Adoption, Assimilation and Sustainability Outcomes of AI and Industry 4.0 Technologies in Supply Chain

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Abstract

The push to digitalise supply chains reflects technology's growing role in improving performance and sustainability. However, access to technology does not guarantee adoption or effective use, as adoption remains uneven with a variety of implementation challenges. Although Artificial Intelligence (AI) and Industry 4.0 Technologies (I4.0T) offer extensive opportunities for supply chain performance improvement, their impact depends on how well organisations integrate and assimilate them.

The overarching aim of this thesis is to examine AI and I4.0T adoption and how adoption develops into sustainability performance in supply chain by evaluating the roles of technology readiness, technological capability and organisational agility in shaping this progression.

This research comprises three interconnected studies: a Systematic Literature Review (SLR) and two empirical investigations. The SLR syntheses existing studies to evaluate AI's contribution to sustainability and its implications for existing theories. The second study applies the Technological, Organisational and Environmental (TOE) framework and incorporates the Technology Readiness Index (TRI) to assess how readiness factors mediate AI and I4.0T adoption. Drawing on Dynamic Capabilities Theory (DCT), the third study investigates how technological capability and organisational agility mediate the relationship between technology assimilation and sustainability performance. The empirical analyses draw from data collected through an online survey from Nigeria, a context that provides valuable insight into how global theories operate beyond developed economies.

By empirically testing this integrated model, this study bridges technology adoption and assimilation literatures often examined separately, enhances TOE's explanatory power by positioning TRI as a mediator between it and adoption outcomes, contributes to DCT by showing how assimilation influences sustainability through distinct capability pathways that

serve different functions and vary in their contribution across sustainability performance outcomes. The study offers practical and policy implications including the need for stage-specific strategies and success factors and the inadequacy of policies focused solely on encouraging adoption.

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Declaration

I declare that this thesis has been composed solely by myself and that it has not been submitted, in whole or in part, in any previous application for a degree.

Parts of this work (Chapter 3) formed the basis of my presentation titled **Technology Readiness Index as a Mediating Mechanism: How TOE Factors Influence AI and Industry 4.0 Adoption** at the Essex Business School Research Conference, September 2025. It also forms the foundation for a submission to EUROMA 2026 Conference titled **Determinants of AI and Industry 4.0 Adoption in Supply Chains: A TOE-Technology Readiness Perspective**

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LIST OF ABBREVIATIONS

4IR: Fourth Industrial Revolution
ABS: Agent-Based Systems
AI: Artificial Intelligence
ANN: Artificial Neural Networks
AMOS: Analysis of Moments Structure Software
BDA: Big Data Analytics
CAC: Corporate Affairs Commission
CB-SEM: Covariance-Based Structural Equation Modelling
CFA: Confirmatory Factor Analysis
CFI: Comparative Fit Index
CIMO: Context Intervention Mechanism Outcome
CIPS: Chartered Institute of Procurement and Supply
CMB: Common Method Bias
CMV: Common Method Variance
CPS: Cyber Physical Systems
CSR: Corporate Social Responsibility
EFA: Exploratory Factor Analysis
EMA: Expectation Maximization Algorithm
ESG: Environment Social and Governance
FL: Fuzzy Logic
GA: Genetic Algorithm
GFI: Goodness-of-Fit Index
GTAI: German Trade and Investment
HTMT: Heterotrait-Monotrait Ratio of Correlations
I4.0R: Industry 4 Revolution
I4.0T: Industry 4.0 Technologies
ILO: International Labour Organisation
IoT: Internet of Things
MCAR: Missing Completely at Random
NRBV: Natural Resource-Based View
RBV: Resource-Based View
RBI: Regression Based Imputation
RFID: Radio Frequency Identification
RMSEA: Root Mean Square Error of Approximation
RPA: Robotic Process Automation
SEM: Structural Equation Modelling
SPSS: Statistical Package for the Social Sciences
SRMR: Standardised Root Mean Square Residual
TCE: Transaction Cost Economics
UAV: Unmanned Aerial Vehicle
VIF: Variance Inflated Factor

Chapter 1 Introduction

1.1 Background

The increasingly integrated global economy, characterised by intense competition, hyper-customisation and constant change, presents complex challenges for organisations (Ismail, Khater and Zaki, 2017). These challenges encompass a range of issues, including evolving customer expectations, geopolitical uncertainties, regulatory compliance and frequent supply chain disruptions. Beyond the forces of globalization, organisations also face heightened pressure to prioritize different customer orientations and satisfy a wide array of stakeholder requirements. Moreover, as supply chains evolve from simple pipelines for moving goods into data-driven complex ecosystems, supply chain management is becoming a key source of organisational performance and competitive advantage (Naz *et al.*, 2022). Moreover, the activities of supply chains increasingly influence economic performance, environmental stewardship and social responsibility. Collectively, these factors place significant pressure on organisations compelling them to reevaluate their operations and supply chain practices. Consequently, organisations seek to embed sustainability into their operations at every level, from operational to tactical and strategic (Shepherd and Günter, 2006; Hao and Demir, 2023). To navigate this landscape, organisations must incorporate expertise and innovation into their products and services (Gieger and Metzger, 2025). Technology offers a transformative opportunity to address these challenges by enabling efficient, intelligent and sustainable supply chains that are both future-proof and competitively advantageous (Gieger and Metzger, 2025).

On the other hand, literature generally recognises supply chain management as vital to achieving a sustainable competitive edge through the efficient planning, execution, and control of activities and operations within supply chains to meet organisational goals (Melo, Nickel and Saldanha-Da-Gama, 2009). This makes managing and measuring supply chain performance more crucial than ever. As noted by Beamon (1999), traditionally, supply chain

performance measures have centred on cost and customer responsiveness, emphasising efficiency, effectiveness and economy (Mangla *et al.*, 2020). However, the focus is now shifting toward integrating environmental and social sustainability metrics alongside economic viability when assessing supply chain performance (Ma, Shi and Kang, 2022). However, gathering and analysing data across these three sustainability dimensions is inherently complex (Qorri, Mujkić and Kraslawski, 2018). Addressing these challenges require advanced tools. This requirement has contributed to an accelerated shift toward digitalised supply chains (Gebhardt *et al.*, 2021).

Consequently, organisations are increasingly turning to digital technologies like Artificial Intelligence (AI) to drive these performance improvements (Zaid, Farooqi and Azmi, 2025). AI's attractiveness stems from advances in computational power and improvement in algorithms which enable AI systems handle increased data generated in supply chains (Rashid and Kausik, 2024). AI, in turn, serves as a catalyst for the innovation and transformation associated with the Fourth Industrial Revolution, also known as Industry 4.0 (I4.0). I4.0 merges the digital and physical worlds, allowing seamless information exchange among machines, systems and humans (Luo and Zahra, 2023). Digital technologies such as AI and I4.0 technologies (I4.0T) enable organisations build flexible, intelligent cyber-physical networks that connect machines, equipment, facilities and people for seamless data exchange. This facilitates real-time monitoring and control of key production parameters, including production status, energy consumption, material flows, customer orders and supplier data, thereby enhancing overall organisational performance (Lopes de Sousa Jabbour *et al.*, 2018).

1.2 Working Definition of Key Concepts

Given the varied interpretations of terms such as adoption, assimilation AI, I4.0T, sustainability and supply chain management in the existing literature, this section presents the working

definitions adopted in this thesis. These definitions are intended to clarify the interpretation and an application of each concept in the context of the research.

Technology Adoption: Technology adoption in the context of this study refers to the point at which an individual or organisation chooses to begin using a particular technology. This is conceptualised as the readiness or inclination of a group of users to utilise technology in ways that benefit them (Kamble et al. 2018). This is a threshold event, a point in time when the organisation commits to the technology.

Assimilation: This study operationalises assimilation at the routinisation and infusion stages of Chatterjee et al. (2002) assimilation continuum, capturing the extent to which AI and I4.0T are embedded in workflows, decision routines and inter-organisational processes, beyond initial adoption or trial. Assimilation is a continuous process, not a single event.

Sustainability: Sustainability in this study is framed in line with Elkington (1997) using the triple bottom line (TBL) approach, which considers economic, environmental, and social dimensions of performance.

Supply Chain Management (SCM): The study adopts definition of Mentzer et al. (2001) which refers to SCM as ‘strategic coordination of the traditional business functions and the tactics across these business functions within a particular company and across businesses within the supply chain, for the purposes of improving the long-term performance of the individual companies and the supply chain as a whole’

Industry 4.0 Technologies (I4.0T): This study refers to I4.0T as a broad ecosystem of interconnected digital technologies that merge the physical and digital worlds to enable intelligence and transparency.

Artificial Intelligence (AI): The study conceptualises AI as computational systems capable of performing tasks that typically require human intelligence and this includes machine learning,

natural language processing, computer vision, predictive analytics and autonomous decision-making.

The distinction between AI and I4.0T is intentional and theoretically grounded. Although they operate together in supply chains, they differ in ways that matter for theory. The defining characteristic of I4.0T is connectivity and integration which enables seamless data exchange between machines, systems, people and processes (Bai et al., 2020; Frank et al., 2019). In contrast, AI's defining characteristics include intelligence, autonomy and the ability to learn from data, adapt behaviour and make or recommend decisions without explicit human programming for each scenario (Dwivedi, 2021; Hendriksen, 2023).

This distinction has clear theoretical implications. AI challenges established frameworks in ways that I4.0T does not. For example, Agency Theory does not account for non-human decision-makers, Stakeholder Theory struggles with opaque, “black-box” reasoning, and the TOE framework treats technology as static, which is insufficient for systems that evolve after deployment (Gabison and Xian, 2025; Hassija *et al.*, 2024). These tensions stem from AI’s autonomy and learning capabilities rather than from connectivity technologies alone.

Empirically, AI and I4.0T also exhibit different adoption dynamics. AI adoption requires advanced data capabilities, governance structures, and organisational acceptance of algorithmic decision-making, whereas I4.0T adoption is more closely associated with digital infrastructure and integration. Treating them as a single construct risk obscuring these differences. At the same time, analysing them together reflects operational reality. AI depends on I4.0T infrastructure, while I4.0T generates data that only AI can effectively leverage. This combined yet differentiated approach is consistent with prior research (Bag et al., 2020; Bai et al., 2020; Hendriksen, 2023). In the empirical model, adoption was operationalised as a unified construct

to reflect this interdependence. The conceptual distinction operates primarily at the theoretical level, informing the research framing and argument development. This aligns with established practice, where constructs are theoretically distinct but empirically combined when they are operationally inseparable. Future research could usefully separate AI and I4.0T adoption to examine whether their effects on sustainability outcomes differ.

1.3 Research Rationale

The relationship between AI and I4.0T and sustainable operations is well established in the literature. For instance, Kache and Seuring (2017) highlight the role of big data analytics in enhancing supply chain visibility and decision-making, while Dalenogare *et al.* (2018) and Fatorachian and Kazemi (2020) demonstrate the positive effects of I4.0T on operational and supply chain performance. Similarly, Min (2019) and Stock and Seliger (2016) emphasise the role of digital technologies in enabling resilience, circularity and sustainable manufacturing practices. In terms of sustainability, prior studies confirm that AI and I4.0T can enhance performance across economic, environmental, and social dimensions (Bai *et al.*, 2020). Across this body of work, recurring themes include improved visibility, data-driven decision-making, operational efficiency, resilience and resource optimisation. Despite these advances (Fatorachian and Kazemi, 2020; Bag *et al.*, 2020), the literature remains uneven in its treatment of sustainability. Existing studies predominantly emphasise environmental outcomes, such as energy efficiency, emissions reduction, and resource optimisation, while giving comparatively limited attention to social sustainability dimensions (Ly and Cope, 2023). This creates an incomplete understanding of how AI and I4.0T contribute to sustainability in a holistic sense.

Beyond sustainability outcomes, a further limitation lies in how technology adoption is conceptualised. The availability of advanced technologies and enabling conditions does not guarantee successful adoption or diffusion (Zemsky and Massy, 2004). Empirical evidence points to uneven adoption rates and implementations that fail to deliver expected benefits

(Dalenogare *et al.*, 2018). Moreover, adoption on its own does not guarantee successful outcomes (Olan *et al.*, 2022), highlighting the need to better understand the mechanisms linking adoption to outcomes (Venkatesh, Raman and Cruz-Jesus, 2024), perhaps considering the huge investments that come with emerging technologies. Despite the promise of technology for enhancing organisational performance, realising its value is contingent upon its acceptance (Kunkel *et al.*, 2022). A thorough understanding of the process that connects adoption to outcomes is therefore imperative. This study's three papers collectively address these by developing a comprehensive and progressive understanding of how AI and I4.0T shape supply chain sustainability through theoretical extension, empirical testing and integration of new constructs such as readiness, technological capability and organisational agility.

Although prior studies have examined determinants of adoption and assimilation (Kamble, Gunasekaran and Sharma, 2018), these processes are often treated as independent rather than as interconnected stages of value creation. On the other hand, research investigating the impact of AI or I4.0T adoption and assimilation has largely focused on overall performance, with limited attention to sustainability specific outcomes (Wamba-Taguimdje *et al.*, 2020; Wamba, 2022; Abdul Wahab and Radmehr, 2024)

Relatedly, while constructs such as technology readiness (Alsheibani, Cheung and Messom, 2018) technological capability (Sony, Antony and Mc Dermott, 2022), and organisational agility (Mrugalska and Ahmed, 2021) have been explored, they are rarely examined together or empirically tested as mediating mechanisms linking adoption to performance outcomes (Blut and Wang, 2020). As a result, the processes through which AI and I4.0T translate into sustainability outcomes remain insufficiently understood This study addresses this limitation by positioning readiness, technological capability, and organisational agility as critical mediating constructs that explain how adoption evolves into tangible organisational and sustainability benefits. In support, Parasuraman and Colby (2015) suggest

that readiness has a significant influence on the success of digital adoption, acting as both a motivator and a barrier. Apart from readiness to adopt, assimilation of these technologies is enhanced through dynamic capabilities such as technological capability to integrate, reconfigure and upgrade technologies to create meaningful value (Khin and Ho, 2019) and agility that enables resilience and ensures organisations can adjust quickly in response to changes (Tallon and Pinsonneault, 2011; Dubey *et al.*, 2020).

At the theoretical level, existing frameworks also struggle to fully capture the unique characteristics of AI and I4.0T. Traditional models such as the TOE framework and Dynamic Capabilities theory were developed in contexts where technologies were largely static and human-directed. This creates a critical gap in integrating these theories with the unique characteristics and challenges presented by AI and I4.0T in supply chain management contexts (Hendriksen, 2023). Again, with the emergence of contemporary AI systems, including generative AI such as ChatGPT, exhibit adaptive, learning, and increasingly autonomous behaviour and as such could actively shape supply chain processes and outcomes (Richey Jr *et al.*, 2023). This challenges existing assumptions about technology as a passive tool and highlights the need to account for AI as an active agent shaping organisational processes and outcomes. Furthermore, the interaction between technological capabilities and social factors, including organisational culture and sensemaking (Makarius *et al.*, 2020) introduces additional complexity that is not fully addressed in current supply chain theories.

These limitations are further compounded by contextual bias in the literature. Most empirical studies are conducted in advanced economies, limiting the generalisability of findings to emerging markets. In contexts such as Nigeria, factors including infrastructural constraints, skills gaps, financial limitations, and institutional challenges significantly shape technology adoption and utilisation (Ade-Ibijola and Okonkwo, 2023; Ola-Oluwa, 2024). Again, Nigeria's collectivist culture and high power distance (PDI = 80) evidenced in the "Oga

at the Top" leadership concentration mechanism is consistent with findings of Srite and Karahanna (2006) that authority signal from senior leadership may override individual technology evaluation. This underscores the need for context-sensitive research that reflects the realities of emerging economies.

Taken together this study addresses three interrelated gaps. First, a theoretical gap exists, as current frameworks struggle to explain the dynamic, autonomous, and evolving nature of AI and I4.0T within supply chains, particularly in relation to sustainability outcomes. Second, a methodological gap is evident in the limited integration of adoption and assimilation as a continuous process and the lack of empirical testing of key mediating mechanisms such as readiness, technological capability, and organisational agility. Third, a contextual gap persists, given the dominance of studies in advanced economies and the limited understanding of how these technologies are adopted and utilised in emerging economies such as Nigeria. Addressing these gaps in isolation would provide only partial insight; therefore, this study adopts an integrated approach that simultaneously advances theory, employs a process-oriented and mediation-based methodology, and situates the analysis within a relevant emerging economy context. This combined approach enables a more comprehensive explanation of how AI and I4.0T translate into sustainable supply chain outcomes

This thesis is grounded in Nigeria as a theoretically strategic setting for examining AI and I4.0T across adoption, assimilation and sustainability outcomes in emerging economies. Nigeria is a critical test environment where the core assumptions underpinning dominant technology and sustainability theories are tested. The SLR which interrogates AI-sustainable supply chain research reveals that most empirical work is set in developed economies, largely built on assumptions of stable infrastructure, institutional certainty and mature data-sharing ecosystems. Examining these mechanisms under conditions of infrastructural fragility, institutional voids and fragmented, relationship-driven supply chains, highlights context-

contingent mechanisms and extends theory by revealing what existing frameworks cannot explain when their foundational assumptions are systematically disrupted.

The adoption study extends TOE and TRI by testing their explanatory power in an environment characterised by regulatory inconsistency and infrastructural unreliability (Khanna and Palepu, 1997; Silvestre, 2015), alongside context-amplified psychological inhibitors shaped by power instability, currency volatility, and prior technology failure. In this setting, environmental constraints and individual perceptions interact in ways not fully captured by standard formulations of either framework, allowing for clearer identification of boundary conditions and mechanism refinement. The assimilation and sustainability study further subjects Dynamic Capabilities Theory to conditions of severe institutional volatility, power instability (Onwude *et al.*, 2023) currency depreciation and rapid naira devaluation (IMF, 2024) and accelerated human capital loss, including the Japa phenomenon (Thomas *et al.*, 2025; Ojubanire *et al.*, 2024), challenging core assumptions of capability accumulation and persistence.

Across all three papers, Nigeria functions not as a case of empirical convenience but as a theoretically demanding context that exposes boundary conditions, refines existing frameworks and advances understanding of how AI and I4.0 enabled technologies translate into sustainability outcomes under extreme institutional and infrastructural constraints.

1.4 Research aims and question

These shifts above have raised concerns about the preparedness of organisations to capitalise on the benefits and mitigate the drawbacks of these disruptive technologies (Dubey *et al.*, 2020; Zaid, Farooqi and Azmi, 2025). This is especially significant as the mechanism for translating the adoption of AI and I4.0T to performance benefits remains largely unclear (Abdul Wahab and Radmehr, 2024; Fatorachian and Kazemi, 2020). The extent to which organisations can exploit these technologies to reap the expected benefits could depend on the significant

impact of organisational assets, capabilities, and commitment on technology readiness (Nguyen *et al.*, 2019).

This study aims to examine what drives technology adoption and how adoption translates into sustainability performance in supply chain by exploring the influence of technology readiness index, technological capability and organisational agility in this transition. To address and fill the mentioned gaps in clearly explaining how supply chain sustainability performance is achieved through AI and I4.0T, this study develops an integrated understanding of their adoption, assimilation and impact on sustainability outcomes guided by the overarching research question:

- *How do Artificial Intelligence (AI) and Industry 4.0 technologies (I4.0T) drive supply chain sustainability performance.*

The thesis examines this central research question through the sequential evaluation of:

1. The existing knowledge base and theoretical progression (Chapter 2) by answering these questions:
    - How has literature evolved in response to AI adoption in developing sustainable supply chains
    - What is the impact of AI adoption on the sustainability performance of supply chains
    - How are supply chain theories adapting to explain AI's role in enhancing supply chain sustainability
2. The factors that drive adoption and how TRI motivates or inhibits them (Chapter 3) based on the following questions:
    - What is the current state of adoption of AI & I4.0T among organisations

- How do technological, organisational and environmental elements impact technology adoption
- How do TRI motivating and inhibiting factors mediate the relationship between TOE factors and the adoption of AI and I4.0T.

3. The mechanism for the translation of adoption into measurable sustainability outcomes through dynamic capabilities (Chapter 4) by answering the following questions:
    - How does the assimilation of AI and I4.0T influence supply chain sustainability performance across economic, social and environmental dimensions?
    - What roles do technological capability and organisational agility play as mediators? What paradoxes emerge during assimilation?

This thesis argues that AI and I4.0T improve supply chain sustainability performance through a non-linear, context-dependent process in which adoption, assimilation and outcomes are structurally separated but conditionally linked. Chapter 2's finding shows that dominant AI-sustainability theories are developed in western context built on assumptions of stable infrastructure, mature institutions and formalised supply chains. This exposes clear boundary conditions and the need for theoretical extension. Chapter 3 demonstrates that adoption is jointly shaped by TOE conditions and technology readiness, where TRI's motivating and inhibiting forces interact with institutional voids and infrastructural instability to produce uneven and context-contingent adoption outcomes. Chapter 4 shows that even where adoption occurs, sustainability performance only emerges through dynamic capabilities formed through technological capability and organisational agility, which are continuously reshaped under infrastructural fragility, institutional volatility and human capital loss. In summary, the thesis establishes that sustainability gains from AI and Industry 4.0 are not automatic products of adoption, but outcomes of a constrained capability-building process that extends TOE, TRI, and Dynamic Capabilities Theory beyond stable-context assumptions.

1.5 Conceptual Connection Across the Three Studies

The three-papers thesis is theoretically connected through a shared interest in how AI and I4.0T shape sustainability outcomes in supply chains. The thesis follows a theoretically integrated progression from literature synthesis to adoption dynamics and finally to capability-based sustainability outcomes. The conceptual model illustrates the theoretical platform, bridging constructs, mediating mechanisms and contextual tensions that collectively integrate the studies into a coherent programme of research. Chapter 2 provides the foundational conceptual layer through a Systematic Literature Review guided by the CIMO-Symphony framework. CIMO identifies the relevant contexts, interventions, mechanisms and outcomes that characterise AI-enabled supply chain sustainability research. Though this framework does not function as the first step in a linear sequence, it underpins the empirical models developed in Chapters 3 and 4. It influences the identification of adoption determinants (TOE), motivational mechanisms (TRI), capability mechanisms (Technological Capability (TC) and Organisational Agility (OA)) and sustainability outcomes. Building on this conceptual base, Chapter 3 empirically examines the determinants of AI and I4.0T adoption. It operationalises the adoption stage using the TOE framework, with TRI functioning as the key mediating mechanism through which technological, organisational and environmental conditions translate into adoption outcomes. Adoption, the structural outcome serves as the bridging construct that connects Chapter 3 to Chapter 4. Chapter 4 extends the theoretical logic by examining how adoption translates into sustainability outcomes. Drawing on Dynamic Capabilities Theory, the study models the role of TC and OA as mutually reinforcing mechanisms and mediators that explain how adoption leads to assimilation and subsequently, to sustainability performance while simultaneously being shaped by contextual paradoxes.

A single integrated survey instrument was used to collect data for the empirical studies. Practically, this approach reduced respondent burden, improved response rates, and enabled comprehensive measurement of adoption and assimilation constructs within one data collection effort. Theoretically, it reflects the reality that adoption and assimilation are not distinct stages in Nigerian supply chains, as organisations often adopt some AI and I4.0T applications while simultaneously assimilating others. This design therefore captures the current state of technology implementation. Implications for inter-study independence and common method variance are addressed in the respective methodology sections. Fig. 1.1 presents a visual representation of the conceptual model showing how CIMO-Symphony scaffolding shapes TOE–TRI driven adoption, which transitions into dynamic capabilities (technological capability and organisational agility) to deliver sustainability outcomes under contextual constraints.

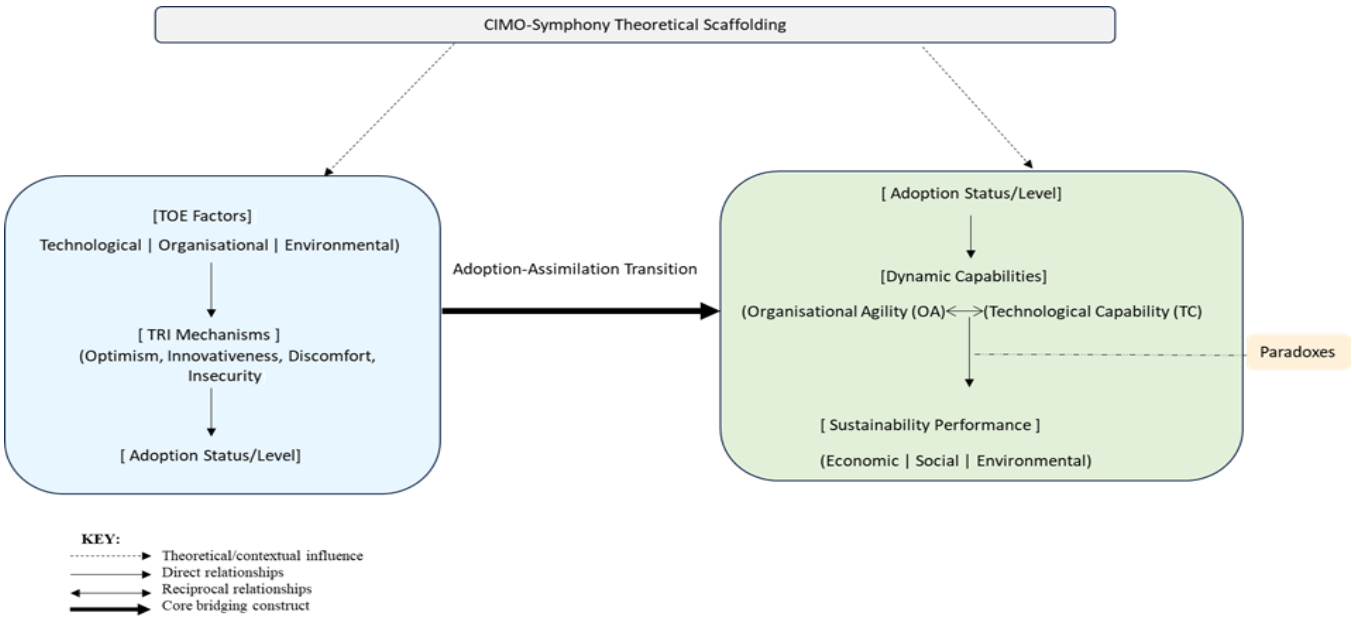

Figure 1.1 Conceptual Connection Model

1.6 Significance to Literature and Practice

This thesis advances a central theoretical claim that digital transformation for sustainability is a contingent, sequentially mediated process in which each stage, from enabling conditions to adoption, from adoption to assimilation, and from assimilation to sustainability outcomes, depends on a distinct organisational mechanism that is neither guaranteed nor automatically triggered by the previous stage. This argument is developed across three interconnected studies. The systematic literature review identifies gaps in existing theories in explaining the disconnect between the promise of digital technologies and observed sustainability outcomes. The adoption study shows that favourable TOE conditions lead to adoption only when TRI motivators are activated, revealing the first mediation gap. The assimilation study demonstrates that adoption translates into sustainability outcomes only when organisations develop technological capability and organisational agility, revealing the second mediation gap. Taken together, these findings reposition the sustainability productivity paradox as a capability gap rather than a technology gap. The Nigerian context further strengthens this contribution by showing that these transition mechanisms vary under conditions of structural constraint and cultural collectivism, thereby establishing important boundary conditions for existing theoretical frameworks. Thesis Structure

The thesis comprises of three distinct but connected studies as follows: Chapter 2 adopts a systematic literature review to present the theoretical and empirical landscape of AI and supply chain sustainability and identifies gaps in the literature and theory. The study introduces symphony orchestra metaphor to enrich the Context Intervention Mechanism Outcome (CIMO) framework and support a comprehensive thematic analysis. In Chapter 3 structural equation modelling and mediation analysis are employed to evaluate the relationship between TOE factors and technology adoption and how the psychological and attitudinal elements of

TRI mediate this relationship, either motivating or inhibiting adoption. Chapter 4 focuses on post adoption by investigating the transition process from assimilation of AI and I4.0T to sustainability performance outcomes. It also identifies the paradoxes and unintended outcomes that arise from adoption. Through Structural Equation Modelling and Mediation analysis, the chapter confirms the mediating role of technological capability and organisational agility in translating assimilation into impact. Finally, Chapter 5 presents the overall discussion and conclusion of the thesis, highlighting the theoretical contributions, practical and managerial implications as well as limitations of the study. It also presents suggestions for future research endeavours.

Chapter 2 AI-Powered Supply Chains: A Review, Framework and Research Agenda for Sustainability Outcomes and Theory Progression

2.1 Abstract

As organisations increasingly adopt Artificial Intelligence (AI) to achieve sustainability goals, understanding its influence on sustainable supply chain performance has become a critical area of research. This paper presents a literature review on the relationship between AI adoption and sustainable supply chain performance. It also explores how supply chain theories are evolving to explain AI's role in advancing sustainability. The study systematically reviews articles published between 2010 and 2023 and reports using PRISMA framework. Introducing a symphony orchestra metaphor it enriches the Context-Intervention-Mechanism-Outcome (CIMO) framework to support a comprehensive thematic analysis.

The review identifies three main gaps: limited attention to AI's negative impacts, underexplored opportunities from integrating AI with other emerging technologies, and scarce research on its implications for traditional supply chain theories. The findings suggest that combining AI with related technologies holds considerable potential to improve sustainability outcomes.

The study calls for further research on the unintended consequences of AI-driven supply chains and on the ability of existing theories, such as Agency and Stakeholder Theory, to incorporate AI's transformative effects. By adopting a holistic view of AI and emerging technologies, this paper advances understanding of their interactive influence on supply chain sustainability and outlines avenues for future inquiry.

Keywords: Literature review, Sustainable supply chain, Artificial intelligence, Technology adoption, Supply chain theories;

2.2 Introduction

As stakeholders become increasingly aware of the socio-economic and ecological consequences of production and consumption, there is growing pressure from governments, consumer rights organisations, and social and environmental advocacy groups to integrate sustainability in supply chains (Kamble *et al.,* 2022). This has heightened awareness of the critical importance of prioritizing sustainability performance within supply chains (Wu *et al.,* 2020). Consequently, organisations face the challenge of addressing complex sustainability demands driven by intensified regulatory oversight, shifting consumer expectations, and growing requirements for social and ethical responsibility. The threats posed to supply chains by unforeseen disruptions further compounded these challenges (Raja Santhi and Muthuswamy, 2022).

Supply chains play a pivotal role in determining an organisation's overall performance including sustainability (Kamal *et al.,* 2023). However, it is becoming increasingly clear that traditional methods focused primarily on production and provision may no longer suffice in addressing the evolving needs of contemporary customers, especially in an era characterised by advanced technologies and the proliferation of big data (Tirkolaee *et al.,* 2021). AI in conjunction with Industry 4.0 technologies (14.0T), such as the Internet of Things (IoT), cloud computing, and autonomous robotics, have revolutionised traditional supply chain practices and enabling the shift to smart, sustainable manufacturing (Dwivedi *et al.*, 2023). These technologies present significant opportunities to enhance sustainability by introducing transformative solutions driven by AI (Bag and Pretorius, 2020).

Existing research on the integration of AI in sustainable supply chains has examined its effectiveness from various perspectives. These include its application in sustainable supplier selection (Ferreira and Borenstein, 2012), sustainable manufacturing (Chatterjee *et al.*, 2021), sustainable logistics and transportation planning (Naz *et al.,* 2022), sustainable product design

(Lee, 2021), enhancing circularity potential (Ada *et al.,* 2021), linking AI and digitalisation to the United Nations Sustainable Development Goals (Asokan *et al.,* 2022; Bai *et al.,* 2020), and advancing green supply chain practices (Feng *et al.,* 2022).

The increased integration of AI into supply chains has generated interest in studies regarding its impact on supply chain operations, sustainability and organisational performance. Although this has facilitated a vibrant discourse on AI's applications in supply chains, the literature remains fragmented across various disciplines and makes it difficult for a clear articulation of how AI adoption contributes to sustainable supply chain performance. Current research focuses mainly on environmental sustainability or a broad "triple bottom line" approach that leaves the social dimensions and AI's own sustainability unclear and under explored. Furthermore, the rapid evolution of AI systems and other emerging technologies appear to have outpaced supply chain theories, with limited literature on its impact on existing theories and how these theories can be upgraded to allow for AI adoption. These gaps reinforce the need for structured understanding and consolidation of the evidence of AI's impact on sustainable supply chain performance and how existing theories evolve to explain these dynamics.

This study aims to systematically review and synthesise existing literature on the relationship between AI and supply chains sustainability performance and how the literature and existing supply chain theories are evolving to explain this relationship. Through this comprehensive review of existing literature, this study addresses the following research questions:

1. How has the literature evolved in response to AI adoption in developing sustainable supply chains?
2. What is the impact of AI adoption on the sustainability performance of supply chains?

3. How are supply chain theories adapting to explain AI's role in enhancing supply chain sustainability?

In the light of the above this review offers several significant contributions to supply chain management, sustainability and organisational performance literature. First, by addressing the current fragmentation across domains, it consolidates the different views on the application of AI in supply chains to improve sustainability performance. Secondly, it provides an assessment of how core theories are extended or challenged in the light of AI adoption in supply chains. Thirdly, it identifies the theoretical gaps and proposes a research agenda for the progression and development of supply chain theories in recognition of AI's unique characteristics.

The remainder of this paper is organised as follows. The next section outlines the review methodology, detailing the data collection and filtering processes, including inclusion and exclusion criteria. Employing the Context-Intervention-Mechanism-Outcome (CIMO) framework, the study presents a detailed thematic analysis of key findings, followed by a discussion of these findings. The paper concludes by discussing contributions to the literature, implications for practice, limitations of the study and opportunities for future research.

2.3 Review Method and Study Design

To thoroughly understand the relationship between AI and sustainable supply chain management, a systematic literature review methodology was employed. By rigorously evaluating relevant scholarly works, this study follows a comprehensive and replicable process, as outlined by (Fan *et al.*, 2022). This approach considers the diverse and interdisciplinary nature of the topic at hand (Snyder, 2019) aimed at providing a comprehensive understanding of the practice and performance of AI in sustainable supply chain management. Additionally, systematic reviews such as this study help overcome the limitations presented by the unsystematic development of knowledge across various mediums and academic fields that

impede coherence, effectiveness, and accessibility of information in the academic environment (Linnenluecke, Marrone and Singh, 2020).

To conduct the literature review, this study adopted the following steps: First, the study determined the primary aim of the research, that is, to conduct a comprehensive review of literature on AI-powered supply chains and their effects on sustainability performance. With the research aim identified, the subsequent steps for (a) planning the review, (b) execution of the review and (c) reporting the review proceeded as outlined below.

2.3.1 Planning the Review

Planning is important to establish a strategy for the review process and ensure a focused search. This planning stage included articulating the research questions, determining and justifying the inclusion and exclusion criteria, developing and refining the review procedure (Xiao and Watson, 2019)

2.3.1.1 Inclusion and Exclusion Criteria

This study based the inclusion of papers for review on the following criteria (a) the type of publication type and language used: Articles and review papers published in peer-reviewed academic journals in the English language included because they provide reliable and rigorously reviewed information through standardised peer-review processes. This ensures validity and reliability. Again, review articles were included because they give a comprehensive analysis and in-depth insights into the state of knowledge regarding AI adoption in supply chains and sustainability performance. (b) Timeline: This was set to studies published between 2010 and 2023 to cover the period of the evolution of AI technologies and their increasing adoption in supply chain operations. This also covers the period of the emergence of I4.0T as well as the growing focus on supply chain sustainability. It also captures both early research on AI in supply chains and recent developments in AI-driven sustainability. (c) Keywords: Studies identified through specific keyword combinations as set in Section 2.3.2.1. It required articles

to feature these keywords in their titles, abstracts or keywords to ensure direct relevance to AI technologies, supply chain management and sustainability performance. (d) Full-text accessibility: This included studies with complete full text accessibility and could be analysed exhaustively to enable a comprehensive assessment of research methodologies, findings, theoretical frameworks and the evolution of supply chain theories in the context of AI adoption (e) Citation chaining and snowballing: Studies identified through forward and backward citation chaining (snowballing) from the initially selected articles. This iterative approach ensured comprehensive coverage of relevant literature, including seminal works and recent developments that may not have been captured through database keyword searches alone.

