SD= Strongly Disagree

S/No.	**Statements**	**Responses**				
		SA	**A**	**UD**	**D**	**SD**
1.	We promptly detect changes in the business environment.					
2.	We promptly identify and seize business opportunities in the business environment.					
3.	We promptly sense threats in the business environment.					
4.	We promptly detect stock re-order levels.					
5.	We promptly sense shopper's reactions to new merchandise					
6.	We are flexible enough to ensure there is on-shelf product availability.					
7.	We are flexible enough to handle shoppers' reactions to new merchandise.					

8.	We are flexible enough to undertake last-minute promotions to meet quarterly sales goals					
9.	We are flexible enough to react promptly to customer orders, tastes, and preferences changes.					
10.	We are flexible enough to seize opportunities that manifest in the marketplace.					
11.	We quickly implement decisions regarding increasing short-term capacity as needed.					
12.	We quickly provide various inbound logistics options, e.g., transportation, warehousing, and stock inventory.					
13.	We quickly adjust our merchandise to meet customer's needs					
14.	We quickly undertake order processing					
15.	We quickly undertake to retail an assortment of supplies					
16.	We differentiate our SKUs					

. Suggest other capabilities related to supply chain agility capability and resilience in your retail chain.

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PART D: SUPPLY CHAIN ANALYTICS CAPABILITY

To what extent do you agree with the following supply chain analytics capability statements?

Where SA= Strongly Agree, A=Agree, UD= Undecided, D =Disagree, SD= Strongly Disagree

S/No.	Statements	Responses				
		SA	A	UD	D	SD
1.	We use retail analytics to improve product placement					
2.	We use retail analytics to increase cross-selling opportunities.					
3.	We use retail analytics in assortment planning to enable assortment optimization					
4.	We use retail analytics in space allocation					
5.	We use retail analytics in product adjacency.					
6.	We use retail analytics to provide our customers with customized recommendations					
7.	We use retail analytics to optimize inventory levels.					
8.	We use retail analytics to decrease inventory shrink					
9.	We have adopted sensors to restock shelves automatically.					
10.	We use location analytics to map how customers move through a store.					
11.	We use a combination of IT tools to track which					

	sections of the store receive the most traffic.					
12.	We use retail analytics to make personalized recommendations and offers					
13.	We use retail analytics to undertake sales forecasting.					
14.	We use retail analytics to optimize the price of our merchandise.					
15.	We use retail analytics to develop better pricing strategies.					
16.	We use retail analytics to optimize multichannel performance.					
17.	We use retail analytics to enhance our social media presence.					

Suggest other capabilities related to supply chain analytics capability and resilience in your retail chain.

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PART E: SUPPLY CHAIN INNOVATION CAPABILITY

To what extent do you agree with the following supply chain innovation capability statements?

Where SA= Strongly Agree, A=Agree, UD= Undecided, D =Disagree, SD= Strongly Disagree

S/No.	Statements	Responses				
		SA	A	UD	D	SD
1.	We use new retail formats to keep abreast of market dynamics and constraints.					
2.	We sell our merchandise through both 'brick and motor stores and online retailing (e-tailing)					
3.	We use open flagship stores in either downtown or high-traffic areas.					
4.	We use open flagship stores in either downtown or high-traffic areas.					
5.	We have a wide assortment of products and a specific in-store layout.					
6.	We possess strong brand equity for our company, creating shoppers' loyalty.					
7.	We have pronounced private labels in some of the categories of our merchandise, such as milk and personal care products					
8.	We make continuous and significant improvements to current retail formats.					
9.	We innovatively stimulate shoppers' demand for					

	products.					
10.	We leverage brand innovations to meet shoppers' needs, tastes, and preferences.					
11.	We undertake retail advertising to create positive touch-point experiences for our shoppers in the interest of parsimony.					
12.	We undertake in-store communications such as viewing in-store posters and seeing prominent displays of on-shelf products.					
13.	We create positive touch-point experiences for our shoppers					
14.	We undertake word-of-mouth communication through social media platforms to create positive touch-point experiences for our shoppers.					
15.	We leverage earned media, such as editorial and news coverage					
16.	We influence shoppers' post-touch effect in a manner that remains in their episodic memory after that.					

