DETERMINANTS OF ADOPTION OF DIGITAL SUPPLY CHAIN TECHNOLOGIES AMONG FAST MOVING CONSUMER GOODS MANUFACTURERS IN NAIROBI COUNTY, KENYA

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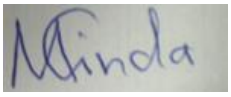
DECLARATION

I declare that this dissertation has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, this dissertation contains no material previously published or written by another person except where due reference is made in the dissertation itself.



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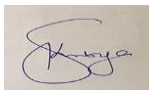

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DEDICATION

To my late father whose legacy of pursuing learning opportunities lives on through me.

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LIST OF ABBREVIATIONS AND ACRONYMS

AI	Adoption Intention
ANN	Artificial Neural Network
BCT	Blockchain Technology
BDA	Big Data Analytics
BI	Behavioral Intention
BCSCM	Blockchain For Supply Chain Management
DOI	Diffusion of Innovation
DSC	Digital Supply Chain
DSCM	Digital Supply Chain Management
DT	Digital Transformation
IoT	Internet of Things
ISSM	Information System Success Model
NACOSTI	National Commission for Science, Technology and Innovation
PBC	Perceived Behavior Control
PDF	Portable Document File
PEOU	Perceived Ease of Use
PU	Perceived Usefulness
SC	Supply Chain
SCM	Supply Chain Management
SCT	Supply Chain Technology
SLR	Systematic Literature Review
SU-IREC	Strathmore University Institutional Review and Ethical Committee
TAM	Technology Acceptance Model
TANEPS	Tanzania National e-Procurement System
TOE	Technology-Organizational-Environment
TPB	Theory of Planned Behavior
TPR	Theory of Perceived Risk
UTAUT	Unified Theory of Acceptance and Use Technology
UTAUT2	Extended Theory of Acceptance and Use Technology

ABSTRACT

The fast-moving consumer goods manufacturer companies are facing numerous challenges in their performance. Key among these challenges are stock outs, poor attainment of lead times, and overproduction thereby indicating an inefficient supply chain. Digitalization has highly been recommended as a means for companies to enhance efficiency of their supply chains while overcoming such challenges. However, it is unclear whether manufacturers of Kenyan FMCGs are using the available digital technologies in an effort to improve performance of their supply chain. Therefore, this research examined the demand-side determinants of digital supply chain adoption among FMCG manufacturers in Nairobi County. Its objectives were to: establish effect of performance expectancy on digital supply chain adoption manufacturers; establish influence of effort expectancy on digital supply chain adoption among FMCG manufacturers; establish influence of social influence on digital supply chain adoption among FMCG manufacturers; and establish effect of facilitating conditions on digital supply chain adoption among FMCG manufacturers. The unified theory of acceptance and use of technology and diffusion of innovation theories guided the study. The positivist research philosophy and a descriptive cross-sectional research design were adopted. The 146 FMCG manufacturing companies in Nairobi County represented the unit of analysis while units of observation were three supply managers selected from top, middle, and low-level of management. This made for a target population of 438 participants. Out of this, 205 participants were selected as the sample size and the research was able to receive back 132 responses from the administered questionnaire. The statistical package for the social sciences was used to analyse the data first using descriptive statistics to summarize data and thereafter testing for linear associations and relationships between variables. The correlation and regression analysis were performed at the 95% confidence level. This data was presented in tables supported by interpretations and discussion. The study findings revealed a positive and significant relationship between performance expectancy and social dimensions of the UTAUT with digital supply chain adoption. Then again, positive but non-significant relationships were observed between facilitating conditions and effort expectancy dimensions of the UTAUT with DSC adoption. It is the study's conclusion that performance expectancy and social influence are important components that managers should consider in their DSC adoption journey. Therefore, the study recommends for government policy on funding for digital hubs that provide innovation and creativity of digital supply chain technologies while providing education and training for FMCG companies to integrate these into their supply chains. In addition, the study recommends for FMCG manufacturing management companies to provide awareness and sensitization of emerging digital technologies in supply chains so as to promote familiarization of these technologies with the existing supply chain system. This study was limited to self-reported data which poses a threat to the internal validity of its findings. Second, a cross-sectional design means it missed out on the opportunity to show how different digital technologies have transformed the supply chains of FMCG manufacturing companies.

CHAPTER ONE
INTRODUCTION

1.1 Background of the Study

The COVID-19 pandemic was a period in which organisations appreciating the significance for adopting digital technologies in their operations (Dadsena et al., 2024). The pandemic resulted in disruption of supply chains and this situation contributed to the increase in the utilization of digitized supply chains (Lee et al., 2024). Majority of companies also adopted digitized supply chains as a means for withstanding ramifications of the pandemic and as a means by which companies could remain with efficiently operating supply chains during a crisis or any future uncertain events (Lee et al., 2024).

The breakdown in the international supply chain during the pandemic shifted focus towards resiliency of supply chains (Zhang et al., 2024). Thus, digitalizing supply chains cuts across sectors including in construction (Amal et al., 2024), health (Al Moteri & Alojail, 2023), manufacturing (Kalaitzi & Tsolakis, 2022; Lee et al., 2024), management information systems (Huang et al., 2023), agri-food supply (Sharma et al., 2024), retail (Daniels & Jokonya, 2021), e-commerce (Zaman et al., 2023), automotive (Simões et al., 2019), freight logistics (Sami et al., 2024), and Fast Consumer Moving Goods (FMCG) sectors (Ngure & Ismail, 2023).

This study focused on the FMCG sector that encompasses manufacturing of products that are sold quickly at relatively low cost, plays a significant role in the global economy. This sector includes a wide range of goods such as food and beverages, personal care items, and household products (Nwabekee et a., 2024). Despite its importance, the sector faces several supply chain challenges across the globe. In Bangladesh, FMCG supply chains are experiencing various challenges due to the interactions between consumers and decision-makers during physical distribution, manufacturing, wholesale and retail (Shakur et al., 2024). In India, FMCG business experiences inefficient supply chains, growing production costs, regulatory demands, and escalating competition from international brands, experts inadequate supply, longer lead times, higher operational expenses, a lack of transparency between supply chain stages (Khayer et al., 2022; Kumar et al., 2025).

According to Kudakwashe and Pooe (2024), the nature of FMCG operations in Africa, unlike in developed countries, is far more susceptible to a wide variety of potential

disruptions and delays, which causes uncertainty. In Nigeria, challenges faced by FMCG companies, including demand volatility, short product life cycles, and complex supply chains (Olutimehin et al., 2024). In south Africa, FMCG industry is heavily affected by challenges such as poor infrastructure, unreliable power and poor technological systems (Magagula et al., 2020). In Kenya, Rono (2023) reported that FMCGs manufacturers were making losses in their sales revenue attributing this to costs associated with the supply chain.

One possible strategy to address these challenges for smoothing the supply chain and logistics operations is to adopt Industry 4.0 based technologies in the FMCG business processes (Shakur et al., 2024). According to Tibokbe & Shankar (2025), emerging technologies in enhancing operational efficiency, market reach, customer satisfaction, engagement, and competitive advantage in the fast-moving consumer goods (FMCG) industry within underdeveloped markets. Kudakwashe and Pooe (2024) notes there remains a paucity of empirical studies in the area of strategies for the minimizing of supply-chain disruption. So far, many studies are conceptual and normative. Therefore, this study sought to examine determinants of adoption of digital supply chain technologies among fast moving consumer goods manufacturers in Nairobi County, Kenya.

Several studies highlight some important digital technologies for supply chains including blockchain technology (BCT) (Shahzad et al., 2024), Internet of Things (IoT) (Schmidt et al., 2023) and big data analytics (BDA) (Nguyen et al., 2023). According to Dadsena et al. (2024), approximately, 67% of companies view digital supply chain (DSC) as a disruptive technology while 40% of companies in the Asia-Pacific region deploy digital solutions to enhance their supply chain performance. Yet, more than 69% of organization leaders agree that social and economic disruption pushed them to hasten their digital business initiatives (Dadsena et al., 2024). Additionally, approximately 80% of actors in leading supply chains accelerated their digitalization after the pandemic (Dadsena et al., 2024).

Correani et al. (2020) caution that adoption of DSC may not always be successful since most firms invest in digital transformation (DT) but fail in achieving their expected business value due to a mismatch in the formulation and implementation of strategy. Thus, before adoption of any technology, it is imperative for companies to understand determinants of this process (Correani et al., 2020). Yang et al. (2021) emphasizes that firms

should strive to analyze motives, purposes, and drivers (why), followed by the methods and processes (how), and the results, outcomes, or impacts (what) for their adoption of DSC.

Notwithstanding the growing interest in DSC, the understanding of the why, how, and what of adopting DSC is scarce. Thus, business leaders and managers are still struggling to align their adoption processes with their drivers so as to attain the expected outcomes of DSC (Yang et al., 2021). In addition, research on barriers and drivers for its adoption of digital supply chain technologies is insufficient (Lu, 2017). Ghadge et al. (2020) cites a lack of comprehensive approaches and strategies for Industry 4.0 in supply chains.

The ideal of DT is significant for improving resilience of FMCG sector supply chain (Perifanis & Kitsios, 2023). DT provides steadfast and fast tempo places priority towards consumer satisfaction and has faced hindrances including disrupted supply chains, erratic demand of products, and need to switch adaptation to market fluctuations (Perifanis & Kitsios, 2023). Tazvivinga and Samuels (2024) indicates that DT contributes to improved transparency, data-informed decision-making, and agility and these are critical for strengthening the FMCG supply chain resilience.

The DT of an organization improves their resilience by enhancing their adaptability, efficiency, and integration to the turbulent or uncertain environment (Perifanis & Kitsios, 2023). Thus, digitalizing the supply chain of FMCG consists of deploying digital tools to improve visibility, become proactive in tackling obstacles, and optimize processes (Shakur et al., 2024). Nonetheless, FMCG manufacturing firms have been shown to be slow in their adoption of DSC technologies to improve resilience of their SCs (Hirsch et al., 2024). According to Hamadneh et al. (2023), limited academic interest has been devoted to enhancing comprehension of determinants of DSC. Therefore, examining determinants of adoption of DSC technologies in Kenya was important and timely.

1.1.1 Adoption of Digital Supply Chain Technologies

Due to the growing interest in digitalizing supply chains, several conceptualization or terminologies used to describe this phenomenon. These include the DSC, Digital Supply Chain Management (DSCM), smart SCM, intelligent SCM, and supply chain 4.0 (Zhang et al., 2024). Notwithstanding these different terminologies, the study uses DSC adoption as its dependent variable. This conceptualization has also been employed in past studies (Ageron et al., 2020; Lee et al., 2024). DSC refers to the application of emerging

technologies in improving performance of supply chains (Ageron et al., 2020). DSC integrates digital applications that are more aligned to consumers/customers, reduce inter and intra-organizational costs, and create additional value for organizations (Shah et al., 2023).

The subject of DSC adoption has been explored in the United States (Büyüközkan & Göçer, 2018), Italy (Rasool et al., 2022), Australia (Nakandala et al., 2023), Norway (Sharma et al., 2022), China (Fu et al., 2023), South Africa (Daniels & Jokonya, 2021), and India (Joshi et al., 2023). Additionally, DSC has been examined in the food sector (Barqawi et al., 2023), retail sector (Daniels & Jokonya, 2021), garments sector (Khan et al., 2024), and the manufacturing sector (Madho, 2023). This much interest from scholars and academicians has resulted to different ways in which DSC adoption has been measured.

Ageron et al. (2020) and Lee et al. (2024) measured DSC adoption by four items namely: knowledge management, networking, collecting, and processing data. Another construct widely used to measure DSC adoption is behavioural intention (BI) (Zhang et al., 2023; Sami et al., 2024; Nguyen & Nguyen, 2023; Adaryani et al., 2024). In their research, Gupta et al. (2020) and Barqawi et al. (2023), DSC adoption was measured by the construct adoption intention (AI) consisting of what advantage it has over existing technologies, how complex it was to use new technology, and degree to which these digital technologies are compatible to those in use.

Therefore, DSC adoption was measured by BI and AI constructs. BI describes the likelihood of an individual's intention to practice a certain behaviour while AI describes degree to which an individual becomes the first to accept and utilize emerging technologies in comparison to others in their social system (Lee et al., 2024; Barqawi et al., 2023). The intention to use DSC in the FMCG was critical to the study while the willingness of supply chain professionals to use DCS contributes to acceptance throughout the organization.

1.1.2 Determinants in Adoption of Digital Supply Chain Technologies

Existing literature indicates there are a variety of determinants to DSC adoption. Daniels and Jokonya (2021), Kalaitzi and Tsolakis (2022), and Hamadneh et al. (2023) found that the five dimensions of the Diffusion of Innovation (DOI) theory influenced DSC adoption. Zaman et al. (2023) and Lin et al. (2021) established that technology acceptance model (TAM) and theory of planned behaviour (TPB) dimensions influenced DSC adoption.

Others (Shahzad et al., 2024; Lin et al., 2021) found that user satisfaction, organizational impact, individual impact, system and information quality had an effect of DSC adoption. In other studies, components of the unified theory of acceptance and use of technology (UTAUT) and the extended unified theory of acceptance and use of technology (UTAUT2) exhibited both positive and negative effects on DSC adoption (Queiroz & Pereira, 2019; Nguyen et al., 2023; Zhang et al., 2023; Shahzad et al., 2023; Sharma et al., 2024). Aamer et al. (2023) found that readiness for supply chain digitalization was influenced by staff training, organizational culture, and top management support.

The above discussion indicates there are different determinants of DSC adoption and these can be categorized under technological, organisational, environmental, and individual factors. This study proposed to adopt those individual factors as it aimed to gather information from SC experts on their use of available digital technologies for SCM. Thus, the UTAUT components of performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC) were adopted as this study's independent variables.

Individually, PE is the belief that a person has that utilizing a system will assist them to make gains in performing their job (Venkatesh et al., 2003). EE is the ease that a person associates with the use of a system. SI explains the perception that a person holds about their use of a system based on the views of those important to them. Facilitating conditions are those factors than an individual believes they exist at the organization and in terms of technology infrastructure for them to adopt a technology (Venkatesh et al., 2003).