In terms of exclusion, articles earmarked for removal included papers not relevant to the research aim, conference papers and their proceedings and book chapters. Conference papers were excluded because they are usually considered preliminary findings which maybe updated later and published as journal articles thereby potentially leading to duplication of content. Moreover, since their peer review is typically less rigorous than journal publications, they may lack the kind of depth of analysis and discussion found in journal articles. Similarly, book chapters were excluded as they often are position papers or conceptual frameworks rather than empirical studies. Again, they may also not undergo the same standardised peer-review process as journal articles. The study adopted this approach to minimise the risk of including incomplete or preliminary work and to ensure consistency in the quality and rigor of included studies. Additionally articles were deemed not relevant to the research aim and excluded if they: (a) did not address AI and its application in supply chain contexts as a primary focus (b) focused exclusively on I4.0T such as blockchain, Internet of Things, additive manufacturing, robotics or big data analytics without specifically examining AI's role or contribution to supply chain sustainability performance (c) centred mainly on other sustainability areas such as circular economy practices, reverse logistics or waste management strategies without explicitly

connecting these to AI adoption or AI-enabled improvements in supply chain sustainability (d) examined AI applications in contexts outside supply chain management such as marketing, finance, human resources or product development without direct relevance to supply chain sustainability performance (e) focused solely on technical AI algorithms, machine learning model development or computer science methodologies without addressing supply chain management applications or sustainability implications or (f) were purely descriptive case studies of general supply chain practices without specific analysis of AI technologies or their sustainability outcomes.

2.3.1.2 Specification of Review Protocol

The review protocol set out the design of the review, highlighting the objectives, identified research questions, inclusion and exclusion criteria, search strategy, screening process, quality assessment procedures, and data extraction, analysis, and reporting methods (Xiao and Watson, 2019).Thereafter, a thorough search in Scopus database was carried out in September, 2023.

Although opinions on preference of databases vary, some key considerations influenced the decision for selecting Scopus. First, Scopus offers access to an extensive range of peer-reviewed literature with approximately 20% greater coverage than Web of Science (Falagas *et al.*, 2008). Similarly, in comparison to Goggle Scholar, Scopus maintains rigorous indexing standards and quality control while Google Scholar includes non-peer-reviewed sources and duplicate entries which can impact the accuracy of citation analysis. Again, as one of the world's largest curated abstract and citation databases, Scopus offers broad global and regional coverage of journals across multiple disciplines. This makes it suitable for this study on the intersection of AI technologies, supply chain management and sustainability performance.

This study recognises that some systematic reviews have used multiple databases, however, this study considered the comprehensive coverage of Scopus, combined with citation chaining

and snowballing techniques sufficient to capture the relevant literature. The search was therefore limited to peer-reviewed journal articles and review papers published between 2010 and 2023, written in English. These filters ensured that the review included only high-quality, accessible research that are directly relevant to the research objectives.

2.3.2 Conducting the Systematic Review

The following sections details the execution of the review.

2.3.2.1 Specification of Search Terms

The study aimed to conduct a comprehensive and thorough search while also ensuring precision in creating search terms and choosing keywords. We carried out the literature survey through a keyword search of the Scopus database using three broad keywords: **ARTIFICIAL INTELLIGENCE, SUSTAINABILITY and SUPPLY CHAIN MANAGEMENT.** This produced a range of potential key terms, namely **ARTIFICIAL INTELLIGENCE** (AI, Machine Learning, Cognitive Computing), **SUSTAINABILITY (**Green, Circular), **SUPPLY CHAIN MANAGEMENT** (SCM, Operations management). Different combinations of these keywords were used as searched terms in Scopus database. The final search query using Boolean operators and identifiers for documents containing the identified keywords in document Titles, Abstracts and keywords as follows: **("Artificial Intelligence" OR ai OR "Machine Learning" OR "Cognitive Computing") AND ("Supply Chain Management" OR SCM OR "Operations management") AND (sustainability OR green OR circular).**

2.3.2.2 Screening and Quality Check

The search identified a total of 262 articles initially using the specified keyword string. Following the review's protocol, excluding non-English journal articles reduced the result to 156 articles. After an initial screening of abstracts and keywords, articles were categorised as Red, Amber or Green according to their relevance using the Traffic Light system. Red articles were irrelevant, Amber articles contained relevant keywords but did not directly address the

research aim and Green articles were considered authoritative and supportive of the topic. The study excluded the 59 Red articles and performed a full text review of the remaining 62 Green and 35 Amber articles. This assessment led to the exclusion of 6 Green articles and the moving of 8 Amber articles to Green, resulting in 64 articles for comprehensive analysis. Citation chaining and snowballing then identified 8 additional relevant articles, bringing the total to 72 journals (Wohlin *et al.*, 2022).

2.3.2.3 Data Extraction and Analysis

The full content of the 72 selected studies was systematically reviewed to extract and code data for thematic synthesis using the established review protocol. To understand the underlying themes, emerging trends and conceptual relationships within the literature and evolving areas of scholarly focus, a keyword co-occurrence analysis was conducted (Shi, Miao and Si, 2019) The analysis was performed using VOSviewer software (version 1.6.18), a widely recognized bibliometric tool for constructing and visualising networks of scientific literature. It is a powerful tool for identifying the intensity of connections among various keywords found throughout a large collection of documents (Van Eck and Waltman, 2010). The parameter for the co-occurrence analysis was set at a minimum threshold of three occurrences per keyword to ensure that only substantive and frequently discussed concepts were included in the visualisation.

2.3.2.4 Reporting

To ensure transparency, the reporting process adhered to the established guidelines of the preferred reporting items for systematic review and meta-analysis (PRISMA) (Page *et al.*, 2021; Moher *et al.*, 2015). Fig 1. presents the PRISMA framework for this study.

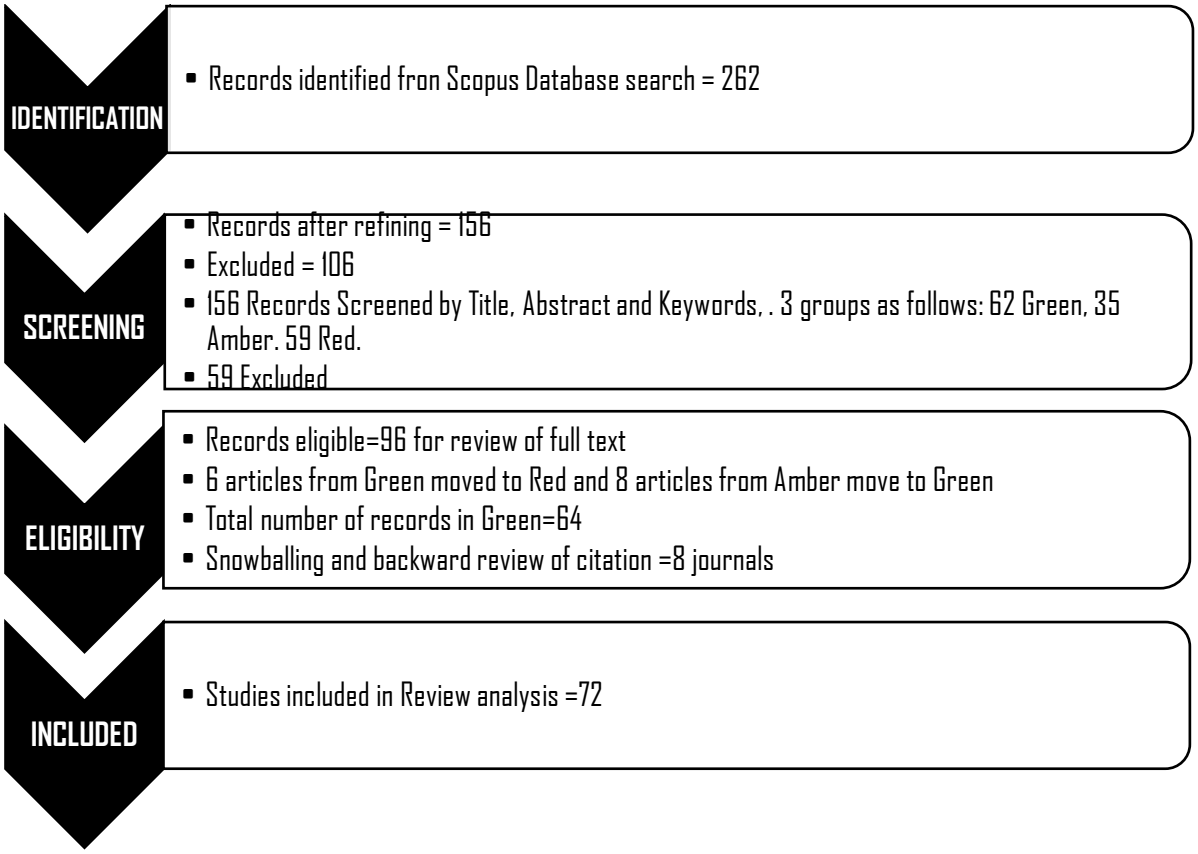

Figure 2.1 PRISMA Framework

2.4 Results and Findings

2.4.1 Distribution of papers and Journal sources:

The distribution of publications on a research topic offers an important indicator of research trends and evolving knowledge in the field (Shi, Miao and Si, 2019). From the 72 selected papers, the majority were published between 2018 and 2023, with 27 and 20 papers published in 2022 and 2023 respectively. This distribution reveals an increase in scholarly interest in AI and supply chain sustainability with a particularly sharp rise evident between 2020 and 2022. This surge in research activity can be attributed to several converging factors: rapid advancements in AI technologies, growing industry adoption, increased cross-disciplinary collaboration, mounting sustainability pressures and government policies promoting digital transformation and environmental responsibility. Notably, several foundational studies on AI applications in supply chains identified through citation chaining

such as Min (2010) are earlier than this surge and provided the conceptual groundwork for subsequent research.

Appendix A presents the journal distribution in Figure A1 and a source-based summary analysis in Table A1, showing details of included journals including the focus of study and sector addressed, methodology and theory employed as well as sample and corresponding data collection method from the 72 studies.

2.4.2 Keyword Co-occurrence Analysis

The VOSviewer analysis identified 543 keywords from the selected studies. Applying a minimum occurrence threshold of three resulted in 45 keywords for analysis. These keywords were further evaluated based on their total link strength with other keywords to identify the most significant co-occurrence patterns. The analysis revealed five distinct thematic clusters centred on 'Artificial Intelligence', 'Sustainability', and 'Supply Chain Management' (Figure 2.2). The network comprises 416 links between keywords with a total link strength of 860, indicating strong interconnections among research themes. The clustering pattern demonstrates the multifaceted nature of AI-enabled supply chain sustainability, with clear thematic boundaries yet substantial interdependencies between clusters.

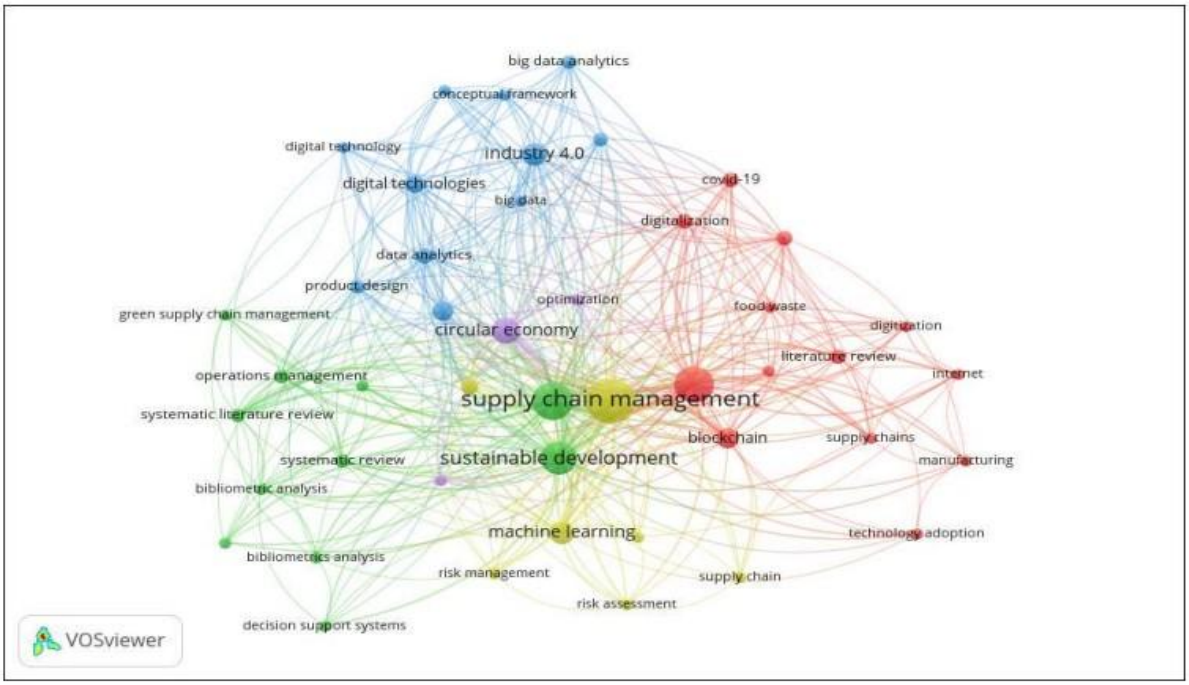

Figure 2.2 Keyword Co-occurrence

The colours indicate clusters assigned to the keywords as follows:

1. The Red Cluster had 13 keywords with Blockchain and COVID-19 prominent aside from Supply chain. This is no surprising considering the increased interest in the effects of the pandemic on Supply chains. Again, technological developments such as the availability of big data, improved computational power, and more sophisticated algorithms, the possibility of the fusion of AI with Blockchain or other emerging technologies such as IoT have caused the surge in interest.
2. AI had the highest co-concurrence in the Green Cluster aside from 10 other keywords such as Sustainable Development and other smaller nodes like Systematic Review/Systematic Literature Review, Bibliometrics/Bibliometric Analysis which seem to point towards the research methods commonly used in the retrieved results.

3. Although the Blue Cluster had 11 keywords, Industry 4.0 and Big Data/Data Analytics appear most frequently in the Blue Cluster with emphasis on Digital technology/technologies.
4. Yellow and Purple, the last two clusters, respectively tallied 7 and 3 keywords. While the Purple Cluster's main theme was Circular Economy, the Yellow Cluster's keywords concentrated on Risk/Risk management for decision-making, particularly supplier selection.

2.4.3 Frameworks and Methods across the Literature:

Most reviewed papers, 40 out of 72, (56%), did not employ a specific theoretical framework. Among those that did, sustainability focused frameworks dominated including the Triple-bottom-line model (Cataldo et al, 2022; Varriale et al, 2023) CSR (Damoah, Ayakwah and Tingbani, 2021) and ESG (Bai and Zhang, 2022; Hao and Demir, 2023). Others applied more established theories, including Resource-based View (Gebhardt *et al.*, 2021), Institutional Theory and Dynamic Capability (Bag and Pretorius, 2020), Resource Dependency (Sharma *et al.*, 2022), Systems theory (Bag *et al.*, 2020), Agency theory (Ivanov, 2023). An interesting integration of Neutrosophic- logic theory which explores Machine Learning in complex supply chains to support proactive decision-making in uncertain environments was employed by Kamal, Abdel-Gawad and Zaki (2023).

In terms of research methods, 41 papers used various forms of review studies, such as systematic, bibliometric and integrative reviews. The papers also include fifteen case studies and five conceptual papers. The multidisciplinary nature of sustainability, combined with the fast-moving development of AI, appears to influence the methodological choices. Additionally, 49% of the articles gathered data through database searches, while seven used surveys, four used interviews, and three applied mixed-method designs. (Appendix A, Table 1A: List of Reviewed Papers).

2.5 Discussion

This study employs Context-Intervention-Mechanism-Outcomes (CIMO) framework to synthesise the selected literature and organise the emerging themes into four clusters. CIMO is a widely used framework in academic research for analysing literature and understanding relationships between key constructs (Denyer, Tranfield and van Aken, 2008). Anderson, Ellwood and Coleman (2017) suggest that 'for a generalisable class of contexts (C), by using a particular intervention (I) it is possible to enable a generative mechanism (M) to achieve an outcome (O)'. Using this structure, the study conducts a thematic analysis of the reviewed studies to explore the complexity of AI adoption for sustainable supply chains. Further, to extend its analytical structure, the study introduces an orchestra metaphor that reconceptualises the CIMO components as interacting and interdependent elements of a coordinated system. Unlike the standard CIMO framework, which can imply a linear relationship between components, the orchestral lens brings to the fore interdependence, concurrence, and emergent outcomes arising from collective interaction. In this analogy, the "Context" functions as the overture that establishes conditions for performance, "Intervention" represents the ensemble of AI technologies and data-driven tools, "Mechanism" reflects the conductor's role in directing and aligning system-wide processes, and "Outcome" represents the final performance, understood as an emergent sustainability result. This reinterpretation shifts the analytical focus from discrete causal links to coordinated system dynamics, where outcomes depend on alignment across multiple interacting elements. The orchestra metaphor is applied as an analytical lens which reveals that sustainable supply chain performance depends not on individual AI technologies in isolation but on the coordination, timing and adaptive capacity of all components operating together. In keeping with Stephens *et al.'s* (2022) perspective on the cognitive value of metaphors in shaping interpretation, this study goes beyond using the orchestral framing as an illustration, to a guide for the synthesis process. The CIMO-Symphony

Orchestra Matrix therefore functions as a methodological extension of the CIMO framework, enabling a more integrative reading of the literature and supporting the identification of overarching patterns across studies. Figure 2.3 illustrates the extended CIMO framework conceptualised through a symphony orchestra metaphor. The matrix represents Context as the overture that sets system conditions, Intervention as the ensemble of AI technologies and data inputs, Mechanism as the conductor coordinating integration and decision processes, and Outcome as the final performance reflecting emergent sustainability results.

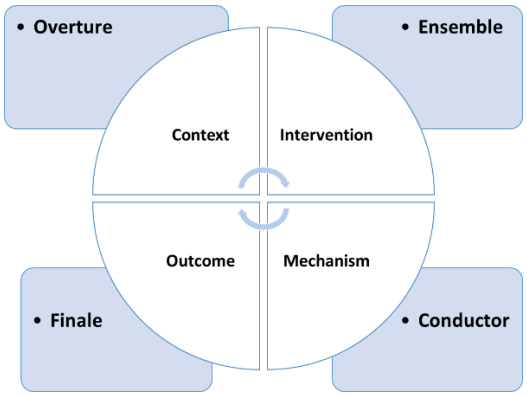

Figure 2.3 CIMO-Symphony Orchestra Matrix

Building on the CIMO–Symphony Orchestra Matrix (Fig. 2.3), the following sections present the thematic findings structured around Context, Intervention, Mechanism, and Outcome clusters. The orchestral lens informed the synthesis by encouraging attention to interdependencies and emergent sustainability outcomes across the reviewed studies.

2.5.1 Context-Overture Theme:

The context theme is the largest identified theme elicited from the review. Overture introduces and sets the tone of the whole performance for the audience in the same way the Context in the CIMO framework outlines the background and circumstances for the adoption of AI for sustainability in supply chains.

Diverse contextual factors influence (i) the adoption of AI for supply chain, (ii) the relevant AI intervention and supply chain use case, (iii) the mechanism for enabling sustainability

improvement and ultimately (iv) the final sustainability outcomes. These relate to various drivers, barriers, challenges and opportunities of AI for sustainable supply chain. The challenges and drivers differ depending on the industry and sector. Table 2.1 presents the context and indicator as discussed in the literature.

Table 2.1 Context-Overture Theme

Context	Indicator	Authors
Drivers	Tightening and tougher environmental standards and regulations, COVID	**Asokan *et al.*, (2022)**
	Circular Economy - optimise resource utilization, reduce waste, and promote circular economy principles	**Bag and Pretorius (2020)**
	Risk Management	**Hao and Demir (2023)**
	Environmental sustainability- Reducing climate change and carbon footprint	**Hong *et al.*, (2021)**
	Risk management, disruptions- Pandemic, Wars	**Raja Santhi and Muthuswamy (2022)**
	Risk Management and prediction,	**Trabucco and De Giovanni (2021)**
	Consumer awareness, supply chain transparency, product traceability	**Tsolakis *et al., (*2022)**
Barriers	Infrastructure and Cost; Required Knowledge, Skill, and Reputation; Law and Regulations; Nature of the Technologies;	**Amentae and Gebresenbet (2021)**
	Data quality, lack of specific skills, high investments, lack of clarity on economic benefits and lack of experience in cost analysis for AI projects	**Cannas *et al.*, (2023)**
	Lack of knowledge and skills to determine suitable implementation approach	**Chauhan *et al.*, (2022)**
	Challenges around design (product, service, supply network), quality management, HR, capacity	**Dhamija and Bag (2020)**
	Environmental, Social, and Technological - Consumer security and privacy, AI biases, personal autonomy, wellbeing, concerns with unemployment, power requirement and energy consumption.	**Kar *et al*., (2022)**
	Technical challenges on data security, large data sets that make it difficult to form a public cloud	**Kumar and Barua (2021)**

	Complex and esoteric, lack of knowledge by decision-makers	**Min (2010)**
	Investment cost, Lack of management support, resistance from employees, unwilling to share data, high complexity, lack of compatibility with existing infrastructure, market uncertainty, too early to adopt the technologies; lack of required resources, data integration and scalability challenges	**Raja Santhi and Muthuswamy (2022)**
	Relies heavily on the effectiveness and accuracy of AI computer software, limited technical knowledge	**Sharma *et al.*, (2022)**
	Technical, Ethical, Legal, Managerial, and Socio-economic considerations. Consumers' limited appreciation of the merits of AI and the high technical complexity and implementation cost	**Tsolakis *et al.*, (2022)**
	Difficulty in obtaining required data sets at the initial stage of implementation	**Wilson *et al.*, (2021)**
Opportunities	Social responsibility, Fair labour practices	**Di Vaio *et al.*, (2020)**
	Develop guidelines and regulations	**Hao and Demir (2023)**
	AI use for social sustainability	**Kamble *et al.*, (2022)**
	Circular Economy - Waste minimization, promoting circular economy principles	**Tavana *et al.*, (2022)**
	Opportunity to enable Industry 5.0 principles	**Varriale *et al.*, (2023)**

2.5.1.1 Drivers of AI adoption for sustainable supply chain

The literature highlighted several key drivers for AI adoption in sustainable supply chains. First, AI enables operational efficiency by reducing energy consumption, optimising processes, and supporting climate-friendly practices. Increasingly stringent environmental regulations also act as a strong driver and organisations need to comply with higher sustainability standards. AI supports this by monitoring operations and ensuring regulatory compliance (Asokan *et al.*, 2022). AI facilitates compliance monitoring and supports adoption of sustainable procedures to meet legal requirements. Second, resource scarcity and growing

concerns about depletion further reinforce the need for efficient resource management. AI contributes by optimising resource use, reducing waste, and supporting circular economy practices across supply chains (Bag and Pretorius, 2020). Again, growing consumer awareness of environmental and social impacts has increased demand for transparency. AI enables end-to-end visibility, allowing customers to track product journeys, validate sustainability claims, and make informed purchasing decisions (Tsolakis *et al.*, 2022). Supply chain agility and resilience also emerge as critical drivers. Keyword co-occurrence analysis highlighted COVID-19 as a recurring theme, reflecting the disruption faced by global supply chains during the pandemic (Yu *et al.*, 2021) and reinforcing the importance of supply chain resilience and adaptability as enablers of sustainability (Raja Santhi and Muthuswamy, 2022; Asokan *et al.*, 2022). Studies consistently show that AI strengthens visibility, improves risk prediction, and enhances agility, contributing to more robust and sustainable supply chain networks (Trabucco and De Giovanni, 2021; Hao and Demir, 2023).

2.5.1.2 Barriers to AI adoption in sustainable supply chains

Despite its potential, several barriers limit the effective use of AI for supply chain sustainability. Cannas *et al.* (2023) highlights key challenges including poor data quality, shortages of specialised skills, high investment costs, limited clarity on economic returns, and insufficient experience in evaluating AI-related costs. These barriers, commonly grouped into technological, organisational, legal or regulatory and ethical categories (Tsolakis *et al.*, 2022), consistent with barriers identified across different geographical regions and sectors by (Raja Santhi and Muthuswamy, 2022) as well as challenges highlighted by (Kar, Choudhary and Singh, 2022). AI effectiveness in supply chain sustainability depends on the accuracy and reliability of data and software. Implementation is often complex, particularly when selecting appropriate AI approaches for sustainability goals (Chauhan *et al.*, 2022; Min, 2010). Decision-makers with limited technical expertise may struggle to understand and fully exploit AI

capabilities (Sharma *et al.*, 2022). Organisational barriers further include financial constraints (Cannas *et al.*, 2023), lack of managerial support (Tsolakis *et al.*, 2022), employee resistance and bias (Raja Santhi and Muthuswamy, 2022) and insufficient training. Addressing skill gaps through targeted learning initiatives can help mitigate these challenges (Dhamija and Bag, 2020).

2.5.1.3 Opportunities of AI for sustainable supply chain

AI presents significant opportunities for advancing ethical business conduct and social responsibility in supply chain management. AI applications help eliminate human rights violations, ensure social responsibility throughout supply chains, and promote fair labour practices (Di Vaio *et al.*, 2020). Beyond social sustainability, AI offers opportunities to improve decision-making and operational coordination across supply chains. As advanced technologies become increasingly integrated with traditional manufacturing systems, AI plays a central role in enabling intelligent, connected, and sustainable supply chain structures. By supporting cyber-physical systems, AI contributes to resilient, adaptive, and human-centric value creation (Varriale *et al.*, 2023).

Returning to the orchestra analogy, the Context-Overture theme reveals that a simple barrier-driver taxonomy obscures the fact that contextual conditions do not merely enable or constrain AI adoption but define the interpretive setting within which adoption unfolds. Much like an overture establishes the tonal direction of a performance, conditions such as regulatory pressure, resource scarcity, transparency demands, skill deficits and infrastructure constraints shape how organisations evaluate and deploy AI interventions. A sophisticated AI solution introduced into a context characterised by skill shortages and high investment costs is unlikely to succeed, not due to technical limitations, but because of misfit with prevailing conditions. This highlights a key implication: contextual readiness must be assessed prior to intervention selection, not after.

2.5.2 Intervention-Ensemble Theme

The second thematic area examines the interventions addressing supply chain sustainability challenges using AI applications and systems. CIMO Intervention-Ensemble component consists of organisational resources employed to attain sustainability including the AI technologies, available sources and kinds of data fed into the AI systems and challenges with obtaining data. The established themes include AI technologies, AI techniques, challenges with data collection and the various sources of data. Table 2.2 presents Intervention-Ensemble themes with the corresponding interventions as identified in the papers reviewed.

Table 2.2 Intervention-Ensemble Theme

Intervention Theme	Intervention	Authors
AI Technology	Machine Learning	**Addou *et al.*, (2023)**
	Artificial Neural Networks (ANN)	**Alavi *et al., (*2021)**
	Genetic Algorithm (GA)	**Dhamija and Bag (2020)**
	Fuzzy Logic (FL), Genetic Algorithm (GA)	**Kazancoglu *et al.*, (2021)**
	Genetic Algorithm (GA)	**Min (2010)**
	Computer Vision	**Onyeaka *et al.*, (2023)**
	Machine Learning	**Tirkolaee *et al.*, (2021)**
	Natural language processing	**Toorajipour *et al.*, (2021)**
	Categorization of AI technologies	**Pournader *et al.*, (2021)**
AI Techniques	Artificial Neural Networks (ANN)	**Pournader *et al.*, (2021)**
	Artificial Neural Networks (ANN), Fuzzy Logic (FL), Agent-Based Systems (ABS), Genetic Algorithm (GA)	**Raja Santhi and Muthuswamy (2022)**
	Artificial Neural Networks (ANN), Fuzzy Logic (FL)	**Sharma *et al.*, (2022)**
	Classification of AI techniques	**Toorajipour *et al.*, (2021)**
Challenges with data source	Data sharing	**Apruzzese *et al.*, (2023)**
	Data complexity	**Cannas *et al.*, (2023)**
	Compatibility and interoperability	**Raja Santhi and Muthuswamy (2022)**
Data source	Social media	**Bechtsis *et al.*, (2022)**
	Devices, sensors	**Kar *et al., (*2022)**
	Customer Feedback	**Onyeaka *et al.*, (2023)**
	Public data	**Pournader *et al.*, (2021)**
	Devices, sensors	**Rejeb and Appolloni (2022)**
	Devices, sensors	**Varriale *et al.*, (2023)**

2.5.2.1 AI Technologies

Although a wide range of AI technologies are leveraged to achieve sustainability, applicable interventions of AI in supply chain are usually determined by the existing contextual factors driving the expected sustainability outcome. Pournader *et al.* (2021) suggest that the functional application areas of AI include, Decision-making, Learning and Sensing. Sensing and interaction are enabled through Natural Language Processing (NLP), speech recognition and computer vision. NLP enhances human-machine interaction by supporting text extraction, classification, translation, text generation and question answering (Toorajipour *et al.*, 2021). Likewise, as AI capabilities develop, computer vision is increasingly being deployed. Onyeaka *et al.* (2023) illustrates this how computer vision and machine learning algorithms enhances crop yields by enabling selective weeds targeting and reduced herbicide use. This contributes to an eco-friendlier approach to agriculture thereby improving sustainability goals in food production. Machine Learning, AI's learning function and most popular branch, focuses on identifying and extracting patterns from large datasets. Machine learning aids in identification of patterns and offering insights that help organisations drive their operations towards sustainability (Tirkolaee *et al.*, 2021).

2.5.2.2 AI Techniques

Although AI technology represents the machines tools and systems for the practical application of AI knowledge, AI techniques refer to the methods, architecture and data formalisations for accomplishing this (Toorajipour *et al.*, 2021). Interestingly, in all the studies reviewed in this paper, AI techniques in supply chain appeared to be one of generally more discussed themes (Sharma *et al.*, 2022; Toorajipour *et al.*, 2021). Consistent with assertion of Raja Santhi and Muthuswamy (2022), Artificial Neural Networks (ANN), Fuzzy Logic (FL), and Agent-Based Systems (ABS), and Genetic Algorithm (GA) are some of the more frequently applied techniques as seen in research on supply chain related issues such as sustainability.

ANNs are the more prominent techniques for processing vast data sets data to identify patterns (Toorajipour *et al.*, 2021) and are used to monitor and control dynamic and complex processes such as the development of sustainable supplier selection process (Pournader *et al.*, 2021) and to reduce the bullwhip effect and distortions of inventory demand (Sharma *et al.*, 2022) thus supporting supply chain sustainability performance. Similarly, Fuzzy Logic/Set theory, a decision support system, is helpful with issues of 'uncertainty and opaqueness' in supply chains (Sharma *et al.*, 2022) helping reduce subjectivity in decision-making (Kazancoglu *et al.*, 2021) for instance in sustainable and circular supplier evaluation (Alavi, Tavana and Mina, 2021). On the other hand, Genetic Algorithm with its root in evolution (Min, 2010) aims at matching production activities with the most suitable resources (Dhamija and Bag, 2020). It has been effectively utilised in supply chain optimization, offering valuable solutions for tackling environmental sustainability concerns. Through the simulation of potential environmental impacts of supply chain operations, Genetic Algorithm has proven to be a crucial tool in analysing supply chain data and promoting sustainability (Kazancoglu *et al.*, 2021)

2.5.2.3 Types of Data Sources:

AI systems rely on data to function effectively. Data sources range from traditional purchase orders, sales records and inventory logs to information from IoTs and blockchains. Therefore, understanding impact of these inputs is vital to fully leverage the power of AI in streamlining and maintaining supply chain operations for sustainability. Similarly, publicly available data from the news, social media, blogs and web offer a wealth of valuable information that can serve as tools for gauging stakeholder opinion on issues such as brand perception, sustainability risk performance, and customer preferences using sentiment and context analysis techniques (Pournader *et al.*, 2021). For instance, Bechtsis *et al.* (2022) highlights the opportunity of leveraging the power of social media data for improving efficiency and sustainability by utilizing consumer data from X (formerly Twitter) to decrease

waste in beef supply chains. Similarly, the suggestion by Onyeaka *et al.* (2023) that NLP can be applied to analyse customer feedback and gain insights to help develop healthier food offerings, increased their demand or improve current products validate the benefit of publicly available data as a source.

2.5.2.4 Challenges with Data sources:

Some of the challenges with data sources included datasets which are often dynamic and complicated, making them unclear in most real-world scenarios. This complexity can have a significant influence on predicting accuracy, which is a fundamental component sustainability decision-making (Cannas *et al.*, 2023). Further, despite AI technologies hailed benefits, data collection and sharing remains difficult as businesses are still hesitant to share their data with other organisations even though they recognise the significance of data protection and have put safeguards in place (Apruzzese *et al.*, 2023). Again technical difficulties arising from data consistency, system compatibility, data interoperability and architectural difficulties may challenge effective network coordination and integration that affect data collection (Raja Santhi and Muthuswamy, 2022).

Viewed through the orchestral lens, the Intervention-Ensemble theme exposes a critical gap in the literature. While the range and sophistication of AI technologies such as Machine Learning, Artificial Neural Networks, fuzzy logic, and genetic algorithms continue to expand, organisations tend to deploy them in isolation rather than as coordinated systems. As in an orchestra, where uncoordinated sections produce noise rather than performance, AI tools generate value only when effectively integrated. Similarly, diverse data sources like sensors, social media, transactional and public datasets all require standardisation and governance to be useful. The core challenge is therefore not the availability of technologies or data, but the lack of integration across them. This points to an important gap in the understanding of the

architectures and capabilities required to coordinate AI systems for sustained supply chain sustainability performance.

2.5.3 Mechanism-Conductor Theme

Various processes, methods, frameworks and activities to ensure effective integration of AI in supply chain form the mechanism of transforming the intervention into successful outcomes in the context of sustainability.

2.5.3.1 AI Integration in Supply Chain Management

This study's analysis reveal that organisations struggle with sustainability issues in areas such as demand forecasting, inventory planning, supplier selection, network design and green supply chain. AI driven supply chain management offers huge potentials for these areas which involve strategic decision-making and proved valuable in the streamlining sustainable supply chain activities. For instance, machine learning methods used to reduce forecast error and prevent the bullwhip effect (Cannas *et al.*, 2023), sustainable supplier selection (Tirkolaee *et al.*, 2021), optimal prices in procurement contracts and bidding decisions (Rejeb and Appolloni, 2022) and incoming order quality validation (Zhang, Li and Peng, 2020).

Similarly, machine learning algorithms can predict equipment failures, enabling maintenance scheduling in advance while real-time demand can help optimise production schedules (Kamal, Abdel-Gawad and Zaki, 2023). Machine learning tools including Microsoft Power BI , AnyLogic, SAP Integrated Business Planning have also been used for constraint balancing, particularly for manufacturers using build-to-order and make-to-stock production processes while reducing supply chain latency for components and parts used in highly customised products (Tirkolaee *et al.*, 2021). From optimizing production schedules and enhancing quality control (Hao and Demir, 2023) to predicting maintenance needs and developing new sustainable products (Feng, Lai and Zhu, 2022), AI proves a valuable asset and plays an increasingly significant role in production. Table 2.3 provides an overview of articles

on AI integration actions that connect the intervention to the outcome in the Mechanism-Conductor theme.

Table 2.3 Mechanism-Conductor Theme

MECHANISM-CONDUCTOR THEME		
Mechanism Theme	**Integration Focus**	**Authors**
AI integration	Reduction of forecast error, Prevention of bullwhip effect	**Cannas *et al.*, (2023)**
	Design of new sustainable products	**Feng *et al.*, (2022)**
	Quality Control	**Hao and Demir, (2023)**
	Optimization of production schedules	**Kama *et al.*, (2023)**
	Optimal prices in procurement contracts and bidding decisions	**Rejeb and Appolloni (2022)**
	Demand forecasting, inventory planning, supplier selection, network design, green supply chain	**Sharma *et al.*, (2022)**
	Supplier selection, constraint balancing, reducing supply chain latency for components and parts	**Tirkolaee *et al.*, (2021)**
	Quality Validation and assurance	**Zhang *et al.*, (2020)**

The Mechanism-Conductor theme captures the most analytically significant aspect of the orchestral metaphor. In an orchestra, the conductor coordinates timing, interpretation and adaptation without directly producing sound. Similarly, in AI-enabled supply chains, mechanisms are not individual tools but the organisational capabilities that coordinate and adapt interventions in response to changing conditions. While the literature identifies specific mechanisms like demand forecasting, supplier selection, inventory management and quality control, it rarely addresses the broader capacity required to integrate and adjust these processes. Therefore, orchestration capability, that is the organisational ability to sequence, coordinate and dynamically adapt AI integration activities becomes vital. This shifts attention from isolated mechanisms to system-level coordination and relates closely to the reconfiguring dimension of Dynamic Capabilities Theory, suggesting an underexplored area for theoretical development.

2.5.4 Outcome-Finale Theme

Outcome in the CIMO framework corresponds closely to the appraisal outcome of the impact and outcomes of the intervention. Table 2.4. summarises the impacts, results or consequences of AI integration in supply chain.