Suggest other capabilities related to supply chain innovation capability and resilience in your retail chain.

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PART F: SUPPLY CHAIN ALIGNMENT CAPABILITY

To what extent do you agree with the following supply chain alignment capability statements?

Where SA= Strongly Agree, A=Agree, UD= Undecided, D =Disagree, SD= Strongly Disagree

S/No.	Statements	Responses				
		SA	A	UD	D	SD
1.	We share information about our sales and demand forecasts with our channel participants in the supply chain.					
2.	We ensure that there is end-to-end supply chain visibility of our retail activities.					
3.	We leverage independent demand from Electronic Points of Sale (EPOS) to meet customers' expectations.					
4.	We share sales data from EPOS to eliminate order blow-outs and decrease losses occasioned by the resulting *Bullwhip Effect.*					
5.	We share information across all echelons in the retail supply chain to optimize capacity utilization					
6.	We use Collaborative Planning Forecasting and Replenishment (CPFR) to collaborate on business plans.					
7.	We use Vendor Managed Inventories to share our retail chain's inventory status with suppliers upstream.					

8.	We treat product categories as strategic business units to plan and achieve sales and profit targets and satisfy customers' needs and preferences.					
9.	We jointly develop category-based plans internally in our retail chains.					
10.	We jointly develop strategic plans externally with suppliers to measure financial performance at the category level.					
11.	We integrate procurement, pricing, and merchandising of all brands in a category.					
12.	We provide various inbound logistics options to facilitate the delivery of inbound goods.					
13.	We adjust inventory, packaging, warehousing, and transportation of goods downstream to meet customers' needs.					
14.	We exhibit demand flexibility regarding order processing,					
15.	We exhibit purchasing flexibility through retailing of an assortment of supplies and differentiation of SKUs					

Suggest other capabilities related to supply chain alignment capability and resilience in your retail chain

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PART G: SUPPLY CHAIN CONFIGURATION

To what extent do you agree with the following supply chain configuration statements?

Where SA= Strongly Agree, A=Agree, UD= Undecided, D =Disagree, SD= Strongly Disagree

S/No.	Statements	Responses				
		SA	A	UD	D	SD
1.	The more channel participants, the higher the order fulfillment rate.					
2.	A less dispersed physical location translates to increased supply chain costs.					
3.	Globalization increases uncertainties, which causes supply chain disruptions. The higher the number of nodes, the less the lead-times					

Suggest other capabilities related to supply chain alignment capability and resilience in your retail chain.

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PART H: RETAIL SECTOR RESILIENCE

To what extent do you agree with the following statements about retail sector resilience?

Where SA= Strongly Agree, A=Agree, UD= Undecided, D =Disagree, SD= Strongly Disagree

S/No.	Statements	Responses				
		SA	A	UD	D	SD
1.	We anticipate and mitigate the impact of disruptions by using safety stocks to buffer unexpected demand					
2.	Our retail chain is robust enough to maintain a desired level of control over structure and function ex-ante to disruption.					
3.	We have pre-defined contingency plans to decrease response time.					
4.	We have redundancy capacities that are used as "shock absorbers" in the event of short-term disruptions.					
5.	We are robust enough to deal with the financial outcomes of potential supply chain disruptions.					
6.	We speedily respond to an influx in demand by reducing the probability of stockouts and lost sales in our retail chain.					
7.	We are speedily responsive to maintain a desired level of control over structure and function ex-post to disruption					
8.	We speedily deploy our pre-defined contingency plans to decrease response time.					
9.	We speedily unleash redundancy capacities such as					

	multiple suppliers and slack resources in our retail chain.					
10.	We speedily deal with the financial outcomes of potential supply chain disruptions in our retail chain.					
11.	We can quickly return the retail supply chain to its original state after a disruption.					
12.	After being disrupted, we can move our retail chain to a new or more desirable state.					
13.	We possess the knowledge management capability to learn from feedback from a disruption to develop better plans and solutions for future ones.					
14.	We maintain a strong market position characterized by financial strength, market share, and loss absorption allowing more investment in the resilience of the retail chain.					
15.	Our contingency planning capability enhances our retail chain's ability to recover through situational analysis. We can rebuild and or reconstruct our retail chain after the disruption.					