The study contributes to knowledge by using the four constructs in the adoption of digital technologies in the supply chain. Supply chain professionals typically evaluate technologies based on their ability to improve inventory management, logistics coordination, and overall operational performance (performance expectancy). Digital supply chain systems are often complex and their adoption cuts across the organization and may face resistance and this requires adequate training and allocation of resources to be successful (effort expectancy) (Shahzad et al., 2024).

The adoption of DSC among leading FMCG companies may result in the adoption of these technologies by smaller firms (social influence). There are environmental factors that may influence the adoption of digital supply chain technologies that may require technological

integration across multiple FMCG organizations including interoperability standards, shared data protocols, and technical support spanning organizational boundaries (Lin et al., 2021). Thus, these constructs emerge as most suitable as this study's independent variables.

1.1.3 Fast Moving Consumer Goods Manufacturers in Kenya

The FMCG industry consists of consumer-packaged products that include groceries and other consumable goods that are purchased regularly. These products are fast-selling usually at a lower cost and consist of non-durable commodities including toiletries, household goods, beverages, packaged foods, drugs, cosmetics, and candies amongst others (Rono, 2023). Majority of FMCG products have low price points, a shorter shelf life, and high sales volumes that requires an efficient SCM to guarantee customer satisfaction and profitability (Wambua et al., 2023). The FMCG distribution chain consists of interrelated mix of related resources and processes in which suppliers, manufacturers, warehouses, logistic services, distributors, retailers, and consumers (Wambua et al., 2023).

The complex logistics management demanded by the sectors vast distribution network presents a challenge for supply chain performance. The FMCGs supply chain is characterized by long distances from raw inputs to transportation of finished products (Wambua et al., 2023). These facilities may be under the operation of an organization of they may be operated by customers, vendors, third-party providers, or companies that the organization has an arrangement with (Wambua et al., 2023).

This dispersion when not handled well could cause a major breakdown in entire supply chains. This is a challenge that SC digitalization could help address. The support for DSC contents that it affords seamless partnership relationships with amalgamated data and business processes by coordinating and harmonizing all elements of the FMCG manufacturing supply chain from inputs to finished product while achieving higher levels of overall performances well as cutting costs (Chauhan et al., 2023).

Muhalia, Ngugi, and Moronge (2021) note that the sector suffers from its complex distribution network and has recently experienced disruptions due to global events such as the Ukraine and Russia conflict and the pandemic. These events have resorted to unprecedented pressure and crisis for the sector. Several studies (Amal et al., 2024; Zaman et al., 2023; Ngure & Ismail, 2023) provide anecdotal evidence on the importance of digitalizing supply chains to enhance resilience in different sectors.

Digitization of transactions and payments tends to allow the value chain actors better manage their cash flow and finances across all layers of the supply chain while also allowing firms to improve their supply chain resilience (SCR) and forecasting on market dynamics, customer preferences, and lead times (Hossain, 2024). Overall, using digital technologies in FMCG supply chains may allow companies to match their production timelines closely with actual demand, reduce stockouts and overproduction and improving time-to-market (Shaji & Hovan, 2023).

The FMCG manufacturing sector is a vibrant sector in Kenya, but its performance has been on the decline. Growth of FMCG via manufacturing sector in relation to GDP has been on a fluctuating trend with 5.7 % in 2015, 5.9 % in 2016, 4.9 % in 2017, 6.3 % in 2018, 5.4 % in 2019 and 1.5 % in 2020 compared to the previous average contribution of 10 % (Rwamba, 2024). The sector faces several challenges in their performance. For example, Otieno (2018) found that lack of managerial support, inadequate communication, and costs of implementation were constraints for effective distribution of products among FMCG manufacturers in Kisumu County.

Otieno (2022) notes that FMCG companies were closing their operations in Kenya due to poor performance such as Cadbury Kenya Limited. Mwangangi (2022) also highlights the exit of the Eveready East Africa (EA) company due to poor performance due to rising expenses and costs despite its position as a forerunner in Kenya's FMCG manufacturing sector. Recently, Rono (2023) reported that FMCGs manufacturers were making losses in their sales revenue attributing this to costs associated with the supply chain. However, among FMCGs in Kenya it is not well understood if these firms have embraced DSC.

1.2 Problem Statement

Supply chain disruptions in Kenya's FMCG sector was reached worrisome levels given the movement restrictions imposed during the COVID-19 pandemic (Langat & Karanja, 2021; Gitau, 2023). There is global evidence that adoption of DSC technologies has better outcomes for FMCG companies. Perifanis and Kitsios (2023) found that digitalizing supply chains in FMCGs firms resulted in swift adaptation to market and environment changes to meet erratic demands and disruptions and overall adaptability. Shakur et al. (2024) concluded that digitalizing FMCG supply chain enhanced visibility, optimized processes, and proactively tackled obstacles. In South Africa, Tazvivinga and Samuels (2024) found that FMCG companies were able to enhance agility, transparency, and data-driven decision-

making by adopting digital technologies in their supply chain thereby bolstering their resilience.

Several studies (Lin, 2014; Cagliano et al., 2021; Kalaitzi & Tsolakis, 2022; Aamer et al., 2023; Hamadneha et al., 2023) have examined determinants of DSC. However, there is a lack of consensus agreement on those factors. Thus, different variables have been found to pose an influence on DSC in different sectors and this makes it difficult to describe these factors efficiently for FMCG manufacturers.

Empirical research into DSC adoption in Kenya is scarce. Some of these studies include Makokha (2017) found that supplier digitization variables influenced organizational performance in Kenya Power through its supply chain. Wanjau (2022) study on supply chain digitalization established that information from public procurement portals, employee digital proficiency, and data consolidation had positive effects on procurement transactions. Ngure and Ismail (2023) examined supply chain digitalization among selected manufacturing FMCG companies finding that taking orders digitally resulted in companies being able to reduce stock holding and thereby enhancing their overall performance. Despite these studies, there is limited evidence of the determinants of supply chain practitioners towards DSC and this warrants this investigation. Therefore, the study aimed to examine determinants of DSC among FMCG manufacturers in Nairobi County.

1.3 General Objective

The purpose of this research was to determine the of adoption of digital supply chain technologies among fast moving consumer goods manufacturers in Nairobi County, Kenya.

1.3.1 Specific Objectives

These specific objectives guided this study.

i. To establish the effect of performance expectancy on adoption of digital supply chain technologies among FMCG manufacturers in Nairobi County
ii. To establish the influence of effort expectancy on adoption of digital supply chain technologies among at FMCG manufacturers in Nairobi County
iii. To establish the influence of social influence on adoption digital supply chain technologies among FMCG manufacturers in Nairobi County
iv. To establish the effect of facilitating conditions on adoption of digital supply chain technologies at FMCG manufacturers in Nairobi County

1.4 Research Questions

This research aimed to answer these questions;

i. What effect does performance expectancy have on adoption of digital supply chain technologies among FMCG manufacturers in Nairobi County?
ii. What effect does effort expectancy have on adoption of digital supply chain technologies among FMCG manufacturers in Nairobi County?
iii. What effect does social influence have on adoption of digital supply chain technologies among FMCG manufacturers in Nairobi County?
iv. What effect do facilitating conditions have on adoption of digital supply chain technologies among FMCG manufacturers in Nairobi County?

1.5 Scope of Study

The study was limited to the following boundaries. Conceptually, there are a myriad of factors that have been found to have a role in DSC adoption. Nevertheless, the study is limited to these four dimensions of the UTAUT as its predictor variables. The dependent variable was DSC adoption measured by behavioural and adoption intention. Second, the study focused on FMCGs manufacturing companies in Kenya but limited its setting to those in Nairobi region as the largest firms in this sector operate from this location. Therefore, FMCGs companies in other regions around the country were not be included in the survey. Theoretically, the research was anchored on UTAUT and DOI theories. In terms of its methods, a positivist paradigm was followed where a descriptive research design was adopted. Lastly, the study was conducted from February to April 2025.

1.6 Significance of the Study

1.6.1 Policy and Decision Makers

This study may be beneficial to policy and decision makers as the FMCG manufacturing sector remains exposed to global crisis that disrupt entire supply chains. These disruptions have negative consequences on logistics and this in turn transfers costs to consumers. Therefore, its findings and recommendations will assist these actors to create policy, guidelines, and standards that will improve adoption of digital technologies to enhance resilience of SCs in among FMCG manufacturing companies.

1.6.2 Top Management

The study hopes to benefit top management in FMCG manufacturing companies. Top management come up with strategies that are aimed to improve better performance of their

companies and the supply chain for these companies remains a critical success factor. Therefore, by identifying those determinants for DSC adoption and making recommendations for top management will make their role easier in implementing activities and actions that will enhance adoption of DSC in their respective companies.

1.6.3 Supply Chain Practitioners

DSC adoption in supply chain activities fall under the purview of professionals and practitioners. Therefore, the study will be of significance to these staff in the selected FMCG companies as it provides the opportunity to understand determinants to DSC adoption activities. Supply chain practitioners will be able to highlight those determinants of behavioural intention and this information if adopted by top management will make it easier to adopt digitalization of the supply chain.

1.6.4 Researchers and Scholars

There is abundant literature on determinants of digitalization of supply chains from a global perspective, less on a regional perspective, and even more scarce for the Kenyan setting. This research will thus contribute to new knowledge and empirical evidence on determinants of DSC adoption in its FMCG industry. Moreover, the UTAUT and DOI have been well explored in terms of adopting digitalization in supply chains but this evidence in the local context is missing; thus, this research will make this contribution. Lastly, suggestions for future research will be outlined.

1.7 Chapter Summary

Ongoing phenomenon of digitalizing supply chains to enhance resilience in face of disruptions posed by global events such as the pandemic and conflict set this chapter. In this chapter, the determinants of digitalization and providing a concise definition of digitalization of supply chains was presented as well as an overview of the FMCGs industry in Kenya. The problem is contextualized and elaborated to show the contribution to knowledge that this study would make.

CHAPTER TWO
LITERATURE REVIEW

2.1 Introduction

This chapter begins by introducing the theories underpinning this study. The empirical literature section analyzes studies in this area showing the similarity and difference between scholars' findings. A literature review and summary of gaps, conceptual framework, and operationalization of variables is also presented at the end of the chapter.

2.2 Theoretical Framework

The study adopted the Unified Theory of Acceptance and Use Technology (Venkatesh et al., 2003) and Diffusion of Innovation (Rogers, 1962) theories.

2.2.1 Unified Theory of Acceptance and Use Technology

Venkatesh et al. (2003) advanced UTAUT theory and its main proposition is that behavioural intention (BI) is the perceived chance of using a new technology. BI is influenced by PE, EE, SI, and FC (Marikyan & Papagiannidis, 2020). PE is the belief that a person has that utilizing a system will assist them to make gains in performing their job (Venkatesh et al., 2003). EE is the ease that a person associates with the use of a system. SI explains the perception that a person holds about their use of a system based on the views of those important to them.

Facilitating conditions are those factors than an individual believes they exist at the organization and in terms of technology infrastructure for them to adopt a technology (Venkatesh et al., 2003). The BI construct describes intention of a user to make plans and take decisions to use a technology. It is a subjective likelihood that a person will perform some behavior (Venkatesh et al. 2003). It is measured by the intent, expectation, and plan to use a technology. Therefore, this construct is used as a proxy to measure DSC adoption.

The UTAUT has been criticized for it being unable to explain BI of users in various settings and thus has limitations in terms of its generalizations due to its constraints in explaining relationships based on different culture, country, age group, community, department, or agency (Marikyan & Papagiannidis, 2023). Two, Shachak et al. (2019) criticized the theory for being too narrow focused and simplistic on the individual and lacks to consider the complex context of socio-technical system (technological, organizational, and social

components). The theory has been accused of narrowing down determinants of technology adoption to individual expectations or perceptions (Bayaga & du Plessis, 2023).

Notwithstanding these limitations, the UTAUT remains an important theory for which to understand decision to use technologies. The UTAUT was therefore used to explain adoption of emerging technologies among FMCG manufacturing SC practitioners. The study was focused on the individual factors of adoption of DSC and the theory thus remained relevant in understanding the decision process of using these technologies in their jobs. The four dimensions were thus adopted as the independent variables of the study. Other research has found positive (Ha & Linh, 2018; Shahzad et al., 2024) and negative (Queiroz & Pereira, 2019; Nguyen et al., 2023) effects of these dimensions on DSC adoption. The inconclusive nature of these outcomes further shows the relevance of testing the UTAUT in the Kenyan context.

The perceived expectancy dimensions apply to the FMCG sector as DSC can be used to improve delivery timelines, demand forecasting, and inventory management and this means managers must promote DCS in the organization to show that it will benefit supply chain staff. Tn terms of effort expectancy, FMCG companies have high complexity and volume and this means that promoting integration and simplicity of digital tools will be significant for better supply chain performance. managers should therefore ensure that staff in supply chains are onboarded and provided with adequate training on DSC.

The social influence dimension of the theory explains the importance of top management in promoting DSC in the FMCG organization and this also includes support from regulators, logistic providers, and retail partners. The facilitating conditions dimension means that FMCG management must strive to provide the adequate infrastructure for DCS adoption in their supply chain including budget allocations to IT, IT support, and sufficient change management practices.

2.2.2 Diffusion of Innovation Theory

Rogers (1983) advanced the DOI theory based on communication, management, and sociology research. The DOI describes a social process in which information of a new technology or innovation is dependent on the idea that it has perceivable channels, mode, and time of being adopted by a company or individual (Rogers, 2003). The DOI is understood by its five dimensions elaborated further in the following paragraph.

The relative advantage dimensions describe the idea that an innovation offers better prospects than the one currently in use. The compatibility dimension elaborates the extent that an innovation matches with existing needs, experiences, and values. The complexity dimension describes if emerging technologies are easy or difficult to use. The triability dimension speaks to the capacity that a person may have to try new technology at a small scale before committing to its full adoption. The observability dimension holds that innovations must give results that can be noticed (Rogers, 2003).