Table 2.4 Outcome-Finale Theme

Outcome Theme	Indicator	Authors
Circular Economy	Recycling, Repurposing	**Liuet *et al.,* (2023)**
	Reuse, Remanufacturing, Recycling	**Nayal *et al.*, (2021)**
	Value creation and capture for economic sustainability	**Wilson *et al.,* (2021)**
Overall Performance	Environmental Impact	**Ada *et al.*, (2021)**
	Supply chain Sustainability	**Dumitrascu *et al*., (2020)**
	Inventory optimization	**Kama *et al.,* (2023)**
	Optimised logistics/ transportation	**Mithas *et al.*, (2022),**
	Procurement efficiency	**Rejeb and Appolloni (2022)**
	Real time visibility	**Sharma *et al.*, (2022)**
	Speed and accuracy	**Toorajipour *et al.*,(2021)**
Resilience and Risk Management	Disruption- Pandemic, War	**Raja Santhi and Muthuswamy (2022)**
	Resilience, Flexibility, Agility	**Trabucco and De Giovanni (2021)**
Sustainability Performance	Social Sustainability Transparency	**Tsolakis *et al.*, (2022)**
	Social Sustainability, SDG	**Asokan *et al.*, (2022)**
	Social Sustainability, SDG	**Damoah *et al.,* (2021)**
	Social Sustainability, SDG	**Di Vaio *et al.*, (2020)**
	Social Sustainability - Responsible sourcing	**Hao and Demir (2023)**
	Environmental - GHG emission reduction, prevention of leakage of hazardous materials, Biodiversity conservation	**Kumar and Barua (2021)**
	Social Sustainability	**Lee (2021)**
	Overall Sustainability	**Naz *et al.*, (2022)**
	Environmental- real time monitoring	**Rusch *et al*., (2022).**
	Environmental- Ecological conservation	**Varriale *et al.,* (2023)**
	Environmental- Energy use, emissions	**Apruzzese *et al.*, (2023)**

2.5.4.1 Overall performance

Supply chain management remains critical to an organisation's performance with the integration and execution of end-to-end operations being the key to attaining excellence

(Kamal, Abdel-Gawad and Zaki, 2023). This review reveals that AI provide unparalleled levels of accuracy, speed and the capacity to manage massive volumes of data for problem-solving (Toorajipour *et al.*, 2021), manage unpredictability, risk and sustainability requirements (Dumitrascu, Dumitrascu and Dobrotă, 2020). Furthermore, the function of AI in demand forecasting, inventory optimisation and real-time tracking helps manage activities to lower stockouts and reduce surplus inventory (Kamal, Abdel-Gawad and Zaki, 2023) while enabling better appraisals of the sustainability performance of suppliers, more effective negotiation strategies, and improved sustainable sourcing decision-making, all positively impacting procurement efficiency and sustainability (Rejeb and Appolloni, 2022). For logistics and transportation, using autonomous AI systems like self-driving trucks and drones optimises logistics, assuring on-time delivery (Mithas *et al.*, 2022). Overall, AI powered automation, predictive analytics and real-time visibility improve supply chain process efficiency and positively impacts sustainability (Sharma *et al.*, 2022).

2.5.4.2 Sustainability performance

AI and other technologies including Blockchain, IoT are expected to play a significant role in the shift towards achieving a sustainable industrial transformation and actively addressing the pressing social, economic, and environmental concerns of our time by promoting social welfare, enhancing circular economic practices, environmental preservation and overall societal welfare (Varriale *et al.*, 2023). This growing emphasis on sustainability in operations and supply chain management is reflected in the research reviewed, with sustainability consistently appearing as a key priority.

In promoting environmental sustainability within supply chain operations, AI effectively streamlines and optimises operations to reduce environmental impact and footprint. AI's predictive analytics capabilities in supply chains aids in accurately predicting demand, optimizing transportation routes, and improving overall energy efficiency, making it possible

for businesses to align their practices with eco-friendly principles. Environmental sustainability indicators are usually specific to a sectors or industry thus influencing focus of AI usage in different sectors or industries. For example, due to the nature of its day-to-day operations, petroleum industry frequently faces allegations of causing environmental damage thus indictors such as reduction of Green House Gas (GHG) emission, prevention of leakage of hazardous materials, conservation of biodiversity (Kumar and Barua, 2021) form the focus of AI implementation in the petroleum industry. Similarly, the importance of AI in Agricultural and Food industry is evidenced in the widespread use of AI and Machine Learning in food preservation (Di Vaio *et al.*, 2020) to reduce waste and managing environmental impact through circularity (Ada *et al.*, 2021). Again, AI plays a crucial role in ensuring sustainable logistics by minimising the environmental impact of operations and promoting ecological conservation (Apruzzese *et al.*, 2023).

Although social sustainability is vital for societal well-being, research on AI's role in this dimension remains limited (Lee, 2021). However, existing work points to significant potential with findings across several studies (Asokan *et al.*, 2022; Di Vaio *et al.*, 2020; Damoah, Ayakwah and Tingbani, 2021) reinforcing these opportunities. For instance, Asokan *et al.* (2022) highlights how AI can strengthen critical aspects of social performance, including employment conditions, health and safety, and ethical business practices. Additionally, AI can support responsible sourcing (Hao and Demir, 2023), improve transparency (Tsolakis *et al.*, 2022) and enhance accountability across supply chains.

Despite AI's positive contributions to sustainability, some studies hint at potential unintended consequences (Kar, Choudhary and Singh, 2022). Some highlighted areas include full lifecycle of AI systems from design, manufacturing, operation and disposal that poses sustainability challenges. Again, emissions generated across the global supply chain of AI components contribute to its carbon footprint, while manufacturing processes and ongoing

system operation often intensify environmental degradation and energy consumption. Additionally, the end-of-life management of AI hardware raises concerns about e-waste, highlighting the need for responsible disposal practices to mitigate environmental risks.

2.5.4.3 Circular Economy

The VOS viewer map identified circular economy and waste management, represented in the in the purple and yellow cluster respectively, as dominant themes (Fig. 2). By recognising the principles of reducing, reusing, recycling and recovering, organisations can shift from linear economy view to a circular approach (Truant *et al.*, 2024). This perspective is particularly valuable for sustainable supply chain management as it promotes smarter product use and manufacturing through the utilisation of recycled and repurposed materials (Liu, Song and Liu, 2023). There is potential for AI optimise the transition from linear to circular economy, thus revolutionising the way we approach supply chain sustainability (Noman *et al.*, 2022).

2.5.4.4 Resilience and Risk Management

The findings also reveal risk management and supply chain resilience as one of the performance outcomes AI adoptions. Various studies including Bag *et al.* (2021) have established the effectiveness of AI in managing supply chain risks and improving resilience. With the COVID-19 pandemic exposing the fragility of supply chains worldwide (Raja Santhi and Muthuswamy, 2022; Hao and Demir, 2023), a greater demand for resilience, flexibility and agility from every link in the supply chain is therefore required (Trabucco and De Giovanni, 2021). Consequently, this emphasises the importance of deploying technologies such as AI to improve risk and resilience of supply chains (Naz *et al.*, 2022).

The Outcome-Finale theme, like a symphony's conclusion, should represent a balanced synthesis of preceding elements. However, the literature reveals an uneven pattern with outcomes are heavily skewed towards environmental performance and operational efficiency, while social sustainability remains underrepresented. This imbalance suggests that the "finale"

of AI-enabled supply chain sustainability is incomplete. In contexts where labour conditions, community impact, and workforce displacement are more pronounced, particularly in emerging economies, social sustainability may be central rather than peripheral. The limited attention to this dimension highlights a critical gap in the literature and underscores the need for a more balanced understanding of sustainability outcomes in AI-enabled supply chains.

2.5.5 Artificial Intelligence and Supply chain Theories

Against the backdrop of growing application of AI in supply chain management, this study examines how established theoretical perspectives explain the transformation of sustainability-oriented supply chain practices. A key finding across the reviewed papers is that theoretical framing remains underdeveloped in many studies. However, where theory is applied, it reveals important tensions that suggest the need for extension rather than replacement of existing perspectives. The following sections 2.5.5.1 -2.5.5.5 demonstrates that while existing theories offer partial explanations of AI-enabled supply chain transformation, they do not fully account for the system-level interactions captured in the CIMO–Symphony framework.

2.5.5.1 Stakeholder Theory

Stakeholder Theory is increasingly challenged by the mediating role of AI systems in shaping stakeholder relationships. Evidence suggests that AI is not only a decision-support tool but also a mechanism that restructures transparency, accountability, and interaction across supply chains. Tsolakis *et al.* (2022) show that AI and blockchain extend traceability and transparency, fundamentally changing firm-consumer interactions. Di Vaio et al. (2020) Di Vaio *et al.* (2020) further demonstrate that AI embeds ethical and social considerations such as labour conditions and responsible sourcing into operational processes. Applying Stakeholder Theory directly to supply chains, Kannan (2018) shows that sustainability performance depends on balancing competing stakeholder interests. Collectively, these studies indicate that

stakeholder relations are increasingly mediated by algorithmic systems, positioning AI as an active intermediary. This challenges the human-centred framing of Stakeholder Theory and suggests the need for an expanded model that incorporates AI-enabled governance structures.

2.5.5.2 Agency Theory

Agency Theory assumes a clear separation between human principals and agents; however, reviewed studies show this boundary is increasingly blurred by autonomous AI systems. Ivanov's (2023) study demonstrates how automated decision systems actively participate in real-time supply chain decision-making, reducing exclusive human control.. This is reinforced by Dubey *et al.* (2020) who show how that AI-enabled analytics systems influence operational outcomes through autonomous decision support, while Olan *et al.* (2021) highlight how AI-driven networks reshape financial and operational governance structures. Together, these studies indicate that AI is becoming embedded within decision hierarchies as a quasi-autonomous actor. This challenges the assumption of exclusively human agency and calls for an extension of Agency Theory to account for hybrid human-AI governance structures.

2.5.5.3 Dynamic Capabilities Theory

Dynamic Capabilities Theory (DCT) is also challenged by the increasing delegation of sensing, seizing, and reconfiguring functions to AI systems. Tirkolaee *et al.* (2021) show that machine learning enhances supplier selection and inventory optimisation through continuous adaptive learning, partially automating sensing and seizing. Feng, Lai and Zhu (2022) demonstrate that AI supports innovation and reconfiguration in digitally enabled supply chains. Nayal *et al.* (2021) further show that AI–IoT integration improves responsiveness and flexibility under circular economy conditions. Overall, these findings suggest that dynamic capabilities are increasingly co-produced by managerial judgment and algorithmic systems. This challenges the human-centric foundation of DCT and points to hybrid adaptive systems where capability development is jointly distributed.

2.5.6 Integrated Theoretical Implication

Across the reviewed studies, AI adoption does not invalidate existing theories but exposes their boundary conditions. Stakeholder Theory is limited by its humanistic framing, Agency Theory by its exclusion of non-human actors, and DCT by its assumption of human-led adaptation. Overall, the evidence suggests AI-enabled supply chains operate as hybrid socio-technical systems where decision-making and adaptation are co-produced by humans and algorithms. This indicates the need for systematic theoretical extension to account for distributed agency, algorithmic governance, and continuous adaptive learning in supply chains.

2.6 Conclusion

This study aimed to investigate the current state of research on the application of AI in achieving sustainability in supply chains by reviewing the research landscape from 2010 to 2023. It sought to highlight the impact of AI adoption on enhancing supply chain performance and evaluate how supply chain theories account for the integration of AI in sustainable supply chain management.

The findings indicate that the application of AI techniques has become a prominent theme in academic discussions on sustainable supply chain management (Toorajipour et al., 2021). Widely utilised AI techniques identified in the literature include Artificial Neural Networks (ANN), Fuzzy Logic (FL), Agent-Based Systems (ABS), and Genetic Algorithms (GA). Furthermore, this study suggests that emerging AI methods, such as data mining integrated with Natural Language Processing, present promising opportunities to advance social sustainability. For instance, sentiment analysis of employee feedback can provide valuable insights into workforce concerns, enabling organisations to take targeted actions to improve employee well-being. Additionally, organisations can leverage data from social media and online platforms to gauge public opinion on sustainability-related social issues, equipping them to address these proactively.

While the reviewed studies predominantly emphasise the positive impacts of AI on economic, social and environmental performance, relatively few investigate its potential negative consequences. Notable concerns include the energy-intensive nature of AI systems, the substantial investment requirements, especially challenging for small and medium enterprises (SMEs) and organisations in the Global South and the risks of exacerbating the digital divide. Moreover, the potential for unintended outcomes, such as ethical dilemmas or adverse societal impacts, warrants closer scrutiny.

Although this study focuses on the role of AI in sustainable supply chain management, its findings are relevant to other emerging technologies and their convergence for sustainability. As Liu *et al.* (2023) note, such technologies are likely designed to function synergistically rather than in isolation. Consequently, adopting a holistic perspective that considers the combined effects of these technologies is essential for organisations striving to achieve their business and sustainability objectives.

2.6.1 Theoretical Contributions

This review offers several strengths that enhance its contribution to the body of knowledge on AI and supply chain management. The review applies a structured and transparent methodological approach, ensuring that the selection, screening and analysis of studies follow clear and replicable procedures. This strengthens the credibility and reliability of the findings. The study also provides a comprehensive synthesis of current knowledge on the intersection of AI, sustainability and supply chain management. By integrating insights across environmental, social and economic dimensions, the review offers a balanced perspective on both the opportunities and challenges presented by AI.

Aside from its strengths, this review offers several theoretical contributions at a time when AI is becoming central to supply chain performance and sustainability. The growing use of autonomous and semi-autonomous systems raises questions about accountability, the

explainability of AI-generated decisions, and the degree of human oversight required in automated environments. These issues introduce new dimensions to existing theories such as Agency Theory by challenging its traditional assumptions about intentionality, control and responsibility. As a result, the review extends the theory's foundational principles to recognise human-AI interaction, algorithmic decision making and the shifting boundaries of managerial agency.

A further theoretical contribution lies in the introduction of the orchestra metaphor within the CIMO framework to support a comprehensive thematic analysis of the literature. By conceptualising AI, humans, data infrastructures, and organisational processes as interdependent "sections" within a coordinated performance, the metaphor helps explain how different components work together to achieve sustainable supply chain outcomes. This approach adds conceptual clarity to the CIMO framework and provides an analytical tool for understanding how AI operates within complex sociotechnical systems such as supply chains.

The review also establishes a conceptual foundation for positioning AI as an active agent rather than a passive tool. This perspective broadens current theoretical debates by acknowledging AI's capacity to initiate actions, influence decisions and shape organisational behaviour. It supports theoretical extensions that recognise AI autonomy, human-AI collaboration, and deeper sociotechnical integration as core elements of future supply chain theory.

Finally, the study presents a review that links digitalisation with sustainability performance. By mapping how AI technologies enable environmental, social and economic improvements across supply chain processes, the review provides a basis for understanding the mechanisms through which digital transformation contributes to sustainability. Through this, it

advances existing theory by showing how technological innovation and organisational processes connect to sustainability outcomes.

2.6.2 Practical Implication

In practical terms, organisations seeking to leverage AI for operational and sustainability benefits must adopt strategies that balance opportunity with caution. This includes evaluating the environmental footprint of AI systems across their lifecycle. Before deploying AI solutions, managers should assess environmental costs linked to data storage, algorithmic training and system use. Choosing energy-efficient architectures, reducing unnecessary model complexity, and using renewable-powered data centres can help offset negative impacts. Again, differences in digital capabilities across partners can widen existing gaps. Managers can help address this through investing in equitable capacity-building programmes for supply chain partners and technical support for smaller or less-resourced partners. This strengthens supply chain resilience and supports collective sustainability performance.

These findings also highlight the importance of anticipating and managing the unintended or adverse consequences that may accompany AI adoption in organisational settings. While AI offers strong potential to support economic sustainability through cost reductions, efficiency gains, and improved decision-making, it may simultaneously fall short in addressing wider sustainability concerns. These include resource and energy intensive computing requirements, uneven technological access that reinforces digital and economic divides, shifting workforce dynamics, over-reliance on algorithmic systems and potential misalignment with SDGs (Varriale *et al.,* 2023; Dhamija and Bag, 2020). Therefore, AI initiatives should be evaluated not only for economic return but also for their contribution to environmental stewardship, circularity, regeneration, and social responsibility. Again, mapping

AI projects against SDGs, circular economy principles or regenerative supply chain goals can guide more responsible investment decisions.

In addition, the review shows that integrating AI into supply chain activities introduces paradoxes and tensions that challenge established theories and managerial assumptions. For example, if AI capabilities are to be viewed through the Resource-Based View, it becomes unclear whether AI is a rare and valuable strategic asset or a rapidly commoditised technology with considerable environmental cost. Similarly, while AI promises to reduce uncertainty and improve governance accuracy, it simultaneously generates new governance challenges related to explainability, accountability and oversight of automated decisions. These tensions demonstrate the need for managers to approach AI adoption with a critical and informed perspective. Therefore, managers should consider that while AI may reduce uncertainty it can also create new governance challenges or contribute to economic gains while generating environmental burdens. Recognising these tensions early allows organisations plan mitigation strategies instead of reacting to problems after they arise.

2.6.3 Limitations

Like most studies, this research has certain limitations. First, the findings are based on articles sourced from a single database, limited to journal articles and review papers and in English. Although this study earlier outlined the rationale for this selection, it recognises that other reputable databases contain relevant material that may not have been captured through this approach. Furthermore, although this study focused exclusively on journal articles to maintain consistency in publication standards by including only studies that have undergone comprehensive peer review and revision processes, it acknowledges that conference papers could represent primary research avenues with rigorous peer review in certain disciplines like computer science and engineering.

This study is bounded by a search period covering 2010 to 2023. While this period captures the foundational and early growth phases of AI adoption in sustainable supply chains, it does not fully reflect the rapid developments that have occurred since mid-2022, particularly the emergence of generative AI and large language models (LLMs). These technologies are beginning to reshape supply chain applications through enhanced decision support, knowledge generation, and increasing levels of automation. As a result, some of the most recent shifts in how AI is conceptualised and deployed, particularly in relation to autonomous systems and human–AI collaboration, are not comprehensively captured within the reviewed literature. This limitation reflects the pace of technological change rather than a methodological shortcoming, and it underscores the need for ongoing updates to the evidence base.

In addition, the studies included in the review were identified using a defined set of keywords, which may have excluded work framed differently or using alternative terminology. Future research could broaden the search strategy by employing a wider range of keywords and comparing results across multiple databases, including Web of Science and others.

2.6.4 Future Research Direction

This review identifies four evidence-based propositions, each grounded in patterns from the 72 reviewed studies and formulated for empirical testing.

2.6.4.1 Paradox Unintended Outcomes

. While most studies emphasise positive sustainability outcomes, a smaller but consistent body of work highlights negative impacts, including energy consumption, e-waste, digital inequality, and SDG trade-offs. This imbalance may reflect publication bias rather than actual outcome distribution. Future research should apply Paradox Theory (Hahn et al., 2015) to examine how organisations simultaneously generate sustainability benefits and costs through AI systems. Empirical studies linking AI adoption to both positive and negative SDG indicators would help build a more balanced evidence base.

2.6.4.2 Social Sustainability deficit in AI-enabled supply chain literature

The review shows that social sustainability outcomes appear as a primary focus in fewer than one-third of studies, with environmental outcomes dominating the literature. This pattern aligns with the concentration of studies in developed economies, where environmental regulation is stronger and social informality is less pronounced. Future research should test whether this imbalance persists in contexts characterised by informal labour, weaker environmental regulation, and stronger community accountability pressures (e.g., Sub-Saharan Africa, South/Southeast Asia, Latin America). Studies using balanced sustainability performance measures across social, environmental, and economic dimensions are needed to determine whether the observed hierarchy is universal or context-dependent.

2.6.4.3 Capability as a driver of AI-sustainability performance

The CIMO analysis shows that sustainability outcomes emerge from coordinated integration of AI across sensing, decision-making and execution, rather than from isolated technologies. However, most studies continue to examine AI tools in isolation. Future research should develop and test an orchestration capability construct, defined as the ability to coordinate, sequence and adaptively govern AI systems toward sustainability goals. This would test whether capability mediates the relationship between AI adoption status and sustainability performance.

2.6.4.4 Technology Convergence

Another theme relates to the convergence of AI with other emerging technologies such as blockchain, IoT, and big data analytics. The synergy of AI and other emerging technologies can push the boundaries of what is currently possible, far surpassing the limitations observed with just one technology (Varriale *et al.*, 2023). The unique features of individual technologies when combined can potentially deliver superior benefits than when used independently. Future research may explore how different configurations of technologies enhance supply chain sustainability outcomes, and which combinations are most effective across environmental,

social or economic dimensions. Understanding these synergies could provide insights into how digital ecosystems evolve and how they reshape sustainable supply chain practices.

2.6.4.5 Advances in Generative AI and LLMs

Future research should examine the implications of recent advances in generative AI and large language models (LLMs) for sustainable supply chains. The rise of LLM-based decision support and increasingly autonomous supply chain agents introduces new challenges related to governance, transparency, and accountability, alongside important social sustainability concerns such as workforce transformation and human-AI collaboration. In addition, the computational intensity of advanced AI systems highlights the need to assess their environmental footprint, including energy use and lifecycle impacts. Addressing these issues will be essential for developing a more current understanding of AI-enabled supply chain sustainability.

2.7 Summary

This chapter identified three interrelated gaps that structure the empirical investigation in this thesis. First, the dominance of environmental outcomes over social sustainability and the underexplored contextual dependence of sustainability effects motivates a deeper empirical examination of how AI adoption outcomes vary across institutional and organisational settings. This gap is addressed in Chapter 3, which investigates how contextual and behavioural factors shape AI and Industry 4.0 technology adoption using a TOE-TRI configuration. Second, the absence of integrated explanatory mechanisms linking technology, organisational readiness, and user cognition highlights the need for a multi-theoretical adoption model. Chapter 3 responds to this by integrating TOE and TRI to explain adoption dynamics in a developing economy context. Third, the identified limitation of theory in explaining post-adoption sustainability outcomes and capability development informs Chapter 4, which examines

sustainability performance through a structured outcome model, extending understanding of how AI adoption translates into triple bottom line impacts.

Chapter 3 Building Readiness for AI and Industry 4.0 Technology Adoption in Supply Chains: A TOE Perspective

3.1 Abstract

The digital transformation of supply chains has intensified interest in Artificial Intelligence (AI) and Industry 4.0 technologies (I4.0T) as key drivers of visibility, efficiency, and sustainability. Although prior research identifies contextual drivers of technology adoption, it frequently overlooks the critical role of internal preparedness in shaping whether these drivers lead to successful adoption. This study addresses this gap by positioning Technology Readiness Index (TRI) as a bridge between potential and actual adoption. Specifically, it explores how technology readiness motivators and inhibitors mediate the relationship between contextual factors and the adoption of AI and I4.0T in supply chains.

Drawing on the Technology Organisation Environment (TOE) framework and the TRI, this study employs Structural equation modelling (SEM) to analyse the relationships among contextual factors, readiness index motivators and inhibitors, and technology adoption, thereby highlighting both direct and indirect effects. The analysis utilises data collected using an online questionnaire administered to organisational respondents from multiple industries in Nigeria at managerial level involved in supply chain, digital transformation, sustainability initiatives or strategic decision making.

Findings indicate that technological and organisational contexts significantly influence adoption primarily through their impact on TRI, which reflects the organisational culture, organisational resources and technology characteristics. Although the environmental context is relevant, it shows a weaker direct relationship. This suggests that external pressures alone do not drive adoption success.

This study extends the TOE framework by further explaining how contextual factors affect adoption choices using the TRI as a mediating construct. It provides a more nuanced explanation of adoption variances in digital supply chains. From a managerial perspective, it emphasises the need to assess and build readiness before implementing extensive digital transformation. The findings also highlight for policy makers the importance of supporting readiness through investments in digital infrastructure, workforce upskilling, and supportive ecosystems to enable technology adoption.

Keywords: Technology adoption; Technology Readiness; TOE framework; Supply chain; Sustainability; Structural Equation Modelling;

3.2 Introduction

Driven by the emergence of novel technologies transforming various domains, including scientific research, personal relationships and economic dynamics, the next few decades are set for remarkable changes in humanity as we navigate an era of information and intelligence Herweijer *et al.* (2018). As the significance of Information and Communication Technologies (ICT) in production, logistics systems, and value creation processes continues to rise, organisations are leveraging these digital tools to address challenges like fluctuating demand, risk management, cost efficiency, and supply chain excellence, thus allowing them to stay competitive in a constantly changing market and increasingly complex global supply chains (Min, 2010; Kamble *et al.*, 2022).The rapid advancement of ICT has resulted in digital disruption (Alshawi, 2007). As organisations navigate this disruption and transition to digital processes, they generate vast amounts of data across their supply chains, which in turn has become one of the key assets for modern businesses (Dubey *et al.*, 2019). Organisations strive to improve the management of these data and embedded information, leveraging it for better decision-making (Min, 2010). To achieve this, organisations must develop the necessary capabilities to collect data from multiple sources, allowing them to derive valuable insights that

can refine, expand or change their strategies and boost future competitiveness (Wanner *et al.*, 2019). Therefore, appropriate tools are necessary to extract significant and meaningful insights that help to develop strong and adaptable supply chains (Arunachalam, Kumar and Kawalek, 2018). AI and various I4.0Ts provide possibilities for organisations to harness and utilize extensive data generated to enhance efficiency, transparency and improve performance in their supply chains (Dalenogare *et al.*, 2018).

Although AI and related systems have gone through several cycles of growth and decline since the term was first coined in the 1950s, the rapid development of incredibly fast data processing machines and technologies for enhanced storage capabilities has rejuvenated further interest in AI systems (Duan, Edwards and Dwivedi, 2019). Along with this, the advent of the Fourth Industrial Revolution (I4.0 or I4R), with the goal of achieving greater operational efficiency and productivity, has triggered increased automation by integrating digital technologies to create a cyber-physical system framework facilitated by Internet of Things (IoT), cloud computing, big data and analytics (Frank, Dalenogare and Ayala, 2019; Lu, 2017). This growth in the adoption of AI and various I4.0 digital technologies has significantly transformed businesses and the management of their supply chains, offering remarkable opportunities in an ever-changing environment for enhanced efficiency, transparency, flexibility, risk management and sustainability (Ben-Daya, Hassini and Bahroun, 2019).

Besides, Ahmed, Jeon and Piccialli (2022) affirm that AI serves as a fundamental enabling technology for I4.0 by enabling the integration and convergence of various technologies that allow software, systems, machines, and devices to sense, perceive, create, comprehend and learn from their own experiences or enhance human activities. AI provides the intelligence layer that power smart manufacturing, autonomous systems and decision support, the key underpinnings of I4.0 (Gupta *et al.*, 2021; Frank, Dalenogare and Ayala, 2019). Some of the technologies associated with I4.0 that are increasingly influencing how products

are created, evaluated, and delivered include automation and robotics, blockchain, cloud computing, the Internet of Things (IoT), big data; simulation, additive manufacturing or 3D printing, RFID and drones (Choi *et al.*, 2022; Ivanov *et al.*, 2018; Li *et al.*, 2017; Wang, Törngren and Onori, 2015; Wamba *et al.*, 2015; Ivan and Yin, 2017; Kamble, Gunasekaran and Dhone, 2019; Rajeb *et al.*, 2023).

Considering the significant benefits that these technologies offer across various operational areas, both researchers and practitioners are eager to learn more about how AI and I4.0Ts are adopted and utilized (Venkatesh, Raman and Cruz-Jesus, 2023), especially as organisations continue to encounter numerous obstacles in their adoption and implementation (Enholm *et al.*, 2022). Besides, there are still questions on how they could or should be integrated into organisational processes irrespective of the increased attention received by these emerging technologies (Fosso Wamba *et al.*, 2022). For instance, Kinkel, Baumgartner and Cherubini (2022) note that the process of adopting new technologies is shaped not just by technological traits, but also by additional structural conditions within the organisation. There are often subtle contextual factors in the adoption of novel technologies that influence the manner, reasons and degree to which organisations embrace these technologies. These factors may differ across industries, geographical areas, types of organisations and are influenced by a combination of technical, social, economic and regulatory elements (Dalenogare *et al.*, 2018). Consequently, further investigation and contextual comprehension of the various dynamics influencing organisations' ability to adopt AI and I4.0T is necessary (Ta, Wendt and Sigurjonsson, 2024; Kruger and Steyn, 2024). This is important as the perception of the significance of these technologies may vary due to differences in competitive environments and diverse requirements could also influence willingness and preparedness to adopt them (Dalenogare *et al.*, 2018).

3.2.1 Research Rationale

In the light of the above and building on the systematic literature review (Chapter 2), which identified the absence of integrated frameworks capturing both organisational readiness and user-level behavioural resistance in AI adoption, this chapter therefore employs TOE-TRI integration to explain how contextual and cognitive factors jointly shape AI and I4.0T adoption decisions. This study proposes that integration of TRI with TOE is significant in the current dynamic terrain of technology adoption research where models need to evolve to account for a wider range of influences, such as swift technological progress, socio-technical systems, and organisational culture (Kruger and Steyn, 2024). Extending this idea, Cheng (2020) emphasises the necessity for a hybrid model given the complexities and nuances of AI and I4.0T. Although there are studies that have integrated TOE with other models, those that have considered a multi-level approach to explore individual technology adoption problems under organisational constraints are limited (Li, 2020). In support of a multilevel approach, Lai and Lee (2020) argue that the increased exposure of organisations to more advanced technological products significantly alter how they engage with users suggesting that individuals' preparedness is a crucial element in the adoption journey. This study incorporates TRI which considers personal attributes in the process of technology acceptance (Parasuraman, 2000). By integrating TRI to effectively connect the analysis of technology adoption at both individual and organisational dimensions this study addresses this gap. Despite a number of studies integrating TOE and TRI (Hradecky *et al.*, 2022), these studies have typically regarded readiness either as a composite construct included with the TOE factors among the independent variables (Pan and Jang, 2008; Amini and Bakri, 2015) or have incorporated the dimensions of TRI as part of the TOE construct. For example Ghaleb *et al.* (2021) considered optimism within the technological dimensions of TOE (Oliveira and Martins, 2011). In the same vein, Aboelmaged (2014) explored the impact of TOE elements on the TRI dimensions related to e-maintenance technology readiness in manufacturing firms but did not consider the mediating role of TRI. In

contrast, by exploring the mediating role of TRI motivating and inhibiting factors on the relationship between TOE and technology adoption, this study goes further to answer ‘why’ and ‘how’ and not only ‘if’ readiness affects technology adoption. This study argues that TRI’s capability to function at multiple levels makes it particularly suitable for addressing its objective of identifying the technological, organisational and environmental factors that influence AI and I4.0T adoption, by connecting the factors related to TOE with technology adoption choices that frequently encompass both individual and organisational considerations. By integrating TRI, the study draws attention to 'readiness' in evaluating the technological, organisational and environmental dimensions of AI and I4.0T (Hradecky *et al.*, 2022). Additionally, this research addresses the inadequacy of traditional models in relation to AI and I4.0T, pointed out by Kruger and Steyn (2024), which frequently require additional expansion to encompass the complexities of emerging technological environments. By proposing an integrated model that goes beyond conventional frameworks, this research aims to address this inadequacy.

3.2.2 Research Question

In the light of the foregoing, there is a significant need and opportunity not only to investigate the elements that affect the adoption of AI and I4.0T, but also how technology readiness influences both the decision to adopt and the degree of adoption (Uren and Edwards, 2023). Therefore, this study asks the question: How do Technology Readiness Index (TRI) motivators and inhibitors mediate the effect of technological, organisational and environmental factors on organisational adoption of AI and I4.0T? The key objectives of this study based on the research question are : (a) to analyse the current state of adoption of AI and I4.0T among organisations in Nigeria (b) to identify the technological, organisational and environmental elements that impact technology adoption (c) to examine the mediating role of TRI factors that motivate or hinder the relationship between TOE factors and the adoption of AI and I4.0T. This

study aims to evaluate the role of technology readiness in adoption process by positioning TRI as a mediator between TOE factors and adoption outcomes.

3.2.3 Paper Structure

The paper is structured as follows: section 3 provides a review of past literature in AI and I4.0T, outlining their definitions and significance, along with the adoption theories and frameworks relevant to these technologies. In section 4, the conceptual framework and hypotheses are discussed to establish the relationships among the TOE dimensions, TRI mediators and adoption outcomes. The research methodology is outlined in section 5, explaining the research design, measurement instruments and variables and data collection and analysis techniques. Section 6 presents the research results and findings, including the descriptive statistics, outcomes of hypothesis testing and mediation analysis. The interpretation of the results is also discussed, focusing on their practical implications and theoretical contributions. In conclusion, a summary of research findings is provided, while recognising the limitations of the study and proposing areas for further research.

3.3 Literature Review

3.3.1 The Fourth Industrial Revolution

The fourth industrial revolution, also known as Industry 4.0, comes on the heels of the last three revolutions triggered by mechanisation, electricity and Information technology respectively. Considered a strategic initiative from Germany and designed to lead the industries currently transforming the manufacturing sector, Industry 4.0 and the corresponding digital transformation has been progressing at a rapid pace since the 2011 Hannover Fair presentation (Xu, Xu and Li, 2018; Ghobakhloo, 2020). This digital transformation involves automated manufacturing and service operations systems that are agile, flexible and customised, enabling the enhancement of capabilities across various domains, including product design, prototyping and development, remote operations services and diagnostics, predictive and preventive

maintenance, traceability, essential health monitoring systems, planning, innovation, agility, and applications that operate in real time (Ghadge *et al.*, 2020).

According to German Trade and Investment (GTAI)(2014), as cited in (Xu, Xu and Li, 2018), I4.0 marks the transition from embedded systems to cyber-physical systems, integrating technologies like the Internet of Things and machine-to-machine communication. This convergence creates a connection between virtual and physical environments, leading to smart factories that effectively manage production complexities within a cyber-physical framework. Similarly, Peres et al., (2020) notes that the rise of the I4.0 initiative has led to more dynamic, interconnected and smart manufacturing environments that leverage advanced intelligent systems to respond flexibly to changing product demands while enabling real-time optimisation across the value chain. Within this framework, AI is recognised as a crucial technology for facilitating digital transformation of manufacturing processes and business models (Peretz-Andersson *et al.*, 2024; Sjödin *et al.*, 2021; Peres *et al.*, 2020). Organisations can leverage AI technologies like machine learning, deep learning and natural language processing to automate tasks, improve resource efficiency and elevate their decision-making processes (Rashid and Kausik, 2024). Additionally, with recent advancements in ICT technologies, various emerging technologies like IoT, big data, and cyber-physical production systems (CPPS) are coming together to deliver digital solutions, making it possible to achieve the necessary flexibility and intelligence (Frank, Dalenogare and Ayala, 2019).

3.3.2 AI and Industry 4.0 Technologies

Although past literature has identified key enabling technologies of I4.0, there are differing opinions on the actual number or combinations of technologies that constitute I4.0 technologies (Bongomin *et al.*, 2020). Fatorachian and Kazemi (2020) considers Machine-to-Machine (M2M) communications, IoT, Cyber Physical Systems (CPSs), AI and Big Data Analytics as I4.0T while Frank, Dalenogare and Ayala (2019) identified IoT, Cloud services,

Big Data and Analytics as the base technologies for I4.0. Again, Rüßmann *et al.* (2015) singled out nine disruptive technologies for I4.0, three less than twelve key technologies recognised in the study by Manyika *et al.* (2013). In contrast Bongomin *et al.* (2020) identified 35 ranked disruptive technologies with 13 identified as key from their review of 70 publications.

The following section explores AI and some of the technologies that are especially significant for I4.0 and considered in this study. However, this review of enabling technologies is not to be considered exhaustive.

3.3.2.1 Artificial Intelligence:

AI has been identified as one of the key technologies that lies in the heart of I4.0 revolution (Toorajipour *et al.*, 2021; Peres *et al.*, 2020), Since this revolution, significant advancements in technological innovation have transformed many manual tasks and processes historically carried out by humans, who had often reached their physical limits. AI offers significant potential for enhancing and substituting these human tasks and activities across various industrial, intellectual and social spheres (Dwivedi, 2021). However, the understanding of what constitutes AI is also continuously changing with the staggering pace of advancements and evolution in AI research (Baryannis *et al.*, 2019). Previous research has established the absence of a universally accepted definition of AI (Kirsh, 1991; Simon *et al.*, 2000; Brachman, 2006; Nilsson, 2009; Monett and Lewis, 2017). This is not surprising given the complexities of 'intelligence' resulting in the term 'Artificial Intelligence' being applied in numerous ways and in a broad spectrum of research areas including computer science, engineering and cognitive science (Wang, 2019). However, Duan, Edwards and Dwivedi (2019) suggest that AI is generally defined as a machine's capacity to learn from experience, adjust to new information and execute tasks similar to those performed by humans. AI also refers to a computational technology comprising a suite of information and communication technologies (ICTs) designed to mimic human intellect, able to infer patterns and draw conclusions from

data, with the primary goals of enhancing productivity, improving efficiency and driving business growth (Olan *et al.*, 2022). AI technologies include Machine Learning, Natural Language Processing, Computer Vision, Speech recognition and Expert systems (Toorajipour *et al.*, 2021). Examples of everyday use case includes Smart Assistants (Siri & Alexa), Customer service/ Helpdesk Chatbots and platforms such as Microsoft Azure AI, SAP, Salesforce.