Was it easy for the respondents to respond accurately to your questions without table borders?

Suggest other ways in which your retail chain exhibits resilience.

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Appendix III: List of Registered Retail Outlets in Nairobi City County

Trading Name	**Branch**
1 Naivas	1. Airport View Branch, Syokimau Area
	2. Buru Buru Branch
	3. Capital Center Branch
	4. Development House Branch
	5. Eastgate - Donholm
	6. Githurai Branch
	7. Green House(Adams Arcade) Branch
	8. Hazina- South B Branch
	9. Jogoo Road(qwetu) Branch
	10. Kahawa West Branch
	11. Kangemi Branch
	12. Kasarani Branch
	13. Kiambu Rd(ciata Mall) Branch
	14. Kilimani Branch
	15. Komarock Branch
	16. Langata Branch
	17. Lavington Curve Branch
	18. Lifestyle - CBD Branch
	19. Moi Avenue Branch
	20. Mountain View Branch
	21. Mountain Mall Branch (Along Thika Road)
	22. New Ronald Ngala Branch
	23. Prestige Plaza Branch
	24. Riruta Branch
	25. Ruaraka Branch
	26. Saika

	27. South C Branch
	28. Tassia[fedha] Branch
	29. Umoja Branch
	30. Utawala Branch
	31. Waterfront(karen) Branch
	32. Waterfront(karen) Branch
2 Quicksmart	1. Quickmart Buruburu, Buruburu Phase 3, Mumias Road.
	2. Quickmart ChakaArgwings Kodhek Road, Nairobi.
	3. Quickmart Donholm Donholm, Outering Road, Nairobi.
	4. Quickmart Eastern Bypass
	5. Quickmart Eastern Bypass 2
	6. Quickmart Embakasi, Road to Utawala Academy, Nairobi.
	7. Quickmart Fedha, Fedha Road, Nairobi.
	8. Quickmart Jipange,Thika Road.
	9. Quickmart Kahawa Sukari, Kahawa Sukari Avenue.
	10. Quickmart Kahawa West, Kahawa Station Road.
	11. Quickmart Kiambu Road
	12. Quickmart Kikuyu Road
	13. Quickmart Kilimani
	14. Quickmart Lavington
	15. Quickmart Mfangano, Hakati Road, Nairobi.
	16. Quickmart OTC, Landhies Road, Nairobi.
	17. Quickmart Outering, Outering Road, Nairobi.
	18. Quickmart Pioneer, Moi Avenue, Nairobi.
	19. Quickmart Pipeline
	20. Quickmart Roysambu
	21. Quickmart Ruai
	22. Quickmart T-Mall
	23. Quickmart Tom Mboya, Tom Mboya Street, Nairobi.
	24. Quickmart Utawala Express