The DOI has been used in other studies previously. For example, Gitau (2023) associated its complexity, triability, and relative advantage dimensions with the digital transformation of supply chains among FMCG manufacturing firms. Gupta et al. (2023) used complexity, relative advantage, and compatibility dimensions to understand AI of DSC technologies among manufacturing firms in India. Faisal and Idris (2020) used DOI to explain the determinant for Supply Chain Technology (SCT) adoption. Therefore, DOI dimensions of relative advantage, complexity, and compatibility as used in Gupta et al. (2023) research were used as a proxy for AI of DSC technologies.

The DOI has received some criticisms despite its wide adoption in innovation adoption. First, DOI is accused of assuming that individuals make rational, well-informed decisions of the innovation. In reality, decisions are often influenced by emotional, social, and cognitive biases, as well as external pressures, making the adoption process less rational (García-Avilés, 2020). The study remained objective and expected respondents to give their decisions to use DSC based on rational thinking. Second, its linear approach of moving from knowledge to persuasion to decision and so on oversimplifies the complex, dynamic, and non-linear nature of how innovations spread. Yet, the adoption process is murky and less predictable with several influences, reversals, and feedback loops that the DOI ignores (García-Avilés, 2020). However, since the study focused on the individual and not the intricacies of the organization, the DOI remained relevant to understand DSC adoption.

The compatibility, complexity, and relative advantage components were used to adapt the adoption intention of DSC adoption among supply chain professionals. The compatibility dimension explains the degree to which that supply chain staff believe that digital technologies match the existing corporate culture, supply chain processes, and existing systems. Complexity dimension describes the level of training and digital literacy that staff may require to be able to use DSC with less complex systems leading to adoption and high

complex systems reducing adoption. Relative advantage dimension speaks to the possible benefits that DSC will provide for FMCG supply chain staff including faster decision-making, lower operational costs, and improved visibility.

2.3 Empirical Literature

This empirical review described various research that have examined adoption of DSC technologies based on the four dimensions of the UTAUT theory. The studies highlighted are presented from a global, regional, and local perspective. The significance of these studies to this research are also highlighted.

2.3.1 Performance Expectancy and Adoption of Digital Supply Chain Technologies

The concept of performance expectancy describes a situation in which individuals trust that utilizing a technology will assist them in overcoming difficulties and assist them attain desired goals in their work (Shahzad et al., 2024). Performance expectancy directly influences the individual perception of a technology and therefore believe that utilizing a specific technology will enhance their performance, efficiency or effectiveness in completing tasks, they are more inclined to adopt that technology (Amal et al., 2024).

The adoption of BCT in supply chains is well represented in the literature. In Vietnam, Nguyen et al. (2023) combined the UTAUT and TOE theories to examine factors that influence BCT adoption in SCM. The targeted group were professionals in supply chain sampled via judgmental sampling method. The results revealed PE had a significant effect on operating BCT in SCM. This study contributes to understanding of BCT is one of the technologies that has become relevant for the ongoing digitalization of supply chains.

In China, Shahzad et al. (2024) adapted the information system success model (ISSM) and UTAUT theories to see what factors had an influence in adoption of BCT in SCM. A questionnaire was administered to professionals in supply chains and PE was confirmed to positively affect BI. In another research, Zhang et al. (2023) investigated BI to use BCT among operation and SCM professionals under UTAUT, TRI, technology affinity, and trust theories. The survey revealed that adoption of BCT was negatively influenced by performance expectancy. The findings suggest that adoption of BCT in supply chains may have a negative relationship with performance expectancy. This study is relevant as it shows the need for more research to determine the direction of this relationship.

In Pakistan, Zaman et al. (2023) evaluated how digital banking contributed to increased resilience of e-commerce service supply chain using Technology Readiness Index (TRI) and TAM theories. Using data collected from five experts in supply chains selected via purposive sampling, PE was confirmed to be a factor explaining adoption. The finding provides evidence that DSC in supply chains provides some aspect of resilience and this is relevant for this study as resilience has been a goal for the FMCG sector in Kenya.

In another research, Zhang et al. (2023) investigated BI to use BCT among operation and SCM professionals under UTAUT, TRI, technology affinity, and trust theories. The sample of 198 respondents from an online survey revealed that adoption of BCT was negatively influenced by performance expectancy. The adoption of BCT in supply chains may result to negative relationship with performance expectancy. This study is relevant as it shows the need for more research to determine the direction of this relationship.

The previous studies suggest the performance expectancy has both positive and negative effects on adoption of technology in supply chain. However, other research does not find any relationship between these variables. For instance, In Brazil, Queiroz and Pereira (2019) evaluated big data adoption among SCM experts using UTAUT theory scale questionnaire administered through LinkedIn. The 152 respondents revealed PE did not have any influence on adoption.

In Tanzania, Shatta et al. (2020) explored determinants of eProcurement adoption framework for green procurement anchored on the TOE and UTAUT of the Tanzania National e-Procurement System (TANePS). A cross-sectional survey used both probability and non-probability methods to select 157 respondents and the analysis revealed that e-procurement adoption was influenced by perform expectancy. This study provides understanding of the performance expectancy construct in explaining adoption of digital supply chain technologies in both public and corporate organizations. The next section of the review focuses on the effort expectancy variable.

2.3.2 Effort Expectancy and Adoption of Digital Supply Chain Technologies

The concept of effort expectancy describes the extent to which that use of a technology or system is easy to an individual (Venkatesh et al., 2003). The evidence has shown that people make the rational decision to start using a technology if it does not need them to put much effort in how to utilize it and essentially use it (Ha & Linh, 2018). Those technologies

designed to minimize user effort and provide a seamless, enjoyable experience are more likely to be adopted because as an individual believes the new method is more comfortable and convenient to apply, they will likely accept that technology (Amal et al., 2024).

The BCT trend in supply chains has received considerable attention from researchers. In Vietnam, Nguyen and Nguyen (2023) assessed effects of effort expectancy on its BI including trust as a mediator variable. The UTAUT and the TOE were used to guide the research and the 281 SCM employees were selected via judgmental sampling. The research outcome indicated a positive effect of effort expectancy on BCT use in SCM. A limitation of this research was the selection of its sample that limited its generalizability of findings.

Using a sample of Malaysian SMEs, Wong et al. (2020) conducted research on BI towards blockchain for supply chain management (BCSCM) anchored on the UTAUT dimensions. The sample consisted of 157 firms from which information shared revealed that EE did not have any effects on BI towards BCSCM. The findings are important for this research as they justify the need for examining the relationship between EE and adoption of digital supply chain technologies as it did not find any connection between these variables.

The adoption of green supply chain practices in supply chains is an emerging concern for the sustainability and resilience of this profession. Thus, moving to a sample of social enterprises, Lian (2023) did an exploration into if and how UTAUT antecedents explained green supply chain innovation administering questionnaires to 410 managers in five states. The analysis did confirm that effort expectancy had a positive effect on adoption of green supply chain innovations. The findings are important for this research as they show the versatility of the EE variable in DSC adoption in supply chains.

While most studies have administered their surveys to supply chain professionals, Ha and Linh (2018) assessed how supply chain experts in food retail supply adopted BCT using an abductive approach in Malta. The sample consisted of 203 end-consumers administered a survey via online and offline methods that incorporated qualitative and quantitative data. EE was found to possess direct positive impacts on BI providing evidence that EE variable was important for professionals as well as end-consumers. Yet, caution is needed in the generalizability of these findings as consumers may have mixed knowledge and information on supply chains.

The domination of e-commerce in the retail sector today necessitates research into what determinants influence its adoption. In their contribution to generating this knowledge, Ngwira and Phiri (2024) combined the UTAUT and Theory of Perceived Risk (TPR) to examine factors influencing consumer and retail good traders BI for e-commerce SCM in Zambia. The data from 329 traders' data revealed that EE had a negative effect on BI of retail and consumer goods traders to adopt e-commerce. The result is important for this research as they will be instrumental in the discussion of its findings as it aims to show support or refute the relationship between these variables. The next section of the review focuses on the social influence variable.

2.3.3 Social Influence and Adoption of Digital Supply Chain Technologies

Social influence describes the degree to which an individual viewpoint is determined by the extent to which others in their environment that dislike or like a technology (Wamba & Queiroz, 2019). It is the extent an individual perceives important others believe the new technology should be used and this can be exerted by family, friends, and peers (Wamba & Queiroz, 2019).

In Brazil, Wamba and Queiroz (2019) aimed to understand BCT adoption practices in supply chain using a model using UTAUT model. The data from surveys administered via LinkedIn to top supply chain experts revealed SI explained BCT behavioural intention. The study's administration or selection of respondents was limited to a social platform that may is not popular among supply chain professionals and therefore limits the generalizability of these findings. However, the study provides more evidence on the versatility of the UTAUT model in understanding digital supply chain technologies adoption.

In China, Lin et al. (2021) used models anchored on ISSM and TPB to assessed blockchain food traceability system (BFTS) adoption factors among consumers. The responses from 300 respondents determined that subjective norms had no effects on BFTS adoption. The study was important in showing the influence of social factors on adoption of digital technology in supply chains. However, its sample consisted of consumers who may not be familiar with the integral aspects of the supply chain. Therefore, this study uses professionals in the supply chain as its respondents.

In Pakistan, Sami et al. (2024) examined BCT usage in the freight logistics sector to find the influence of PEOU, PU, subjective norms, Perceived Behavioural Control (PBC), and

attitude. The sample consisted of 245 logistics sector operators. Output indicated that cultural and social factors (subjective norms) had an influence on BI. The study while showing the influence of social factors on BI of BCT in supply chains, it did not use the UTAUT dimension of SI. Yet, it will make an important contribution to the discussion of the present research findings.

Using desk review research, Martins et al. (2020) did an evaluation of obstacles and challenges that Industry 4.0 innovations may place on supply chains. Out of the studies reviewed, 20 challenges were identified and categorized under four groups namely: financial, legal, and environmental challenges, technical challenges, socio-cultural challenges, and technological challenges. this study was a desk review of past studies and its findings and conclusions are devoid of empirical evidence. However, it remains relevant for this research as it contributes to socio-cultural influence in DSC adoption supply chains.

In Korea, Park (2020) explored those factors that influence utilization of BCT in logistic industry applying the TOE and UTAUT theories employing cross-sectional research. There were 158 supply chain managers contacted that had a minimum of ten years' experience and data processed from this group indicated SI had an effect on adoption intention of BCT. The findings are important as they justify the use of SI and UTAUT as a framework for selecting determinants for adoption of digital supply chain technologies. Its use of supply chain managers also informs the selection of management staff in supply chain as respondents in this study. The next section of the review focuses on the facilitating conditions.

2.3.4 Facilitating Conditions and Adoption of Digital Supply Chain Technologies

Facilitating conditions is the degree that a person is able to trust that real-world and structural infrastructure is already present to allow for the utilization of the system (Francisco & Swanson, 2018). It is the anticipated expected level of technical and organizational infrastructure that can support the utilization of a technology (Francisco & Swanson, 2018). These facilitating conditions go beyond the technology that is being examined but also speaks to the organizational culture that may either promote or hinder adoption of a technology (Francisco & Swanson, 2018).

Using UTAUT, Al Moteri and Alojail (2023) investigated the motivations of professionals in using IoT in the health sector in Saudi Arabia to show those factors that influence its use

in e-HMS. The survey contacted 210 users of IoT selected via convenience sampling methods. The results indicated of the contribution of facilitating conditions in reducing costs, improving patient outcomes, increasing effectiveness and efficiency to supply chains. The findings are limited to the health sector's supply chain that has specific parameters. However, the findings provide evidence of the versatility of the UTAUT dimensions across industries.

In Iran, Adaryani et al. (2024) investigated the BI for BCT among poultry supply chain managers extending the UTAUT by including trust, objective and subjective knowledge, and information literacy. The model analysis revealed that having adequate technical infrastructure was a prerequisite FC for intention to adopt BCT. The findings prove the significance of facilitating conditions. However, these findings are interpreted with caution as other factors were considered in the model.

In China, Shahzad et al. (2023) used the UTAUT2 theory in an effort to find those factors influencing acceptance of BCT in SCM among SC professionals. Using feedback from SC professionals, it was concluded that FC did have an increasing effect on continued intention for BCT adoption in SCM. However, in their model, the study included additional factors namely personal innovativeness in technology and user's self-efficacy and these may have had an effect on the found effects. Moreover, their research was not limited to any sector and collected information from professionals in different fields.

Limiting their research to the agricultural sector in In India, agri-food chain, Sharma et al. (2024) investigated determinants of BCT and BI anchored on the UTAUT2 theory with additional factors of transparency and interfirm trust. The data from agri-food chains information revealed that FC drove BCT adoption and also on BI of stakeholders. The research was not limited to SC professionals but included different actors in the agri-food chain in India suggesting the results may not be attributed to professionals in the supply chain who are the population of interest in this research.

In India's construction industry, Amal et al. (2024) assessed the employees' perceptions of e-procurement using the UTAUT theory with attitudes of employees as a mediator variable. The sample was 305 respondents from private construction companies and their data indicated that FC was a determinant in adoption of e-procurement system. The findings support the contribution of FC in BI of e-procurement technology; however, introduction

of a mediating variable may have influenced the outcome of this research. Therefore, generalization of these findings may be limited.

In Tunisia, Ennajeh and Najjar (2024) tested the UTAUT model in adoption of BCT considering trust as a mediator variable in the Management Information Systems (MIS) sector. The 95 respondents from technology-based sectors revealed FC explained adoption intention. Furthermore, trust was a mediator variable on adoption intention of BCT in SCM. The results provide evidence of the role of FC in AI of BCT but does not inform on the direction of this relationship whether it is positive or negative. The findings are relevant for this research as they highlight the need for research to confirm whether the relationship between these variables is positive or negative. The next section of the review provides a summary of research gaps.