3.3.2.2 Additive manufacturing

One of the innovative manufacturing technologies aimed at enhancing production and driving the momentum for I4.0 is Additive manufacturing (AM) (Ivan and Yin, 2017). This technology creates three-dimensional (3D) solid objects using a series of additive or layered development frameworks. (E.g. Material extrusion, Sheet lamination; Binder jetting). The International Organisation for Standardization ISO/ASTM52900 (2015) defines AM as a "process of joining materials to make parts from 3D model data, usually layer upon layer, as opposed to subtractive manufacturing and formative manufacturing methodologies.'' AM presents organisations with opportunities to leverage advancements in manufacturing and fabrication technology through localized production utilizing basic materials, potentially reducing the costs of introducing new products and enabling differentiation that can enhance a company's competitive (Franco *et al.*, 2020; Oettmeier and Hofmann, 2017).This approach can lead to reduced carbon footprints, less reliance on non-renewable resources, and increased local autonomy in manufacturing and distribution processes, thus enhancing supply chain efficiency and sustainability (Akbari, 2023). This makes AM particularly effective for producing make-to-order components and products, rapid prototyping, production tooling, end-use parts production and spare parts production (Naghshineh and Carvalho, 2022) and allows for cost-effective options for customisation and personalisation (Franco *et al.*, 2020).

3.3.2.3 Big Data Analytics (BDA)

With rapid advancements in technology, data is now produced at a much quicker pace and in much larger quantities than ever before (Duan and Xiong, 2015). Extensive amounts of data, which come from a variety sources and forms, are generated within their supply chains as organisations become more digital (Davenport, 2006). These large and complex data sets referred to as 'Big Data' refer to large sets of information that exceed the capacity of regular database software to capture, store, manage and analyse (Arunachalam, Kumar and Kawalek, 2018). Big data is essential for enhancing search, analysis and visualisation in data analytics while addressing key challenges related to data capture, storage, transfer and sharing in predictive analytics within system architecture (Gunasekaran *et al.*, 2017). Big data becomes valuable when meaningful insights can be extracted from it (Dubey *et al.*, 2019). Big Data Analytics (BDA) involves investigating these extensive datasets to reveal concealed patterns and hidden correlations, offering the ability to measure various dimensions of a business in detail thereby enabling more informed decision-making and improving management practices (McAfee *et al.*, 2012). With BDA organisations can manage, understand and assess the volume, variety, velocity, veracity and value of data to produce actionable insights that deliver continuous value, evaluate performance and create competitive advantages (Wamba *et al.*, 2015). For instance, route optimisation tools, demand forecasting tools, order picking systems, inventory and warehouse management solutions (Ivanov *et al.*, 2018) are some of the BDA replacing traditional data mining and handling techniques for analysing large volumes of data that afford supply chains greater flexibility and agility in managing uncertainty and volatility in their environments (Bag *et al.*, 2020; Nunez-Merino *et al.*, 2022).

3.3.2.4 Blockchain

The contemporary supply chain often involves hundreds of steps, diverse geographical areas, numerous invoices and payments, and multiple individuals and organisations, and can take

months to complete, depending on the item, making the management of the entire production and delivery process in modern supply chains incredibly complex (Marr, 2018). Given the complexity and lack of visibility in most supply chains, there is growing interest in the potential of blockchains to revolutionise supply chain management.

Aside from the complexities of globalisation, diverse regulatory frameworks, and varying cultural and social factors in contemporary supply chain networks make assessing information and managing risks challenging (Ivanov *et al.*, 2018). Across various supply chain sectors, including agriculture, food, pharmaceuticals and luxury goods, traceability is increasingly viewed as a crucial requirement and competitive advantage (Agi and Jha, 2022). The provenance of high-value and luxury items, often reliant on physical documentation, is susceptible to loss or manipulation. Alongside this, inefficient transactions, fraudulent activities, theft and poor supply chain practices foster mistrust and highlight the necessity for improved information sharing and verification methods (Saberi *et al.*, 2018). Blockchain can mitigate this by enabling supply chain participants engage with one another and generate, authenticate, confirm and securely archive various types of data including product details, certifications, location information and transaction logs by functioning as a decentralised database of information gathered from sensors and other interconnected devices (Agi and Jha, 2022). Using a Distributed Ledger Technology (DLT), blockchain enables multiple parties to maintain a shared, tamper-proof record of digital transactions. This technology is perhaps most associated with the first decentralized digital currency Bitcoin, which uses blockchain technology to record and verify transactions. Food supply chains can utilise blockchain technology to enable supply chain participants swiftly verify authenticity or pinpoint the source of potential problems through digital capture and preservation of critical data such as production details, origins, temperature conditions during storage and transit, shelf life etc in a centralised database (Chandan, John and Potdar, 2023; Akinbamini *et al.*, 2025). Again,

blockchain removes the need for any third-party intermediary by providing a peer-to-peer platform for transactions to help organisations achieve better visibility and transparency, reducing data tampering and other fraudulent activities (Kamble, Gunasekaran and Dhone, 2019; Hartley and Sawaya, 2019).

3.3.2.5 Cloud Computing

'Cloud' is a type of parallel and distributed system consisting of a collection of inter-connected and virtualised computers that are dynamically provisioned and presented as one or more unified computing resource(s) based on service-level agreements established through negotiation between the service provider and consumers'' (Buyya, Yeo and Venugopal, 2008). Cloud computing involves the delivery of various computing services offerings including servers, storage, databases, networking, software, analytics and intelligence via internet, this facilitating faster innovation, flexible resources and economical scaling (Deskera, 2025). Cloud systems facilitate concurrent data access for multiple supply chain users, providing continuous information availability, reducing costs and infrastructure complexity, enhancing operational efficiency (Li *et al.*, 2017) and allowing supply chains become more flexible and adaptable (Ivanov, Dolgui and Sokolov, 2022b). Erboz (2017) identified three main categories of cloud computing: (i) Infrastructure as a Service (IaaS): This model provides users with virtualised computing resources, such as servers, storage and networking capabilities. (ii) Platform as a Service (PaaS): This option provides users with a platform to develop, run and manage applications without the need to handle the underlying infrastructure. (iii) Software as a Service (SaaS): This approach delivers software applications over the internet using a subscription-based model. Google Drive provided by Google, Windows Azur by Microsoft, and BlueCloud by IBM are some of the most widely recognised types of cloud systems (Haug, Kretschmer and Strobel, 2016)

3.3.2.6 Cyber Physical Systems

Often regarded as the next generation of embedded systems Cyber-Physical Systems (CPS) integrate various enabling technologies, including computation, information and communication technology, as well as advanced planning and control techniques to merge the digital components of computing and communication with the dynamics and physics of physical systems functioning in the real world, effectively blurring the lines between the physical and cyber domains with enhanced levels of interaction (Javaid *et al.*, 2023). These systems enable future technology developments by integrating computational and physical functions, enabling innovative interactions with humans, communicating with and improving the physical environment through computation, communication and control (Baheti and Gill, 2011). CPS encompass a diverse array of applications including automotive systems, process control systems, asset management, manufacturing processes, medical devices and assisted living technologies, distributed robotics, such as telepresence and telemedicine, traffic control and safety initiatives, access control and monitoring, Heating Ventilation and Air conditioning (HVAC), water management systems and energy conservation efforts for sustainability. These applications illustrate the versatility and significance of CPS across various sectors (Lee, 2015). CPS can effectively be deployed to address challenges in production, logistics, quality control, planning and scheduling within supply chains (Tonelli *et al.*, 2021). CPS in combination with technologies such as cloud computing, IoT, and big data, is a vital technology for achieving Smart Manufacturing (Wang *et al.*, 2016)

3.3.2.7 Internet of Things (IoT)

The term “Internet of Things” (IoT) denotes the integration of wireless communication features with sensors and computing that allow distinctly identifiable objects to transmit data via the internet with minimal or no human intervention (Wang, Törngren and Onori, 2015). IoT contributes to the concept of “anytime, anywhere, any media, anything” communication by

facilitating communication with and between intelligent devices (Atzori, Iera and Morabito, 2010). The definition of IoT varies depending on the technologies employed for its realisation. However, the core concept is that objects within an IoT can be distinctly identified in their virtual representations, with all items capable of sharing data and, if necessary, processing information according to established protocols (Li, Xu and Zhao, 2015). Kevin Ashston has been widely credited with first using the term "Internet of Things" in 1999 in relation to linking all equipment to the current network using various information sensors, such as RFID sensors, infrared sensors, global positioning systems and lasers to track products along the supply chain (Rebelo, Pereira and Queiroz, 2022; Yu and Tie-Ning, 2012). With the progress in smart sensors, energy-efficient wireless communication, and sensor network innovations, numerous 'things' can be connected as part of IoT (Li, Xu and Zhao, 2015). IoT minimises the need for human involvement and participation as much as possible in the delivery of efficient and effective autonomous services by connecting multiple objects or 'things' (including devices, machinery, structures, buildings, and gadgets) in an online environment (Awoyemi, Alfa and Maharaj, 2020). Organisations are incorporating these new technologies into their Supply Chain Management (SCM) processes to address supply chain challenges such as excess inventory and shortages, delays in product delivery, and difficulties in sharing real-time information (Taj *et al.*, 2023). Some of the benefits of IoT for SCM include the advancement of real-time SCM by minimising data distortion and enhancing business intelligence; improved supply chain performance through the reduction of delays in data gathering, evaluation, and decision-making; and enhanced integration of interorganisational business processes (Haddud *et al.*, 2017). In addition, IoT applications are relevant across plan, source, make, deliver, return and enable processes of SCM (Ben-Daya, Hassini and Bahroun, 2019).

3.3.2.8 Radio Frequency Identification (RFID)

Supply chains need constant monitoring and regular optimisation as numerous factors such as fluctuating demands, altering routes, significant disruptions and compliance challenges constantly affect operations (Unhelkar *et al.*, 2022). Radio Frequency Identification (RFID) is an effective technology for sourcing big data in supply chains for required monitoring and optimisation. RFID was originally created for tracking and identification, however, increasing interest in various other potential uses has led to the creation of a new variety of wireless sensor devices that are RFID-based (Xu, Xu and Li, 2018). According to Tebaldi *et al.* (2023) with changing consumer behaviour, spread of ecommerce and the need for omnichannel sales options, particularly for Fast-Moving Consumer Goods (FMCG), the focus of RFID, initially at the pallet/case level for improving logistics processes, has evolved to enable item-level tagging for handling in-store processes and buyer experience. RFID refers to technologies that enable wireless communication between an object (or tag) and a reading device (or reader) to automatically track and identify those objects (Bai *et al.*, 2020). They are categorised as wireless automatic identification and data capture (AIDC) technologies that include barcoding, optical recognition, biometrics, card technology, contactless memory technology (Wamba et al, 2008). RFID consists of three components: a tag made up of a chip linked to an antenna; a reader that sends out radio signals and receives responses from tags; and then a middleware that connects the RFID hardware with enterprise applications (Sarac, Absi and Dauzère-Pérès, 2010). Often, the automatic and ongoing sensing features of RFID can facilitate more automated manufacturing processes by freeing up human labour from certain workflows (Xu, Xu and Li, 2018). Angeles (2005) discusses the case studies of Unilever, Chevrolet and United Biscuits to illustrate the practical use of RFID, showing that distribution process can be optimised at various stages including receiving and check-in, put-away and replenishment, order fulfilment and shipping. Angeles (2005) highlights: Unilever's use of RFID to monitor pallets within their warehouses, resulting in increased daily pallet handling and improved

information reliability; Chevrolet Creative Services adopting RFID to manage shipping manifests thereby reducing human errors and accelerating the processing of crates; United Biscuits employing RFID to track the movement of raw materials in food manufacturing, a practice that significantly enhancing both operational efficiency and information accuracy. Collectively, these examples signify the capacity of RFID to simplify Logistics, minimise errors, and improve information management across industries.

3.3.2.9 Robotic Process Automation (RPA)

Aside from the rapid pace of technological advancement, the emergence of the pandemic has also contributed to the acceleration of digital transformation compelling organisations to focus on transforming essential business operations and processes, modifying their business models and improving the automation of their business processes (Choi, R'bigui and Cho, 2021). Viale and Zouari (2020) note that lower-value business processes are often overlooked in business process improvement initiatives, perhaps due to their unappealing benefits-to-cost ratio. Therefore, automation is a possible strategy which could free resources in these less valuable sections of an organisation and diminishes the necessity for ongoing management and oversight (Wanner *et al.*, 2019). Organisations are increasingly applying Robotic Process Automation (RPA) to redesign, optimise and automate many repetitive tasks in supply chain process activities across sourcing, operations and logistics (Hartley and Sawaya, 2019). RPA is a broad term that combines robotics with business process automation and involves software licenses, referred to as bots, that replicate human actions to automate repetitive, mundane and rule-driven business tasks, often described as "swivel chair work" (Lacity and Willcocks, 2016). The Institute of Electrical and Electronics Engineers (IEEE) Corporate Advisory Group, 2017 cited in Huang and Vasarhelyi (2019) defines Robotic Process Automation (RPA) as "a preconfigured software instance that uses business rules and predefined activity choreography to complete the autonomous execution of a combination of

processes, activities, transactions, and tasks in one or more unrelated software systems to deliver a result or service with human exception management". RPA's range of functions encompasses data entry, performing basic calculations, accessing and pulling data from Enterprise Resource Planning (ERP) systems, filling out forms, replying to emails opening files, signing into applications, transferring files or folders, scraping information from web pages, retrieving data from PDF files or images, among others (Costa, Mamede and Silva, 2022; Hartley and Sawaya, 2019). RPA also offers enhancements in process performance, efficiency, scalability, auditability, security, and compliance in supply chains (Hofmann, Samp and Urbach, 2019).

3.3.2.10 Simulation

In today's competitive business environment, companies must manage international supply chains and unpredictable markets while overseeing production across different regions. To succeed, they need to deliver excellent products and customer service. Consequently, companies that do not frequently evaluate their strategies may jeopardize their competitive edge (Terzi and Cavalieri, 2004). Simulation enables organisations to evaluate risks, expenses, implementation hurdles and effects on operational performance by developing planning and exploratory models aimed at enhancing decision-making as well as the design and operation of complex and intelligent production systems (de Paula Ferreira, Armellini and De Santa-Eulalia, 2020). Simulation, provides a vital problem-solving approach for the analysis of complex production systems (Negahban and Smith, 2014). Data gathered and assessed from extensive data sets and cloud systems serve as the foundation for virtual simulation models that can assess possible scenarios related to product design, development, manufacturing and supply chain systems (Ghadge *et al.*, 2020). By utilising simulation for process testing and optimisation before implementing changes in the actual physical setting, organisations can decrease transition times, lower risks, shorten setup periods and enhance quality control for future

operations and services (Ghadge *et al.*, 2020; de Paula Ferreira, Armellini and De Santa-Eulalia, 2020). Scheidegger, Banerjee and Pereira (2018) note that simulation is often the most efficient and economical method, and at times the sole approach for identifying causal relationships, determining essential parameter estimates and understanding how processes evolve over time, enabling assessment of system optimisation before putting it into practice.

3.3.2.11 Unmanned Aerial Vehicles (UAV) / Drones

Often classed as either terrestrial (automated guided vehicles) or aerial (unmanned aerial vehicles), autonomous robots represent a significant I4.0T with potentials to improve the supply chain (Okwu *et al.*, 2022). Unmanned Aerial Vehicles (UAVs) or pilotless aircraft systems, often referred to as Drones, have been utilised in a wide range of applications such as industrial monitoring, photography, military surveillance missions, disaster rescue and assistance efforts, parcel delivery and agricultural practices (Rejeb *et al.*, 2021). They are especially beneficial for activities that are repetitive, dangerous or require unpleasant tasks (Chiang *et al.*, 2019). The high level of manoeuvrability that drones offer can greatly improve various logistics operations (warehousing, inventory management, transportation and route optimization) and reduce the overall expenses in the supply chain (Shavarani *et al.*, 2019.) They also represent a cutting-edge approach to enhance logistics responsiveness and efficiency due to their rapid speed, aerial capabilities and ability to operate autonomously (Sah, Gupta and Bani-Hani, 2021). Previous research indicates that drone technology can be harnessed to meet the growing sustainability expectations of customers (Hwang, Lee and Kim, 2019). In theory, drones could lead to decreased energy use and reduced greenhouse gas emissions, contributing to a smaller carbon footprint and promoting environmental sustainability (Chiang *et al.*, 2019). Utilising drones can turn a company's logistics operations into a strategic advantage, creating social value and improving sustainability across the triple bottom line (Hwang, Lee and Kim, 2019)

3.3.3 Technology Adoption

The modern global economy emphasises the effective use of both human intellectual capital and technology as organisations increasingly recognising technology as a vital strategic tool for achieving business success and ensuring sustainable performance (Fatorachian and Kazemi, 2020). In this context, organisations leverage the emerging technologies for digital transformation aimed at streamlining processes, enhancing business strategies, maximising resources, and ultimately establishing a competitive advantage (Grover, Kar and Dwivedi, 2022). Literature asserts that AI enhances productivity and assists in making informed decisions (Chatterjee *et al.*, 2021). Consequently, the rise of AI and I4.0T has shown significant impact on manufacturing, product development, services and supply chain (Grover, Kar and Dwivedi, 2022). AI continues to transform supply chain and operations management, revolutionising areas such as demand forecasting, inventory management in real-time, and maintenance practices (Venkatesh, Raman and Cruz-Jesus, 2023). This is particularly evident when AI is integrated with other I4.0T. For instance, AI in conduction with blockchain is anticipated to promote greater automation, enhance connectivity within supply chain networks and improve traceability of commodity flows (Karakas, Acar and Kucukaltan, 2024.) AI's effectiveness is maximised with large datasets, (Roh, Heo and Whang, 2019). When combined with IoT, it facilitates the generation and analysis of substantial real-time data. Thereby eliminating delays between data collection and analysis, and enabling prompt responses (Ben-Daya, Hassini and Bahroun, 2019). These benefits derived from AI and I4.0T is only fully realised with wide adoption.

However, Zemsky and Massy (2004) highlight a common misconception regarding technology adoption: the belief that developing technology guarantees its adoption and embracing innovation is not always assured. The diffusion and adoption of new technologies, such as AI and I4.0T is often complex and vary among individuals, organisations and even

countries (Hariri and Roberts, 2015; Rogers, 2003). Understanding the factors that influence adoption has become increasingly important, as technology continues to play a crucial role in enhancing productivity and competitiveness (Oliveira and Martins, 2011). Extending this idea, Venkatesh, Raman and Cruz-Jesus (2023) assert that the challenge of technology adoption and utilisation by various stakeholders remains a key interest of both researchers and practitioners regardless of the technology being adopted and its promised benefits. Despite the increased attention generated by emerging technologies, how these technologies could or should be integrated into organisations remains unsettled (Akter *et al.*, 2022; Fosso Wamba *et al.*, 2022). Further, AI and I4.0T embody intricate interconnected technology clusters or ecosystems instead of isolated innovations which presents challenges of technology attributes and the transformational nature of AI and I4.0T questions some of the most basic research assumptions particularly regarding technology adoption and usage (Schuetz and Venkatesh, 2020). This potentially limits how our current knowledge applies to AI and I4.0T. Schuetz and Venkatesh (2020) further argue that this presents a unique chance for new theory development which this study seizes to propose research questions which, it aims to address to yield interesting, influential and original theoretical and practical contributions.

3.3.4 Technology Adoption Models

Existing literature is replete with theories and frameworks that explain the acceptance of digital innovations generally, on both individual and organisational scales. According to the research conducted by Kruger and Steyn (2024) the eight leading models for technology adoption in the context of AI and I4.0 are: the Technology Acceptance Model (TAM) (Davis, 1985; Davis, 1989), Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), the TOE framework (Tornatzky and Fleischer, 1990); Theory of Planned Behaviour (TPB)(Ajzen, 1985; Ajzen, 1991), Diffusion of Innovation (DOI)(Rogers, 1995; Rogers, 2003), Theory of Reasoned Action (TRA)(Fishbein and Ajzen, 1975), TRI

(Parasuraman, 2000) and Information Systems Success Model (ISSM)(DeLone and McLean, 2003). Majority of these models are predominantly behavioural and scholars have traditionally applied in technology adoption studies to predict intention and actual behaviour at the individual level (Li, 2020), although some studies have made efforts to adapt models such as the TAM from a personal level to an organisational context (Yu and Tao, 2009). However, in predicting adoption at the organisational level, a considerable number of studies have used the theoretical lens of DOI and TOE frameworks (Kinkel, Baumgartner and Cherubini, 2022). In terms of firm-level adoption, Oliveira and Martins (2011) point out that DOI identifies the internal and external features of the organisation that serve as key factors for its innovativeness. These align with the technology and organisational context found within the TOE framework. However, the TOE framework introduces a vital and additional aspect: the environmental context. The inclusion of the environmental dimension makes TOE framework better able to explain firm-level innovation diffusion than DOI (Hsu, Kraemer and Dunkle, 2006).

However, several of these overarching theories of technology adoption can also guide the comprehension of the factors that influence adoption of new and emerging technologies such as AI and I4.0T as well as provide frameworks that explain it. The following section presents a brief review of some of the more popular adoption theories and readiness frameworks based on the research focus.

3.3.4.1 The Technology Acceptance Model (TAM)

The TAM, developed by Davis in 1989, is a significant framework for understanding individual technology acceptance. TAM posits that two primary factors influence user acceptance are (a) Perceived Usefulness (PU): refers to the extent to which an individual believes that using a specific system will enhance their job performance and (b) Perceived Ease of Use (PEOU): the degree to which a person feels that operating a certain system requires minimal effort. These factors affect the user's attitude toward the technology, which in turn

influences their intention to use it, ultimately leading to actual engagement with the system. TAM has been validated in multiple studies and settings, demonstrating strong construct reliability and has been widely applied across various technologies, including enterprise software and information systems (Venkatesh and Davis, 2000), manufacturing (Chatterjee *et al.*, 2021), retail (Kim, Park and Choi, 2017), finance (Singh, Sahni and Kovid, 2020), skills development (Molino *et al.*, 2020; Skoumpopoulou *et al.*, 2018), mobile technologies and applications (Park and Chen, 2007), e-learning systems (Cheng, 2011) and healthcare information technologies (Holden and Karsh, 2010). TAM however does not consider organisational, social and environmental factors that affect technology adoption and views adoption as a singular event rather than as a process that evolves over time thus simplify the complexity of adoption decisions, especially regarding new technologies (Kruger and Steyn, 2024; Chatterjee *et al.*, 2021)

3.3.4.2 Unified Theory of Acceptance and Use of Technology (UTAUT)

By integrating eight pre-existing models of technology acceptance, Venkatesh et al. (2003) established a unified theoretical framework that identifies four primary factors influencing intention and usage: (i) *Performance Expectancy*: Comparable to perceived usefulness, it reflects the extent to which an individual believes the technology will support job performance; (ii) *Effort Expectancy*: Similar to perceived ease of use, it indicates the level of ease that comes with using the technology; (iii) *Social Influence*: The extent to which an individual feels that key individuals in their life expect them to adopt the new technology; (iv) *Facilitating Conditions*: The extent to which an individual believes that the necessary organisational and technical infrastructure is in place to facilitate the use of the technology. The UTAUT model also includes gender, age, experience, and voluntariness of use as moderating variables. This integration of the model allows for a thorough combination of various theoretical viewpoints, context sensitivity due to the inclusion of moderating factors, and the

incorporation of social elements that were absent from TAM. While UTAUT has been utilised in numerous studies, it is not without shortcomings, mostly concerning its complexity and the challenges of implementing its constructs across different contexts (Dwivedi et al., 2019). Nevertheless, with the model enhancement introduced by Venkatesh, Thong, and Xu (2012) aimed at providing greater clarity in understanding user behaviour and capturing consumer acceptance scenarios. It has been employed by Marchewka and Kostiwa (2007) to understand student's perception of use of course work management software and by Wamba and Queiroz (2020) to evaluate usage examples at an organisational level.

3.3.4.3 Diffusion of Innovation Theory (DOI)

Rogers (2003) DOI theory, commonly referred to as Innovation Diffusion Theory (IDT), explains the mechanisms behind the spread of innovations within social systems (Oliveira and Martins, 2011). The main components consist of: Innovation attributes such as relative advantage, compatibility, complexity, trialability, and observability; Communication channels that refer to the methods of transmitting information about innovations; Social system which denotes the environment in which diffusion takes place; Adopter categories including innovators, early adopters, early majority, late majority, and laggards; and the Diffusion process encompassing knowledge, persuasion, decision, implementation, and confirmation (El Malouf and Bahemia, 2023; Sahin, 2006). The strength of DOI lies in its ability to consider the individual, organisational and societal levels of analysis and how innovations spread over time. Its relevance across a variety of technological and social contexts is demonstrated by its extensive application in areas such as educational technology (Sahin, 2006), healthcare innovation (Greenhalgh and Peacock, 2005) and sustainable supply chain practices (Zhu, Tian and Sarkis, 2012).

Despite the significance of DOI, scholars have noted certain drawbacks. Studies suggests that the theory tends to be pro-innovation, operating under the assumption that all

innovations are inherently uniform and beneficial, and that non-adoption is a result of individual choices rather than systemic factors (MacVaugh and Schiavone, 2010; El Malouf and Bahemia, 2023). Additionally, Lyytinen and Damsgaard (2001) contend that the DOI framework may neglect important elements of complex technologies and the learning-centric aspects of technology, as well as the importance of institutional contexts.

3.3.4.4 Technology-Organisation-Environment (TOE) Framework

The TOE framework developed by Tornatzky and Fleischer (1990) provides a broader organisational-level perspective on technology adoption. According to the model, three contextual aspects influence adoption: *Technological Context*: Includes both internal and external technologies relevant to the firm focusing on characteristics such as compatibility, relative advantage, and complexity of the current internal practices and equipment of the firm as well as externally available technologies; *Organisational Context*: Refers to the descriptive characteristics of the organisation including managerial structure, resource availability, size, and scope; *Environmental Context*: refers to the organisation's business context encompassing industry characteristics, market structure, regulatory environment, and support infrastructure (Oliveira and Martins, 2011; Kruger and Steyn, 2024). The framework's flexibility and complementarity make it relevant for assessing organisations readiness and acceptance and has successfully been applied studies of AI and I4.0 related technology such as, E-maintenance technology (Aboelmaged, 2014), E-commerce technologies (Zhu, Kraemer and Xu, 2003), Enterprise systems (Ramdani, Kawalek and Lorenzo, 2009), Cloud computing (Low, Chen and Wu, 2011), IoT technologies (Hsu and Yeh, 2017) and Big data analytics (Chen, Preston and Swink, 2015).

3.3.4.5 Technology Readiness Index (TRI)

The TRI is a well-established framework for evaluating how ready individuals are to adopt new technologies. According to Parasuraman (2000) technology readiness reflects

"people's inclination to accept and utilize new technologies to achieve objectives in personal and professional settings." The initial model, TRI 1.0, comprises a 36-item scale that analyses the relationship between motivators (*optimism, innovativeness*) that facilitate technology readiness and inhibitors (*discomfort, insecurity*) that hinder it. Due to the considerable shifts in the technology landscape, user feedback from diverse applications over time and insights from extensive research, the authors refined and updated this model to create a more succinct and modern scale that is neutral regarding technology (Parasuraman and Colby, 2015). Although TRI 2.0 is considerably more streamlined than TRI 1.0, the creators of TRI 2.0 acknowledge that the sub-scales related to inhibitors (discomfort and insecurity) exhibit some deficiencies in certain psychometric properties, particularly concerning convergent validity. In this regard, (Parasuraman and Colby, 2015) suggests investigating the structural stability and invariance of the TRI across different contextual environments in future research (for instance, in countries with varying cultures). Regardless, studies utilising the TRI have demonstrated its capability to forecast individual readiness for the adoption of innovative technologies. The TRI has been validated across various domains, including self-service technologies (Liljander *et al.*, 2006) e-learning (Kaushik and Agrawal, 2021), travel technologies (Wang, So and Sparks, 2017) and electronic health record systems (Alsyouf and Ishak, 2017)

3.3.5 Comparative Analysis of Variations in Adoption Theories and Models

Technology adoption theories and models exhibit notable variations based on their perspective. With respect to the *primary focus and level of analysis* models such as the TAM and UTAUT primarily explore how behavioural intentions affect user acceptance. In contrast, frameworks like DOI and TOE consider organisational factors. Again, the *degree of technology specificity* varies as certain models, like TAM, focus on general factors influencing technology adoption, while others concentrate on specific user-driven factors. Broader models like TOE and DOI are applicable across various technologies, whereas technology specific models, such

as the AI Readiness Model, provide customised insights (Kim, Park and Choi, 2017). Theories can also be viewed from *variance versus process perspectives*. Variance-based theories, including TAM and UTAUT, emphasise individual and technological characteristics that influence adoption rates. Conversely, process theories like DOI examine the dynamic interactions and processes that drive adoption over time (Jeyaraj and Sabherwal, 2008). On the other hand, the *Rational-economic* theories focus on individual optimisation, cost-benefit analysis, and utility maximisation, while *Social-institutional* theories highlight the often-interrelated roles of social norms, cultural contexts (Im, Hong and Kang, 2011), and institutional pressures in adoption, as illustrated by Institutional Theory (Chersoni, 2019).

As this study primarily focuses on analysing the interactions and process of technology adoption at the organisational level, TOE and TRI are suitable frameworks for evaluating AI and I4.0T adoption.

3.3.6 Justification for TOE Framework and Technology Readiness Index

The two theories predominantly used in studies of technology innovation adoption at the organisational level are DOI and TOE (Hossain, Quaddus and Islam, 2016). However, Oliveira and Martins (2011) opine that the TOE framework, an extension and integration of DOI and TAM, is better able to explain firm-level technology adoption as it accounts for environmental influences. The TOE framework's strength is found in its comprehensive approach, taking into account the complex relationship of technological capabilities, organisational conditions and external influences to provide a complete perspective on the readiness for adoption (Wong *et al.*, 2020).

This paper considers TOE framework particularly suitable for this organisational technology adoption study because of its key attributes. Aside from providing a comprehensive organisational level perspective for examining technology adoption, the TOE framework provides an analytical lens that extends beyond individual behavioural models such as the TAM

or the UTAUT. These individual level models primarily assess behavioural intentions, whereas the TOE framework examines the structural and contextual determinants of adoption across the organisation. Again, the framework's flexibility and applicability make it suitable framework for achieving the objectives of this study. Furthermore, the fact that the TOE framework integrates multiple dimensions of influence (technological dimension, organisational capability and environmental pressures) enables a more complete understanding of adoption processes. Its explanatory power cuts across technological, industrial and national cultural contexts (Baker, 2012).

However, scholars have highlighted certain limitations of the TOE framework. Baker (2012) pointed out that most of the theoretical advancements related to the TOE framework have primarily focused on listing various factors relevant to different adoption scenarios without integrating new constructs into the framework. Furthermore, TOE's adaptability and ease of integration can prove a disadvantage, making it lack specificity and overly reliant on customisation (Awa, Ojiabo and Orokor, 2017; Baker, 2012; Prakash, 2025). To address this limitation, the study integrates the TRI as a complementary construct that account for individual level behavioural readiness to enhance the explanatory depth of the TOE framework.

When integrated with the TOE framework, TRI can serve as a mediating construct that links organisational contexts with individual technology adoption behaviours. Therefore, TOE and TRI operate as complementary mechanisms explaining what neither can predict alone. TOE's conjunctive logic specifies the enabling conditions for adoption, while TRI explains the psychological activation that converts those conditions into action. Together, they predict that favourable conditions lead to adoption only when TRI motivators are activated. TOE captures these structural conditions, while TRI translates them into behavioural activation.

3.4 Theoretical Concept and Hypotheses Development

3.4.1 An Integrative Approach

As indicated by Lee and Shim (2007), it may not be practical to establish a universal theory that fits all types of innovations. Considering the varied nature of innovations, it seems unlikely that one theoretical model can sufficiently encompass the processes of adoption and diffusion for every kind of AI and I4.0T innovation (Kimberly and Evanisko, 1981). Affirming this, Kruger and Steyn (2024's) review of adoption models asserts that additional extensions of technology adoption models are frequently required to reflect the intricacies of emerging technological paradigms. Besides, Li (2020) affirms the general consensus that two separate categories of theories are essential for explaining technology adoption at both the individual and organisational levels. Therefore, to adequately reflect inter-level interactions within organisations, examining adoption in organisations necessitates inquiring how an individual's personality traits and viewpoints affect the application of firm-level frameworks like TOE in exploring technology adoption (Baker, 2012). Moreover, the role of TRI as a mediating mechanism in organisational technology adoption remains underexplored as it is often used as an indicator of adoption intention or attitude, particularly at the individual level.

3.4.2 Conceptual Framework and Hypotheses

Following extensive review of literature, this study narrowed its focus on identified factors within the TOE framework related to technology readiness and subsequent adoption. Considering the integrative approach adopted, the study developed a conceptual framework using these constructs from the TOE framework and TRI. While both frameworks individually offer valuable insights, concurrent use can help amplify their effectiveness by providing a macro-level view of the organisational and environmental factors influencing technology adoption while delving into the micro-level psychological readiness of employees to adopt AI and I4.0T. The conceptual model is shown in Figure 3.1

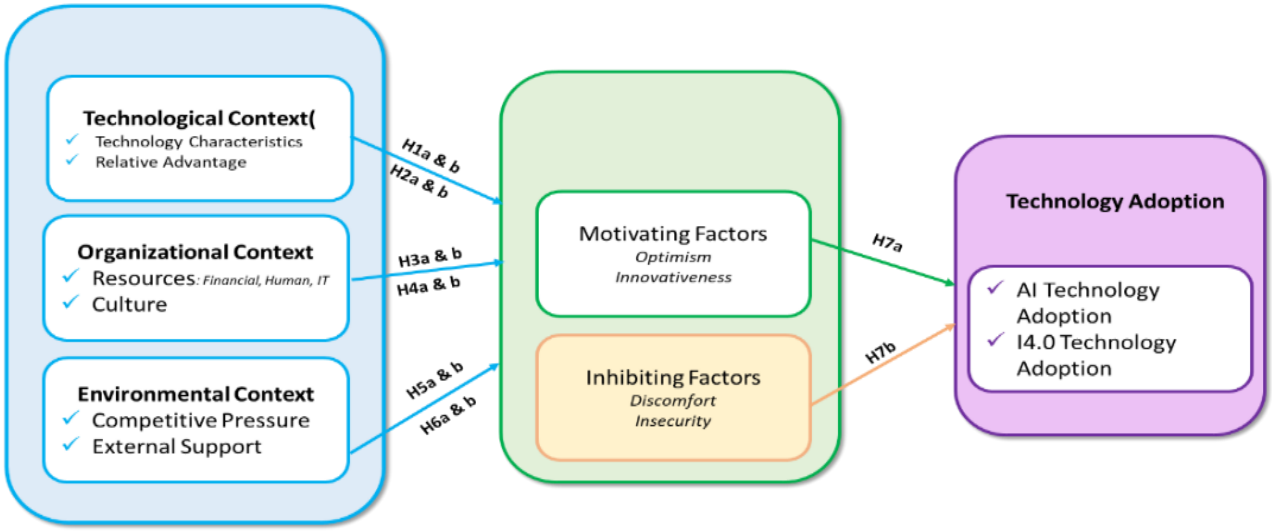

Figure 3.1 Conceptual Model

3.4.2.1 Technological Dimensions

Various theoretical frameworks have identified the technological dimension an influential factor with strong predictive capabilities regarding the technology adoption (Zhu and Kraemer, 2005; Zhu *et al.*, 2010; Jere and Ngidi, 2020). Extending this idea, Gutierrez, Boukrami and Lumsden (2015) explains that the technological context encompasses both internal and external technologies relevant to the organisation and these include technologies accessible in the market as well as those currently utilized within the organisation (Lin and Chen, 2012; Oliveira and Martins, 2011). The existing technology within an organisation establishes the potential for how extensively new technology can be integrated (Baker, 2012). The technology framework, including computer hardware, software and networking technologies are essential for deploying new technological solutions across an organisation (Aboelmaged, 2014).