	25. Quickmart Utawala Main
	26. Quickmart Waiyaki Way
	27. Quickmart Westlands
3 Chandarana FoodPlus	1. Yaya Center, Argwings Kodhek Rd, Kilimani
	2. Adlife Plaza, Ring Rd, Kilimani
	3. The Well Mall, Langata Rd, Karen
	4. Karen, Karen Shopping Center
	5. Lavington Green Mall, James Gichuru Rd, Lavington
	6. ABC Place, Waiyaki Way, Westlands
	7. Waiyaki Way, Westlands, Peace Towers, Ngara Rd
	8. Diamond Plaza, Fourth Parklands Avenue
	9. Highridge, Masari Rd, Parklands
	10. Mobil Plaza, Muthaiga Rd
	11. Rosslyn Riviera Mall, Limuru Rd
	12. Ridgeways Mall, Kiambu Rd
	13. Signature Mall, Mombasa Rd
	14. The Stop at Rhapta, Rhapta Rd, Nairobi
	15. Riverside Square, Riverside Drive, Nairobi
	16. New Muthaiga Mall, Thigiri Ridge, Nairobi
4 Carrefour	1. The Hub Karen Carrefour Branch, Dagoretti Road, Karen, Nairobi, Kenya
	2. The Village Market Carrefour Branch, Limuru Road, Village Market, Nairobi, Kenya.
	3. Galleria Shopping Mall Carrefour Branch, Junction of Magadi and Langata Road, Nairobi, Kenya
	4. The Sarit Centre Carrefour Branch, Sarit Centre, Karuna Road, Westlands, Nairobi, Kenya
	5. The Junction Mall Carrefour Branch, Ngong Road, Nairobi, Kenya

	6. Thika Road Mall Carrefour Branch, TRM Drive, Nairobi, Kenya
	7. Two Rivers Carrefour Branch, Limuru Road, Nairobi, Kenya
	8. Carrefour Mega, Uhuru Highway opposite Nyayo Stadium, Nairobi, Kenya
	9. Carrefour Westgate, Westgate Shopping Mall at Westlands, Nairobi, Kenya
	10. Carrefour Southfield, Southfield Mall at Embakasi, Nairobi, Kenya
	11. Carrefour Supermarket NextGen, nexgen shopping mall, Nairobi, Kenya
5 Cleanshelf	1. Cleanshelf Lang'ata Branch, Lang'ata Road, Nairobi
	2. Cleanshelf Wendani Branch, Kahawa Wendani Estate, Nairobi.
	3. Cleanshelf Shujaa Mall Branch, Shujaa Mall, Spine Road, Next to Sosiani Estate, Nairobi.
	4. Cleanshelf Kahawa West Branch, Colimor Lane, Kahawa Station Road, Nairobi.
	5. Cleanshelf K-Mall Branch, K-Mall, Komarock Estate, Nairobi.
6 Tuskys	1. Tuskys Enkarasha, Kenyatta Avenue, Nairobi
	2. Tuskys Imara, Tom Mboya Street, Nairobi.
	3. Tuskys Eastlands, Buruburu/Mumias Rd.
	4. Tuskys T-Mall, Langata Road, Nairobi.
	5. Tuskys Athi River, Nairobi
7 Game Stores	1. The Water Front, Karen, Nairobi, Kenya.
	2. Garden City Mall, Off Thika Road, (Junction 7)

8 **Uchumi**	1. Uchumi, Langata Branch, Nairobi.
	2. Uchumi, Nairobi West Branch, Nairobi.
	3. Uchumi, Ngong Road Branch (Adams), Nairobi.
9 **Choppies**	1. Choppies Store, Embakasi, Southfield Mall, Airport Road, Nairobi, Kenya.
	2. Choppies Store HQ, Central Business Park, Road C, off Enterprise Road, Nairobi, Kenya
	3. Choppies Store, Tom Mboya, Oshwal Building, Next to Odeon Tom Mboya Street, Nairobi, Kenya.
10 **Shoprite**	1. Shoprite Garden City Store, Garden City Mall, Nairobi, Kenya
	2. Shoprite, Westgate, Nairobi, Kenya

Source: Retail Trade Association Kenya; 2019

Appendix IV: Research Permit

REPUBLIC OF KENYA

NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Ref No: **986178**

Date of Issue: **02/July/2021**

RESEARCH LICENSE

This is to Certify that Mr.. Desmond Mwangi Wairimu of Jomo Kenyatta University of Agriculture and Technology, has been licensed to conduct research in Nairobi on the topic: Relationship between dynamic supply chain capabilities and supply chain resilience in large retail chains in Kenya for the period ending : 02/July/2022.

License No: **NACOSTI/P/21/11597**

986178

Applicant Identification Number

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