2.4 Summary of Research Gaps

In Table 2.1, each reviewed study is listed along with its findings and emerging gaps that the present study will fill. Several determinants have been identified to influence DSC adoption. However, these determinants have not considered the technological factors (performance and effort expectancy), human factors (social influence), and environmental factors (facilitating conditions). Thus, using the UTAUT is a novel approach to document those determinants that explain may explain DSC adoption of digital supply chain technologies. Methodological, most studies on the adoption of digital supply chain technologies have been conducted from the Western and Asian context and there is less evidence from Kenya on the determinants of DSC adoption of the supply chain in FMCG manufacturing sector. In terms of methods, there are mixed methods, qualitative, and desk-related research that did not collect data on DSC adoption in the context of the FMCG manufacturing sector.

Table 2.1: Summary of Knowledge Gaps

Author	Topic	Methodology	Findings	Research gaps	Study filling gap
Nguyen et al. (2023)	Blockchain adoption in logistics companies in Ho Chi Minh City, Vietnam	Cross sectional research design	Performance expectancy had significant effects on operating BCT in supply chain management	The research was limited to BCT technology in supply chains	The study considers all digital technologies available for supply chain practitioners
Zaman et al. (2023)	How digitalization in banking improves service supply chain resilience of e-commerce sector? a technological adoption model approach	A desk research/ literature review design	Performance expectancy was the most critical factor	The research was limited to secondary data and qualitative analysis	This study adopts a quantitative data analysis of data gathered from supply chain practitioners
Zhang et al. (2023)	Understanding Blockchain Technology Adoption in Operation and SCM in Pakistan	Cross sectional research design	Performance expectancy had a negative influence on BCT adoption	The research was limited to BCT technology in supply chains	The study considers all digital technologies available for supply chain practitioners
Queiroz & Pereira (2019)	Intention to Adopt Big Data in Supply Chain Management: A Brazilian Perspective	Cross sectional research design	Performance expectancy had no significant effect on big data adoption	The research was limited to big data in supply chains	The study considers all digital technologies available for supply chain practitioners
Shahzad et al. (2024)	Blockchain technology adoption in supply chain management: An investigation from UTAUT and information system success model	Cross sectional research design	Performance expectancy positively influenced behavioural intention to use BT in SCM	The research was limited to BCT technology in supply chains	The study considers all digital technologies available for supply chain practitioners
Shatta et al. (2020)	Determinants of e-procurement adoption model for green procurement in developing countries: Experience from Tanzania	Mixed method research design	Performance expectancy had direct and indirect influences towards e-procurement system adoption	The research was limited to e-procurement system adoption	The study considers all digital technologies available for supply chain practitioners

Nguyen & Nguyen (2023)	Factors Influence Blockchain Adoption in Supply Chain Management Among Companies Based in Ho Chi Minh City	Cross sectional research design	Effort expectancy had significant effects on behavioral intention in using BCT in SCM	The research was limited to BCT technology in supply chains	The study considers all digital technologies available for supply chain practitioners
Ha & Linh (2018)	The Adoption of Blockchain in Food Retail Supply Chain Case	Cross sectional research design	Effort expectancy had direct positive impacts on behavioral intention.	The research was limited to grocery retail industry	The study will be conducted in the FMCG manufacturing sector
Sami et al. (2024)	Examining Factors Influencing the Integration of Blockchain Technology in the Freight Logistics Sector of Pakistan	Cross sectional research design	Social influence (subjective norms) had an effect on behavioral intention to use BCT	The study was limited to the freight logistic industry adoption of BCT	This study will be conducted on available digital technologies for the supply chain in the FMCG industry
Wamba & Queiroz (2019)	The Role of Social Influence in Blockchain Adoption: The Brazilian Supply Chain Case	Cross sectional research design	Social influence predicted behavioural intention to adopt BCT	The study was limited to the freight logistic industry adoption of BCT	This study will be conducted on available digital technologies for the supply chain
Lin et al. (2021)	Consumers' Intention to Adopt Blockchain Food Traceability Technology towards Organic Food Products	Cross sectional research design	Subjective norms had no significant correlation with the usage intention of BFTS	The study was limited to food sector	This research will be conducted in the FMCG
Martins et al. (2020)	Supply Chain 4.0 challenges	Systematic literature review	Socio-cultural factors had an effect on adoption of digital technology in supply chains	The research was limited to secondary data and document data analysis	This study adopts a quantitative data analysis of data gathered from supply chain practitioners
Park (2020)	A Study on Sustainable Usage Intention of Blockchain in the Big Data Era: Logistics and Supply Chain Management Companies	Cross sectional research design	Social influence exerted significant effects on attitude and sustainable usage intention of BCT	The research was limited to logistics companies	This study will be conducted in the FMCG manufacturing sector

Al Moteri & Alojail (2023)	Factors influencing the Supply Chain Management in e-Health using UTAUT model	Cross sectional research design	Facilitating conditions influenced adoption of IoT	The study was limited to the health sector	This study will be conducted in the FMCG manufacturing sector
Adaryani et al. (2024)	Antecedents of blockchain adoption in the poultry supply chain: An extended UTAUT model	Cross sectional research design	Technical infrastructure was one of the facilitating conditions on behavioral intention to adopt BCT	The research was limited to poultry supply chain	This study will be conducted in the FMCG manufacturing sector
Shahzad et al. (2021)	Blockchain technology adoption in supply chain management	Cross sectional research design	Facilitating conditions had a progressive impact on intention to use BCT in SCM	The research was limited to BCT	This study considers all digital technologies used in the supply chain
Sharma et al. (2024)	Blockchain adoption in agri-food supply chain management	Cross sectional research design	Facilitating conditions explained BCT adoption	The study was limited to the agri-food supply chain and adopted the UTAUT2 model	The study adopts the UTAUT and DOI as its theoretical framework
Amal et al. (2024)	Technology Adoption in Material Procurement: An Empirical Study Applying the UTAUT Model Among Construction Companies in India	Cross sectional research design	Facilitating conditions were significant in determining e-procurement adoption	The research was limited to e-procurement in the construction sector	The study considers digital technologies for the supply chain in the FMCG manufacturing sector
Ennajeh & Najjar (2024)	Blockchain Technology Adoption Through the UTAUT Model: Exploring the Mediating Role of Trust in Technology	Cross sectional research design	The findings stipulated importance of facilitating conditions as drivers of the adoption intention of BCT	The research was limited to BCT adoption in technology sector supply chains	This study considers all digital technologies used in the supply chain

Source: Researcher (2025)

2.5 Conceptual Framework

Figure 2.1 illustrates hypothesized relationship between variables and their corresponding indicators.

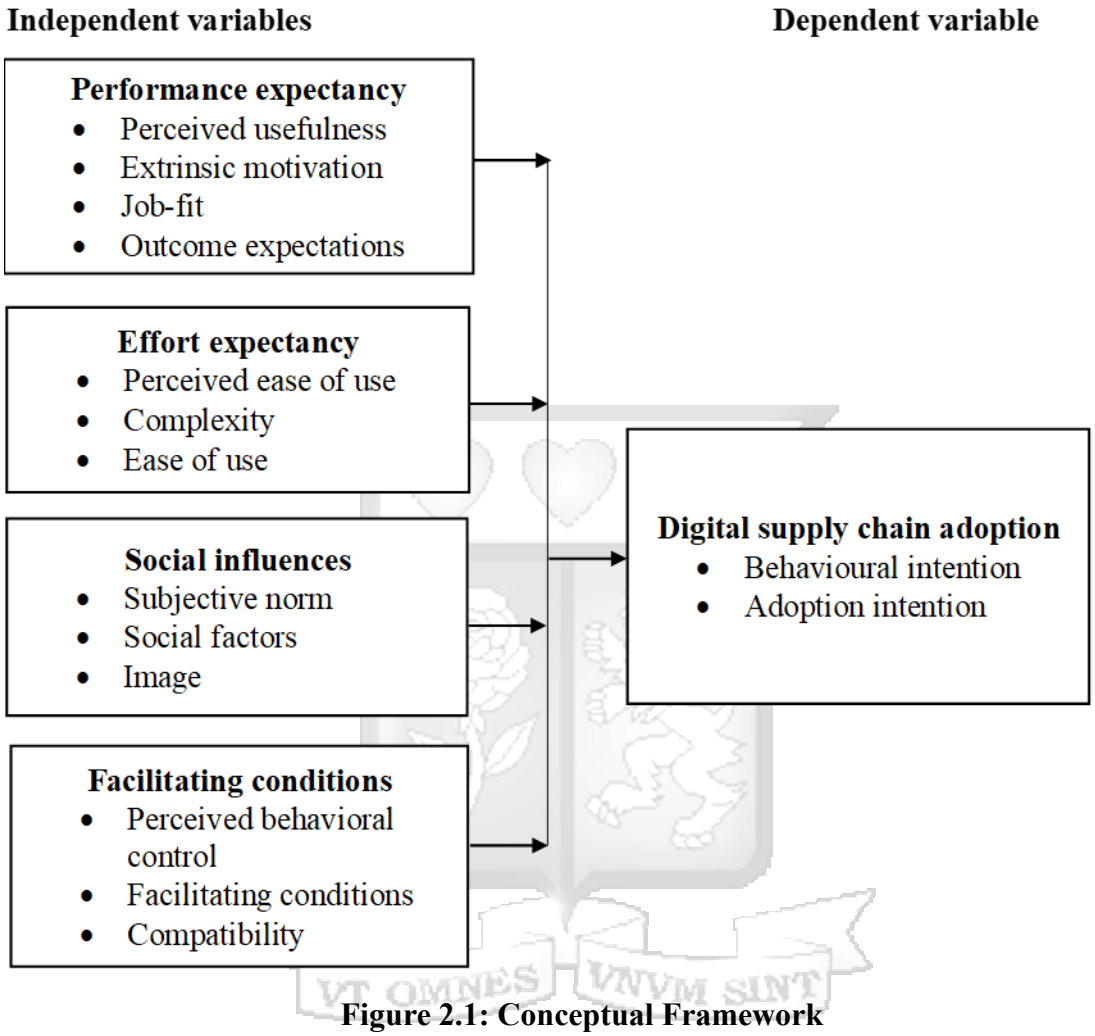

Figure 2.1: Conceptual Framework

Source: Researcher (2025)

2.6 Operationalization of Variables

Operationalizing variable makes concepts used in a study clear and standardized for measurement (Gonzáles, 2021). Table 2.2 shows the operationalization of variables based on empirical studies and theories guiding this research.

Table 2.2: Operationalization of Study Variables

Variables	Indicators	Measurement	Scale
Performance expectancy	• Perceived usefulness • Extrinsic motivation • Job-fit • Outcome expectations	5-point likert scale	Ordinal scale
Effort expectancy	• Perceived ease of use • Complexity • Ease of use	5-point likert scale	Ordinal scale
Social influence	• Subjective norm • Social factors • Image	5-point likert scale	Ordinal scale
Facilitating conditions	• Perceived behavioural control • Facilitating conditions • Compatibility	5-point likert scale	Ordinal scale
Adoption of digital supply chain technologies	• Behavioural intention • Adoption intention	5-point likert scale	Ordinal scale

Source: Researcher (2025)

2.7 Chapter Summary

The UTAUT and DOI theories were introduced, described, critiqued, and justified as the appropriate theoretical framework for this study. The empirical literature is also presented along its specific objectives and research gaps are identified and addressed in Table 2.1. The conceptual framework and operationalization of variables are included.

CHAPTER THREE
RESEARCH METHODOLOGY

3.1 Introduction

In this chapter, the philosophy the research adopted is introduced and justified as well as the research design adopted. The target population is explained and from this a sample size was calculated and the sampling method is further justified. The data collection instrument used is described and its quality was determined using valid and reliable measures that are further described. The data analysis, diagnostic tests, and ethical considerations are all presented.

3.2 Research Philosophy

A research philosophy assists one to specify their choice of research methods (Saunders et al., 2012). It is an important component for research for the following reasons, one, to clarify research design; two, to make sure that outcomes of a research are meaningfully interpreted; and three, exploring the main meanings of insights of human affairs associated to research questions (Kabir & Ullah, 2019). In selecting a philosophy, researchers must select their ontology (how reality is constructed) and epistemology (how knowledge is obtained).

There are three main research philosophies namely: pragmatism, interpretivism, and positivism. In this case, the positivist research philosophy was adopted. The positivist philosophy asserts that procedures adopted in natural sciences can be used in the social sciences. Several reasons can be outlined for using positivism for this study. First, it emphasizes on being objective and employing a structured methodology in which the researcher keeps a distance from the research participants (Kabir & Ullah, 2019). In doing this study, the researcher designed an instrument (questionnaire) and administered it to respondents using drop-and-pick and online method of administration so as to distance the principal investigator with participants.

Second, the positivist research begins by stating theories or hypothesis and adopts methods that are aimed to provide support or dismiss those theoretical assumptions made while leading to accepting and rejection of stated hypothesis (Kabir & Ullah, 2019). In fulfilling this principle, the research was anchored on the UTAUT and DOI theories that were used to operationalize the variable constructs.

Third, positivism emphasizes on structure and this means following a systematic approach to collection and analysis of data using standardized measures that have been deemed valid and reliable (Kabir & Ullah, 2019). In fulfilling this principle, the study used a structured questionnaire to collect primary data from respondents that was analysed using statistical tools (Saunders et al., 2012). Lastly, it emphasizes on generalization of findings from research; in this study, the aim was to generalize them to supply chain managers in the FMCG sector in Nairobi County.

3.3 Research Design

Descriptive cross-sectional research design was use to its usefulness in describing the desired features of a sample that is under investigation. This design is used in circumstances where there is an intention to make inference of findings to a sample that represents a population (Achimugu & Salihu, 2021). Therefore, descriptive cross-sectional research design was suitable in collecting the data from supply chain professionals in reference to their readiness to use DSC in their jobs in FMCGs. The design has also been used in other studies (Adaryani et al., 2024; Nguyen & Nguyen, 2023; Shahzad et al., 2024) and this supports the decision to adapt it to this research.

3.4 Target Population

There were 146 firms in Nairobi County (Appendix 4) and these represented the study's units of analysis. The units of observation are three (3) supply chain managers in each of the 146 FMCG manufacturers in Nairobi County thereby making for a sampling frame of 438 participants. The FMCG manufacturing firms were enlisted from the Kenya Association of Manufacturers (KAM) website.