3.4.2.1.1 Technology Characteristics:

Readiness for adoption can be influenced by various characteristics of new technologies, such as compatibility, complexity, trialability, and observability (Rogers, 1995). Compatibility involves the extent to which the innovation fits with the values, experiences and needs of potential users, while complexity is evaluated based on how difficult the technology

and its implementation are (Bhattacharya and Wamba, 2018). On the other hand, trialability and observability pertain to the opportunity to test the innovation prior to adoption and to witness the advantages of the innovation in practice, respectively (Badghish and Soomro, 2024). Despite their perceived advantages, these technology characteristics creates the perception that the adoption of AI and I4.0T is risky alongside concerns over unpredictability, privacy and security challenges and a lack of expertise (Wong *et al.*, 2020). This can heighten employee apprehension and distress regarding shifts and changes that may come with adoption of AI and I4.0T which in turn could impact their readiness and acceptance of AI and I4.0T integration.

Therefore, AI and I4.0T solutions that are easy to understand, allow pilot testing on a small scale and produce visible results, promotes optimism and innovativeness. When employees can gain hands-on experience and see success stories first hand, it builds trust and reduces uncertainty or hesitation. This perceived ease and transparency help lower insecurity and discomfort thus reducing adoption inhibitors.

Therefore, the following hypotheses are put forward:

- H1a.Technology characteristics of AI and I4.0T are positively associated with technology readiness motivating factors
- H1b. Technology characteristics of AI and I4.0T are positively associated with reducing technology readiness inhibitors

3.4.2.1.2 Relative Advantage

The perceived benefits that a technological factor offers to organisations is a key determinant in the acceptance of technological innovations (Rogers, 1983). Referred to as relative advantage, prior studies, including Thong (1999) and Lee (2004) have thoroughly examined its influence on the technological adoption of organisations. A higher perception of

relative advantage associated with an innovation increases its likelihood of being adopted (Alshamaila, Papagiannidis and Li, 2013). However, depending on the individual readiness traits these advantages of AI and I4.0T could have different perceptions. Relative advantages can confirm and strengthen employees' positive views of AI and I4.0T as providing increased control, flexibility, efficiency to improve job performance thus, increasing readiness for adoption. Again, the clarity with which the relative advantages are demonstrated may influence how much discomfort and scepticism people feel about a technology's ability to work well. Therefore, when AI and I4.0T clearly improve efficiency, productivity or decision-making, they strengthen optimism and innovativeness. Users feel confident exploring tools that deliver measurable benefits. This helps reduce inhibitors, thereby easing insecurity and discomfort about adoption.

Consequently, the following hypotheses are proposed:

- H2a. Relative advantages of AI and I4.0T are positively associated with technology readiness motivating factors
- H2b. Relative advantages of AI and I4.0T are positively associated with reducing technology readiness inhibitors

3.4.2.2 Organisational Dimension

Researchers have contended in previous studies that an organisation's structural characteristics greatly affect its behaviour regarding technology adoption (Kimberly and Evanisko, 1981). Several organisational variables, including the quality of human resources, leadership abilities of top management, organisational resources and the culture within the organisation, have been explored in relation to the adoption of innovations (Oliveira, Thomas and Espadanal, 2014; Gutierrez, Boukrami and Lumsden, 2015). This study focuses on organisational culture and organisational resources comprising, financial, human and IT.

3.4.2.2.1 Organisational Resources

According to Awa *et al.* (2016) organisational factors of adoption are descriptive and are directly linked to the availability and utilization of internal resources. In support, To and Ngai (2006) assert that availability of resources is a significant factor influencing the uptake of various new technologies within organisations and represents the level and diversity of resources available within the organisation that can be committed to embrace new technology. Such organisational resources include financial, human and technical infrastructure (Neumann, Guirguis and Steiner, 2022). Technology adoption necessitates costly capital, people, and technology expenditures (Iacovou, Benbasat and Dexter, 1995).

The availability of financial resources acts as a safeguard against potential implementation challenges and facilitates robust technology support systems in readiness for the integration of AI and I4.0T (Ramdani, Chevers and Williams, 2013; Jöhnk, Weißert and Wyrtki, 2021). Having slack resources encourages innovation and allows for experimentation with new AI and I4.0T through pilot projects, thereby improving trialability and observability (Nohria and Gulati, 1996). The presence of skilled human resources, including access to technological expertise, sufficient staffing for transitions and opportunities for comprehensive skill development and on-the-job training, helps alleviate the discomfort and insecurity that can hinder the willingness to embrace AI and I4.0T (Igbaria, Parasuraman and Baroudi, 1996). The availability of financial, human, and IT resources are a vital basis for readiness in organisations. With sufficient funds and infrastructure organisations can invest in new technologies and training. Optimism and innovativeness naturally increase when employees feel adequately supported and equipped. At the same time, perception of fewer barriers or risks reduces insecurity and discomfort associated with technological change.

In line with the role of organisational resources for technology adoption, the following hypotheses are made:

- H3a. Availability of organisational resources has a positive association with enhancing AI and I4.0T readiness motivators
- H3b. Availability of organisational resources has a positive association with reducing AI and I4.0T readiness inhibitors

3.4.2.2.2 Organisational Culture

Culture shapes the environment where AI and I4.0T are implemented. García-Machado and Martínez-Ávila (2019) opine that while culture can vary according to an organisation's unique characteristics, it generally consists of a set of shared values and standards expressed throughout the organisation. Similarly, Hitka *et al.* (2015) note that corporate culture is a pivotal influence behind organisational decisions and actions and involves a combination of concepts, beliefs, attitudes, and values that guide the organisation over time. The integration of AI and I4.0T often requires substantial changes in organisational structure and employee culture (Neumann, Guirguis and Steiner, 2022). Previous research by Duan, Edwards and Dwivedi (2019) recognised culture as a key element affecting technology acceptance. Agreeing with Martins and Terblanche (2003), Mu, Kirsch and Butler (2015) provide further insight, adding that organisational culture lies at the heart of organisational innovation. Thus, cultures that emphasise innovation and learning enhance readiness for technology adoption, promoting positive attitudes toward technology, encouraging continual exploration of new technologies, rewarding innovative technological applications, and fostering a psychologically safe space for technological experimentation (Igbaria, Parasuraman and Baroudi, 1996). Conversely, top-down technology enforcement without user input and applying rigid implementation approaches can cause discomfort and increased resistance to technology, which can impede technology readiness (Jones, Jimmieson and Griffiths, 2005). A supportive culture fosters innovativeness and optimism motivating acceptance of AI and I4.0T tools while resistant culture can inhibit progress and adoption.

Additionally, while a strong organisational culture can support AI and I4.0T adoption, it may also create resistance to change, especially in traditional industries with deeply rooted practices. (Mikalef *et al.*, 2022). A culture that encourages innovation, continuous learning, and openness to change fosters innovativeness and optimism. In contrast, a restrictive or risk-averse culture can hinder progress. Therefore, a supportive culture not only promotes proactive technology adoption but also helps lower insecurity and discomfort by reinforcing a sense of collective confidence and shared purpose.

Consequent on the above, the study hypothesised the following relationships:

- H4a. Favourable organisational culture enhances AI and I4.0T adoption readiness motivators
- H4b. Favourable organisational culture mitigates and reduces AI and I4.0T adoption readiness inhibitors

3.4.2.3 Environmental Dimension

Environmental readiness factors indicate external pressures and influences that drive an organisations to seek technological innovation and can either facilitate or obstruct organisational readiness in adopting new technologies (Nguyen, Nguyen and Dang, 2022). Gutierrez, Boukrami and Lumsden (2015) point out that the broader macro environment where an organisation functions comprising its industry, market components and the presence of technology service providers. Wong *et al.* (2020)) explain that market dynamics, competitive pressures and regulatory support are also environmental elements that affect the uptake of new technologies. Isomorphic pressures from government, competitors and customers are likely to motivate firms to embrace and utilise AI (Gibbs and Kraemer, 2004). Numerous environmental factors, including market pressure, customer pressure, stakeholder influences, governmental and environmental regulations, have been examined in existing research (Badghish and

Soomro, 2024). This research specifically focuses on competitive pressure and external support within the context of AI and I4.0T adoption.

3.4.2.3.1 Competitive Pressure

As noted by Porter (1985), the competitive advantages of organisations are often fleeting rather than enduring, with various factors, including contemporary technologies, reshaping industry structures, changing the dynamics of competition and enabling new methods to surpass competitors. Embracing new technology is often a strategic imperative for remaining competitive in the marketplace (Lippert and Govindarajulu, 2006; Iacovou, Benbasat and Dexter, 1995). Previous research has indicated that competitive pressures and the expectations of market participants serve as strategic imperatives and significant motivators for adopting innovations (Zhu, Kraemer and Xu, 2003; Nguyen, Nguyen and Dang, 2022). Moreover, the fear of missing out (FOMO) is also an influential factor driving the enthusiasm surrounding AI and I4.0T, leading to the emergence of herd behaviours (Faiz, Le and Masli, 2024; Mari, Mandelli and Algesheimer, 2024). Przybylski *et al.* (2013) define FOMO as a "pervasive apprehension that others might be having rewarding experiences from which one is absent." The fear of losing opportunities for career advancement through the adoption of new technology can enhance technology readiness, particularly when employees recognise that gaining new skills and distinguishing themselves from colleagues can boost personal opportunities (Mari, Mandelli and Algesheimer, 2024).

Further, competitive pressure often arises when organisations see technology adoption as a strategic necessity to maintain or improve market position. Usually, organisations are driven to maintain or enhance market position especially when they operate in very competitive markets. This often stimulates innovation particularly where AI and I4.0T are considered enablers of differentiation and growth rather than sources of disruption. The expectation that

AI and I4.0T can help organisations gain competitive edge reduces apprehension and uncertainty that in turn reduces insecurity and discomfort that inhibit adoption.

Consequently, these hypotheses are proposed:

- H5a. Competitive pressure is positively associated with improving AI and I4.0T adoption readiness motivators
- H5b. Competitive pressure is positively associated with the reduction of AI and I4.0T adoption readiness inhibitors

3.4.2.3.2 External Support

According to Bodas-Freitas and Corrocher (2019), external support for adopting technology encompasses assistance and resources given from outside an organisation to aid in the successful integration and use of new technologies, which can come in various forms including direct financial support, expert consulting or advice from peers in related fields. Support from external sources, like government or regulatory bodies, typically involves providing assistance or creating conditions for employees or organisations to facilitate technology diffusion. Badghish and Soomro (2024) further emphasise that the regulations and policies established by the government to oversee and regulate industry use of new technologies are crucial factors influencing innovation diffusion, particularly as technologies like AI and I4.0T are emerging and regulations have yet to be fully developed. Al-Hawamdeh and Alshaer (2022) point out the vital role government plays in providing the framework to guide the complex process of adopting new technologies. Additionally, indirect support may be offered by suppliers, consulting firms or public research institutions, typically in the form of advice and consultancy aimed at addressing knowledge barriers to adoption (Bodas-Freitas and Corrocher, 2019). Related to this is the influence of organisational partnerships which research has shown to be significant to adoption of AI and I4.0T, particularly as companies often depend on trading partners for technology design and implementation (Nguyen, Nguyen

and Dang, 2022; Gutierrez, Boukrami and Lumsden, 2015). Vendor support, which includes reliable technical assistance and opportunities to leverage the experiential knowledge of suppliers, can be a key source for building capabilities that alleviate employee discomfort, insecurity and perceived risk associated with technology adoption (Scupola, 2003; Jeyaraj, Rottman and Lacity, 2006).

Therefore, external support increases readiness by providing knowledge, resources, policy frameworks that can facilitate adoption through assistance from vendors, industry partners and regulatory authorities as well as favourable government policies. External support provides organisations with the necessary guidance and support to navigate complex technological change. This helps to reduce insecurity and discomfort by decreasing the level of perceived risks with AI and I4.0T.

This leads to the following hypotheses:

- H6a. External support positively influences the motivators of readiness toward AI and I4.0T adoption.
- H6b. External support positively influences reduction of inhibitors of readiness toward AI and I4.0T adoption.

3.4.2.4 Technology Readiness Motivators and Inhibitors

According to Parasuraman (2000) technology readiness refers to an individual's or an organisation's inclination to embrace and utilise new technologies, which consists of four distinct components: optimism, innovativeness, discomfort, and insecurity. Optimism involves having a positive outlook on technology and belief that it offers greater control, adaptability, and efficiency. Innovativeness signifies the propensity to be an early adopter of technology and to take the lead as a trendsetter or influencer. Discomfort is characterised by a perceived lack of control over technology and the sensation of being pressured or overwhelmed by it, whereas

insecurity reflects a distrust in technology and doubt about one's capability to use it effectively (Kaushik and Agrawal, 2021).

Research has approached the constructs of technology readiness index in various ways: (a) as a four-dimensional construct to analyse the individual impacts (Lam, Chiang and Parasuraman, 2008; Son and Han, 2011); (b) categorising them into two dimensions as motivators and inhibitors (Jin, 2013); and (c) adopting a one-dimensional view by merging the four dimensions into an overarching concept (Vize *et al.*, 2013). This study has opted for the two-dimensional motivator-inhibitor framework because it strikes a balance between the overly broad yet simplified one-dimensional model and the more detailed but complicated four-dimensional model (Blut and Wang, 2020). Moreover, this approach aligns with the perspective of Clohessy and Acton (2019) that the TOE framework can help uncover the technological, organisational, and environmental obstacles (inhibitors) and incentives (motivator) affecting the adoption of technological innovations. Moreover, understanding technology readiness (motivators and inhibitors) can shed light on how technological elements (e.g., relative advantage and technology features), organisational factors (resources and culture), and environmental influences (competitive pressure and external support) impact the adoption of AI and I4.0T.

In essence, readiness for AI and I4.0T adoption is not determined by technological availability alone. How the surrounding conditions influence users' confidence, enthusiasm, and perceived capability also influence their readiness index. Favourable conditions across technological, organisational and environmental dimensions encourage experimentation, help to build confidence and minimise resistance. Positioning TRI as a mediator between TOE factors and AI and I4.0T adoption outcomes reveal that external pressures and organisational conditions alone are insufficient. Even when technology is available and the environment is supportive, adoption depends on whether organisations possess the cognitive, attitudinal and

skill-based readiness to effectively interact with AI and I4.0T and this determines how ready an organisation and its employee are to adopt AI and I4.0.T

Therefore, the following hypotheses are proposed:

- H7a. Technology Readiness motivators mediates the relationship between TOE factors and the adoption of AI and I4.0T
- H7b. Technology Readiness inhibitors mediates the relationship between TOE factors and the adoption of AI and I4.0T

3.5 Research Methodology

3.5.1 Introduction

According to the famous American astronaut, Neil Armstrong, research is creating new knowledge (Fisher, 2021). Our knowledge, beliefs, perspectives and behaviours are shaped by our worldview, which encompasses our attitudes, values, narratives and expectations about and perspective on the world. The various ways to gain knowledge identified by Privitera (2017) include tenacity, intuition, authority, rationalism and empiricism. Further, Privitera (2017) explains that knowledge gained through tenacity is by habit or superstition and is often inaccurate while, intuition is based on feelings not facts although it can lead to the formation of hypotheses in research, particularly in areas where there is little or no prior knowledge. On the other hand, information derived from authoritative sources may inspire new ideas regarding the research topic, but these ideas need to undergo thorough scientific evaluation as they are often prone to bias (Trivedi, 2020). Again, logical thought can also aid in formulating a research hypothesis, but it is essential that all hypotheses are validated through the scientific method (Privitera, 2017). Scientific method is an empirical approach that systematically collects and analyses data to test hypotheses and address questions. The goal of research is to maintain objectivity and impartiality while enhancing knowledge (Benner, Hughes and Sutphen, 2008).

It contributes to the existing body of knowledge by providing new insights or perspectives on a subject, detailing the characteristics of individuals or objects, or identifying causal relationships between different factors (Eyisi, 2016).

3.5.2 Research Philosophy

The aim of research is to answer questions utilising methodologies informed by paradigms, philosophical beliefs and various methods or procedures (Alele and Malau-Aduli, 2023). Researchers' worldviews, which include their convictions and philosophical assumption regarding the nature of reality and how it can be understood shape their perspectives and approach to inquiry (Guba and Lincoln, 1994). These sets of beliefs and assumptions known as research paradigm guide the structure and execution of research (Cresswell, 2013). A paradigm consists of a collection of theories, assumptions and ideas that shape an individual's worldview and their interactions with others or their environment. Based on this, a researcher interprets the world and assesses the methodological aspects of their study to determine the appropriate methods for data gathering and analysis (Kivunja and Kuyini, 2017). Myers and Avison (2002) advise that the best approach to establishing valid research is to adhere to an appropriate research paradigm, as this helps researchers maintain clarity and offers a better perspective in relation to other alternatives. Research paradigms are made up of four philosophical components: axiology, ontology, epistemology, and methodology which guide the planning and execution of research projects (Cresswell, 2013). According to Denzin and Lincoln (2011), three philosophical assumptions: being (ontology); knowing (epistemology) and acting (axiology) are relevant to research.

3.5.2.1 Ontology:

Ontology is the study of being; the examination of existence (Crotty, 1998). Ontological assumptions pertain to what makes up reality, what truly exists in the world from which knowledge can be gained, essentially what is true (Scotland, 2012). Moon and Blackman

(2014) notes that ontological assumptions aids researchers in understanding the level of certainty they can have about the nature and existence of the subjects they are investigating. Moon and Blackman (2014) further illustrates ontology as a continuum with two extreme endpoints: realism and relativism. According to Guba and Lincoln (1994), realist researchers aim to uncover universal truths by minimizing subjectivity and bias. In contrast, relativist researchers believe that reality is shaped by individual experiences and varies across social and cultural contexts. They emphasise understanding personal interpretations of experiences, recognising that multiple realities can coexist (Pretorius, 2024).

3.5.2.2 Epistemology

The ontological beliefs impact epistemological understanding. While ontology addresses the fundamental nature of reality, epistemology pertains to the most suitable approaches for investigating such a reality. The concept of epistemology is derived from the Greek term epistêmê, which refers to knowledge and simply refers to the study of knowledge or the methods through which it is acquired (Krauss, 2005). Epistemology significantly enhances the researcher's confidence in their data and affects how researchers approach the process of identifying and seeking answers during their investigations (Kivunja and Kuyini, 2017). Epistemology raises essential questions such as What constitutes Knowledge? What is the connection between the individual who knows and the information that is known? How do we obtain knowledge and what are its boundaries? Is it reliable? Should we explore it further? What is regarded as acceptable knowledge within our field? (Krauss, 2005; Alele and Malau-Aduli, 2023).

There are different epistemological perspectives, including positivism, interpretivism, critical theory, and pragmatism. Interpretivism emphasises the subjective construction of knowledge through individual experiences and social interactions, typically using qualitative methods to explore personal narratives (Scotland, 2012). Critical theory examines how power

dynamics and societal structures shape knowledge, aiming to reveal social injustices, fairness and the use of power in supply chain relationships (Gregory, Atkins and Dwivedi, 2024). Pragmatism prioritises practical application, combining theoretical robustness with real-world relevance, often using mixed methods to evaluate interventions. Positivism focuses on gaining knowledge through objective observation and measurable data, often involving controlled trials to assess effectiveness (Alele and Malau-Aduli, 2023).

3.5.2.3 Axiology

Axiology is the aspect of research that focuses on the researcher's comprehension of values and their significance in the research process. It investigates concepts of right and wrong, assesses the extent of development and various forms of perceptual biases (Guba and Lincoln, 1994). Axiology clarifies the significance of the research process, reflects on the values researchers attach to their work, and directs their quest for knowledge (Cresswell, 2013). Researcher's axiological stance will determine whether their vales will shape the research or whether they will be morally neutral and how they will deal with the values of the participants.

Having considered the research philosophies that operate based on the various ontological and epistemological stance, the current study adopts a positivist philosophy which has informed the research questions, methods and interpretations. As technology adoption is a complex process and shaped by various influences, a well-organised research methodology is vital. By adopting a positivist perspective, the study maintains an objective view in the identification of measurable factors affecting technology adoption. This enables statistical analysis to determine causal relationships through objective techniques fully detached from personal values and biases of the researcher. Table 3.1 summarises the research paradigms adopted for this study.

Table 3.1 Research Paradigm

Descriptors	Positivism
Origins	Founded in the hard/natural sciences
Focus	Explanation, realism, objectivism
Ontology	Truth and laws are universal
Epistemology	Objectivism; Observable and measurable facts
Axiology	Value free: extrinsic purpose of research project
Outcome	Causal explanation and prediction as contribution
Methods	Deductive, Quantitative methods of analysis

(Adapted from Saunders, Lewis and Thornhill (2009)

3.5.3 Research Approach to Theory Development: Deductive

The study's approach to theory development is influenced by its research philosophy. Saunders, Lewis and Thornhill (2016) identify three primary methods for developing theories: deductive, inductive, and abductive. *Deductive* reasoning involves drawing specific conclusions from a general principle and is typically applied in testing theories. In contrast, *inductive* reasoning focuses on constructing theories by starting with specific observations to establish a broader generalisation. *Abductive* reasoning approach adopts a pragmatist perspective and strives to mitigate the limitations associated with the earlier approaches by combining deduction and induction. This study adopts a deductive reasoning approach to explore the determinants of AI and I4.0T adoption. Drawing from technology adoption theories (TOE and TRI), this study develops hypotheses about specific determinants that are subsequently tested through analysis of collected data.

3.5.4 Methodological Choice: Quantitative

Methodology refers to the strategic plan or framework that guides the selection and application of specific methods within a given research paradigm (Crotty, 1998). It encompasses the overall study design, methods and procedures employed in a well-structured study aimed at uncovering answers. This can include aspects such as data collection, survey tools, participant selection and data analysis (Kivunja and Kuyini, 2017). Some of the methodological choices previously applied in supply chain management research include: *Quantitative Approach* (focusing on objective measurement and positivism, assuming a single

reality); *Qualitative Approach* (emphasising understanding diverse perspectives and subjective experiences); *Mixed Methods Approach* (combines multiple methods and adapts research to specific contexts).

This study considers mono-method quantitative research appropriate to enable testing of the generated hypotheses, using numerical data collected through surveys. The study acknowledges that the structure of a quantitative approach can often be linear and rigid, thus requiring researcher's detachment. This may be challenging for the study to truly capture, understand or appreciate group or individual perspectives (Shank and Brown, 2007; Lune and Berg, 2017). Eyisi (2016) advises a cautionary approach with this methodological choice to prevent biases in data collection and interpretation especially when conducting a thorough examination of phenomena such as technology adoption. However, the potential for researcher bias in data collection or analysis is significantly minimised in this study as researcher did not interact directly with participants, instead gathered data through questionnaires (Lim, 2025).

On the other hand, a benefit offered by this method is an opportunity to extend interactions observed within one group to other groups enhancing generalisation (Polit and Beck, 2010). This way, the findings of this study can be considered valid rather than coincidental (May and Williams, 1998). Furthermore, since quantitative method primarily involves hypothesis testing, clear guidelines and objectives are followed instead of relying on guesswork (Lichtman, 2013). This makes it possible for the process to be repeated in different contexts with consistent outcomes (Shank and Brown, 2007). Replicability is a significant merit of this methodological choice. Again, the reliance on statistical data in quantitative research helps conserve time and resources by streamlining the process of describing and analysing research findings, saving the researcher extensive time and effort (Bryman, 2016).

3.5.5 Research Strategy: Survey

In determining the execution of the research, the study considered an approach aligned with data needed for the affective investigation and achievement of the objectives of the study. To achieve this, the study considered several factors: the choice of a deductive reasoning process for hypothesis testing, the level of interference, the research setting and the time horizon. As the unit of measurement forming the basis of the sample is organisations, a survey strategy was deemed appropriate because it enables organised data collection from a broad population regarding how readiness influences the relationship between TOE factors and technology adoption. Besides, of the three primary research designs in the context of information systems behavioural studies, survey has been established as the most dominant designs (Orlikowski and Baroudi, 1991). Moreover, survey research is a key methodology frequently utilised by researchers in supply chain management to gather empirical data because of its effectiveness in achieving an acceptable response rate, thus allowing for more reliable generalisation of the findings (Melnyk *et al.*, 2012). Providing further insight, Dooley (2009) highlights the significance of surveys in his evaluation of the empirical modelling discourse within operations and supply chain management. Again, scholars have acknowledged the prominence of survey methods, along with their superiority over other empirical techniques (Flynn *et al.*, 1990; Scudder and Hill, 1998; Frohlich, 2002). The prevalence of survey research is understandable given that they are generally low-cost to conduct; they are effective in outlining the characteristics or traits of large groups; can be administered through multiple approaches; numerous questions can be posed regarding a topic; and achieving high reliability is straightforward (Melnyk *et al.*, 2012).

Additionally, this study considers a cross-sectional time limit which offer a glimpse into the current elements that affect adoption choices most suitable for the survey to investigate to the factors that influence technology adoption at a particular moment.

3.5.6 Research Design

The research design provides a comprehensive framework to guide the techniques for data collection and analysis (Bryman and Bell, 2007). It is important to select appropriate research design to ensure a good link between the theory and the empirical data gathered to address the research question (Barroga and Matanguihan, 2022). The following sections discusses the techniques for data collection and analysis utilised for this study.

3.5.6.1 Questionnaire

This study choose online questionnaire for primary data collection because it facilitates data collection aimed at testing the effectiveness of the formulated TOE and TRI concepts in relation to AI and I4.0T adoption, examining the hypothesised connections between them and assessing the boundaries of its model's validity (Forza, 2002). Furthermore, the survey methodology is useful for ensuring anonymity, minimizing interviewer bias and enhancing overall validity and reliability while providing a cost-effective solution that allows for a relatively simple data collection process that can be completed at users' convenience (Jere and Ngidi, 2020; Wu, Zhao and Fils-Aime, 2022). Additionally, to determine the conformity of the observed data from the questionnaire to earlier established theoretical models and to examine the validity and reliability of the measurement tools used for data collection this study utilises SEM.

SEM, an extension of General Linear Modelling (GLM) techniques, typically refers to various statistical models that utilise empirical data to evaluate the validity of theoretical concepts (Lei and Wu, 2007). However, unlike other GLM applications, SEM is capable of modelling complex pathways of relationships including mediation, interaction and indirect effects (Nunkoo and Ramkissoon, 2012). It also effectively analyses relationships that involve latent constructs for more precise estimates of the connections between latent variables by addressing measurement error in observed variables (Hair *et al.*, 2021). By integrating various

techniques such as factor analysis (which identifies underlying factors from observed variables) and multiple regression (which evaluates how one group of variables predicts another) within a single framework, SEM offers a thorough approach to analyse complex interrelations (Stein, Morris and Nock, 2012; Ullman and Bentler, 2012).

3.5.6.2 Operationalisation and Measurement

Bryman and Bell (2011) recommend the use of previously used and validated questions and categories for operationalisation and measurement of model constructs. Therefore this study conducted a detailed and extensive review of relevant literature to identify measures to enable an empirical evaluation of the constructs of the proposed framework. The constructs were operationalised to ensure measurability and objectivity, improve reliability and facilitate comparison (Bhandari, 2023). Further, the measures for each of the various constructs measuring TOE, TRI, AI and I4.0T adoption factors, were derived from scales that have been previously validated in prior studies to guarantee reliability and validity (Meadows, 2003). Specifically, the five measurement items in each of the scales assessing Relative Advantage (RAQI) and Technology Characteristics (TCQI) were adapted from the research of Gutierrez, Boukrami and Lumsden (2015); Abdekhoda, Dehnad and Zarei (2019); Oliveira, Thomas and Espadanal (2014) which evaluates the technological influence on AI and I4.0T adoption. Similarly, using five items each focusing on Organisational Resources (ORQI) and Organisational Culture (OCQI) influences taken from studies by Malik *et al.* (2021); Gutierrez, Boukrami and Lumsden (2015) this study evaluates organisational factors. Additionally, the items utilised to assess the environment construct were adapted from Gutierrez, Boukrami and Lumsden (2015); Bhattacharya and Wamba (2018); Bin Naeem *et al.* (2024); Nguyen, Nguyen and Dang (2022) to determine the impact of Competitive Pressure (CPQI) and External Support (ESQI) on AI and I4.0T adoption respectively. To assess the mediating role of technology readiness on TOE factors in the adoption of AI and I4.0T, measurement scales for the

motivating (MFQI) and inhibiting (IFQI) factors were adapted from the work of Tunmibi and Okuonghae (2023). Finally, the implementation of AI and I4.0T considered the level of well established, operational processes within the organisation and was measured using scale adapted from Neumann, Guirguis and Steiner (2022); Nagarajan (2024).The details of the measurement scales for all the construct are presented in Table B1, Appendix B.

3.5.6.3 Pilot testing

The study thoroughly evaluated each question of the entire survey by pre-testing before final distribution. The evaluation assessed how well the questions were understood, determined whether all items were essential, checked the overall flow of the questionnaire and ensured the suitability of questionnaire's length. The online questionnaire was shared with two academics and five supply chain experts to ensure diverse perspectives and a range of insights. Subsequent follow-up meetings with the academics and telephone conversations with the supply chain experts reviewed their feedback. Although the questionnaire's general feedback was positive, some of the suggestions offered include reducing the information in the cover letter, making the definitions in the introduction concise or leaving them in collapsible, on-demand form, removing or rewording some questions that appeared repeated, expanding some questions or splitting them, enabling multiple choices for some questions for better clarity and highlighting some typographical errors to improve the questionnaire’s adequacy and clarity. There were also suggestions on improving the format. These suggestions were incorporated to refine the questionnaire and ensure the relevance of the items included in the final version.

3.5.7 Data Collection

For data collection, the study used Qualtrics online survey platform to create the survey questionnaire. The questionnaire used Likert scales as a standardised means to capture respondents’ range of opinions about AI and I4.0T adoption beyond the binary yes or no

answers (Koo and Yang, 2025). Likert scales are common in social science research and are frequently used to obtain nuanced data that enables the assessment of latent constructs, such as attitudes, opinions, and beliefs which are not directly observable (Leung, 2011). They are familiar and easy to understand, cognitively less demanding than open-ended questions, which reduces respondent burden (Wise and Sidarus, 2025). Besides, Likert items are suitable for parametric statistical methods because they provide sufficient gradation to detect variation in responses without overwhelming respondents and when summed, provide approximate continuous data (Norman, 2010). Although existing literature show that optimal scale points are between 5-point and 7-point, to strike a balance between reliability, validity and response bias, the study opted for the 5-point especially as the 7-point scale could have a longer completion time, may increase survey fatigue, with slightly more cognitive burden for respondents (Wise and Sidarus, 2025). Furthermore, 5-point Likert scale helped avoid sensitivity issues and allowed for effective assessment of internal consistency and reliability (Taherdoost, 2016a). The two-part questionnaire comprises of an initial section with an information letter detailing the purpose of the survey, the risks and benefits of participation, considerations regarding data privacy and security and the Research and Ethics Committee's approval. Included also in this part is a consent form agreement for participation in the survey. The subsequent part contained question items related to nine distinct scales measuring TOE and TRI factors as well as AI and I4.0T adoption. The concluding section of this part contained the demographic questions placed at end of the survey to encourage the provision of honest answers and minimise the risk of 'stereotype threat' (Gilovich, Keltner and Nisbett, 2006). A copy of the questionnaire is included in Appendix D

The study collected data over a four-month period from 8th September 2024 to 17th January 2025. Reminder emails were sent twice in October 2024 (week one and four), twice in early December 2024, and once in the second week of January 2025.

3.5.7.1 Sampling and Sample size

Rahi (2017) states that 'Population' refers to all individuals or items that one aims to study, while 'sampling' involves choosing a segment of that population for investigation. The target population is businesses in Nigeria. According to the Corporate Affairs Commission (CAC), as at September 2024, Nigeria has a total of 4.9 million registered companies (Awe, 2025). Aside from large number of the population of Nigerian businesses, their geographical dispersion is an added challenge for access, making it impractical to study the whole population. However, insights about the larger group can be provided by a smaller subset of the population (Malhotra and Birks, 2007). Sampling is beneficial as it not only simplifies the research process but also reduces the costs associated with studying the entire target population. In addition, Cooper, Schindler and Sun (2003) suggest that sampling enables quicker data collection, enhances accuracy of results, and is cost-effective. The choice of sampling method is influenced by both theoretical and practical considerations. There are primarily two categories of sampling methods: *probability* sampling and *non-probability* sampling. Probability sampling entails the random selection of participants, whereas non-probability sampling does not involve random methods. The goal of probability sampling is to form a representative sample in which every individual in the population has an equal chance of being chosen, enabling researchers to make broader inferences about the population. In contrast, non-probability sampling is frequently utilized for exploratory studies or in situations where a representative sample isn't critical (Taherdoost, 2016b).

For this quantitative study, a simple random probability sampling was employed. To enhance the generalisability of the outcomes, the CIPS (Chartered Institute of Procurement and Supply) Nigeria members' database, LinkedIn.com database and other contacts were utilised. These databases offered the advantage of being able to connect with a wide array of respondents who have varied characteristics, including their job titles, educational backgrounds, and locations across Nigeria (Nguyen, Nguyen and Dang, 2022). Job function

at the level of manager and above formed the main criteria for inclusion. The rationale lies in the assumption that managers and executives typically possess a working understanding of the technologies in their organisation and a wider perspective on their organisation's goals and strategies for technology adoption and usage. The survey link was distributed among the respondents all in Nigeria, with the data stored anonymously on the Qualtrics platform. A total of 454 (318 LinkedIn connections, 109 direct emails; 27email forwards) invitations to participate were sent and 304 responses received. After data cleaning: removing duplicates, invalid, non-engaged responses and dealing with missing data, a total of 192 responses were considered by this study.

Data for this study were collected using a single integrated survey instrument, which also provided data for the assimilation and sustainability analysis in Chapter 4. Both studies draw on the same respondents who reported on TOE conditions, technology readiness and adoption decisions in this chapter, and on assimilation, capabilities and performance outcomes in Chapter 4. This design was deliberate. Practically, a single data collection reduced respondent burden and improved response rates. Theoretically, it reflects the coexistence of adoption and assimilation in practice, where organisations simultaneously adopt some AI and I4.0T applications while assimilating others. However, methodological implications, including inter-study independence and common method bias, are addressed in Section 4.5.1.7.3 and 4.8.3. Limitations specific to this chapter are noted in the relevant section.

Given the choice of SEM for investigating the sample data and the moderate complexity of the model, this study considered several rules-of-thumb and studies in determining sample size to ensure meaningful results are obtained. However, existing literature proposes different thresholds and guidelines to determine appropriate sample size for SEM. Earlier studies recommend 10 times the number of participants as there are variables (Nunnally, 1978). Further, Boomsma (1985) proposes having a minimum of 100 to 200 responses, while Bentler

and Chou (1987) recommends 10 observations for each estimated parameter. On the other hand, Hair *et al.* (1995) suggest sample sizes of 100 or greater as appropriate while Bollen and Noble (2011) advocate for at least 100 respondents where the model is of average complexity.

However, more recent studies using Monte Carlo simulation analysis have reassessed the conventional guidelines for selecting sample sizes, offering suggestions that fall below the previously established thresholds above (Wolf *et al.*, 2013). For instance, MacCallum *et al.* (1999) found that where communalities are above 0.60 with multiple items per factor, smaller sample sizes can be utilised. Guadagnoli and Velicer (1988) suggest that higher correlation coefficients over 0.80 also require smaller samples while Iacobucci (2009) propose that as few as 50 cases might suffice for factor analysis.

In addition to these considerations, this study assessed the sample's size sufficiency using the Bartlets Test for sphericity and Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy. Acceptable scores of <0.001 and 0.885 respectively were achieved (Hair *et al.*, 1995; Tabachnick and Fidell, 2013). Having considered all these, this study deems the collected dataset sufficient for analysis.

3.5.8 Data Analysis Technique and Procedure

This study utilises the SPSS 28 software for data management and statistical analysis. The AMOS software, a covariance-based method for examining models that include variables with measurement error, is employed for SEM (Gefen and Straub, 2000). The following preliminary analysis are carried out in SPSS Software: Data screening: checking for missing values, outliers, and normality (Skewness and Kurtosis); Descriptive statistics: frequencies and measures of central tendency; Reliability analysis: Cronbach Alpha Indicator; Exploratory Factor Analysis (EFA): conducted to examine the initial factor structure,

Following the two-step approach for the SEM analysis of the data recommended by Anderson and Gerbing (1988), AMOS is used to validate the measurement model and test the

structural relationships among latent variables. At the first step, this study uses Confirmatory Factor Analysis (CFA) to assess the measurement model by evaluating both convergent and discriminant validity. Convergent validity is evaluated using factor loadings values, Average Variance Extracted (AVE) and composite reliability while discriminant validity is based on the Fornell-Larcker criterion.

This study incorporates model-fit measures from three categories comprising Absolute fit indices, Incremental fit indices and Parsimonious fit in the assessment of the model's overall goodness of fit in line with the recommendation of Hu and Bentler (1999) to adopt indices that possess various measurement properties. The next step analysis utilises SEM for structural model assessment, testing the hypothesised paths among latent constructs and the overall model structure. Finally, the study conducts the mediation analysis step using the "Indirect Effects", AMOS Plugin.