3.5 Sampling Design and Sample Size

In each of these firm, a senior executive (top management), department head (middle management), and a supervisor (low-level management) of supply chain were selected using purposive. The selection of these respondents was done using purposive sampling method. It is the deliberate choice of an informant due to the qualities the informant possesses (Adeoye, 2023). Thus, the sampling frame consisted of 438 management staff from which 205 respondents were determined as the sample size using the Krejcie and Morgan (1970) sample size table (Appendix 5). Thereafter, simple random sampling method was used to select the 205 respondents. In simple random sampling, there is an equal opportunity to be included in a is entirely based on chance (Noor et al., 2022).

$$s = \frac{3.841 * 243 * 0.5 * 0.5}{0.0025 * (243 - 1) + 3.841 * 0.5 * 0.5}$$

Where:

S = Required Sample size

X 2 = 3.841

N = Population Size

P = Population proportion (assumed to be 0.5, (50%)

d = Degree of accuracy (5%)

3.6 Data Collection

Data collection can be distinguished from its sources namely primary and secondary. In this case, primary source of data collection was used. In regards to type of data, the study generated quantitative data rather than qualitative using a structured questionnaire to gather information. The questionnaire was administered using the drop-and-pick later method and online administrations facilitated by Google forms distributed via a link shared with respondents on their email and WhatsApp contacts.

The questionnaire consists of 3 sections. Section one sought general information (respondent and company) that will use both close and open-ended items to elicit data on respondent qualification, highest level of education, company subsector, firm size, and digital technologies used in supply chains. Section two sought information on the independent variables and section three measured adoption of DSC using six statements. In each of these sections, the 5-point Likert scale was applied. This scale offers a reliable way to collect participants' opinions and the decision to use 5 instead of 7 point is to drive simplicity in the data being collected (Joshi et al., 2015).

3.7 Research Quality

Determining the reliability and validity of the questionnaire will be used to demonstrate and communicate the rigour and trustworthiness of the research process (Drost, 2011). To establish reliability and validity of the instrument, a pilot study was conducted with 11 participants. Steps taken to ensure validity and reliability are further explained. Bujang et al. (2024) suggests that a sample size of 10 respondents as sufficient to assess the reliability.

3.7.1 Validity

Validity demands that a tool should be accurate in representing those constructs it aims to measure and can be distinguished between internal and external validity (Lauwaert, 2023). Internal validity refers to whether results are legitimate based on how respondents were reached, data was recorded, and how the analysis was done (Lauwaert, 2023). On the other hand, external validity refers to whether results can be generalised to other samples (Lauwaert, 2023). Thus, internal validity was improved by using probability methods of sampling that allow for scientific and proven methods of selecting participants into a sample size. The external validity of the instrument was enhanced by using constructs from the UTAUT model supported by the DOI which have been proven as valid and reliable in previous empirical studies.

3.7.2 Reliability

Reliability demands that an instrument be able to replicate results in different contexts if all factors remain the same (Kamper, 2019). Different forms of reliability exists but this research focused on the internal consistency that is recommended for Likert scale items. The Cronbach's Alpha Coefficient (α) statistic is proposed to confirm reliability of each scale whereby a score of above 0.7 was used as the threshold for accepting reliability. Table 3.1 shows the reliability statistics met threshold for accepting the instrument as valid and reliable.

Table 3.1: Reliability Statistics

Scales	Cronbach's Alpha	N of Items
Performance expectancy	0.857	4
Effort expectancy	0.903	4
Social Influence	0.797	4
Facilitating conditions	0.869	4
DSC adoption	0.823	6

Source: Pilot data (2025)

3.8 Data Analysis and Interpretation

The statistical package for the social sciences (SPSS) Version 27 was used to analyze data. The data collected was first checked for completeness and those with any errors were excluded from the analysis and those that met the quality standards were included in the analysis. Descriptive statistics were the first form of analysis to be performed, and this

consisted of using frequency and count distributions on the nominal level data (general information). This was followed by mean and standard deviation scores for ordinal level data summary. Thereafter, inferential statistical analysis followed. First, a composite variable was created to perform correlation coefficient statistic to determine association. The Pearson product-moment correlation (*r*) coefficient which is a value that ranges from -1 to +1 and is commonly used for data that meets a normal distribution and was tested between the variables at the 95% confidence level. This test was done to determine monotonic association between 2 variables in which an increase in one variable, so does the value of the other variable (positive association); or as the value of 1 variable increases, the other variable value decreases (negative association).

Multiple linear regression analysis was tested at 95 % confidence interval. The proposed regression model is thus presented as:

$$Y = ß_0 + ß_1X_1 + ß_2X2 + ß_3X_3 + ß_4X_4$$

Where:

$ß_0$ = Constant

$ß_1$- $ß_4$ = Coefficients

Y = DSC adoption

X_1 = Performance Expectancy

X_2 = Effort Expectancy

X_3 = Social Influence

X_4 = Facilitating Conditions

3.9 Tests for Statistical Assumption

Statistical tests make assumptions about the data. In performing regression analysis, checking that the data meets a normal distribution, that the groups being compared have similar variance, and the data is independent. The statistical assumption tests are further described in the subsequent subsection.

3.9.1 Normality Test

Normality tests are applied to the residuals from a linear regression model. To test normality, the study used the graphical method of using a bar graph and drawing a normality curve where a "bell shaped" curve indicates that the data is normally distributed. The

Shapiro– Wilk test is a test of the composite hypothesis that the data are normally distributed (Khatun, 2021). The null-hypothesis of this test is that the population is normally distributed. Thus, if the p-value is less than the chosen alpha level, then the null hypothesis is rejected and there is evidence that the data tested are not from a normally distributed. In other words, the data are not normal. On the contrary, if the p-value is greater than the chosen alpha level, then the null hypothesis that the data came from a normally distributed and population cannot be rejected (Khatun, 2021).

3.9.2 Heteroscedasticity Test

Heteroscedasticity becomes present when variance of errors is different across observations thereby rendering estimate of the standard errors inconsistent by being too small or too large. This results in incorrect inferences (Rosopa, Schaffer, & Schroeder, 2013). This is a violation of linear regression statistical assumption (Astivia & Zumbo, 2021). The graphical means of checking for Heteroscedasticity was used using a scatterplot graph (Raza et al., 2023). Additionally, the Breusch-Pagan Lagrange Multipliers (LM) test as one of the most important tests for heteroscedasticity in linear regression models was used. The null hypothesis states there is variance in the residuals while the alternative hypothesis states the variance of the residuals is not constant (Halunga et al., 2017). Therefore, p values greater than 0.05 demonstrates that data is homeostatic and acceptance of the null hypothesis. On the other hand, p values lower than 0.05 indicates rejection of alternative hypothesis and indicates that data possesses heteroscedasticity (Halunga, 2017).

3.9.3 Multicollinearity Test

Multicollinearity manifests itself in a dataset when high correlations exist between independent variables (Shrestha, 2020). This then can cause some of the important variables in research to be insignificant while increasing the variance between regression coefficients leading to instability that causes interpretation problems (Shrestha, 2020). Using the variance inflation factors (VIFs) were used to confirm whether there exists any multicollinearity. VIF values closer to 1 indicate no multicollinearity while those values close to 10 indicate presence of multicollinearity (Shrestha, 2020). VIF and tolerance values that are considered to be not affected by multicollinearity if not less than 0.1 for the tolerance and not greater than 10 for the VIF (Adeboye et al., 2014).

3.10 Ethical Considerations

In fulfilling its ethical considerations, ethical clearance was obtained from Strathmore University Institutional Ethical Review Committee (SU-IERC) followed by obtaining a research license from the National Commission for Science, Technology and Innovation (NACOSTI). Thereafter, other ethical standards were guaranteed. First, voluntary participation provided the space for participants to decide or not decide to be involved in a survey with no presence of coercion or pressure. This means that participants have the choice to withdraw at any moment without feeling any obligation to continue (Ederio et al., 2023).

Second, informed consent refers to participants' full awareness of the risks and procedures involved in research where they must give their permission to be interviewed (Ederio et al., 2023). This ethical standard was met by providing participants with an informed consent form (Appendix 1) for them to read and give their written consent and electronic consent on the physical and online forms respectively. Third, the anonymity principle means that readers have no knowledge of participants, and the data provide cannot be linked to a particular individual (Ederio et al., 2023). This principle was ensured by not asking participants to give any personally identifying information such as their address, phone contacts, emails, names, and physical address.

Fourth, the confidentiality principle describes that researchers' may know their participants but also decide to exclude any personal information they give in the survey and therefore guarantee participants' right to privacy (Ederio et al., 2023). This means a researcher should protect their personal data at all costs. Therefore, information provided by participants was not accessible to anyone else expect the researcher and the data analyst and will therefore not be accessible to any individuals not directly involved in the research.

Fifth, the principle of potential harm and risks means that all likely forms or sources of harm to participants. Harm can emerge in various forms including social, physical, psychological, and legal harm (Ederio et al., 2023). There are no foreseeable risks. According to Mejorada et al. (2021), ideas are considered academic or intellectual property and there are severe consequences for those researchers that do not acknowledge cited sources. Therefore, any material sourced from other works was cited appropriately and a plagiarism report was attached to show the research meets the minimum required threshold of 20%.

Sixth, the physical forms collected were only accessible to the researcher and were then kept under lock and key until completion of the data collection exercise. The online forms were saved to the researcher's Google drive and were not accessible to any other persons. After completion of data collection, both soft and hard copies of the forms were shared with a data analyst who used the researcher's personal computer to input the data and run the analysis. Lastly, the findings were shared on a PowerPoint presentation during the final defense of the report. The final report was saved in portable document file (PDF) and shared to the public on the Strathmore University portal for public access.

3.11 Chapter Summary

In this chapter, the positivist philosophy was selected as well as a descriptive research design for this study. The unit of analysis were 146 FMCG manufacturing firms while units of observation were 428 supply chain managers selected via purposive sampling method out of which simple random sampling was used to select the 205 respondents. A structured questionnaire for data collection was developed along with the data analysis techniques, tests of assumption, and ethical considerations.

CHAPTER FOUR

PRESENTATION OF RESEARCH FINDINGS

4.1 Introduction

This chapter presents highlights the findings of the study. It consists of several subsections including the attained response rate, general information section, and descriptive statistics section aligned to the four specific objectives. The correlation coefficient results, diagnostic tests, and the multiple linear regression analysis are also presented.

4.2 Response Rate

There were 205 questionnaires administered and out of these, 132 surveys were returned and subsequently used to perform analysis indicating a 64.4% response rate. Mugenda and Mugenda (2019) explained that a 60% response as good, 50% as acceptable, and response rates above 70% as very good. Based on this classification, the response rate was adequate and this can be attributed to those companies that may not be tech savvy being unable to comprehend the DSC questions.

Table 4.1: Response Rate

Categories	Number	Percent
Distributed questionnaires	205	100.0
Returned questionnaires	132	64.4
Non-returned questionnaires	73	35.6

Source: Primary data (2025)

4.3 General information

In Table 4.2, the general information of respondents and the companies they represent is given. Beginning with gender, the findings show there were more female respondents than male respondents as indicated by 53.8% and 46.8% respectively implying that there is an element of gender diversity in FMCG manufacturing companies as women were represented in management levels. The majority were in the 26–33-year age group representing 63.6% of respondents with those between 34-41- and 42-49-year age groups representing 34.1% and 2.3% respectively. The findings indicate a level of diversity in terms of age as a relatively youthful; population are represented in the sample showing organizations were providing opportunities for this demographic in their management level staff. There were more respondents with a Bachelor's degree than those with a Master's degree as shown by 58.3% and 41.7% respectively this can be attributed that management

level entry position requires a minimum of an undergraduate degree with those in these positions are likely to further their education to postgraduate level.

There were more respondents that had been with the present organization for 6 – 10 years representing 49.2% followed by those with 2-5 years (34.1%), 11-15 years (15.2%), and less than 1 year (1.5%). This output suggests that those respondents with more than six years' experience were in the sample and therefore improved credibility of findings as they are more likely to have observed the digitalization of supply chains in their organization. The majority of companies included in the survey had more than 250 employees accounting for 76.5% of the sample with those with 50 -249 employees accounting for 18.9%. Those with 10 – 49 employees and less than 10 employees respectively accounted for 3.0% and 1.5%. This finding suggest that large enterprises were well represented in the sample and these are organizations that have the resources to digitalize their supply chains to a great extent and therefore improve the internal validity of findings.

Table 4.2: General Information

Gender	**Frequency (n=132)**	**Percent**
Female	71	53.8
Male	61	46.2
Age group		
26-33 years	84	63.6
34-41 years	45	34.1
42-49 years	3	2.3
Education level		
Bachelor Degree	77	58.3
Master Degree	55	41.7
Years in organization		
11-15 years	20	15.2
2-5 years	45	34.1
6-10 years	65	49.2
Less than 1 year	2	1.5
Company size		
10 - 49 employees	4	3.0
50-249 employees	25	18.9
Less than 10 employees	2	1.5
More than 250 employees	101	76.5

Source: Primary data (2025)

4.4 Descriptive Analysis

This section focuses on summarizing the Likert scale data for interpretation based on their mean and standard deviation scores. The mean scores were interpreted following Lindner and Lindner (2024) summated scale as follows: strongly agree = 5-4.51, agree = 4.5-3.51, neither agree nor disagree = 3.5-2.51, disagree = 2.5-1.51, strongly disagree = 1.5 - 1.

4.4.1 Performance Expectancy

Based on Lindner and Lindner (2024) summated scale, the findings reveal agreement on the average mean score for performance expectancy at 4.27 and standard deviation 0.987 as shown in Table 4.3. The respondents agreed that using digital technologies in their work place assisted them complete tasks faster (M=4.49, SD=0.815). There was agreement among respondents with the item the use of digital technologies in my work will enhance my task completion as indicated by mean value 4.35 and 0.847 standard deviation. A mean score of 4.27 and standard deviation of 1.166 reveals respondents' agreement with the item the use of digital technologies in my work place will improve my productivity. The respondents agreed available digital technologies were useful in their everyday work life by mean score of 3.95 and standard deviation 1.121.