3.5.9 Preliminary Analysis and Data Screening

Data preparation is essential in SEM, as it is in other statistical analyses. Aside from the fact that errors can easily occur when inputting data into computer files, SEM is highly dependent on specific distributional assumptions regarding the data which can could lead to biased results if ignored and can cause illogical outcomes being produced by the SEM software (Kline, 2016). This study carried out preliminary analysis in SPSS software to prepare, clean and transform data for accuracy. Data accuracy relates to the data quality which comprises criteria such as integrity (completeness and validity), consistency (conformance and uniformity) and density (missing values).

3.5.9.1 Missing Data

The database check revealed missing values in the data. However, the chi-square values for Little's Missing Completely at Random (MCAR) test confirmed that values are missing completely at random (Li, 2013). With the results of the subsequent Missing Variable Analysis

(MVA), responses with more than 5% missing values in some variables were removed. Furthermore, to fix the missing data, preserve the sample size and still have good parameter estimates, the imputation technique was adopted (Eekhout *et al.*, 2014). This study considered both the Expectation Maximisation Algorithm (EMA) and Regression Based Imputation (RBI) approaches as options for fixing the missing data without reducing sample size through deletion. However, the comparison of original mean to mean results from both imputation approaches showed closely matched means as seen in Figure 3.2. The study opted for RBI approach as a more flexible statistical method for dealing with missing data and its ability to provide unbiased estimates by using all available data (Ryder *et al.*, 2011). Additionally, the negatively worded IFQI scale items measuring the inhibitors of technology readiness were reverse coded before analysis and the items denoted with 'R'. Find below Figure 3.2: Missing Data Imputation Comparison Chart

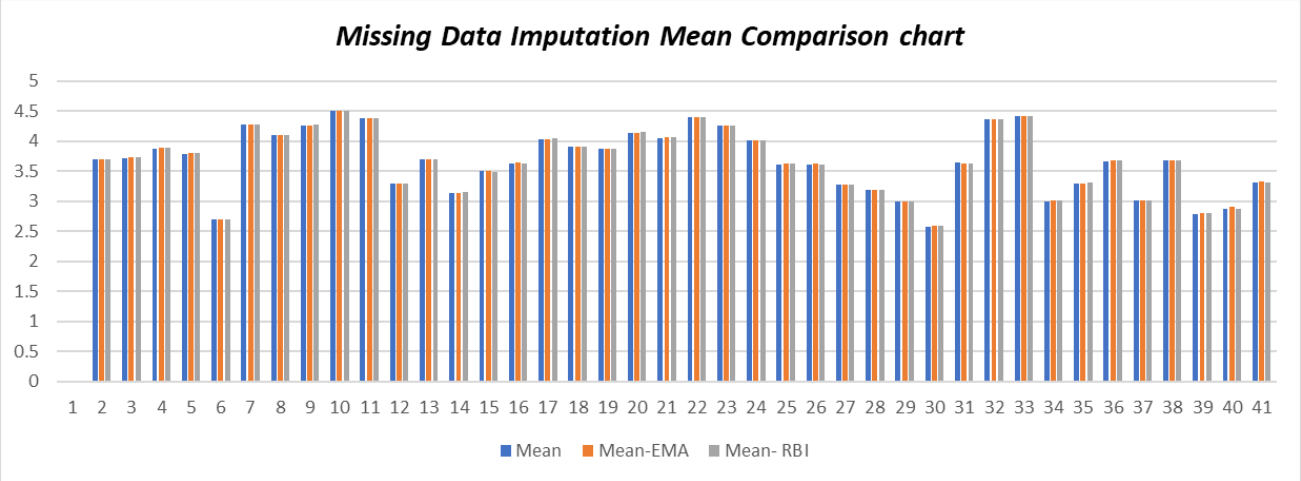

Figure 3.2 Missing Data Imputation Chart

3.5.9.2 Normality

Testing for normality of data distribution in multivariate analysis is one of the essential first steps before inferential statistical (Hair et al., 2010). To determine normality the Kolmogorov-Smirnov and Shapiro-Wilk tests were used to determine if the data met the necessary normality assumption. Though the Kolmogorov-Smirnov test and the Shapiro-Wilk statistics results suggest that the assumption of univariate normality may not have been met,

the following important points informed the decision on normality (a) Likert-scale data often violates the normality assumption due to its ordinal, bounded and limited nature (Field, 2024) (b) the study's sample size of 192 considering that in samples with n > 30, normality tests like Shapiro-Wilk are frequently too sensitive, picking up on slight departures from normal distribution as statistically significant (Kline2016) (c) the study's plan to use SEM with AMOS for analysis, which can handle non-normally distributed data through robust estimation methods such as Bollen–Stine bootstrapping or bootstrapped standard errors (Bentler and Chou, 1987; Byrne, 2013).,

In addition, Table B2, Appendix B presents a table of Skewness and Kurtosis where skewness values for this study range from about -2.3 to +0.29 with the highest absolute skew (-2.318) still inside Kline (2016) approximate acceptable threshold of up to about ±3. For Kurtosis, values range from about -1.01 to +7.01 with largest kurtosis value in the table at 7.005. This is below acceptable approximate threshold of up to about ±10 (Kline, 2016). Even in cases where normalcy is broken, Norman (2010) supports the use of parametric tests and SEM techniques with Likert-scale data. Similarly, Hair *et al.* (2019) also note that although Likert data often violate normality, a good sample size can mitigate this issue when using SEM. So, despite the observed moderate normality, the data were considered suitable for SEM without any data transformation or point removal. Additional evaluations for multivariate normality and outliers (i.e. Mahalanobis distance) were conducted in later stages of the analysis. Table B3, Appendix B presents result of the test for normality.

3.5.9.3 Outliers

It is not unusual to come across one or more values that seem inconsistent or don't fit well with the overall data set (Lewis, 2001). These values are referred to as outlying observations or outliers. Hawkins (1980) defines an outlier as "an observation which deviates so much from other observations as to arouse suspicions that it was generated by a different

mechanism". This study collected the primary data using online questionnaire designed with Likert-scale response items which can often show instances of outliers. Since outliers, differ from other data points, they can significantly influence conclusions about relationships of the variable. However, outliers in Likert-scale data pose unique challenges because extreme responses may reflect either genuine attitudes or measurement issues (Bakker and Wicherts, 2014) These outliers according to Liu, Wu and Zumbo (2010) may inflate Cronbach's alpha estimates and misrepresent the results reliability measures, especially where response categories in measurement scales are few. In the case of Likert scale data, outliers remain a complex and debatable issue with some researchers suggesting that they do not really exist in Likert-scales (Gaskin, 2021b). Besides, to label extreme responses like "Strongly Agree" or "Strongly Disagree" as outliers without context could be misleading as they may reflect genuine opinions rather than irregularity in data. In assessing credibility of extreme responses, this study accounted for the research context, survey design and response trends. Using boxplots and histograms the study conducted initial outlier evaluations. Subsequent Mahalanobis distance analysis detected 12 multivariate outliers based on chi-squared probabilities performed in SPSS. However, considering the nature of Likert data, statistical extremity alone was not deemed adequate reason for their removal. As discussed by Osborne and Overbay (2004), eliminating data points without a theoretical basis could compromise the dataset's representativeness. These outliers were further reviewed to check if they were inconsistent and showing contradictory answers on similar items or displayed patterns to show too fast or inattentive responses (Meade and Craig, 2012). These responses were deemed to represent valid perspectives and therefore included.

3.5.9.4 Bias Control Measures

When data is collected using self-administered questionnaires there is a risk of Common Method Bias (CMB) because both the independent and dependent variable are captured by the

same response method (Kock, Berbekova and Assaf, 2021). Though conceptually different from Common Method Variance (CMV), defined as a systematic error variance that due to use of a common method to measure the different constructs of the study, both are related. This is because when relationship between the measured variables is affected by CMV, CMB is usually present (Jakobsen and Jensen, 2014). Podsakoff *et al.* (2003a) suggests that this bias misrepresent the relationships between variables due to shared variance associated to the method used. The validity and reliability of empirical results can be affected by this bias (Baumgartner and Steenkamp, 2001). The study adopted some measures to mitigate this risk, implementing procedural and statistical controls in accordance with best practices suggested by Kock, Berbekova and Assaf (2021). For instance, in designing the survey, the wording of items and the direction of scales were varied, complex and ambiguous items avoided, clear instructions and survey kept concise while also ensuring the anonymity of responses (Podsakoff *et al.*, 2003a).

This study further implements statistical control using Harman's single-factor test to assess CMB to apply an unrotated exploratory factor analysis to all measurement items. As illustrated by results of the Harman's test presented in Appendix B, Table B4, first factor explained 27.87% of the total variance. This is less than 50%, suggesting that CMB was not a significant issue in this research (Korsgaard and Roberson, 1995).

3.6 Results

3.6.1 Demographics of Respondents

Although the sample consists of managers, of the 192 respondents considered, 64% hold positions from senior manager and above, with 44% having more than six years work experience within the organisation, thus possessing a solid working knowledge of practices within the organisation. The profile of the respondents indicate that a significant portion of

them are 36 years and older (84%) and are mostly employed in private limited companies (49%), which have more than 500 employees (41%). Furthermore, respondents span a diverse array of sectors, including Consumer Goods (14%); Telecommunications (14%); Oil & Gas (14%); Healthcare/ Pharmaceuticals (13%); Professional Services (7%); Financial Services (6%); as well as 'Others' (9%), involved in Social Ecommerce, Education, Wine and Spirit, and Heavy Equipment. Demographic characteristics of the respondents are presented below in Table 3.2:

Table 3.2 Participants Demographics

Job Level		
	N	%
Owner	16	8%
CEO/MD	15	8%
Vice President	4	2%
Chief -Level Officer	7	4%
Director	17	9%
Associate /Deputy Director	14	7%
Senior Manager/Principal Specialist	49	26%
Manager/ Senior Specialist	59	31%
Other	11	6%
Total	192	100%

Experience in Organisation		
	N	%
Less than 12 months	27	14%
1 to 5 years	80	42%
6 to 10 years	44	23%
11 to 15 years	24	13%
16 to 20 years	10	5%
More than 20 years	7	4%
Total	192	100%

Age		
	N	%
Below 25 years	2	1%
26 -35 years	28	15%
36-45 years	89	47%
46 -55 years	60	30%
56 - 65 years	10	5%
Above 65 years	1	1%
Prefer not to say	2	1%
Total	192	100%

Ownership type		
	N	%
Sole proprietorship	10	5%
Partnership	9	5%
Private limited company (Ltd)	95	49%
Public limited company (Plc)	36	19%
Partnership	2	1%
Subsidiary of a Multinational Corporation	30	16%
Other (Please state)	10	5%
Total	192	100%

Size: Employees		
	N	%

1-9 employees	17	9%
10-49 employees	42	22%
50-249 employees	40	21%
250-500 employees	16	8%
More than 500 employees	77	40%
Total	192	100%

Size: Turnover (NGN)

	N	%
Below N10 million	6	3%
N10 million - N25 million	5	3%
Above N25 million but below N100 million	33	17%
Above N100 million	148	77%
Total	192	100%

Sector

	N	%
Agriculture/ Agro-Business	9	5%
Consumer Goods	27	14%
Financial Services	11	6%
Professional services	13	7%
Healthcare/ Pharmaceuticals	25	13%
Telecommunications	27	14%
Oil & Gas	27	14%
Power & Energy	12	6%
Information Communication and Technology (ICT)	10	5%
Construction/Real Estate	6	3%
Retail Services	2	1%
Food & Hospitality	6	3%
Other	17	9%
Total	192	100%

3.6.2 Distribution of Technologies:

There is a varying degree of responses regarding adoption of specific AI and I4.0 T as summarised in Table 3.6 The data indicates that among the top identified most prevalently implemented technologies Cloud Computing rates as the most adopted technology. There were 138 mentions representing 28.3% of all technology references in 72.6% of surveyed organisations implementing it. Big Data and Analytics also shows high number of adoption as it recorded 108 mentions being 22.2% of total references and 56.8% of organisations using it. Close to this is AI which ranks as the third most adopted technology with 40.5% of organisations implementing it as seen with 77 mentions (15.8% of total). Some of the more moderately adopted technologies include IoT which saw significant adoption mentions 52 times (10.7% of all technology references) and 27.4% of organisations having implemented it. RFID follows closely with 37 mentions (7.6% of total) and used by 19.5% of organisations. Some of technologies showed lower adoption rates based on the responses. RPA was adopted by 10.5% of organisations while Cyber-physical systems showed a 9.5% adoption by

organisations. Again, Simulation technologies were adopted by 6.8% of organisations, Additive manufacturing (3D printing) by 4.2%, Unmanned Aerial Vehicles (Drones) by 3.7% and Blockchain by 2.6%. Table 3.3 summarizes the Technology Frequency.

Table 3.3 Technology Frequency

Technology Frequencies	Responses		
	N	Percent	Percent of Cases
Additive manufacturing (3D printing)	8	1.6%	4.2%
Artificial intelligence	77	15.8%	40.5%
Big data and analytics	108	22.2%	56.8%
Blockchain	5	1.0%	2.6%
Cloud Computing	138	28.3%	72.6%
Cyber-physical systems	18	3.7%	9.5%
Internet of Things (IoT)	52	10.7%	27.4%
Simulation	13	2.7%	6.8%
Radio Frequency Identification (RFID)	37	7.6%	19.5%
Robotic Process Automation (RPA)	20	4.1%	10.5%
Unmanned Aerial vehicle (UAV) (Drones)	7	1.4%	3.7%
Other (please specify)	4	0.8%	2.1%
Total	487	100.0%	256.3%

3.6.3 Technology Versus Sector Comparison

The data shows varying levels of technology adoption across 13 industry sectors. Cloud Computing (138 adoptions) and Big Data and Analytics (108 adoptions) emerge as the most widely implemented technologies across all sectors. Oil & Gas, Consumer Goods, and Telecommunications stand out as the leading sectors embracing multiple I4.0Ts. The levels of adoption and the variety of technologies adopted differ across the different industry sectors. In terms of popularity, Cloud Computing with 138 adoptions has the highest adoption rate overall notably favoured by in Telecommunications (21), Consumer Goods (23), and Oil & Gas (18). On other hand, Big Data and Analytics with 108 adoptions is common with Consumer Goods and Oil & Gas with 24 and 17 adoption instances respectively. Again, Oil & Gas (12) and Consumer Goods (13) show significant uptake of AI ranking third with 77 adoptions. IoT which is fourth in popularity with 52 adoptions is especially prevalent in Telecommunications (10) and Oil & Gas (10). RFID with 37 adoptions moderately adopted mainly in Consumer Goods (10) with Oil & Gas/Telco having 8 each. The lowest adopted technologies include Blockchain (5 adoptions), Drones (7 adoptions) and Additive Manufacturing (3D printing) (8 adoptions).

Industry specific adoptions show AI (12), Big Data (17), Cloud (18), and IoT (10), adopted across 28 Oil & Gas organisations. Consumer Goods appears to emphasise data-centric technologies, particularly Big Data (24), Cloud (23), AI (13), and RFID (10) as seen across 28 organisations. Telecommunications (26 organisations) shows a balanced technology mix focusing on Cloud (21), IoT (10), Big Data (9), AI (7), and RFID (8 while Healthcare/Pharmaceuticals (25 organisations concentrated mainly on Cloud (17) and Big Data (11). The results also showed a limited adoption of other technologies. For the adoption in Professional Services across 14 organisations, it reveals Cloud (9), AI (8), and Big Data (6) as commonly adopted technologies. The Power & Energy sector (12 organisations) also indicate significant Cloud adoption (7), with some adoptions of IoT (5) and Cyber-physical systems (4) while Financial Services (11 organisations) show a limited mix of technologies focusing mainly on Cloud (8) and Big Data (7). For Agriculture/Agro-Business the primarily utilised technologies are Big Data (5) and Cloud (7) while Information Communication Technology have low but mixed use of technologies with AI (8), Big Data (7), and Cloud (8). Finally, Construction/Real Estate reveal low overall adoption, with some use of AI (3) and Big Data (4). Table 3.4 illustrates a cross tabulation of Technology versus Sector Analysis

Table 3.4 Technology – Sector Analysis

	TECHNOLOGIES- SECTORS CROSS TABULATION													
	Agriculture/ Agro-Business	Consumer Goods	Financial Services	Professional services	Healthcare/ Pharmaceuticals	Telecommunications	Oil & Gas	Power & Energy	Information Communication and Technology (ICT)	Construction /Real Estate	Retail Services	Food & Hospitality	Other	Total
Additive manufacturing (3D printing)	0	2	0	1	0	2	1	0	0	0	0	1	1	8
Artificial intelligence	4	13	3	8	4	7	12	1	8	3	3	2	9	77
Big data and analytics	5	24	7	6	11	9	17	4	7	4	4	4	6	108
Blockchain	0	0	0	1	0	2	0	0	2	0	0	0	0	5
Cloud Computing	7	23	8	9	17	21	18	7	8	3	2	6	9	138
Cyber-physical systems	1	2	0	0	0	3	4	4	4	0	0	0	0	18
Internet of Things (IoT)	3	5	1	2	4	10	10	5	5	1	1	1	4	52
Simulation	0	1	0	1	0	3	3	0	2	0	0	0	3	13
Radio Frequency Identification (RFID)	1	10	0	0	1	8	8	2	3	0	1	1	2	37
Robotic Process Automation (RPA)	0	5	2	2	1	2	2	1	3	0	0	0	2	20
Unmanned Aerial vehicle (UAV) (Drones)	0	0	0	0	0	1	3	0	0	2	0	0	1	7
Other (please specify)	0	0	0	1	0	1	2	0	0	0	0	0	0	4
Total	9	28	11	14	25	26	28	12	10	6	4	6	11	190

Percentages and totals are based on respondents.

a Dichotomy group tabulated at value 1.

3.6.4 Variables Descriptives

The mean scores for AI adoption and I4.0T adoption are 2.76 and 2.84, respectively, with both showing high variability (mode of 2 and standard deviation above 1.33, along with negative kurtosis). The TOE factor's relative advantage category (B2_RA variables) records the highest scores, with means between 4.09 and 4.50; B2_RA4 stands out with a mean of 4.50 and kurtosis of 6.772. Competitive pressure (B5_CP group) also shows high means (3.61 to 4.39), with B5_CP1 notable for a mean of 4.39 and kurtosis of 4.193. Organisational Culture (B4_OC) items were consistently high, with means from 3.88 to 4.14 and negative skewness throughout. Motivating Factors variables (C1_MF) show mixed ratings, but C1_MF1 (mean 4.36) and C1_MF2 (mean 4.40) perform strongly. In contrast, Inhibiting Factors variables (C2_IF) have the lowest scores, with C2_IF2R at a mean of 2.41 and all variables showing negative kurtosis. Similarly, External Support variables (B6_ES) are moderate to low, especially B6_ES4 with a mean of 2.58. Table B5, Appendix B summarises the descriptive statistics of the variable.

3.6.5 Factor Structure

The study uses Exploratory Factor Analysis (EFA) as a descriptive data technique to identify the appropriate number of underlying factors and to determine which observed variables serve as valid indicators for the different latent constructs by examining the size and varying degrees of the factor loadings (Brown and Moore, 2012). The exploratory factor analysis conducted estimated multiple solutions with different numbers of factors using the Principal Axis Factoring (PAF) extraction method (Gaskin, 2021c). PAF was favoured because it considers co-variation and identifies the smallest number of factors that can explain the shared variance or correlation among a group of variables Podsakoff (Ullman, 2006). Utilising the varimax rotation method (with Kaiser Normalization), the analysis reduced number of variables that have extreme loadings (either high or low) on a factor, making it easier to

understand and interpret the data structure by pinpointing a variable associated with a specific factor (Tabachnick and Fidell, 2001). These solutions were evaluated in the light of TOE and TRI theoretical frameworks and the most appropriate solution chosen. Items with factor loadings below 0.5 on their corresponding latent variable or a negative impact on the scales' Cronbach's alpha values were eliminated (Tabachnick and Fidell, 2013). Additionally, Kaiser or mineigen greater than 1 criterion (K1), the default retention criterion on SPSS, was considered to retain factors with eigenvalues greater than 1. Again, cross-loading items were excluded while ensuring all constructs had a minimum of three loading items to ensure the strength of the factor (Costello and Osborne, 2005). Additionally, through data screening, descriptive analysis, factor analysis, interpretation of findings, and evaluation of reliability, EFA ensured that having isolated the key constructs or dimensions found in the data only relevant items are retained (Kline, 2014). The EFA is summarised and presented in Table 3.5

Table 3.5 Exploratory Factor Analysis

Rotated Component Matrix[a]

	Component							
	1	2	3	4	5	6	7	8
A3i:AI_ADP	0.027	0.173	0.21	0.258	-0.002	0.149	**0.815**	-0.021
A3ii: I40_ADP	0.045	0.136	0.24	0.248	-0.017	0.146	**0.823**	0.023
B1_TC1	0.207	-0.038	**0.72**	0.194	0.285	0.024	0.097	-0.006
B1_TC2	0.073	0.193	**0.789**	0.07	0.196	0.227	0.168	-0.045
B1_TC3	0.295	0.319	**0.706**	0.103	-0.008	-0.006	0.215	-0.081
B1_TC4	0.22	0.161	**0.744**	0.101	0.064	0.134	0.105	-0.068
B2_RA1	**0.716**	0.243	0.249	0.183	-0.037	-0.045	-0.091	-0.037
B2_RA2	**0.741**	0.186	0.141	0.132	0.049	-0.002	-0.115	-0.078
B2_RA3	**0.759**	0.274	0.175	0.21	0	0.013	-0.12	-0.057
B2_RA4	**0.735**	0.07	0.265	0.192	-0.038	0.067	-0.11	-0.052
B3_OR1	0.103	0.071	0.242	**0.658**	0.16	0.283	0.171	0.057
B3_OR2	0.217	0.078	0.012	**0.785**	0.117	0.082	0.135	0.002
B3_OR3	-0.038	0.424	0.208	**0.505**	0.102	0.158	0.374	0.026
B3_OR4	0.133	0.419	0.135	**0.533**	0.158	0.146	0.264	-0.042
B3_OR5	0.194	0.283	0.269	**0.507**	0.195	0.289	0.156	-0.124
B4_OC1	0.312	**0.729**	0.177	0.105	0.239	0.172	0.114	0.089
B4_OC2	0.264	**0.798**	0.188	0.074	0.187	0.185	0.105	0.024
B4_OC3	0.278	**0.739**	0.207	0.115	0.155	0.093	0.217	0.032
B4_OC4	0.288	**0.707**	0.023	0.193	-0.033	0.096	-0.023	-0.061
B5_CP1	**0.723**	0.34	0.056	0.001	0.177	-0.016	0.19	0.085
B5_CP2	**0.783**	0.177	0.044	-0.063	0.182	0.078	0.226	0.055
B5_CP3	**0.761**	-0.013	-0.006	-0.015	0.116	0.209	0.238	0.049
B6_ES2	0.058	0.163	0.205	0.167	**0.644**	0.099	-0.015	-0.088
B6_ES3	0.148	0.108	0.07	0.202	**0.82**	0.055	0.015	-0.11
B6_ES4	0.052	0.102	0.118	0.01	**0.796**	0.191	0.009	-0.089
C1_MF3	0.05	0.036	0.056	0.088	0.283	**0.731**	0.147	0.028
C1_MF4	0.07	0.21	0.167	0.212	0.081	**0.764**	0.095	-0.107
C1_MF5	0.079	0.321	0.118	0.285	0.028	**0.636**	0.083	-0.206
C2_IF3R	0.03	0.02	0.079	-0.126	-0.184	0.163	-0.079	**0.756**
C2_IF4R	0.028	0.043	-0.1	0.113	-0.19	-0.12	0.004	**0.83**
C2_IF5R	-0.079	-0.031	-0.122	0	0.092	-0.234	0.083	**0.752**

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a Rotation converged in 7 iterations.

3.6.6 Reliability

Following the recommendation of Bagozzi, Yi and Singh (1991), the study assessed the internal reliability of the measurement model prior to exploring the proposed relationships. Composite reliability (CR) and Cronbach's alpha was utilised to determine internal reliability and consistency of the nine scales. Cronbach's alpha examines the extent of shared variance, or covariance, between the items that constitute the questionnaire in relation to the total

variance to evaluate the reliability (Tavakol and Dennick, 2011; Bland and Altman, 1997). The Cronbach alpha reliability coefficient for each scale ranged from 0.735 to 0.913. A value of 0.7 is generally acknowledged by literature as acceptable value (Bagozzi, Yi and Singh, 1991). Additionally, construct reliability (CR), also referred to as composite reliability, is also recommended as a suitable measure of reliability especially for SEM based studies (Fornell and Larcker, 1981). CR is derived from the congeneric model that does not necessitate identical factor loadings among items (Cheung *et al.*, 2024). CR values equal to or greater than 0.7 indicate adequate reliability implying that the total error variance accounts for less than 30% of the variance of the latent variable (Hair, 2009). In this case, both CR and Cronbach's alpha exceeded 0.70, thus confirming internal reliability. Table 3.6 presents the scores.

Table 3.6 Reliability Analysis

Scale	**CA**	**CR**
ADOPT	0.917	0.92
TCQI	0.756	0.851
RAQI	0.888	0.887
ORQI	0.831	0.791
OCQI	0.903	0.906
CPQI	0.796	0.850
ESQI	0.768	0.782
MFQI	0.735	0.755
IFQI	0.710	0.737

3.6.7 Measurement Model

After identifying the factors, loading patterns, and inter-correlation in the EFA, confirmatory factor analysis (CFA) was used to confirm and validate the identified factor structure. All are statistically significant, loading above 0.50 indicating a good relationship between the items and their constructs (Kline, 2016). Similarly, model reported good fit indices presented in Table 3.7 as follows:

Table 3.7 Measurement Model Fit Indices

MEASURE	THRESHOLD	ESTIMATE	SOURCE
CMIN/DF	Between 1 and 3	1.405	(Hu and Bentler, 1999; Papke-Shields, Malhotra and Grover, 2002)
CFI	>0.95	0.949	(Schumacker and Lomax, 2004; Hu and Bentler, 1999)
SRMR	<0.08	0.053	(Hu and Bentler, 1999)
RMSEA	<0.06	0.046	(Hu and Bentler, 1999; Hair *et al.*, 1995)
TLI	>0.90	0.941	(Schumacker and Lomax, 2004)

Figure 3.3 and Table 3.8 give further details of the CFA model and standardised regression weights or factor loadings respectively.

Table 3.8 Standardized Regression weight

Item		Construct	Estimate
QID9	<---	ADPQI	0.925
QID11	<---	ADPQI	0.920
TCQID10_1	<---	TCQI	0.693
TCQID10_2	<---	TCQI	0.810
TCQID10_3	<---	TCQI	0.801
TCQID10_4	<---	TCQI	0.761
RAQID13_1	<---	RAQI	0.833
RAQID13_2	<---	RAQI	0.810
RAQID13_3	<---	RAQI	0.879
RAQID13_4	<---	RAQI	0.725
ORQID14_1	<---	ORQI	0.646
ORQID14_2	<---	ORQI	0.591
ORQID14_3	<---	ORQI	0.785
ORQID14_4	<---	ORQI	0.759
OCQID15_1	<---	OCQI	0.865
OCQID15_2	<---	OCQI	0.885
OCQID15_3	<---	OCQI	0.859
OCQID15_4	<---	OCQI	0.664
OCQID15_5	<---	OCQI	0.766
CPQID16_1	<---	CPQI	0.851
CPQID16_2	<---	CPQI	0.853
CPQID16_3	<---	CPQI	0.716
ESQID17_2	<---	ESQI	0.618
ESQID17_3	<---	ESQI	0.841
ESQID17_4	<---	ESQI	0.745
MFQID19_3	<---	MFQI	0.583
MFQID19_4	<---	MFQI	0.782
MFQID19_5	<---	MFQI	0.762
IFQID20_3R	<---	IFQI	0.534
IFQID20_4R	<---	IFQI	0.945
IFQID20_5R	<---	IFQI	0.568

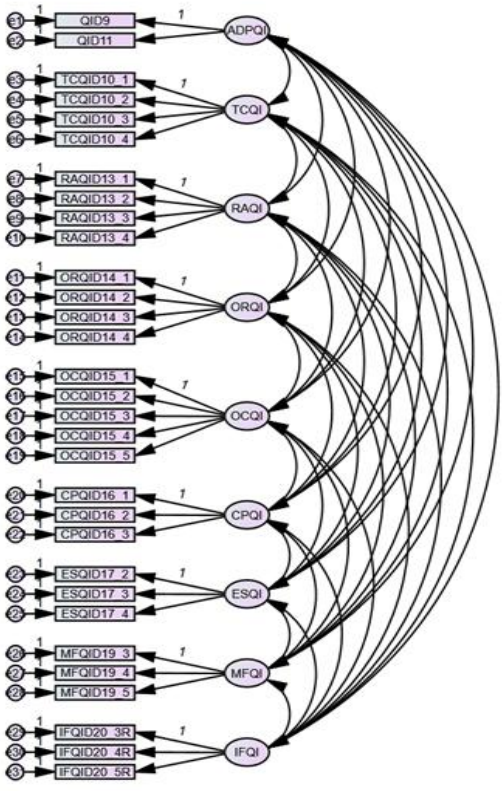

Figure 3.3 CFA Model

3.6.7.1 Validity

The CFA's correlation estimation techniques flexibility in assessing validity proves beneficial, as it requires only a well-defined model and not restricted to a specific model (Rönkkö and Cho, 2020). Both convergent and discriminant validity were tested by estimating a measurement model in which all indicators are associated with the constructs they are intended to measure and do not have direct relationships with unrelated constructs (Fornell and Larcker, 1981; Hair, 2009). Convergent and discriminant validity are essentially two aspects of the same concept: convergent validity necessitates a positive correlation between various tests assessing the same construct, whereas discriminant validity requires no correlation among tests measuring different constructs (Gaskin, 2021a). This study considered both the Fornell-Larcker criterion for convergent validity, which stipulates that the Average Variance Extracted (AVE) must exceed 0.5, and the Hair *et al.* (2019) requirement for AVE greater than 0.5, standardised factor loadings for all items at least 0.5 and a minimum composite reliability of 0.7. The discriminant validity was benchmarked on the Fornell-Larcker criterion, which provides that the AVE of both constructs must be greater than the square of the correlation between the two constructs, the Kline criterion for discriminant validity, which requires a correlation between the two constructs of below 0.85 (Kline, 2016). Table 3.8 outlines the values of convergent and discriminant validity of this study.

Table 3.9 Validity

CONSTRUCTS	CR	AVE	MSV	MaxR(H)	ADPQI	TCQI	RAQI	ORQI	OCQI	CPQI	ESQI	MFQI	IFQI
ADPQI	0.92	0.851	0.413	0.92	**0.923**								
TCQI	0.851	0.59	0.359	0.857	0.481***	**0.768**							
RAQI	0.887	0.663	0.548	0.897	0.160*	0.497***	**0.814**						
ORQI	0.791	0.49	0.48	0.809	0.643***	0.597***	0.375***	**0.7**					
OCQI	0.906	0.66	0.428	0.921	0.399***	0.599***	0.567***	0.654***	**0.812**				
CPQI	0.85	0.654	0.548	0.864	0.227**	0.446***	0.740***	0.386***	0.637***	**0.809**			
ESQI	0.782	0.548	0.206	0.811	0.189*	0.404***	0.268**	0.454***	0.422***	0.323***	**0.741**		
MFQI	0.755	0.51	0.48	0.776	0.454***	0.498***	0.277**	0.693***	0.570***	0.283**	0.441***	**0.714**	
IFQI	0.737	0.501	0.081	0.903	0.012	-0.170†	-0.036	-0.004	-0.001	0.049	-0.284**	-0.238*	**0.708**

Notes: Column/row headings are as follows: ADPQI = Adoption; TCQI =Technology Characteristics; RAQI = Relative Advantage; ORQI = Organizatinal resources; OCQI = Organizational Culture; CPQI = Competitive Pressure; ESQI =External Support; MFQI = Motivating Factors; IFQI = Inhibiting Factors; CR = Composite Reliability, AVE = Average Variance Extracted; MSV = Maximum Shares variance; MaxR(H)= Maximum H Reliability; Diagonal values in bold are square roots of AVE values per construct, off diagonal values are the correlations of the variables.

Produced using Gaskin, James and Lim (2019) "Master Validity Tool", AMOS Plugin. Gaskination's StatWiki.

The reliability results show very strong internal consistency across all constructs with composite reliability (CR) values ranging from 0.737 on inhibiting factors (IFQI) construct to 0.92 on the adoption (ADPQI) construct. The values all exceed the recommended threshold of 0.7 (Hair *et al.*, 2010). The high CR shown for ADPQI implies very strong reliability of the adoption construct. All the constructs except Organisational resources (ORQI) construct met the AVE requirement. Although the AVE for ORQI fell short of the 0.50 threshold, it is still considered acceptable since its CR is above 0.70 (Fornell and Larcker, 1981). Moreover, studies suggest that AVE is a restrictive measure and CR alone can be considered in the evaluation of convergent validity (Malhotra, 2020). The observed variables therefore meet the convergent validity requirements. The Fornell and Larcker (1981) criterion is used to determine the discriminant validity of constructs . As illustrated in Table 3.8, the square root of the AVE of each latent construct, in bold on the diagonal, is greater than the correlations between the latent constructs in the corresponding columns and rows. Finally, the value of maxr (h) (Maximum H Reliability) is higher than the CR value. As a result, discriminant validity is established across the constructs.

3.6.7.2 Constructs Correlations

The study conducted Pearson correlation analysis to examine the interrelationships among the constructs. The relationships between the constructs presented in the matrix tabulated in Table 3.9 show significant inter construct relationship. The results using the composites of each constructs items indicate a significant, moderate and positive correlation between TRI motivating factors (MFQI_Comp) and TOE constructs (TCQI_Comp, RAQI_Comp, OCQI_Comp, COQI_Comp, CPQI_Comp, ESQI_Comp). The correlation between motivation factors and AI and I4.0T adoption (ADPQI_Comp) is also significant, moderate and positive. On the other hand, whereas the correlation between TRI inhibiting factors (IFQI_Comp) and all the TOE constructs shows a low and negative correlation, that is

only significant in its correlation with external support (ESQI_Comp) and motivating factors (MFQI_Comp). Table 3.9 presents the inter construct relationships results.

Table 3.10 Inter Construct Correlations

			Pearson Correlatios								
	Mean	Std. Deviation	TCQI_Comp	RAQI_Comp	ORQI_Comp	OCQI_Comp	CPQI_Comp	ESQI_Comp	MFQI_Comp	IHQI_Comp	ADPQIComp
TCQI_Comp	3.67	0.75	1								
RAQI_Comp	4.30	0.74	.430**	1							
ORQI_Comp	3.45	0.87	.502**	.376**	1						
OCQI_Comp	4.01	0.85	.497**	.546**	.562**	1					
CPQI_Comp	3.99	0.65	.393**	.658**	.398**	.587**	1				
ESQI_Comp	3.13	0.78	.378**	.296**	.490**	.417**	.418**	1			
MFQI_Comp	3.74	0.71	.415**	.443**	.606**	.564**	.497**	.418**	1		
IHQI_Comp	2.88	0.74	-0.124	-0.115	-0.051	-0.042	-0.121	-.229**	-.204**	1	
ADPQIComp	2.80	1.29	.387**	.161*	.546**	.362**	.209**	.214**	.359**	0.036	1

. Correlation is significant at the 0.01 level (2-tailed).
. Correlation is significant at the 0.05 level (2-tailed).

3.6.8 Structural Equation Modelling

Upon meeting the validity criteria, the study completed an analysis of the structural model to demonstrate the relationships among the constructs. Figure 3.4 illustrates the results of the model analysis.

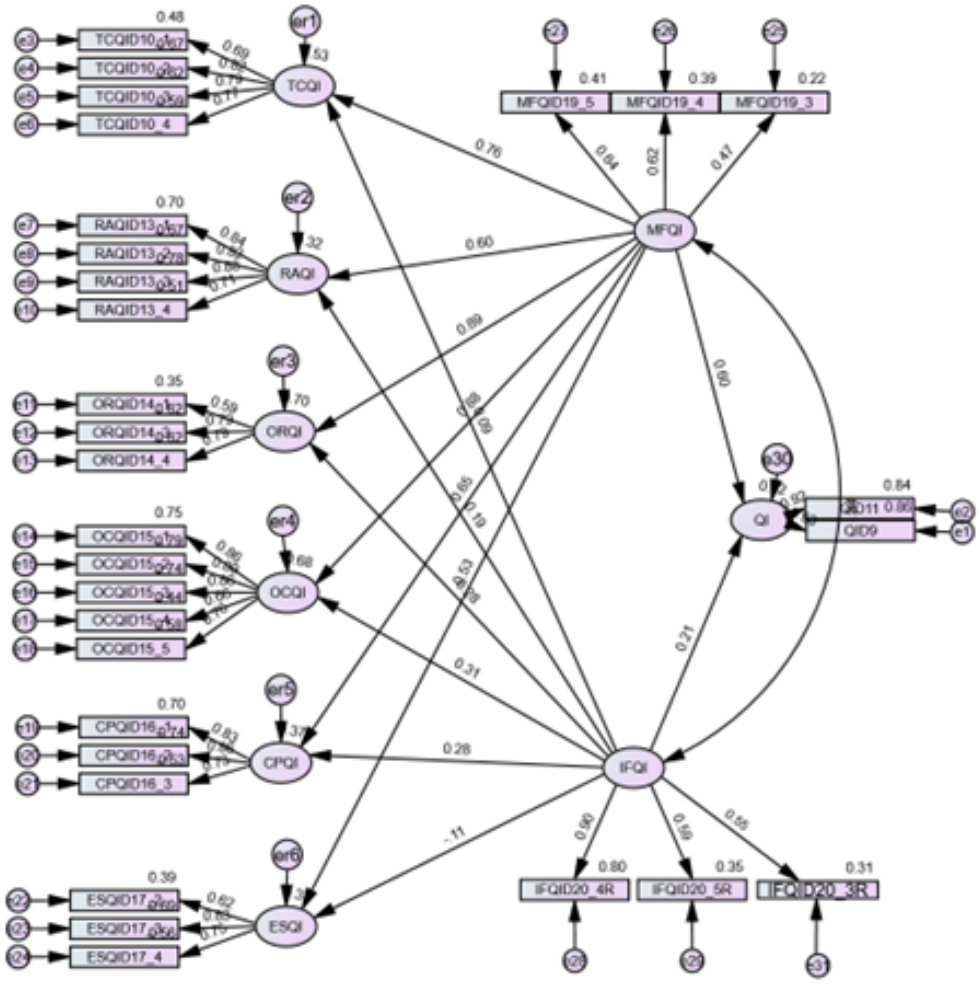

Figure 3.4 Structural Equation Model

The study relied on several statistical tests to determine how well the model fits the data. Aside from the chi-square (x^2), degree of freedom(*df*) and normed x^2 (the ratio of x^2 to the degree of freedom), studies have recommended using fit indices that possess various measurement properties, including an incremental fit index such as comparative fit index (CFI) and a fit index based on residuals, like the standardised root-mean-square residual (SRMR) (Hu and Bentler, 1999). Again, depending on effect size, evidence from Monte Carlo studies indicates that direct measures of fit are more adept at identifying model misspecifications compared to incremental fit measures (Fan, Thompson and Wang, 1999). Furthermore, Kline (2016) recommends the model chi-square, the RMSEA, the CFI and the SRMR as minimum indices that should be reported. Consequently, the following fit measures known to effectively

detect model misspecification while being less reliant on sample size were utilised: CFI; the Tucker-Lewis index (TLI); RMSEA, SRMR, as well as the goodness-of-fit index (GFI), chi-square (x^2) and degree of freedom(*df*).

Table 3.11 summarises statistics for the various metrics calculated to assess how well the structural model corresponds to the data utilising RMSEA, SRMR, GFI, TLI, CFI, and the normed chi-square values. Hu and Bentler (1999) and Schumacker and Lomax (2004) recommend CFI values of ≥ 0.9 and TLI >0.9, along with RMSEA ≤ 0.08 (Hu and Bentler, 1999; Byrne, 2013; Hair *et al.*, 2010) and normed $\chi^2 \leq 2.0$ indicate a good model fit (Hu and Bentler, 1999; Papke-Shields, Malhotra and Grover, 2002), while a GFI ≥ 0.8 is considered to represent a reasonable and acceptable fit (Doll, Xia and Torkzadeh, 1994). Find Table 3.11 with a summary of the model fit indices.

Table 3.11 Structural Model Fit

Measure	Estimate	Threshold	Interpretation	Source
CMIN	672.33	--	--	
DF	390	--	--	
CMIN/DF	1.724	Between 1 and 3	Excellent	Hu and Bentler (1999); Papke-Shields et al., (2002)
CFI	0.909	>0.95	Acceptable	Schumacker and Lomax (2004), Hu and Bentler (1999)
SRMR	0.084	<0.08	Acceptable	Hu and Bentler (1999)
RMSEA	0.062	<0.06	Acceptable	Hu and Bentler (1999); Hair et al, 1995; Bryne (1991)
GFI	0.805	≥0.80	Acceptable	Doll et al (1994)
TLI	0.898	>0.90	Excellent	Schumacker and Lomax (2004); Bryne (1991)

3.6.9 Significance Test of Individual Parameters

The significance of the relationships among the different variables is evaluated using the p-value obtained from the analysis. Each unstandardized regression coefficient reflects the change in the dependent (AI and I4.0T adoption) and mediating variables (TRI motivating and inhibiting factors) per one-unit change in the predictor variables (TOE factors). Also reflected are the values of the unstandardized estimate (S.E.), the Critical Ratio (C.R) which is the estimate divided by the standard error. The probability value associated with the null hypothesis

indicating that the test is zero is displayed under the P column. The p-values indicate the statistical significance of the computed coefficients (Byrne, 2001). Low p-values (below 0.05) indicate that changes in the predictor lead to changes in the predicted outcome. In contrast, p-values above 0.05 are considered insignificant, implying there is no relationship between the predictor and predicted outcome.

Table 3.12 Regression Weights

			Estimate	S.E.	C.R.	P	Label
TCQI	<---	MFQI	1.053	0.198	5.319	***	Supported
RAQI	<---	MFQI	0.854	0.169	5.062	***	Supported
ORQI	<---	MFQI	1.184	0.229	5.163	***	Supported
OCQI	<---	MFQI	1.43	0.237	6.046	***	Supported
CPQI	<---	MFQI	0.751	0.145	5.173	***	Supported
ESQI	<---	MFQI	0.607	0.141	4.312	***	Supported
ESQI	<---	IFQI	-0.062	0.05	-1.231	0.218	Not Supported
CPQI	<---	IFQI	0.162	0.053	3.051	0.002	Supported
OCQI	<---	IFQI	0.244	0.07	3.495	***	Supported
ORQI	<---	IFQI	0.179	0.063	2.854	0.004	Supported
RAQI	<---	IFQI	0.13	0.061	2.129	0.033	Supported
TCQI	<---	IFQI	0.062	0.058	1.072	0.284	Not Supported
ADPQI	<---	MFQI	1.364	0.268	5.098	***	Supported
ADPQI	<---	IFQI	0.236	0.097	2.417	0.016	Supported

Significance of Estimate *** p < .001; ** p < .01; * p < .05.

Table 3.11 shows that at 0.05 significance level there is a positive significant relationship between TRI motivating factors and technology characteristics, relative advantage, organisational resources, organisational culture, competitive pressure and external support, thus, supporting H1a, H2a, H3a, H4a H5a, H6a. On the other hand, while the paths between TRI inhibiting factors and relative advantage, organisational resources, organisational culture, and competitive pressure are significant, supporting H2b, H3b, H4b and H5b, the paths to technology characteristics (H1b) and external support (H6b) were not supported. Supported also is the significant relationship between AI and I4.0T adoption and TRI motivators and inhibitors.

3.6.10 Mediation Analysis

The results of the specific indirect effects of TOE factors on AI and I4.0T adoption through TRI inhibitors and motivators show that the paths through motivating factors to AI and I4.0T adoption are all significant (technology characteristics: p-value = 0.002, p<0.010; relative advantage: p-value = 0.011, p<0.050; organisational resources: p-value = 0.001, p<0.010; organisational culture: p-value = 0.006, p<0.010; competitive pressure: p-value = 0.011, p<0.050; and external support p-value = 0.003, p<0.010). Conversely, the indirect effect paths through inhibiting factors to AI and I4.0T adoption, while significant for organisational resources (p-value = 0.089, p<0.10), organisational culture (p-value = 0.084, p<0.10) and competitive pressure (p-value = 0.093, p<0.10), was significant for technology characteristics (p-value = 0.221) and external support (p-value = 0.201). Table 3.12 illustrates these result

Table 3.13 Indirect effects

Indirect Effect: Technology Readiness Inhibiting Factors					
Indirect Path	Unstandardized Estimates	Lower	Upper	P-Value	Standardized Estimates
TCQI_IFQI	0.015	-0.014	0.835	0.477	1.000
RAQI_IFQI	0.031	-0.005	1.770	0.221	1.000
ORQI_IFQI	0.042	0.000	0.508	0.089	1.000†
OCQI_IFQI	0.058	0.002	1.453	0.084	1.000†
CPQI_IFQI	0.038	0.000	1.608	0.093	1.000†
ESQI_IFQI	-0.015	-0.218	0.014	0.201	1.000

Indirect Effect: Technology Readiness Motivating Factors					
Indirect Path	Unstandardized Estimates	Lower	Upper	P-Value	Standardized Estimate
TCQI_MFQI	1.437	0.753	3.05	0.002	1.000**
RAQI_MFQI	1.165	0.448	3.086	0.011	1.000*
ORQI_MFQI	1.615	0.903	3.232	0.001	1.000**
OCQI_MFQI	1.952	1.016	4.012	0.006	1.000**
CPQI_MFQI	1.025	0.354	2.805	0.011	1.000*
ESQI_MFQI	0.828	0.454	1.684	0.003	1.000**

Significance of Estimates: *** p < 0.001; ** p < 0.010; * p < 0.050; † p < 0.100

Analysis utilized Gaskin, James and Lim (2019) "Indirect Effects", AMOS Plugin. Gaskination's StatWiki. AMOS Plugin).

3.7 Discussion

This study was undertaken with the following objectives aimed at investigating the determinants of adoption of AI and I4.0T: (a) to analyse the current state of adoption of AI and I4.0T among organisations in Nigeria; (b) to identify the technological, organisational, and environmental elements that impact technology adoption; and (c) to examine the mediating role of Technology Readiness Index (TRI) factors that motivate or hinder the relationship between TOE factors and the adoption of AI and I4.0T. The study develops and empirically evaluates a model using primary data collected via online questionnaires from 192

professionals across 13 industry sectors in Nigeria. The findings of this study offer several important insights into the complex relationships between the dimensions of TOE, TRI and AI and I4.0T adoption and adds to the existing body of knowledge on the adoption complex technologies.

3.7.1 AI and I4.0 Technology Adoption

The frequency table analysis reveals moderate-low adoption rates with AI (A3i:AI_ADP) and I4.0T (A3ii: I40_ADP) variables showing high standard deviations of >1.33 and negative kurtosis. This implies significant variability in adoption levels across organisations. Analysis in Table 3.7 reveal a three-tier adoption pattern with Cloud Computing Big Data and AI collectively reaching mainstream adoption with 66.3% of all technology mentions while technologies like Blockchain, Drones, and 3D Printing remain at innovator or early adoption stages. IoT and RFID are still growing as they show meaningful but not yet mainstream adoption with collective 18.3% of technology mentions. Across all the sectors, Cloud computing and Big Data and Analytics appears as the leading technologies most widely adopted. This finding is corroborated by Statista (2024) report of a noticeably significant increase in demand for cloud-based solutions in the public cloud market in Nigeria. Perhaps, the expanding adoption of digital transformation across various sectors as well as Nigeria's sizable population and its progressing digital economy is an influencing factor. Similarly, government initiatives aimed at promoting digital transformation are also boosting the adoption of public cloud services (Africa Digital Economy Forum, 2024). Again, the growth of remote work and e-commerce environment as a result of the COVID-19 pandemic has also played a role in enhancing market expansion of cloud computing products and services (Ogidiaka *et al.*, 2022).

The results also indicate uneven distribution of technology adoption with sectors like Construction/Real Estate, Retail, Food & Hospitality showing significantly lower adoption

rates overall. Oil & Gas, Consumer Goods, and Telecommunications sectors on the other hand have the highest overall technology adoption rates and with the greatest mix in technology implementation. A review of the cluster of the adopted technology reveals distinct clusters with Cloud and Big Data & Analytics forming a *Data & Intelligence Cluster*. AI is also within this cluster showing a growing adoption of intelligence layers. This maybe an indication that organisations consider these technologies as foundational and complementary to their digital transformation journey. On the other hand, there appears to be early experimentation with advanced physical-digital integration technologies represented in the level of maturity of the *Physical-Digital Integration Cluster* seen in the IoT and RFID related adoption patterns, indicating their complementary role in connecting physical and digital environments. The remaining technologies cluster together as *Specialized Applications.* Their low adoption rates could be because they are employed for specific use cases rather than broad organisational transformational requirements as in the case of Additive manufacturing or Drones.

Furthermore, AI and I4.0T Adoption and readiness motivating factors relationship reports the strongest path coefficient (1.364, $p < 0.001$). This suggests a possible two-way relationship where successful initial adoption could increase motivation for further implementation. This strong relationship between motivating factors and adoption emphasises that organisational motivators are crucial for successful implementation. Surprisingly, the relationship between adoption and inhibiting factors is positive and significant (0.236, $p = 0.016$). This may be because as organisations become more aware of inhibiting factors, they seek to address them, rather than deterred by these challenges, thereby potentially increasing their chances of successful adoption.

3.7.2 TOE Dimensions Impact on Readiness and Subsequent Adoption

The following section discusses the significant correlations between all TOE factors and the readiness motivating factors and the more complex scenario presented by inhibiting factors of readiness for adopting technology.

3.7.2.1 Technology Characteristics (H1a & H1b)

There is a significant relationship existing between technology characteristics and technology readiness motivators. The result of analysis of direct effects between TCQI and MFQI show a strong, significant link based on the regression weights results (Estimate = 1.053, S.E. = 0.198, C.R. = 5.319, $p < 0.001$). The relevance of this relationship is confirmed by the indirect effects analysis that showed substantial indirect effect (1.437, $p = 0.002$) strongly supporting H1a. The implication is that AI and I4.0 technology characteristics such as reliability and compatibility can significantly enhance the motivation to adopt these innovations. For H1b that hypothesised a significant relationship between technology characteristics and technology readiness inhibitors revealed a weak and non-significant correlation (Estimate = 0.062, S.E. = 0.058, C.R. = 1.072, $p = 0.284$). This was further validated by a non-significant indirect effect (0.015, $p = 0.477$) on adoption through inhibiting factors. This means that H1b is not supported. This points to the fact that the obstacles to adoption could mainly arise from organisational and environmental factors rather than the technology itself as characteristics of technology do not substantially affect inhibitors. Blut and Wang (2020) supports this view as they found that personality traits in form of motivators and inhibitors have more significant role in influencing technology readiness than the specific characteristics of the technology itself. The study by Lin and Hsieh (2007) emphasised that technology readiness inhibitors of discomfort and insecurity are the result of individual perceptions of control and trust instead of the inherent technology characteristics.

3.7.2.2 Relative Advantage (H2a and H2b)

H2a proposes that a significant relationship exists between relative advantage and technology readiness motivators. The direct effect analysis reveals a robust and significant association (Estimate = 0.854, S.E. = 0.169, C.R. = 5.062, $p < 0.001$) between relative advantage (RAQI) and technology readiness motivators (MFQI). The subsequent analysis of indirect effects reinforces importance of this link. The results show a notable indirect effect (1.165, $p = 0.011$) on adoption through motivating factors. This provides strong support for H2a. Organisation's readiness to adopt these technologies significantly increases when they can identify clear benefits of AI and Industry 4.0 technologies over existing systems. In contrast, the results for H2b that proposes that a significant relationship exists between relative advantage and the mitigation of technology readiness inhibitors is mixed. The analysis of direct effects indicates a weak yet significant relationship (Estimate = 0.13, S.E. = 0.061, C.R. = 2.129, $p = 0.033$) between them. However, the analysis of indirect effects shows a non-significant indirect effect (0.031, $p = 0.221$) regarding adoption through inhibiting factors which only partially supports H2b. Although there is a direct significant relationship between relative advantage and inhibiting factors, this pathway does not have a substantial mediating effect on adoption. Though insecurity and discomfort, may be triggered by implementation concerns of AI and I4.0T, they do not have a major influence on the adoption process. It appears that their general beliefs about the positives of technology are more strongly considered when assessing a specific technology, rather than their beliefs about disadvantages. Blut and Wang (2020) analysis on technology readiness also supports this result as they revealed that motivators have a more significant indirect impact on technology usage while inhibitors show a less pronounced indirect effect, suggesting that inhibitors do not play a substantial mediating role in the influence of perceived relative advantage on adoption choices.

3.7.2.3 Organisational Resources (H3a & H3b)

The results of H3a hypothesising a significant relationship between organisational resources and enhanced technology readiness motivators revealed a strong and significant correlation (Estimate = 1.184, S.E. = 0.229, C.R. = 5.163, $p < 0.001$) as shown in standardised regression weights results. The analysis of indirect effects of this relationship further corroborates this, showing a significant indirect effect (1.615, $p = 0.001$) on adoption through motivating factors, strongly supporting H3a. Previous studies (Tornatzky and Fleischer, 1990; Baker, 2012) have also found that organisational resources play a crucial role in enhancing motivation for adoption, confirming that the availability of financial, technical, and human resources is a key driver for technology readiness and subsequent adoption decisions. Related to this, is the direct effect analysis for H3b that indicate a significant relationship (Estimate = 0.179, S.E. = 0.063, C.R. = 2.854, $p = 0.004$) between organisational resources and reduction of technology readiness inhibitors. However, the indirect effects analysis shows only a marginally significant indirect effect (0.042, $p = 0.089$) on adoption through inhibiting factors. Although, H3b is supported by this, it has a weaker mediation effect indicating that while organisational resources have a significant impact on reducing inhibiting factors, the link leading from resources through inhibitors to adoption is only marginally significant. This suggests that though resource-related considerations may create some implementation barriers, these barriers have a limited influence on the ultimate decision to adopt. Additionally, inhibiting factors, could still arise even in resource-rich organisations, perhaps due to the complexity of allocating resources or integrating technology. The results from previous studies validate these findings. For example, Cenfetelli and Schwarz (2011) reveals that although barriers such as discomfort and insecurity could have a negative impact on intentions to use technology, their role as mediators between organisational resources and adoption behaviour is limited. This shows that even where organisational resources are allocated to address these inhibitors, their direct effect on their adoption decisions may not be significant. In line with this Mishra, Mishra

and Abdalhamid (2023) also find that while organisational resources can help mitigate barriers, the overall effects of these inhibitors on the adoption process remain minimal. A focus on measures to manage inhibitors may not significantly drive technology adoption on their own. Rather a comprehensive approach that considers both enablers and inhibitors could ensure a more effective adoption

3.7.2.4 Organisational Culture (H4a & H4b)

The earlier study of Schein (2010) offers an understanding of how organisational culture shapes common assumptions, values, and beliefs that could impact the adoption of new technologies. This study finds that organisational culture exhibits the strongest relationship, affirming that culture is a crucial factor driving readiness and subsequent adoption, aligning with Duan, Edwards and Dwivedi (2019) earlier recognition of culture as an influential factor in technology acceptance. These results indicate that while organisational cultures that promote innovation greatly enhances motivation for adopting AI and I4.0T, it can also face inhibiting factors. This may be due to resistance during the actual implementation process notwithstanding the supportive culture of innovation. The analysis of direct effects reveals a strong link (Estimate = 1.43, S.E. = 0.237, C.R. = 6.046, $p < 0.001$) between organisational culture and technology readiness motivators. The analysis of indirect effects further confirms this relationship, showing the most significant indirect effect (1.952, $p = 0.006$) on adoption through motivational elements. This strongly supports H4a, emphasising the importance of an innovation-oriented culture for the effective implementation of AI and I4.0T. In relation to H4b, organisational culture shows a notable impact on inhibiting factors, with a slight indirect effect on adoption, suggesting that even beneficial organisational cultures can raise some implementation challenges that can marginally hamper the adoption process. This is reflected in the direct effect analysis which indicate a significant relationship (Estimate = 0.244, S.E. = 0.07, C.R. = 3.495, $p < 0.001$) between organisational culture and reduction of technology

readiness inhibitors. H4b is supported, though with marginal mediation significance as seen in the analysis of indirect effects on adoption through inhibiting factors (0.058, p = 0.084). This reiterates Melitski, Gavin and Gavin (2010) finding that individual perception of organisation culture is positively linked to individual willingness to adopt technology.

3.7.2.5 Competitive Pressure (H5a & H5b)

The link between competitive pressure and technology readiness motivators is statistically significant as proposed by H5a. This is confirmed by the strong relationship (Estimate = 0.751, S.E. = 0.145, C.R. = 5.173, p < 0.001) between competitive pressure and technology readiness motivators as shown in the direct effect analysis which is further emphasised by the analysis result showing a substantial indirect effect (1.025, p = 0.011) on adoption through motivational factors. Equally supported is H5b, but with marginal mediation significance. The direct effect analysis presented significant results (Estimate = 0.162, S.E. = 0.053, C.R. = 3.051, p = 0.002) between competitive pressure and reduction of technology readiness inhibitors. The indirect effects analysis found a marginally significant indirect effect (0.038, p = 0.093) on adoption through inhibiting factor. These results affirm findings of other studies that competitive pressure notably boosts motivation for adoption, highlighting that external market dynamics are significant drivers of technology readiness and subsequent adoption (Gangwar, Date and Ramaswamy, 2015; Alsheibani, Cheung and Messom, 2018). Again, competitive pressure significantly affects reduction of inhibiting factors, although this pathway has a small indirect effect on adoption, indicating that although market pressures can mitigate inhibition issues, it can also heighten certain inhibiting factors, possibly due to stress during implementation or rushed deployments to catch up with competitors. For instance Su, Zhang and Wu (2023a) in their study exploring how market pressures and organisational readiness affect the development of digital marketing adoption strategies in small and medium enterprises (SMEs) found that competitive pressure increased the frequency and complexity of

adoption decisions, leading to implementation challenges. The pressure to adopt AI and I4.0T to stay competitive if not mitigated may lead to rushed adoption decisions without sufficient preparation, causing implementation difficulties that could slightly hinder the adoption process (Faiz, Le and Masli, 2024).

3.7.2.6 External Support (H6a & H6b)

External support includes third party support from vendors/partners and as found in earlier studies by Baker (2012), external influence include government regulation. The indirect effects analysis which shows meaningful indirect effect (0.828, p = 0.003) on adoption via motivating factors further validate the significant relationship (Estimate = 0.607, S.E. = 0.141, C.R. = 4.312, p< 0.001) between external support and technology readiness motivators (MFQI). This shows a strong support for H6a is which indicates that assistance from third parties such as vendors, consultants as well as government policies serves as significant drivers for technology readiness and subsequent adoption. Interestingly, the relationship between external support and technology readiness inhibitors is negative (-0.062) but not statistically significant (p = 0.218). The indirect effects analysis corroborates this with a non-significant indirect effect (-0.015, p = 0.201) on adoption through inhibiting factors. Therefore, H6b is not supported. Chaurasia and Verma (2020) also find that the relationship between external support, particularly government support, and technology adoption is not significant. This suggests that the influence of external support is primarily to enhance positive motivations and rather than mitigate barriers to adoption. Besides, government regulation can have either a beneficial or a detrimental effect on innovation. For instance, the findings of Haneem, Kama and Abu Bakar (2019) in the context of their study of IT innovation adoption in local governments, external support factors such as government policy support and third party financial assistance, significantly influence technology adoption by creating a supportive environment that increase organisational readiness and motivation while a study of small-scale

agribusiness enterprises in Somalia and their ICT adoption reveal that vendor assistance and government initiatives, is not significantly related to technology adoption (Abdullahi *et al.*, 2021).

3.7.3 Mediating Role of TRI (H7a & H7b)

Following the third objective of the study to examine the mediating role of TRI motivating and inhibiting factors on the relationship between the TOE dimensions and AI and I4.0T adoption, this study proposes that TRI motivators and inhibitors significantly mediate the relationship between TOE factors and adoption of AI and I4.0T in H7a and H7b respectively. The analysis of indirect effects reveal notable and meaningful indirect influences of all TOE factors on adoption via technology readiness motivators with the following results technology characteristics (1.437, p = 0.002), relative advantage (1.165, p = 0.011), organisational resources (1.615, p = 0.001), organisational culture (1.952, p = 0.006), competitive pressure (1.025, p = 0.011), and external support (0.828, p = 0.003). The indirect effects analysis of inhibiting factors mediating role show mainly non-significant or only marginally significant influences of TOE factors on adoption through technology readiness inhibitors as seen in technology characteristics (0.015, p = 0.477), relative advantage (0.031, p = 0.221), organisational resources (0.042, p = 0.089), organisational culture (0.058, p = 0.084), competitive pressure (0.038, p = 0.093), and external support (-0.015, p = 0.201). This shows that the motivators associated with technology readiness significantly mediate the relationship between TOE factors and the adoption of AI and Industry 4.0 technologies supporting H7a. On the other hand, H7b is only partially supported since inhibitors only marginally mediate the relationship between certain TOE factors namely, organisational culture, organisational resources and competitive pressure and the adoption of AI and I4.0T. The role of inhibiting factors is then secondary and potentially less important in the adoption process compared to motivating factors.

3.7.4 Significance of Findings

The results suggest that in driving the adoption of AI and I4.0T, readiness motivators have a much stronger influence than inhibitors. Organisations respond more positively to factors such as clear benefits from new technology, reliable technology design, available resources, supportive culture, competitive pressure and external assistance, which increase readiness, than to efforts focused mainly on reducing inhibitors. Although, readiness inhibitors such as discomfort or uncertainty could still exist, they only contribute marginally to the adoption process. This suggests that adoption strategies should concentrate on building motivation, strengthening internal capability, and communicating value rather than relying heavily on barrier reduction. The findings also point to the importance of developing an innovation-oriented culture and investing in resources that enhance preparedness, as these have the greatest influence on adoption outcomes.

The results offer substantial evidence for many of the proposed relationships, especially regarding motivating factors, while uncovering a more complex view of inhibiting factors. The results indicate a largely positive trend towards the adoption of AI and I4.0T, highlighting how organisational culture, available resources, and technology traits boost motivation, which subsequently leads to adoption. Although inhibiting factors exist, they appear to have a lesser influence on the adoption process

The following section discusses the significance of the research findings in relation to the objectives.

3.7.4.1 Understanding Adoption State and Drivers in the Nigerian Context

There are several reasons for the importance of having a contextual understanding of adoption of AI and I4.0T including the factors that influence it. For complex technologies like AI and I4.0T, they evolve depending on the context and time (Lyytinen and Damsgaard, 2001). This results in groups, organisations and industries attributing different meanings to the

technology due to factors such as local culture, economic conditions and the surrounding infrastructure including the education system and government policies shape these interpretations. This is no different for Nigeria, a country with immense potential as Africa's largest economy to leverage digital transformation for economic growth and development (World Bank, 2025). Furthermore, Nigeria is characterised as a 'bellwether' for Africa and can serve as a representative example of significant trends on the continent because it exhibits typical traits common throughout the continent, including considerable changes in demographics, rapid urbanisation and an unequal advancement in digital technology (Ojubanire *et al.*, 2024). Like most other African countries Nigeria faces peculiar challenges of financial constraints, skill shortages and infrastructure deficits that differ from developed countries where most adoption frameworks have been established (Vinuesa *et al.*, 2020). Moreover, the dominance of foreign focused AI and I4.0T products and services could offer technology solutions that may not be consistent with local technology development goals. By identifying the unique drivers in this context, this research addresses a significant gap in technology adoption literature that has largely focused on Western perspectives. Additionally, the Nigerian government's recent emphasis on technological development and ambition to develop a digital economy, highlighted by the National Digital Economy Policy & Strategy (2020–2030) (NDEPS) can benefit from this sort of empirical data on adoption drivers. A better understanding of these factors can provide critical information for Nigerian policymakers aiming to develop effective digital transformation strategies, enabling more precise and impactful interventions.

3.7.4.2 Identifying the Impact of Elements of the TOE Framework

The partial and asymmetric mediation pattern requires a nuanced interpretation. The findings do not suggest full mediation of TOE-adoption relationships, but rather distinct mechanisms. Motivating readiness factors consistently mediate all pathways to adoption,

whereas inhibiting factors mediate only internally controllable conditions and are not influenced by externally driven factors. This reveals a structural asymmetry: internal TOE conditions shape both motivation and resistance, while external conditions influence motivation but not inhibition. This refines, rather than replaces, traditional TOE logic. Prior studies treat structural and environmental conditions as direct and proportionate drivers of adoption (Baker, 2012; Oliveira and Martins, 2011). The findings challenge this assumption by showing that motivating mechanisms respond consistently across conditions, whereas inhibiting mechanisms respond only to factors under managerial control. This adds precision to prior TOE-TRI integrations, which typically treat readiness as a single construct, by identifying how different TOE conditions link to distinct readiness mechanisms (Blut and Wang, 2020).

The non-significant effects of technology characteristics (H1b) and external support (H6b) reinforce this distinction. In contrast to the significant effects of organisational resources (H3b), culture (H4b), competitive pressure (H5b) and relative advantage (H2b), only internally controllable factors reduce inhibitors. This indicates that discomfort and insecurity are endogenously generated, rooted in capability gaps, cultural resistance and uncertainty about internal competence. External conditions may enhance understanding of AI and I4.0T or facilitate implementation, but they do not resolve the underlying psychological and organisational barriers that sustain resistance (Parasuraman, 2000; Uren and Edwards, 2023). This aligns with evidence that external drivers build motivation without alleviating internal constraints (Liang *et al.*, 2007; Su, Zhang and Wu, 2023b) highlighting the need for internal capability development and cultural change to enable assimilation.

The finding that organisational culture has the highest requires deeper critical analysis across national and Multinational Corporation (MNC) contexts. Nigerian companies in Nigeria operate within a single institutional environment where organisational culture directly reflects

high power distance and collectivist national cultural characteristics. Nigeria's collectivist culture and high power distance (PDI = 80) reshape TOE's organisational and environmental dimensions by making organisational culture a higher-level influence on TRI motivators through the "Oga at the Top" (Gidi Magazine, 2025) leadership concentration mechanism. This makes culture the dominant meta-determinant of TRI motivators. MNCs face dual institutional pressures from parent company requirements and Nigerian host country conditions. This creates adoption dynamics that TOE's single-context framework does not fully capture.

3.7.4.3 Investigating the TRI's Role

The positive and statistically significant direct relationship between inhibiting factors and adoption is a theoretically unexpected finding. Though counter-intuitive, especially as standard TRI theory predicts that discomfort and insecurity suppress adoption by creating psychological resistance (Parasuraman, 2000), there are alternative interpretations within the TOE-TRI framework considering the Nigerian context and sample characteristics. A primary interpretation is capability-based learning, where higher perceived inhibitors reflect greater exposure to technological complexity among more digitally mature organisations. Within TOE, stronger technological and organisational readiness increases both adoption likelihood and awareness of implementation challenges, consistent with absorptive capacity arguments (Cohen and Levinthal, 1990). Further, higher TRI inhibitors may reflect greater cognitive awareness of implementation complexity rather than resistance to adoption. A second interpretation is institutional pressure, where organisations adopt AI and I4.0T due to environmental (TOE-E) forces such as competitive, regulatory or supply chain expectations, despite recognising internal constraints (DiMaggio and Powell, 1983; Oliveira and Martins, 2011). This is particularly relevant in developing economy contexts, where external legitimacy pressures rather than readiness could drive adoption (Awa, Ojiabo and Orokor, 2017). Third, a paradoxical engagement interpretation suggests that organisations simultaneously recognise

barriers while continuing adoption due to strategic necessity and competitive pressure. This reflects a tension within both organisational context (TOE-O) and behavioural readiness (TRI), where contradictory cognitions coexist rather than inhibit action (Smith and Lewis, 2011). Moreover, environmental turbulence and urgency, may make organisations operating under uncertainty (TOE-E) adopt technologies for survival despite high perceived constraints. Finally, the escalation of commitment (Ross and Staw, 1993) or sunk cost logic where organisations already investing in digital transformation may continue adoption even when they perceive increasing barriers. Here, inhibitors rise because adoption is already underway, not despite it. Barriers may have become visible after adoption decisions began. Organisations continue with adoption to justify investment.

3.8 Conclusion

3.8.1 Overview

This comprehensive analysis of the relationships among TOE factors, TRI dimensions and technology adoption offers substantial evidence for many of the proposed relationships, especially regarding motivating factors, while uncovering a more complex and detailed view of inhibiting factors. The results indicate a largely positive and growing trend towards the adoption of AI and I4.0T. The findings also highlight how organisational culture, organisational resources, and technology characteristics boost motivation and subsequent adoption. The study finds that even with the existence of inhibiting factors they appear to have less influence on the adoption process.

This study's results provide several important insights and key implications for technology adoption. Organisational culture emerges as the main TOE factor, demonstrating the strongest relationship with the motivating factors in the TOE framework. This emphasises the need to cultivate a culture that supports innovation as this is crucial for the successful adoption of technology. Also, the significant influence of organisational resources on

motivating factors highlights the necessity of adequately allocating resources before implementation. Interestingly, the positive connection between inhibiting factors and technology adoption, though paradoxical, indicates that organisations that are successfully implementing AI and I4.0T tend to recognise and manage these inhibitors rather than avoid them. The findings also indicate that external support contributes significantly to motivation but has no significant effect on inhibitors. This indicates that it functions more through positive reinforcement rather than by reducing barriers to adoption. The study's findings further affirm the importance of internal motivations over external barrier mitigation. Ultimately, the study advocates for a comprehensive approach that considers technological, organisational, and environmental dimensions to ensure successful adoption of AI and I4.0T, as all factors in the TOE framework significantly impact technology readiness motivating factors.

3.8.2 Theoretical Contributions

This paper's integration of TOE framework with TRI contributes in several ways to the theory on technology adoption in supply chains by examining how technological, organisational and environmental factors influence the adoption of AI and I4.0T through the mediating role of TRI. The study shows how the TRI reshapes assumptions within the TOE framework. The integration of TRI shifts TOE's positioning of technological, organisational and environmental conditions as direct drivers of adoption to create a stepped process that indicates that these influences often work through an organisation's readiness state. TRI also brings in behavioural elements such as optimism, innovativeness, discomfort and insecurity (Parasuraman & Colby, 2015), which sit outside TOE's mainly rational and context-oriented structure. By applying the TOE–TRI relationship in the Nigerian supply chain context, the study extends existing theoretical models in several meaningful ways.

First, the study advances the theory of technology readiness as a mediating mechanism. While TRI is often conceptualised as a psychological construct related to optimism,

innovativeness, discomfort and insecurity, it plays a more influential role than typically acknowledged. The findings suggest that readiness is an important pathway through which TOE elements translate into adoption. By theorising technology readiness as a mediating mechanism that connects organisational and contextual factors to AI and I4.0T adoption, this paper offers an explanatory lens for understanding the pathways through which technical and psychological preparedness jointly shape adoption outcomes. However, this TRI mediated view extends and enriches rather than replaces TOE. It positions TOE factors as foundational though not sufficient to explain adoption. It indicates that psychological readiness related mechanisms intervene in ways that shape TOE contexts for adoption strength and timing (Parasuraman and Colby, 2015). This highlights the need for adoption theory to integrate readiness more centrally rather than treating it as a secondary or peripheral variable.

In addition, by highlighting psychological readiness, this paper challenges the expectation within TOE that organisations facing similar conditions will respond in similar ways. TRI shows that organisations exposed to identical contextual factors may still differ in their adoption decisions because beliefs, comfort levels and dispositions differ. Furthermore, TOE generally treats contextual factors as stable but TRI introduces a dynamic element to adoption because readiness changes over time. These distinctions are relevant, particularly for AI and I4.0T, where trust, transparency and adaptability influence how quickly organisations move from knowledge of technology to its implementation. Besides, as AI and I4.0T are often clusters or ecosystems of technology rather than isolated innovations, this makes them complex and quite different from the discrete technologies of earlier periods. This complexity presents challenges to the traditional ways of defining and operationalizing technology features (Duan, Edwards and Dwivedi, 2019). Traditional adoption models do not adequately reflect the iterative and phased nature of AI and I4.0T implementation process (Bag et al., 2021). This

study's model shifts the focus from direct effects to process-oriented explanations by introducing readiness.

Similarly, this study recognises that technology adoption concurrently follows both rational economic and social institutional pathways and that their relative influence differs by technology type and organisational context. The results support a dual approach model for technology adoption as it highlights both motivating and inhibiting factors. But it also indicates a notable asymmetry in their impacts. Motivating factors emerged as the primary and stronger pathway to adoption, while inhibiting factors play a less significant secondary role. This advocates for a positive psychology perspective in technology adoption as it stresses the importance of building strengths by enhancing motivators as opposed to merely mitigating weaknesses by reducing inhibitors. This highlights an unequal effect of motivators and inhibitors and therefore calls for a reassessment of technology readiness. It suggests that readiness might more accurately be viewed as an outcome of a positive outlook instead of a balance of positives and negatives. So, in alignment with emerging trends in organisational psychology that emphasise positive behaviours and strengths-focused strategies (van Zyl *et al.*, 2023) this study advocates for more focus on increasing motivating elements.