Table 4.3: Performance Expectancy Descriptive Statistics

Items	Mean	Std. Deviation
The available digital technologies are useful in my everyday work life	3.95	1.121
The use of digital technologies in my work will enhance my task completion	4.35	0.847
The use of digital technologies in my work place will assist my task completion faster	4.49	0.815
The use of digital technologies in my work place will improve my productivity	4.27	1.166
Composite mean score	**4.27**	**0.987**

Source: Primary data (2025)

4.4.2 Effort Expectancy Items

Table 4.4 shows a composite mean score of 3.75 indicating respondents' agreement with the effort expectancy statements. Individually, the findings show the highest ranked item was the item to learn and use digital technologies as a supply chain professional will be easy for me as shown by a mean of 3.92 implying agreement with this statement. The respondents were in agreement that it was easy for me to attain skills in using digital technologies in my role as a supply chain professional as shown by a mean score of 3.85.

There was agreement among respondents that using digital technologies in their work will be easy as revealed by a mean score of 3.70 while a mean value of 3.53 also indicated respondents were in agreement that early experience with digital technologies for supply chains were clear and understandable.

Table 4.4: Effort Expectancy Descriptive Statistics

Effort expectancy Items	N	Mean	Std. Deviation
My ability to learn and use digital technologies as a supply chain professional will be easy for me	132	3.92	0.856
My early experience with digital technologies for supply chains will be clear and understandable	132	3.53	1.129
The use of digital technologies in my work will be easy for me	132	3.70	1.082
It will be easy for me to attain skills in using digital technologies in my role as a supply chain professional	132	3.85	0.878
Composite mean score		**3.75**	**0.986**

Source: Primary data (2025)

4.4.3 Social influence Items

Table 4.5 show respondents were in agreement with the items as shown by a mean score of 4.14 and 0.770 standard deviation. The respondents agreed individuals whose opinions they valued supported their DSC adoption as indicated by mean score of 4.29 and standard deviation 0.705. The respondents agreed those individuals that influence their behaviour supported their DSC adoption by mean value of 4.08 and standard deviation of 0.811. The respondents agreed those significant others supported their DSC adoption.

Table 4.5: Social Influence Descriptive Statistics

Social influence Items	Mean	Std. Deviation
Those significant others to me are of the opinion I should adopt digital technologies in my work	4.04	0.795
Those individuals that influence my behaviour are of the opinion I should adopt digital technologies in my work	4.08	0.811
Those individuals whose opinions that I value are of the opinion I should adopt digital technologies in my work	4.29	0.705
Composite mean score	**4.14**	**0.770**

Source: Primary data (2025)

4.4.4 Facilitating conditions Items

Table 4.6 shows that respondents were in agreement with the items as shown by a composite mean score of 3.56 and standard deviation of 0.973. The item specific results indicated that

respondents were in agreement that they would be able to receive support if they experienced challenges in adoption of digital technologies as shown by a mean score of 3.81 and standard deviation of 1.049. There was also agreement among respondents on having reasons and resources needed to adopt technologies were readily as indicated by a mean value of 3.70 and standard deviation of 1.08. The respondents neither agreed or disagreed on having the necessary knowledge to adopt digital technologies at work as shown by a mean score of 3.45 and standard deviation of 0.935. The respondents neither agreed or disagreed that the available digital technologies for supply chains were compatible with the technologies they were using presently as shown by a mean score of 3.27 and 0.820 standard deviation.

Table 4.6: Facilitating Conditions Descriptive Statistics

Facilitating conditions Items	Mean	Std. Deviation
I have the reasons and resources required to adopt digital technologies for my work	3.70	1.089
I have the necessary knowledge to adopt digital technologies for my work	3.45	0.935
The available digital technologies for supply chains are compatible with existing technologies I use	3.27	0.820
I will be able to receive support from others if I experience difficulties in my adoption of digital technologies in my work	3.81	1.049
Composite mean score	**3.56**	**0.973**

Source: Primary data (2025)

4.4.5 Digital Supply Chain Adoption

The respondents were in agreement with all the statements as shown by a composite mean score of 4.19 and 0.844 standard deviation as shown in Table 4.7. The respondents were in strong agreement that adopting digital technologies would afford them relative advantage over other professionals in the profession as indicated by a mean score of 4.62 and standard deviation of 0.636. The output shows strong agreement among respondents that they expected to adopt digital technologies as shown by a mean score of 4.59 and standard deviation of 0.653. There was also strong agreement among respondents that they had every intention to use digital technology in their work in the near future as shown by a mean score of 4.55 and 0.734 standard deviation.

Table 4.7: Digital Supply Chain Adoption Descriptive Statistics

Items	Mean	Std. Deviation
I have every intention to use digital technology in my work in the near future	4.55	0.734

I expect to adopt digital technologies in my role as a supply chain professional	4.59	0.653
I am planning to adopt digital technology in my role as a supply chain professional	3.99	1.129
My adoption of digital technologies in my role will afford me relative advantage over others	4.62	0.636
My adoption of digital technologies in my role as a supply chain professional will be compatible with the present processes, technology, and tools	3.82	0.827
The use of digital technologies is a complex process to implement in my role as a supply chain professional	3.58	1.085
Overall mean score	**4.19**	**0.844**

Source: Primary data (2025)

4.5 Diagnostic Tests

Before performing the correlation and regression analysis, it was imperative that the dataset was checked for the minimum requirements including a normal distribution, no heteroscedasticity and collinearity issues as summarized in the following sections.

4.5.1 Normality

The study adopted the graphical means by which to determine if the data fits a normal distribution in favour of statistical methods of checking for normality. A look at Figure 4.1 shows that the data fit a normal distribution by the "bell curve".

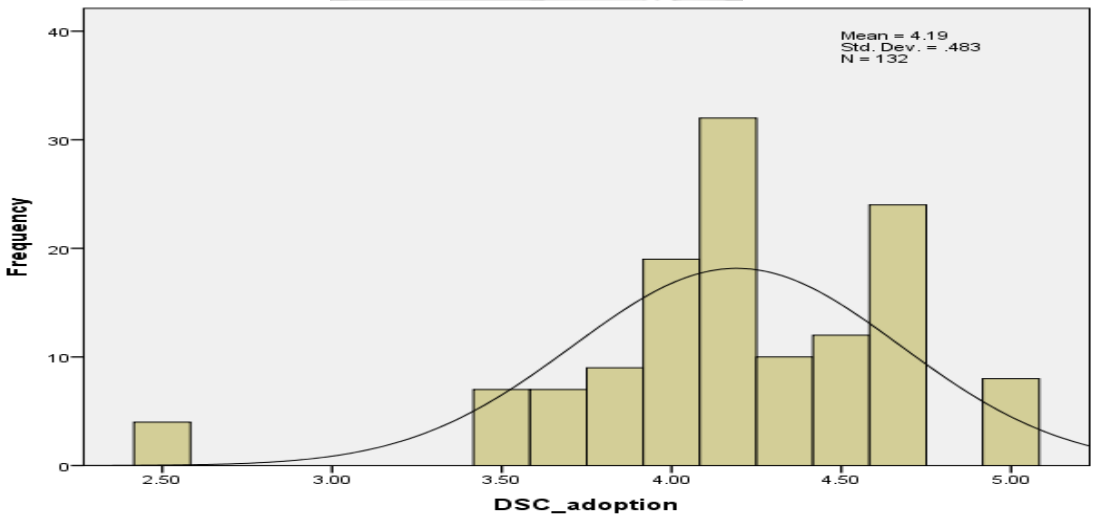

Figure 4.1: Normality Test

Source: Primary data (2025)

In addition to this, the Shapiro-wilk test was done to check if data met the standard of normality. Table 4.8 shows the p value was greater than 0.05 which means that the data met threshold for normality.

Table 4.8: Test of Normality

	Statistic	df	Sig.
Employee burnout	.763	132	.204

a. Lilliefors Significance Correction

4.5.2 Heteroscedasticity

This refers to data with unequal variability (scatter) across a set of second, predictor variables and this poses a problem of interpreting regression results. Therefore, it is imperative to check that data is not homoscedastic. Using an illustration, one should look out for cone shaped dots in the scatter plot which indicate the presence of homoscedasticity. Figure 4.2 does not show any pattern and therefore leads to the conclusion there are no heteroscedasticity concerns.

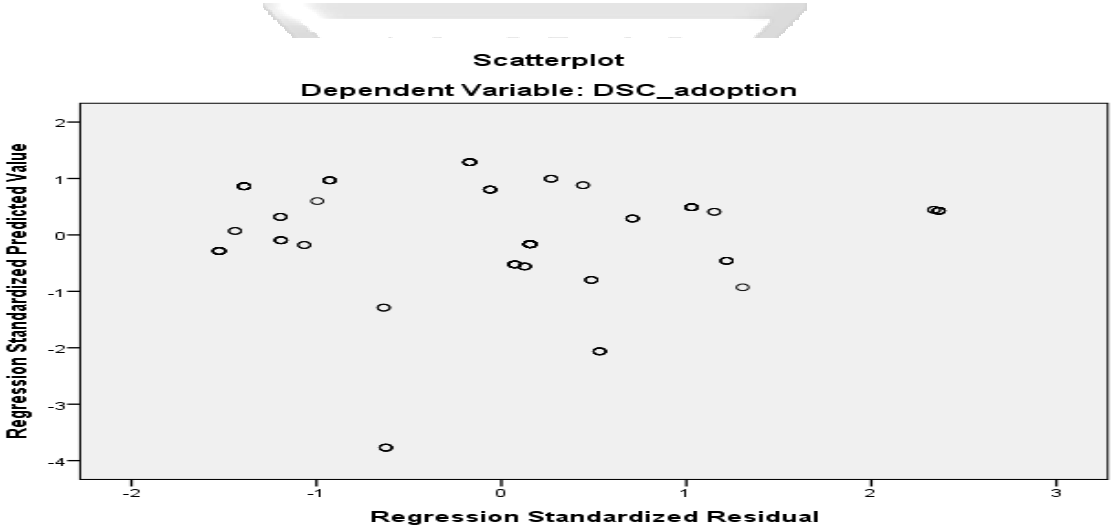

Figure 4.2: Scatterplot to Check for Heteroscedasticity

Source: Primary Data (2025)

In addition to the graph test, the study also performed the Breusch-Pagan test which is used to check for heteroscedastic data. Table 4.9 shows the p value was 0.054 that is greater than 0.05 which means that the data did not exhibit heteroscedastic characteristics.

Table 4.9: Breusch-Pagan test

Test	Value
Breusch-Pagan Statistic	3.55
Degrees of Freedom (df)	1
p-value	0.054

4.5.3 Multicollinearity

Multicollinearity testing was determined using VIF and tolerance scores shown in Table 4.10. VIF and tolerance values that are considered to be not affected by multicollinearity if not less than 0.1 for the tolerance and not greater than 10 for the VIF (Adeboye et al., 2014). Based on the findings, the VIF and tolerance values for the independent variables met the threshold for concluding there was no multicollinearity present in the data.

Table 4.10: Collinearity Statistics

Variables	Tolerance	VIF
Performance expectancy	0.345	2.896
Effort expectancy	0.392	2.550
Social influence	0.349	2.869
Facilitating conditions	0.561	1.782

Source: Pilot study data (2025)

4.6 Correlation Analysis

After performing the diagnostic tests, the researcher next performed the correlation test to establish the nature of relationship between the independent and dependent variables. A positive and statistically significant association between the variables at both 95% and 99% confidence levels as summarized in Table 4.11. Specifically, there was a positive and significant association between performance expectancy and DSC adoption ($r = 0.786$, $p < 0.05$); effort expectancy and DSC adoption ($r = 0.679$, $p < 0.05$); social influence and DSC adoption ($r = 0.753$, $p < 0.05$); and facilitating conditions and DSC adoption ($r = 0.563$, $p < 0.05$).

According to Evans (1996), correlation coefficients can be classified as: <0.20 as very weak, between 0.20-0.39 as weak, 0.40-0.59 as moderate, 0.60-0.79 as strong, and >0.80 as very strong. Thus, strong linear association was observed between performance expectancy, effort expectancy, social influence and DSC adoption while a moderate association between facilitating conditions and DSC adoption. This means there is a linear association between the variables as an increase in independent variables exhibits an increase in DSC adoption and this necessitates further investigation by performing regression analysis.

Table 4.11: Correlation Coefficients

		Performance expectancy	Effort expectancy	Social influence	Facilitating conditions
Performance expectancy	Pearson Correlation	1			
	Sig. (2-tailed)				
Effort expectancy	Pearson Correlation	.745**	1		
	Sig. (2-tailed)	0.000			
Social influence	Pearson Correlation	.716**	.675**	1	
	Sig. (2-tailed)	0.000	0.000		
	N	132	132	132	
Facilitating conditions	Pearson Correlation	.536**	.392**	.640**	1
	Sig. (2-tailed)	0.000	0.000	0.000	
DSC adoption	Pearson Correlation	.786**	.679**	.753**	.563**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000
	N	132	132	132	132

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

Source: Primary data (2025)

4.7 Multiple Regression Analysis

Multiple linear regression was performed to determine the direction and magnitude of independent variables on a dependent variable. These findings are summarized in form of three tables presented and interpreted in this subsection of the analysis.

4.7.1 Model Summary

The R coefficient quantifies the strength and direction of the linear relationship between two variables and the value of 0.837 shows a positive linear relationship between the independent variables and DSC adoption. The coefficient of determination (R^2) measures the proportion of variance in the dependent variable that is predictable from the independent variables in a regression model. Table 4.12 indicates the model explained 70% of variability in the composite measure of DSC adoption.

Table 4.12: Model Summary

R	R Square	Adjusted R Square	Std. Error of the Estimate
.837a	0.700	0.691	0.2687

a Predictors: (Constant), Facilitating conditions, effort expectancy, social influence, performance expectancy

Source: Primary data (2025)

4.7.2 Model Significance

Table 4.13 indicates the goodness of fit of the model and it confirms it was statistically significant as the *p* value is less than 0.05 ($p = 0.000$) is below 5% and the calculated *F* statistic is positive = 13.382. This result implies that the model is a suitable predictor of DSC adoption.

Table 4.13: ANOVA results

	Sum of Squares	df	Mean Square	F	Sig.
Regression	21.413	4	5.353	74.144	.000
Residual	9.169	127	0.072		
Total	30.582	131			

a Dependent Variable: DSC adoption
b Predictors: (Constant), Facilitating conditions, effort expectancy, social influence, performance expectancy

Source: Primary data (2025)

4.7.3 Coefficients

The study findings revealed a positive and significant relationship between performance expectancy and DSC adoption as shown by a t-value 5.238 and p value of 0.000 implying that a unit increase in performance expectancy would result in a 0.250 increase in DSC adoption. There was a positive but non-significant relationship between effort expectancy and DSC adoption as indicated by a t value 1.443 and p value of 0.152 suggesting a unit increase in effort expectancy would result in a 0.062 increase in DSC adoption but this was not significant. The results revealed a positive and significant relationship between social influence and DSC adoption as shown by a t value of 3.786 and p value of 0.000 implying a unit increase in social influence would result in a 0.213 increase in DSC adoption. There was a positive and non-significant relationship between facilitating conditions and DSC adoption as shown by a t value of 1.340 and p value of 0.183 implying that an increase in facilitating conditions would result in a 0.053 increase in digital supply chain adoption.

Table 4.12: Coefficients

Variables	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	1.825	0.144		12.701	0.000
Performance expectancy	0.250	0.048	0.433	5.238	0.000
Effort expectancy	0.062	0.043	0.112	1.443	0.152
Social influence	0.213	0.056	0.312	3.786	0.000
Facilitating conditions	0.053	0.039	0.087	1.340	0.183

a Dependent Variable: DSC adoption

Source: Primary data (2025)

The findings show that only performance expectancy and social influence had a positive and significant effect on DSC adoption. Thus, the completed regression model is presented as:

$$Y = 1.825 + 0.250\ X_1 + 0.213\ X_2$$

Where:

$ß_0$ = Constant

$ß_1$- $β_2$ = Variable coefficients

Y = DSC adoption

X_1 = Performance expectancy

X_3 = Social influence

4.8 Chapter Summary

Descriptive statistics revealed that performance expectancy had the highest mean scores followed by social influence, effort expectancy, and facilitating conditions while the correlation analysis revealed a positive linear association between these variables and DSC adoption. The regression results show the model explained 70% of variation on DSC adoption and this was statistically significant. In addition, positive and significant relationship between performance expectancy, social influence and DSC adoption was found. Then again, a positive but non-significant relationship was observed between facilitating conditions, effort expectancy and DSC adoption.

CHAPTER FIVE
DISCUSSIONS, CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This chapter presents the discussion of findings with previous studies reviewed in the literature and this is done for each of the objectives while presenting conclusions also based on the specific objectives. The recommendations are made for policy, practice, and theory while limitations of the study and suggestions for future research are given.

5.2 Summary of the Findings

This research examined demand-side determinants of DSC adoption among FMCG manufacturers in Nairobi County. Its objectives were to: establish effect of performance expectancy on DSC adoption among FMCG manufacturers; establish influence of effort expectancy on DSC adoption among FMCG manufacturers; establish influence of social influence on DSC adoption among FMCG manufacturers; and establish effect of facilitating conditions on DSC adoption among FMCG manufacturers. The study was anchored on UTAUT and DOI theories of technology adoption.

The UTAUT theory hypothesis is that behavioural intention to a technology is influenced by performance expectancy, effort expectancy, social influence, and facilitating conditions. On the other hand, DOI describes a social process in which information of a new technology is dependent on the idea that it has perceivable channels, mode, and time of being adopted by a company or individual. The positivist research philosophy and a descriptive cross-sectional research design were adopted. The 146 FMCG manufacturing companies in Nairobi County represented the unit of analysis while units of observation were represented by supply chain top, middle, and low-level of management staff making for a sampling frame of 438 participants. Out of this, 205 participants were selected using simple random sampling from which 132 completed responses were received.

The mean scores revealed that performance expectancy had the highest ranking among the four dimensions followed by social influence, effort expectancy, and facilitating conditions. There was a positive and statistically significant linear association between the four variables and DSC adoption. A positive and significant relationship between performance expectancy and social influence with DSC adoption was reported. However, facilitating conditions and effort expectancy did not have any effect on DSC adoption.

5.2.1 Performance Expectancy and Digital Supply Chain Adoption

The concept of performance expectancy describes a situation in which individuals trust that utilizing a technology will assist them in overcoming difficulties and assist them attain desired goals in their work (Shahzad et al., 2024). Performance expectancy directly influences users' perceptions of the utility of a technology. If individuals believe using a specific technology will enhance their performance, efficiency or effectiveness in completing tasks, they are more inclined to adopt that technology (Amal et al., 2024). The findings of this study revealed a positive and significant relationship between performance expectancy and digital supply chain adoption.

This finding is in line with previous studies that have found positive relationship between this variable and adoption of digital technologies in the supply chain. These studies include those that have focused on the use of blockchain technology (BCT) in supply chain activities. For instance, Nguyen et al. (2023) revealed performance had a significant effect on operating BCT in supply chain management (SCM) in Vietnam. The other evidence comes from China where Shahzad et al. (2024) findings were able to show a positive relationship between performance expectancy and behavioural intention (BI) towards BCT among professionals in supply chains.

The descriptive findings revealed that respondents were in agreement with all items on performance expectancy. This means that professionals in supply chain felt positively that digital technologies available in the market were of use in their work; it would improve their task completion; it would contribute to faster accomplishment of tasks in their work; and it would contribute positively to their productivity. The findings provide support for the UTAUT theory dimension of performance expectancy in terms of supply chain profession in Kenya's context.

The relationship between performance expectancy and digital supply chain adoption is not always positive as some studies have shown. Thus, this study's findings contradict such studies, for example, Zhang et al. (2023) revealed that adoption of BCT had a negative relationship with performance expectancy. However, caution is important to conclude on this finding since the research was limited to blockchain technology (BCT). Yet, others, like Queiroz and Pereira (2019) research on big data adoption in Brazil found performance expectancy did not have any influence on big data adoption. However, challenges of associated with big data in developing countries could be attributed to this outcome as data

collection and storage holds less importance to financial performance. The results therefore imply that performance expectancy is an important variable to consider in DSC adoption and management. The study provides support for the performance expectancy dimension of the UTAUT theory.

5.2.2 Effort Expectancy and Digital Supply Chain Adoption

The concept of effort expectancy describes the extent to which that use of a technology or system is easy to an individual (Venkatesh et al., 2003). The evidence has shown that people make the rational decision to start using a technology if it does not need them to put much effort in how to utilize it and essentially use it (Ha & Linh, 2018). Those technologies designed to minimize user effort and provide a seamless, enjoyable experience are more likely to be adopted because as an individual believes the new method is more comfortable and convenient to apply, they will likely accept that technology (Amal et al., 2024). In this study, there was a positive but non-significant relationship between effort expectancy and DSC adoption.

This finding corroborates previous studies that found no relationship between these variables. One such study was Wong et al. (2020) in Malaysia that found no association between behavioural intention and effort expectancy towards BCSCM. Ngwira and Phiri (2024) research in Zambia revealed effort expectancy had negative effect on BI among consumer and retail traders' adoption of e-commerce. These findings do not support the UTAUT dimension of effort expectancy at least in the supply chain profession in Kenya. The descriptive findings show moderate agreement with the effort expectancy statements demonstrating respondents were not confident of their skills and knowledge to utilize available DSC in their jobs.

The result however also contradicts previous evidence that shows a positive and significant effect of effort expectancy on adoption of digital technologies in the supply chain. For instance, Lian (2023) did confirm that effort expectancy had a positive effect on adoption of green supply chain innovations while Ha and Linh (2018) research in Malta were able to determine that EE possessed direct positive impacts on BI providing evidence that EE variable was important for professionals as well as end-consumers. The contradictory results imply that effort expectancy is not a critical determinant of DSC adoption and management in FMCGs may not need to pay attention to this variable in the short-term towards adoption of digital technologies in their supply chains.

5.2.3 Social Influence and Digital Supply Chain Adoption

Social influence describes how a person's perspective is influenced by others in their environment. It is the extent an individual perceives important others believe the new technology should be used (Wamba & Queiroz, 2019). It has been enlightened as the degree to which an individual sees other in their social network and organization believe they should use the new system (Zhang et al., 2024). Social influence can be exerted by family, friends, and peers. The descriptive findings show agreement with the statements on social influence indicating there is a high cohesion and clan culture in FMCG companies. Thus, social influence was found to possess a positive and significant relationship with DSC adoption.

These findings corroborate several researchers that earlier gave evidence of a positive relationship between the variables including Sami et al. (2024) research in Pakistan that revealed cultural and social factors (subjective norms) had an influence on behavioural intention for supply chain managers to use digital technologies in their work. In another investigation, Park (2020) data from supply chain managers in Korea confirmed that social influence had an effect on adoption intention of BCT.

The descriptive findings revealed respondents were in agreement with all statements on social influence. This means respondents felt favourable that their significant others would support their decision to adopt DSC; that those individuals who influenced their behaviour supported their use of DSC; and that those individuals who they valued their opinion supported their adoption of digital technologies at their work. These findings provide support for the UTAUT theory in the supply chain profession in the Kenyan context.

The findings contradict earlier evidence that show no relationship between social influence and digital supply chain adoption. In China, Lin et al. (2021) findings revealed social influence had no effects on blockchain food traceability system (BFTS) adoption. Using evidence from Brazil, Queiroz and Pereira (2019) data from SCM experts revealed social influence did not explain behavioral intention to adopt digital technologies. Hence, social influence was not a critical determinant of DSC adoption and managers should pay attention to this factor in their adoption of digital technology in the supply chain. The study provides support for the social influence dimension of the UTAUT theory.

5.2.4 Facilitating Conditions and Digital Supply Chain Adoption

Facilitating conditions is the degree that a person is able to trust that real-world and structural infrastructure is already present to allow for the utilization of the system (Francisco & Swanson, 2018). It is the anticipated expected level of technical and organizational infrastructure that can support the utilization of a technology. These facilitating conditions go beyond the technology that is being examined but also speaks to the organizational culture that may either promote or hinder adoption of a technology (Francisco & Swanson, 2018). The present study found a positive but non-significant relationship between facilitating conditions and digital supply chain adoption.

This result is in agreement with research that established a positive relationship between facilitating conditions and DSC adoption. For instance, Adaryani et al. (2024) study in Iran revealed that having adequate technical infrastructure was a prerequisite facilitating condition for DSC adoption in supply chain activities. In China, Shahzad et al. (2023) research among supply chain managers concluded that facilitating conditions did have an increasing effect on continued intention for BCT adoption in SCM. Figueiredo et al. (2022) established that facilitating conditions was a determinant for predicting intention to adopt innovation in supply chain finance among Brazilian companies.

The descriptive statistics indicated that respondents were in the middle ground with some of the statements on facilitating conditions. These statements were having the necessary knowledge to adopt digital technologies for my work results suggesting that respondents were not confident of their knowledge when it comes to some digital technologies that are common in supply chains. In addition, the respondents neither agreed or disagreed that available digital technologies for supply chains are compatible with existing technologies they use at work. Hence, facilitating conditions is not a critical determinant of DSC adoption and managers should not pay much attention on this variable when undertaking DSC adoption. The research does not provide support for the UTAUT theory as per its facilitating conditions dimension.

5.3 Conclusion

The study concludes that performance expectancy and social influence have positive outcomes on DSC adoption implying that management should focus on these two factors to improve its adoption in FMCG supply chains. The study concludes that effort expectancy and facilitating conditions do not have any effects on DSC adoption implying that these

factors do not require immediate attention from management for swift adoption of DSC adoption in FMCG supply chains.

5.4 Recommendation

The research makes the following recommendations for policy, practice, and theory.

5.4.1 Recommendations for Policy

Performance expectancy and social influence were found to positively contribute to DSC adoption. Therefore, the study recommends for policy that rewards companies that are digitalizing their supply chains and those that are able to improve their key performance indicators (KPIs) in terms of reducing turnover and improving lead times. Secondly, to improve adoption of DSC, government and other stakeholders in the FMCG industry should appoint digitalization ambassadors to champion its adoption in supply chains.

5.4.2 Recommendations for Practice

The findings indicated facilitating conditions and effort expectancy did not contribute to DSC adoption. Therefore, management of FMCG companies should continuously ensure that staff are provided with onboarding, training, and support during to improve their adoption of DSC. In terms of facilitating conditions, management should in the long-term orchestrate budgetary allocation to DSC and formulate change management strategies towards adoption of DSC.

5.4.3 Recommendations for Theory

The findings provided support for the social influence and performance expectancy dimensions of the Unified Theory of Acceptance and Use of Technology. However, its effort expectancy and facilitating conditions dimensions were not supported. Thus, this study makes its contribution to theory by providing the cultural context of Kenya and the applicability of the theory to DSC adoption Using its performance expectancy and social influence dimensions.

5.5 Limitations of the Research

This study was limited to self-reported data which poses a threat to the internal validity of its findings. However, this was delimited by using constructs from the empirical review literature and supported by well-established theories of technology adoption. Furthermore, the study was limited to primary data and the study would have benefitted from secondary data that is based on a digitalization index for supply chains. However, there is limited

accessibility and availability of digitalization of supply chains data in developing countries. The cross-sectional nature of the study means it missed out on the opportunity to show how different digital technologies have transformed the supply chains of FMCG manufacturing companies.

5.6 Suggestions for Further Research

The findings provided support for the social influence and performance expectancy dimensions of the Unified Theory of Acceptance and Use of Technology. However, its effort expectancy and facilitating conditions dimensions were not supported. Therefore, the study recommends for further research on the dimensions of effort expectancy and facilitating conditions to shed more light on the role of these variables in digital supply chain adoption. Secondly, the research scope extended to FMCG manufacturing firms. Therefore, there is need for a similar study to be undertaken in other sectors such as floriculture and agriculture which make significant contributions to Kenya's gross domestic product (GDP). Lastly, the study recommends for future research to use a longitudinal research design so as to capture the evolution of digital technologies in the FMCG sector supply chain.

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APPENDICES

APPENDIX 1: LETTER OF INTRODUCTION

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Cell: +254 703 034 414/6/7
X/Twitter/Tiktok: @SBSKenya
Facebook/Linkedin: Strathmore University Business School

Email: **sbsinfo@strathmore.edu** or visit **www.sbs.strathmore.edu**

Strathmore UNIVERSITY BUSINESS SCHOOL

20 Years of Developing Great African Leaders

26th March 2025

To Whom It May Concern.

Dear Sir/Madam,

RE: FACILITATION OF RESEARCH - LINDA MWENDE MASAKU

This is to introduce Linda Mwende Masaku, who is a Master of Business Administration student at Strathmore University Business School, admission number MBA/75837/23. As part of our MBA program, Linda is expected to do applied research and undertake a project. This is partially fulfilling the requirements of the MBA course. To this effect, she would like to request appropriate data from your organization.

Linda is undertaking a research paper on **" Determinants of Adoption of Digital Supply Chain Technologies Among Fastmoving Consumer Goods Manufacturers in Nairobi County, Kenya."** The information obtained from your organization shall be treated confidentially and shall be used for academic purposes only.

Our MBA seeks to establish links with industry, and one of these ways is by directing our research to areas that would be of direct use to industry. We would be glad to share our findings with you after the research, and we trust that you will find them of great interest and of practical value to your organization.

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

Yours sincerely,

Alois Njenga.
Manager, MBA Programs.
Strathmore University Business School.

Strathmore University Business School is a Proud member of:

Association of African Business Schools AABS EFMD AACSB

APPENDIX 2: QUESTIONNAIRE FOR SUPPLY CHAIN MANAGERS IN FMCG MANUFACTURING COMPANIES IN NAIROBI COUNTY

Section A: Respondent Profile

1. Please indicate your gender

Male ( )

Female ( )

2. Please indicate your age group

18 – 25 years ( )

26-33 years ( )

34-41 years ( )

42-49 years ( )

50+ years ( )

3. Please indicate your highest education level

Diploma ( )

Bachelor Degree ( )

Master Degree ( )

Doctorate Degree ( )

4. Please indicate your educational qualification

Procurement ( )

Supply chain management ( )

Logistics ( )

Operations management ( )

Other (*Specify*) ……

5. Size of the company

Less than 10 employees ( )

10 - 49 employees ( )

50-99 employees ( )

Section B: Determinants of Digital Supply Chain Management

Using the following5-point Likert scale, please indicate to what extent you agree with the following statements as a supply chain practitioner in your organization. Where: 1 – Strongly disagree, 2 – Disagree, 3 — Neither agree or disagree, 4 –Agree, 5 – Strongly Agree

Performance expectancy Items		**1**	**2**	**3**	**4**	**5**
6	The available digital technologies are useful in my everyday work life					
7	The use of digital technologies in my work will enhance my task completion					
8	The use of digital technologies in my work place will assist my task completion faster					
9	The use of digital technologies in my work place will improve my productivity					
Effort expectancy Items		**1**	**2**	**3**	**4**	**5**
10	My ability to learn and use digital technologies as a supply chain professional will be easy for me.					
11	My early experience with digital technologies for supply chains will be clear and understandable					
12	The use of digital technologies in my work will be easy for me					
13	It will be easy for me to attain skills in using digital technologies in my role as a supply chain professional					
Social influence Items		**1**	**2**	**3**	**4**	**5**
14	Those significant others to me are of the opinion I should adopt digital technologies in my work					
15	Those individuals that influence my behaviour are of the opinion I should adopt digital technologies in my work					
16	Those individuals whose opinions that I value are of the opinion I should adopt digital technologies in my work.					
Facilitating conditions Items		**1**	**2**	**3**	**4**	**5**
17	I have the reasons and resources required to adopt digital technologies for my work					
18	I have the necessary knowledge to adopt digital technologies for my work					
19	The available digital technologies for supply chains are compatible with existing technologies I use					
20	I will be able to receive support from others if I experience difficulties in my adoption of digital technologies in my work					

Section C: Digital Supply Chain Adoption

Using the scale provided, please indicate to what extent you agree with these statements. Where: 1 – Strongly disagree, 2 – Disagree, 3 — Neither agree or disagree, 4 –Agree, 5 – Strongly Agree

Items		**1**	**2**	**3**	**4**	**5**
21	I have every intention to use digital technology in my work in the near future					
22	I expect to adopt digital technologies in my role as a supply chain professional					
23	I am planning to adopt digital technology in my role as a supply chain professional					
24	My adoption of digital technologies in my role will afford me relative advantage over others					
25	My adoption of digital technologies in my role as a supply chain professional will be compatible with the present processes, technology, and tools					
26	The use of digital technologies is a complex process to implement in my role as a supply chain professional					

Thank You for Your Participation

APPENDIX 3: FMCG MANUFACTURING FIRMS IN NAIROBI COUNTY

S/No.	Firm
1	21st Century Food & Packing Ltd
2	A.S.P Internat Herbal Soap Ltd
3	Ab Food & Beverages
4	Abony Dairies Ltd
5	Ace Chemicals
6	Achal Impex Inc
7	AFD Food Co.Limited
8	Afrego Kenya Limited
9	Afrego Kenya Ltd
10	Africa Spirits Ltd
11	African Cotton Industries Ltd
12	Bakemark Ltd
13	Bakers Yard Ltd
14	Bakeville Ltd
15	Bakex Millers
16	Bakhresa Food Products Limited
17	Bakhresa Group
18	Balaji Group E.A Ltd
19	Balm Industries Ltd
20	Balm Industry Ltd
21	Baraka Highland Honey
22	Baraka Kenya Limited
23	Can Co Egypt
24	Candy Kenya Ltd
25	Cannon Chemicals Limited
26	Cannon Chemicals Ltd
27	Canon Chemicals Ltd (Nrb)
28	Capital Bakery
29	Capwell Industries
30	Capwell Industries Ltd
31	Carrefour Supermarket
32	Centrofood Industries Ltd
33	Ceres Fruit Juice (Pty) Ltd Sa.
34	Chai Bora Kenya Ltd
35	Chamu Supplies Ltd
36	Delight Promotions Ltd
37	Delmonte (K) Limited
38	Delta Millers Ltd
39	Deluxe Food Ind ltd
40	Deluxe Food Ind. Ltd
41	Demka Dairy
42	Derbby'S Investments Ltd
43	Dessra Ventures Ltd
44	Destiny Packers
45	Devkan Enterprises Ltd
46	Dexe Group
47	Diamond Foods
48	Diamond Industries Limited
49	Emrok Tea Factory (EPZ) Ltd
50	Energy Beverages LLC
51	Ennsvalley Bakery
52	Eris Industries
53	European Perfumes & Cosmetics
54	Everest Industries Ltd
55	Flame Tree Africa Ltd.
56	Flame Tree African Ltd
57	Flavour Toast Ltd
58	Food Security Millers Ltd
59	Foremost Bakers
60	Foshan Boydfia Imp & Co.Ltd Fosh
61	Foshan boyida imp & exp co.ltd
62	Foster Clark Products Ltd
63	France Davey Cosmetic Int Group
64	Fresh Blend Company Ltd
65	Gatunguru Tea Factory Co. Ltd
66	Ghandour Industries
67	Giant Millers Ltd
68	Gibsons Coffee Ltd
69	Gift Of Zanzibar
70	Giloil Company Limited
71	Giloil Company Ltd
72	Haco Tiger Brands (Ea) Ltd.
73	Haco Tiger Brands East Africa Lt
74	Hadco Group
75	Hanse Impex Co.ltd
76	Happy Cow Ltd
77	Happy Eaters Kenya Ltd
78	Haruss International Ltd
79	Hatima Mills Ltd
80	Hayat Kimya San
81	Hc Industries
82	Healthy U-2000 Limited
83	Icobo Company Ltd
84	Ikumbi Tea Factory Co. Ltd
85	Imaan Bakers
86	Imenti Tea Factory Co. Ltd
87	James Finlay (Kenya) Ltd
88	Jamhan Holdings Ltd
89	Jasiri Flour Mills Ltd
90	Jesa Farm Dairy Ltd
91	Jikaze Millers
92	Jinxing Industry
93	JM Millers
94	Kabarnet Mineral Water Ltd
95	Kabianga Dairy Ltd

96 Kaimosi Tea Estate Ltd
97 Kaisugu Ltd Kericho
98 Kajjohs Ltd
99 Kamindi Ltd
100 Kangaroo Brands Ltd
101 Kanice Digital Millers Ltd
102 Kapa Oil Industries
103 Lakeside Dairy Ltd
104 Libra Foods Products Ltd
105 London Distillers Ltd
106 L'oreal
107 M & M Products Ltd
108 Mill Bakers Ltd
109 Mini Bakeries Ltd
110 Mister's Bakers Ltd
111 Modern Industries Company.
112 Nestle Foods Kenya Ltd
113 Norda Industries Ltd
114 Nutrimatrix Enterprises Nairo
115 Only You Cosmetics Co Ltd
116 Orbit Chemicals
117 Oxfords Industries Ltd
118 P.Z Cussons
119 Patco Industries Ltd
120 Pembe Flour Mills Ltd
121 Pepsi Company Ltd
122 Procter & Gamble
123 Proctor & Alllan
124 Promasidor (Kenya) Ltd
125 Proto Chemicals Ltd
126 Quickmart Ltd
127 Red Bull GmbH
128 Roc Cosmetics (k) Ltd
129 Royal Converters Ltd
130 Royal Swiss Bakery Ltd
131 Sama Pasta Company
132 Sasini Kenya Ltd
133 Sassy Cosmetics and Beau Ltd
134 Savannah Brands
135 Servechem (K) Ltd
136 The Coca-Cola Company
137 Top Food EA Ltd
138 Topland Millers
139 Tropikal Brands (Africa) Limited
140 Tru Food Ltd
141 Unga Holdings Limited
142 Unilever Kenya Ltd
143 United Biscuits
144 Uzuri Foods Limited
145 Vipingo Industries
146 Wrigley's Company

APPENDIX 4: SAMPLE SIZE TABLE

Table 3.1

Table for Determining Sample Size of a Known Population

N	S	N	S	N	S	N	S	N	S
10	10	100	80	280	162	800	260	2800	338
15	14	110	86	290	165	850	265	3000	341
20	19	120	92	300	169	900	269	3500	346
25	24	130	97	320	175	950	274	4000	351
30	28	140	103	340	181	1000	278	4500	354
35	32	150	108	360	186	1100	285	5000	357
40	36	160	113	380	191	1200	291	6000	361
45	40	170	118	400	196	1300	297	7000	364
50	44	180	123	420	201	1400	302	8000	367
55	48	190	127	440	205	1500	306	9000	368
60	52	200	132	460	210	1600	310	10000	370
65	56	210	136	480	214	1700	313	15000	375
70	59	220	140	500	217	1800	317	20000	377
75	63	230	144	550	226	1900	320	30000	379
80	66	240	148	600	234	2000	322	40000	380
85	70	250	152	650	242	2200	327	50000	381
90	73	260	155	700	248	2400	331	75000	382
95	76	270	159	750	254	2600	335	1000000	384

Note: N is Population Size; S is Sample Size *Source: Krejcie & Morgan, 1970*

APPENDIX 5: ETHICAL APPROVAL

Strathmore UNIVERSITY

2nd April 2025

Ms Masaku Linda,
linda.masaku@strathmore.edu

Dear Ms Masaku,

RE: Determinants of Adoption of Digital Supply Chain Technologies Among Fast-Moving Consumer Goods Manufacturers in Nairobi County, Kenya

This is to inform you that SU-ISERC has reviewed and **approved** your above **SU-masters** proposal. Your application reference number is **SU-ISERC2793/25.** The approval period is from **2nd April 2025 to 1st April 2026.**

This approval is subject to compliance with the following requirements:

i. Only approved documents including (informed consents, study instruments, MTA) will be used.
ii. All changes including (amendments, deviations, and violations) are submitted for review and approval by SU-ISERC.
iii. Death and life-threatening problems and serious adverse events or unexpected adverse events whether related or unrelated to the study must be reported to SU-ISERC within 72 hours of notification.
iv. Any changes anticipated or otherwise that may increase the risks or affected safety or welfare of study participants and others or affect the integrity of the research must be reported to SU-ISERC within 72 hours.
v. Clearance for the export of biological specimens must be obtained from relevant institutions.
vi. Submission of a request for renewal of approval at least 60 days prior to the expiry of the approval period. Attach a comprehensive progress report to support the renewal.
vii. Submission of an executive summary report within 90 days of completion of the study to SU-ISERC.

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

Yours sincerely,

Mr Ambrose Rachier,
Chairperson; SU-ISERC

Ole Sangale Rd, Madaraka Estate. PO Box 59857-00200, Nairobi, Kenya. Tel +254 (0)703 034000
Email admissions@strathmore.edu www.strathmore.edu

APPENDIX 6: RESEARCH LICENSE

REPUBLIC OF KENYA

NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Ref No: **192698**

Date of Issue: **04/April/2025**

RESEARCH LICENSE

This is to Certify that Miss.. Linda Mwende Masaku of Strathmore University, has been licensed to conduct research as per the provision of the Science, Technology and Innovation Act, 2013 (Rev.2014) in Nairobi on the topic: DETERMINANTS OF ADOPTIONOF DIGITAL SUPPLY CHAINTECHNOLOGIES AMONG FASTMOVING CONSUMER GOODSMANUFACTURERS IN NAIROBICOUNTY, KENYA for the period ending : 04/April/2026.

License No: **NACOSTI/P/25/417818**

192698

Applicant Identification Number

Director General
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