Additionally, the implementation of advanced technologies requires decision making and actions across various organisational levels. Many existing models primarily concentrate on either the organisational or individual levels, overlooking the interactions across these different levels. The integrated framework of the study's conceptual model builds on these established theories while addressing their shortcomings. By combining macro level organisational elements with individual psychological factors, the study's validated integration of TOE and TRI results in a more thorough explanatory framework which represents a significant theoretical advancement.

Finally, as this study is set in the context of Nigeria, the findings broaden the understanding of how the TOE framework operates in emerging markets with uneven technological maturity and unpredictable environmental conditions. It highlights the necessity for context specific view, demonstrating that technology adoption in developing countries such as Nigeria involves distinct factor interactions that may not be reflected in the models shaped by the needs, priorities, and values of developed economies that are driving the AI development (Vinuesa et al., 2020). As TOE studies often assume relatively stable digital infrastructure and consistent institutional support, the Nigerian context shows that factors such as the lack of infrastructure, logistical inefficiencies, weak regulatory enforcement and uncertain external conditions reshape the influence of the TOE elements on adoption decisions. This highlights the limitations of the TOE framework and demonstrates contextual factors that are different from those in developed economies that could influence the direction of its relationships. On the other hand, TRI is often conceptualised as a psychological or attitudinal construct, however, in markets where digital infrastructure is unstable and exposure to advanced technologies limited, readiness is shaped not only by internal attitudes but also by these broader contextual conditions. This provides a more grounded understanding of readiness in developing economies and suggests that the evaluation of TRI is not solely an attitudinal construct but also a response to contextual constraints. Therefore, the study contributes to a more nuanced interpretation of TOE and TRI.

3.8.3 Practical Implications

This study demonstrates that successful adoption of AI and I4.0T in supply chains depends not only on the effective management of the interaction between technological, organisational and environmental conditions, but also the organisation's overall TRI. The results offer several insights that can support organisational practice, managerial decision making and broader policy considerations.

In terms of organisational practice, the significant influence of organisational culture, both directly and indirectly through technology readiness motivators makes a case for more focus on cultural transformation encouraging innovation. The findings draw attention to its critical importance in the technology adoption process. This view goes beyond conventional TOE frameworks, which typically treat technological, organisational and environmental factors equally, suggesting that organisational elements such as culture should be given more consideration in models of technology adoption. Given the prominent role of organisational culture, organisations should prioritise initiatives aimed at cultural transformation that encourage innovation, risk-taking, and openness to technology, especially during the implementation of AI and I4.0T projects.

Furthermore, the findings have important implications for organisational strategy for the implementation of AI and I4.0T. The significant mediating role of motivators suggests that organisations should focus resource allocation strategy primarily on investing in boosting positive motivations instead of solely reducing barriers. This positive perspective toward technology adoption, should also guide their competitive strategy as well as the utilisation of external support. Organisations should approach AI and I4.0T adoption as an opportunity for competitive advantage rather than a threat. The notable influence of competitive pressure as a motivating factor supports focusing on the positive potential of technology rather than the dangers of lagging behind. Besides, differing effects of external support motivators and inhibitors indicate that organisations should seek to enhance positive motivations by leveraging external support, such as highlighting successful case studies and offering training, rather than concentrating on overcoming barriers.

The findings, which reinforce the importance of motivators and the key role they play in shaping how the TOE elements influence adoption outcomes, have significant implications for managerial decision making. Managers should prioritise communicating the relative

advantages of AI and I 4.0T. When employees and decision makers can see clear, tangible, and easy to understand benefits of these systems, they respond more positively. Again, with competitive pressure also playing a significant role in motivating adoption, managers can use market comparisons, customer expectations, and industry benchmarks to support their case for investing in new technologies. However, managers should ensure that competitive pressure is not the major driver of the implementation, as rapid adoption without adequate preparation can create avoidable challenges, resource misalignment and difficulties during integration. Again, although the findings also show that the inhibitors present have limited influence on final adoption decisions, managers should not ignore discomfort or uncertainty. Early employee involvement, user training, and phased implementation can help address concerns about adoption. Finally, managers should recognise that external support from vendors, consultants, and government initiatives improves readiness primarily by lifting motivation. External input should be used to build capability through training, pilot projects, and structured support rather than expecting it to eliminate internal barriers on its own.

For policy makers in Nigeria, these results could provide valuable insights that are essential for developing effective policies and digital transformation strategies. Considering the Nigerian government's recent emphasis on technological advancement through policies like the National Digital Economy Policy and Strategy (2020-2030) (NDEPS), empirical evidence on the determinants of adoption could inform more targeted and effective interventions that can address the challenges of rapid AI and I4.0T advancement. This study’s findings confirm that broader infrastructural and institutional conditions impact technology readiness. This relationship highlights the need for policy interventions that strengthen the technological, organisational and environmental foundations that enable effective adoption of AI and I4.0T.

The findings point to several policy actions that can support the effective adoption of AI and I4.0T in Nigerian supply chains. One area is in strengthening digital infrastructure such

as broadband connectivity, stable electricity supply and improved network coverage which could reduce uncertainty and build organisations' confidence in digital tools. Again, the NDEPS considers workforce development very important and places strong emphasis on digital literacy and workforce training. Promoting digital skills initiatives and vocational training as well as encouraging partnerships between industry and academia can drive this agenda and by helping to build talent base that is better prepared to work with advanced technologies. Furthermore, familiarity with digital tools can also shape employees' readiness and their confidence in using them. Similarly, results indicate that organisations in this study benefited from external support and exposure to best practices. Therefore, grants, tax reliefs and other financial incentives could ease the cost burden of digital adoption, especially for small and medium-sized firms which form a good number of Nigerian businesses. Again, national digital innovation hubs and technology support centres could also play an important role in raising technology readiness. For organisations that lack in-house expertise, availability and access to public digital innovation hubs and technical support centres could provide shared expertise and help reduce barriers for organisations.

3.8.4 Limitations

As with other studies, there are some considerations when interpreting the results of this study. Despite the significant findings and contributions, this research acknowledges some limitations than can affect the generalisability and interpretational scope of the results. These limitations also provide directions for future research activities.

This study's sample is skewed toward medium and large organisations, despite Nigeria's private sector being dominated by SMEs. This reflects a common bias in technology adoption research, where more resource-rich and digitally advanced organisations are more likely to participate. This may lead to overstated adoption levels of AI and I4.0T and understated effects of readiness and resource constraints as larger organisations are better

positioned to absorb financial, technical and operational challenges. This is particularly relevant for inhibiting factors, which may appear less significant in this study but are likely to be binding constraints for SMEs. The findings nonetheless suggest that readiness assessment and capability development are critical, especially for smaller organisations where failed adoption carries greater risk. Future research should explicitly target SMEs using data collection approaches better suited to reaching smaller and more informal organisations. Furthermore, the sample composition is predominantly privately limited companies with limited number of public listed companies and foreign-owned subsidiaries and multinational affiliates. This limits the study's ability to test whether the culture-dominance finding is ownership-type-specific or more general. In multinational subsidiaries where adoption is often mandated by parent governance rather than culturally activated, the culture-dominance finding would be predicted to be weaker. This qualifies the culture finding as applying most directly to Nigerian companies' contexts and identifies multi-group analysis across ownership types as an important future research direction.

As noted in the methodology, data for this chapter and Chapter 4 were collected using a single integrated survey from the same respondent pool. The integrated design also increases exposure to common method bias. However, the observed differential path patterns, including the asymmetric mediation and the positive inhibitor-adoption relationship, are theoretically coherent and not consistent with uniform method inflation. A further discussion is provided in Section 4.5.1.7.3 and 4.8.3 of Chapter 4. The cross-sectional nature of this study presents a significant limitation. Data were collected at a single point in time, which limits the ability to fully establish causality between TOE factors, technology readiness, and AI and I4.0T adoption. Technology adoption is inherently a process that unfolds over time, and cross-sectional data may not capture the temporal dynamics and feedback loops that may exist in this process. For instance, successful initial adoption might enhance motivation for further

implementation, creating a reinforcing cycle that the current research model cannot fully capture.

3.8.5 Future Research Directions

These limitations suggest several promising directions for further studies. For example, future research can build upon this study's findings and limitations to develop more comprehensive and nuanced models of AI and I4.0T adoption, ultimately providing more effective guidance for both theory development and practical implementation.

Future research could employ longitudinal designs for a better understanding of the temporal dynamics and potential feedback loops in the adoption process, particularly the relationship between initial adoption and subsequent enhancement of motivating factors. Longitudinal studies could explore how motivators and inhibitors evolve over time as organisations become more familiar and comfortable with AI and I4.0T.

Again, this study’s cross-sectional time line primarily focused on adoption decisions rather than post-adoption outcomes such as implementation success, technology assimilation or performance impacts. The relationships between TOE factors and technology readiness might differ when considering these longer- term outcomes. An extended model which includes post-adoption outcomes such as implementation success, organisational performance and sustained use could provide a more comprehensive understanding of the technology adoption process.

This study’s findings also point to promising future research directions focused on what happens after organisations adopt AI and I4.0T, particularly what determines whether these tools are used effectively over time. While the findings show strong motivators and relatively weak inhibitors at the adoption decision stage, adoption itself is usually not the end of the process. As organisations move into post adoption and perhaps assimilation stages, these

motivators and inhibitors may change and new tensions, unexpected outcomes and paradoxes can emerge. Such changes can reshape both the impact and value delivered by the technology. Future research could therefore examine how organisations navigate the tensions and paradoxes that arise once AI and I4.0T are implemented in supply chain operations.

In terms of research methods, mixed methods could be an alternative methodological choice**.** By combining quantitative surveys with qualitative case studies deeper insights into the contextual factors influencing adoption decisions and the mechanisms through which TOE factors influence technology readiness could be gained. Apart from being mindful of the effects of negatively worded questionnaire items, future research can also expand the conceptualization of inhibitors. Perhaps more nuanced conceptualisations and measurements of inhibiting factors like distinguishing between different types of barriers such as technical, organisational, psychological might have different effects on adoption.

Cross-cultural comparative studies would be a fruitful area for further work that could yield richer insights. Replicating the study across different cultural and geographical contexts would enhance the generalisability of findings and highlight how cultural factors moderate the relationships observed.

Overall, the adoption findings explain the first transition point, that is, from favourable TOE conditions to adoption through TRI motivator activation. However, adoption is only the starting point. The shift from adoption to assimilation, from initial use to deep integration into workflows, decisions and strategy, is explained by organisational learning theory and Chatterjee, Grewal and Sambamurthy (2002) assimilation continuum. These frameworks predict that assimilation develops through experiential learning, institutional pressure and routinisation, rather than the psychological mechanisms that drive adoption. This clear

separation between adoption and assimilation provides the theoretical basis for Chapter 4's empirical analysis.

Chapter 4 From Digital Assimilation to Sustainability Outcomes: The Mediating Role of Technological Capability and Organisational Agility

4.1 Abstract

The growing pressure for sustainability across global supply chains has intensified interest in Artificial Intelligence (AI) and Industry 4.0 technologies (I4.0T) as potential enablers of environmental efficiency, social responsibility and economic resilience. While organisations are increasingly adopting these technologies, many organisations struggle to translate digital adoption into measurable sustainability outcomes. Evidence suggests that the challenge lies in assimilation. However, there is limited attention given to how assimilation translates into measurable sustainability outcomes or through what organisational mechanisms this occurs. This study addresses this gap by investigating the mediating roles of technological capability and organisational agility in the relationship between technology assimilation and economic, environmental, and social sustainability performance.

Grounded in the Dynamic Capabilities and Triple Bottom Line (3BL) frameworks, this study tests a model linking technology assimilation to sustainability outcomes. Structural equation modelling (SEM) is applied to test the hypothesised relationships and indirect effects using data collected from online survey of organisations implementing AI and Industry 4.0 technologies.

Findings reveal that technology assimilation positively impacts sustainability outcomes. This effect is indirect, operating through technological capability which enhances the firm's ability to integrate and reconfigure digital resources and organisational agility which supports rapid adaptation to sustainability and market demands. These mechanisms explain why some organisations achieve sustainability benefits from digitalisation while others are less successful.

This study advances the integration of digitalisation and sustainability research by demonstrating that the dynamic interplay of capabilities drives sustainability performance outcomes. It explains how technological capabilities and organisational agility bridge the gap between digital assimilation and sustainability outcomes. Again, it emphasises that digitalisation initiatives must go beyond technological acquisition to focus on capability development and organisational learning. Further, it provides guidance for organisations and policymakers to focus on capability building, agile structures, and digital skill development to translate digital investments into tangible sustainability impact.

Keywords: Technology Assimilation; Dynamic Capability, Technological capability; Organisational Agility; Sustainability; Supply chain

4.2 Introduction and Context

Innovations enabled by the internet and emerging digital technologies have shifted consumer behaviour and expectations, intensified competition and heightened the need for digital transformation across various sectors (Verhoef *et al.*, 2021). As these rapid advancements in digital technologies continue to reshape industries, organisations face increasing pressure to rethink how they operate and compete and consider the need for organisational digitalisation (Queiroz *et al.*, 2019). Furthermore, the renewed rise of Artificial Intelligence(AI) and its convergence with Industry 4.0 technologies (I4.0T) such as IoT, Cloud Computing, Big Data Analytics, Blockchain, 3D Printing, and Cyber-Physical Systems, further strengthens this shift (Büyüközkan and Göçer, 2018; Agrawal and Narain, 2023). These technologies are reshaping how organisations create value and manage operations (Robertsone and Lapiņa, 2023) including transforming supply chains from traditional sequential structures toward systems that are more connected, data-driven and responsive (Agrawal and Narain, 2023; Dubey *et al.*, 2017). Alongside this, organisations are operating in a global environment with increased expectations for sustainability (Ahi and Searcy, 2015) with stricter regulations,

environmental concerns and stakeholder pressure also adding complexity to this landscape (Kamble *et al.*, 2022). Despite increased awareness, many sustainability issues remain unresolved. Shipping, for example, still generates 3.1% of global CO_2 emissions (Schlanger, 2018), while labour violations continue across several industries (International Labour Organization ILO, 2022). Circular supply chain practices also remain difficult to scale (Calzolari, Genovese and Brint, 2021).

4.2.1 Technology Potential and Assimilation

AI and I4.0T hold significant potential to address these sustainability pressures by improving visibility, efficiency and resource use (Dubey *et al.*, 2017; Bag *et al.*, 2020; Nishant, Kennedy and Corbett, 2020). For instance, AI-enabled energy management systems, blockchain-supported transparency and data-driven optimisation tools offer new opportunities to reduce emissions and strengthen supply chain accountability (Malakar *et al.*, 2025). However, adopting these technologies is not enough. The extent to which AI and I4.0T tools contribute to sustainability depends on how well organisations integrate and embed them into routines and decision-making structures (Chatterjee, Grewal and Sambamurthy, 2002; Wamba, 2022). When technologies are acquired but not fully integrated, assimilation gaps appear (Fichman and Kemerer, 1997).

Factors such as ease of use, compatibility with existing processes and the extent to which teams can observe and experiment with the technology shape the assimilation of these technologies (Rogers, 2003). Again, organisational barriers such as disconnected teams, limited change management and outdated legacy systems often slow the progress of integrating AI and I4.0T into organisational processes and routines (Ben-Daya, Hassini and Bahroun, 2019; Fosso Wamba, Akter and de Bourmont, 2019; Toorajipour *et al.*, 2021). External pressures, including short-term investor priorities and regulatory gaps can also divert attention away from long-term sustainability efforts which limit assimilation (Whiteman, Walker and Perego, 2013; Saberi *et*

al., 2018). When assimilation is weak, digital technologies may fail to achieve their intended outcomes. This gap between acquisition and real use can produce conflicting or unintended effects such as increased electronic waste from rapid upgrade cycles (Bocken *et al.*, 2014), rebound effects where efficiency gains drive higher consumption (Alcott, 2005), governance issues associated with transparency technologies (Saberi *et al.*, 2018) and risks of labour displacement through automation (International Labour Organization ILO, 2022). These examples highlight the need to look beyond adoption and focus on how technologies are embedded within organisational processes.

4.2.2 Dynamic Capabilities for Integration

Access to AI and I4.0T alone is not sufficient to overcome these challenges. Organisations must develop strong technical and organisational capabilities (Purvis, Sambamurthy and Zmud, 2001) by restructuring operations and developing complementary capabilities that support experimentation, adaptation and continuous change (Olan *et al.*, 2022; Ostadi, Barrani and Aghdasi, 2024). Dynamic capabilities such as routines for managing ongoing transformation are essential for navigating fast-changing digital environments (Ellström *et al.*, 2021). In these environments, organisations thrive when they can integrate, build and reconfigure resources effectively (Teece, Pisano and Shuen, 1997). For instance, technological capabilities help turn raw technological resources into operational strengths such as analytics, automation and integration that enable organisations to extract value from AI and I4.0T investments beyond mere adoption (Peppard and Ward, 2016). With strong IT infrastructure, real-time analytics and system interoperability, organisations can match AI and I4.0T with sustainability goals (Baryannis *et al.*, 2019). Another essential capability which adds further support for AI and I4.0T integration is agility. Agility allows organisations to adjust quickly to market shifts and emerging sustainability pressures while supporting flexible network structures and coordinated decision-making (Mrugalska and Ahmed, 2021). The

organisation's agility in sensing the market, making operational adjustment and network reconfiguration enables them to quickly respond to sustainability challenges and opportunities and provides the flexibility needed to manage paradoxes effectively (Cichosz *et al.*, 2025).

4.2.3 Problem Statement and Knowledge Gap

Various studies have mapped the intersection of AI and I4.0T and sustainability (Kamble, Gunasekaran and Sharma, 2018; Franciosi *et al.*, 2018). However, several gaps in knowledge still exist. First, though there is a growing interest in understanding assimilation processes and outcomes, research appears more focused on primary adoption and the factors influencing it than on assimilation (Gallivan, 2001), with empirical studies on the relationship between AI and I4.0T applications and sustainability outcomes remaining limited. Alongside this, existing research on AI and I4.0T in sustainable supply chains remains largely conceptual, with limited empirical evidence on sustainability performance impacts (Tavana *et al.*, 2022). Where empirical studies exist, they often address only one dimension of sustainability rather than the economic, social and environmental dimensions jointly (Müller, Kiel and Voigt, 2018). This leaves a critical gap in understanding how AI and I4.0T adoption and assimilation translates into comprehensive sustainability outcomes. Following Ghobakhloo's (2020) call for further investigation, this study contributes by examining how the assimilation of AI and I4.0T influences supply chain sustainability performance across all three dimensions.

Secondly, despite the growing literature examining AI and I4.0T adoption in supply chains, researchers have highlighted a persistent lack of comprehensive frameworks that explain the mechanisms through which these technologies translate into performance, particularly sustainability performance outcomes (Patrucco *et al.*, 2025; Hao and Demir, 2024). Existing studies have predominately examined the direct relationships between technology adoption and performance outcomes without exploring the mediating mechanisms (Cui, 2025). This approach fails to explain the intermediate processes that converts technological

investments into sustainability outcomes (Wamba-Taguimdje *et al.*, 2020; Dubey *et al.*, 2019). These studies tend to examine technology assimilation and sustainability performance in isolation. Although past studies like Liu *et al.* (2013), Mikalef and Pateli (2017) and Wamba (2022) explored organisational agility as a mediator the dual mediating roles of agility and technological dynamic capabilities remain underexplored. No previous study to the best of the author's knowledge and through intensive search in peer-reviewed databases, including Scopus, Web of Science and ScienceDirect, has empirically explored AI and I4.0T assimilation, technological capability, organisational agility and sustainability performance holistically. Together, these mediators potentially create a multiplicative effect that can significantly enhance sustainability outcomes. This study offers valuable insights for both scholarly research and management in understanding the technology versus sustainability relationship by assessing how these two mediating factors work together, potentially creating a multiplicative effect on sustainability outcomes when both are strong.

Thirdly, as focus of competition moves from between individual organisations to their supply chains (Hausman, 2004), continuous evaluation, improvement and management of supply chain performance is very vital. Although scholars including Gunasekaran, Patel and McGaughey (2004) and MacBryde *et al.* (2006), have acknowledged the importance of focusing on supply chain performance, it has traditionally been viewed through the lens of cost, speed, quality, dependability and flexibility. However, increased globalization, technological innovations, access to information and environmental concerns draws attention to the importance of sustainability focused performance management. By directing the focus of supply chain performance to the underexplored area of sustainability outcomes, this study enables a comprehensive evaluation that recognises the joint importance of resource measures (resource consumption i.e. technology), output measures (triple bottom line) and flexibility measures (dynamic capabilities) in line with the recommendation of Beamon (1999).

Lastly, existing research frequently views the relationship between technology and sustainability as a linear, positive connection and neglects the underlying tensions and contradictions that exist (Van der Byl and Slawinski, 2015). As general-purpose technologies, AI and I4.0Ts present infinite possibilities and are therefore expected to produce unintended outcomes and paradoxes due to their innovative, pervasive, and constantly evolving nature (Jovanovic and Rousseau, 2005). Studies suggest that the paradox view offers a valuable and insightful perspective for effectively addressing the significant challenges that exist within technology assimilation for supply chain sustainability performance (Dieste, Sauer and Orzes, 2022; Cichosz *et al.*, 2025). Furthermore, identifying paradoxes in relation to adoption and assimilation of technologies enables an extension of the diffusion of innovation paradigm beyond the 'either/or' outcomes that fail to capture the tensions resulting from the contradictions associated with technology (Mick and Fournier, 1998). Moreover, the paradox perspective is relatively new approach in management and has not been extensively applied to AI and I4.0T and sustainability relationship contexts (Kocabasoglu-Hillmer *et al.*, 2023). Therefore, as AI and I4.0T continue to develop, studying and understanding these paradoxes at this stage of evolution provides an opportunity to influence and enhance the trajectory of their development (Charlwood and Guenole, 2022).

4.2.4 Research Aims and Objectives

These identified knowledge gaps, together with the limitation highlighted in Section 2.5.5, where Dynamic Capabilities Theory was found to under-explain hybrid human-AI adaptation and algorithmically enabled reconfiguration, highlight the need for empirical research that demonstrates how AI and I4.0T are translated into measurable sustainability outcomes. Addressing this gap, this study examines how AI and I4.0T assimilation influences the development of technological capabilities and organisational agility, and how these in turn affect sustainability performance across environmental, economic, and social dimensions. It

also addresses potential unintended consequences and paradoxes that may emerge during implementation. By integrating these perspectives, the study investigates how AI and I4.0T assimilation shapes supply chain sustainability outcomes, while also capturing the tensions and trade-offs embedded in this process. To address these aims the study guided by the following research questions:

- *How does AI and I4.0T assimilation influence sustainability performance across economic, social, and environmental dimensions;*
- *What roles do technological capability and organisational agility play as mediating mechanisms in the relationship between AI and I4.0T assimilation and sustainability performance outcomes; and*
- *What paradoxes or tensions arise with assimilation of AI and I4.0T into organisational operations.*

These questions drive the study's objectives, which are to evaluate the impact of AI and I4.0T assimilation on sustainability performance, assess the mediating effects of technological capabilities and organisational agility and identify the paradoxes and tensions associated with AI and I4.0T transformation. Together, these aims, research questions, and objectives establish a coherent foundation for analysing the mechanisms through which digital technologies impact sustainable supply chain performance.

4.2.5 Structure of the Paper

The rest of the paper is organised as follows: Section 2, presents a synthesis of the literature on the intersection of digital technologies and sustainability in supply chain management as well as the paradox of technology adoption and sustainability. Section 3 discusses the theoretical foundations of the study and research hypotheses. Next, the research design including a review of operationalisation of the constructs, sampling, data collection procedure are presented in Section 4. The statistical analyses and the discussion of the results

follow in Sections 5 and 6 respectively. The study concludes with the implications of the results for theory and practice, limitations of this study and future research directions.

4.3 Literature Review

4.3.1 Digital Transformation in Supply Chains

In the contemporary business environment, market success has gone beyond price and quality to include the way organisations manage their planning, procurement, manufacturing, storage and sales processes as the key determinants of market success (Mohsen, 2023). Competition increasingly occurs at the supply chain level rather than between individual firms (Poluha, 2016) driving organisations to enhance supply chain performance (Genovese *et al.*, 2017). In response, organisations are upgrading operations towards more intelligent, flexible and agile systems suited for global and dynamic environments (Zhong *et al.*, 2017).

Digital transformation refers to the use of digital technologies to fundamentally reshape organisational operations, value creation and stakeholder engagement (Robertsone and Lapiņa, 2023; Vial, 2019)). This represents a shift from linear models to interconnected, data-driven ecosystems that improve visibility, efficiency and sustainability (Dubey *et al.*, 2017; Bai *et al.*, 2020). The digital revolution in supply chains is not merely about adopting new technologies but fundamentally reimagining how value is created, delivered, and captured across global networks (Verhoef *et al.*, 2021; Queiroz *et al.*, 2019).

The rise of AI and Industry 4.0 (I4.0) has accelerated this shift (Min, 2010; Toorajipour *et al.*, 2021). I4.0 integrates cyber-physical systems, IoT, cloud and cognitive computing to enhance automation, transparency and coordination (Kagermann, 2014; Schwab, 2016). Supporting technologies include Blockchain (Dolgui *et al.*, 2020) ; Cloud Computing (Ivanov, Dolgui and Sokolov, 2022a); the Internet of Things (IoT) (Li, Xu and Zhao, 2015); Big Data (Wamba *et al.*, 2015); Additive Manufacturing (Ivan and Yin, 2017); Radio Frequency Identification (RFID) (Unhelkar *et al.*, 2022), Robotic Process Automation (RPA)(Lacity and

Willcocks, 2016), Simulation (de Paula Ferreira, Armellini and De Santa-Eulalia, 2020), and Drones (Rejeb *et al.*, 2021).

Despite these advances, organisations often fail to realise full value due to limited assimilation. While adoption reflects initial implementation, assimilation involves embedding technologies into routines and strategy (Olan *et al.*, 2022; Cooper and Zmud, 1990). Persistent "assimilation gaps" highlight the disconnect between adoption and effective use (Fichman and Kemerer, 1997; Purvis, Sambamurthy and Zmud, 2001). Prior research identifies leadership, infrastructure, strategy and coordination as key drivers (Armstrong and Sambamurthy, 1999; Chatterjee *et al.*, 2021), yet existing frameworks remain focused on general business processes with limited attention to sustainability implications (Sabherwal and King, 1991).

4.3.2 Supply Chain Sustainability

The most common viewpoints of sustainability in supply chain operations and management stem from either equating sustainability to sustainable developments as defined by the Brundtland Commission's influential report to mean, 'the ability to meet the needs of the present without compromising the needs of future generations' (Brundtland Commission, 1987) or the Triple Bottom Line view of social, economic and environmental dimensions as espoused by Elkington (1997). It has evolved from voluntary initiatives to a core organisational requirement driven by regulatory and stakeholder pressures (Seuring and Müller, 2008; Genovese *et al.*, 2017)

Supply chains play a central role in sustainability due to their influence on resource flows and operational practices (Ashby, Leat and Hudson-Smith, 2012). Studies have identified several factors driving the integration of sustainability in supply chains (Ben-Daya, Hassini and Bahroun, 2019). Key drivers include consumer awareness (Badghish and Soomro, 2024), ESG-focused investment (Spiliakos, 2018), regulatory pressures, cost efficiency (Carter and Dresner, 2001), reputation and brand image (Zailani *et al.*, 2012), risk management (Giannakis

and Papadopoulos, 2016). However, implementation remains challenging. High upfront costs, limited visibility across multi-tier supply chains and difficulties in measuring impacts hinder progress (Bratt, Sroufe and Broman, 2021; Wognum *et al.*, 2011; Ahi and Searcy, 2015)

4.3.3 The promise of AI and I4.0T for sustainability

AI and I4.0T are widely viewed as enablers of sustainability through improved efficiency, transparency and resource optimisation (Stock and Seliger, 2016). They enhance economic performance (Ghobakhloo, 2020; Beltrami *et al.*, 2021; Antony, Sony and McDermott, 2023), support social outcomes such as workplace safety (Müller, Kiel and Voigt, 2018; Kamble, Gunasekaran and Gawankar, 2018) and enable environmental monitoring and optimisation (Oztemel and Gursev, 2020).

The impact of digital technologies and the relationship between AI and I4.0T and sustainability has been of great interest to both practitioners (Beltrami *et al.*, 2021). The literature, however, presents two contrasting perspectives. On one hand is a more popular optimistic view in which studies position AI and I4.0T as powerful tools for advancing sustainability goals. This dominant view highlights benefits such as improved efficiency, reduced waste, enhanced transparency and new business models (Dalenogare *et al.*, 2018; Wamba and Queiroz, 2020; Saberi *et al.*, 2018). These technologies generally contribute to the accomplishment of the Sustainable Development Goals (SDGs (Vinuesa *et al.*, 2020).

In contrast, the more critical minority view highlights unintended environmental, economic, and social consequences of AI and I4.0T for sustainability. These include technostress and information overload (Pirkkalainen and Salo, 2016) broader risks such as cyber vulnerability and resource consumption (Gimpel and Schmied, 2019) environmental costs of AI infrastructure (Strubell, Ganesh and McCallum, 2020) Social concerns include surveillance, reduced autonomy and algorithmic management (Zuboff, 2019; Cirillo *et al.*, 2021; Gmyrek, Berg and Bescond, 2023)(Zuboff, 2019; Cirillo et al., 2021; Gmyrek et al.,

2023). Lifecycle impacts and hidden labour exploitation further complicate sustainability claims (Crawford and Joler, 2018)

4.3.4 The Paradox of Technology Adoption

The integration of AI and I4.0T introduces persistent tensions between efficiency and sustainability. While these technologies offer control and optimisation, they can also generate uncertainty, dependency and unintended consequences (Mick and Fournier, 1998; Brix-Asala *et al.*, 2018) These tensions are not merely implementation challenges that can be resolved once. Instead, they are persistent contradictions that require ongoing navigation (Dieste, Sauer and Orzes, 2022). Paradoxes are "contradictory yet interrelated elements that exist simultaneously and persist over time" (Smith and Lewis, 2011).

Several key paradoxes emerge with the integration of AI and I4.0T. For instance, Efficiency gains may increase overall consumption resulting in the J*evons Paradox* (Binswanger, 2001; Herring and Roy, 2007). With the *Automation versus Employment Paradox*, automation improves productivity but risks job displacement and reduced work quality (ILO, 2018; Gmyrek, Berg and Bescond, 2023). Similarly, with some AI and I4.0Ts, a *Transparency versus Privacy Paradox* can arise where technologies that enhance transparency may simultaneously raise privacy concerns (De Cremer, Nguyen and Simkin, 2017).

Again, as AI and I4.0T develop paradoxes continue to emerge. Such paradoxes include *Accuracy versus Energy Paradox* involving trade-offs between accuracy and energy consumption in AI system Mill, Garn and Ryman-Tubb (2022) *Innovation versus Obsolescence Paradox* arising from the impact of AI and I4.0T on existing systems. Innovations like AI and I4.0T, though vital for sustainability contribute to shorter product life cycles, increased electronic waste, and accelerated resource extraction (Müller, Kiel and Voigt, 2018; Chiarini, 2021). Furthermore, with the *Intelligence versus Opacity Paradox* the sophistication of AI systems and its complex, multi-layered structures that enable pattern recognition capabilities

could obscure the reasoning process. The learning and pattern recognition abilities of AI lead to a lack of clarity that masks the reasoning process as the intricate multi-layered structures complicate critical elements of validation (Lipton, 2018). This lack of clarity could complicate the understanding and scrutiny of sustainability claims. For instance, ESG scoring and environmental risk assessments might rely on opaque AI algorithms that include biases or inaccuracies that could potentially diminish accountability (Morley *et al.*, 2021).

Overall, these paradoxes illustrate the complex nature of real-world systems, emphasise the pressures of applying technological solutions to sustainability challenges. and reinforce the need for a balanced, “both/and” approach to managing competing (Smith and Lewis, 2011).

4.4 Development of Conceptual Model and Hypotheses

Having established the conditions and mechanisms through which adoption occurs in Chapter 3, this chapter addresses the theoretically distinct question of what happens after adoption. Specifically, it examines how the progressive deepening of AI and I4.0T integration into organisational processes generates measurable sustainability outcomes. This transition from adoption to assimilation to impact requires a different theoretical architecture than the adoption stage, one that explains not the decision to adopt but the organisational transformation that follows. At the assimilation stage, organisational learning and institutional diffusion explain why adoption does not automatically deepen into integration. Assimilation develops through accumulated experience, routine formation and progressive embedding in decision processes (Fichman and Kemerer, 1997). Institutional pressures, competitive, normative and regulatory, further drive diffusion beyond initial adoption (Chatterjee et al., 2002).

4.4.1 Theoretical Foundation

The study integrates two complementary theoretical perspectives, Dynamic Capabilities Theory (Teece, Pisano and Shuen, 1997) and Tripple Bottom Line (Elkington, 1998), to develop its conceptual model. The Dynamic Capability Theory provides the core

explanatory logic for how organisations sense opportunities, seize them through capability development, and reconfigure resources in response to changing environments. The Triple Bottom Line framework complements this and structures the assessment of sustainability outcomes across economic, environmental and social dimensions. Applied to AI and I4.0T, this implies that adoption and assimilation generate sustainability value only when organisations develop the capabilities to interpret technological opportunities, embed them into processes and continuously adapt operations as conditions evolve.

4.4.1.1 Dynamic Capabilities Theory

Dynamic capabilities theory has its roots in and extends the Resource-Based View (RBV). However, Teece, Pisano and Shuen (1997) extend the RBV and describe dynamic capabilities as an organisation's ability to integrate, build and reconfigure internal and external competencies in response to rapidly changing environments. They comprise three key activities: sensing to identify opportunities and threats through environmental scanning; seizing involving mobilising resources to act on these opportunities through investments and business model innovation and transforming to realign organisational structures and strategies to maintain coherence especially when adopting new or disruptive business models (Teece, 2018).

The selection of Dynamic Capabilities Theory (DCT) as the theoretical framework for explaining the assimilation-to-sustainability relationship was considered and justified against other credible alternatives. Though DCT is grounded in and extends the Resource-Based View (RBV) (Barney, 1991), RBV only explains performance through valuable and inimitable resources. It cannot account for divergent sustainability outcomes among organisations with similar AI and I4.0T resources, especially in a dynamic environment where technologies and sustainability requirements continuously evolve. What drives performance is not possession but reconfiguration, which RBV does not theorise but DCT does. Similarly, Absorptive capacity theory (Cohen and Levinthal, 1990) explains variation in knowledge uptake but is

limited to acquisition and exploitation. It does not capture the broader process of organisational restructuring required to respond to sustainability pressures, including redesigning processes, reconfiguring supply chain relationships and adapting strategic orientation. In relation to Institutional theory (DiMaggio and Powell, 1983), operationalised in this study through TOE environmental factors, it explains adoption via mimetic, normative and coercive pressures but cannot explain why organisations facing similar pressures achieve different performance outcomes. DCT fills this gap by focusing on the capability differences that determine whether adoption translates into sustained performance advantage. DCT is therefore selected because it uniquely explains how organisations sense sustainability opportunities created by AI and I4.0T, seize them through capability development and reconfigure processes in response to evolving demands. This dynamic, process-oriented logic makes it the most appropriate framework for explaining the assimilation-to-sustainability relationship. While its human-centred assumptions require qualification in the context of increasingly autonomous AI systems, it provides the most coherent theoretical foundation for this study within conventional organisational assumptions.

4.4.1.2 Triple Bottom Line (TBL) Framework

Organisations are under tremendous pressure to develop and incorporate sustainability solutions not just within their boundaries but particularly across the supply chain network. This trend is driven by the availability of information and stakeholders' heightened awareness of environmental and social issues and their increased interest and concern for the development and use of products (Saeed and Kersten, 2019). Sustainability is defined by the Brundtland Commission (1987) report as "development that meets the needs of the present without compromising the ability of future generations to meet their needs." Since the report's publication, more attention has been drawn to Corporate Social Responsibility (CSR) as an important governance priority (Hussain, Rigoni and Orij, 2018). Despite the attention given to

it and organisations taking it as a goal, measuring the extent of an organisation's sustainability can still be challenging. Elkington (1997) introduced a contemporary approach to CSR by highlighting and advocating for equal consideration of triple impact of the economic, environmental and social dimensions of sustainability on organisational performance, contending that for organisations to accurately assess the full cost of its activities it must measure performance across all three areas of *people, profit and planet*. The triple bottom line approach enables organisations align their goals with the environmental and social realities of their environment and thereby strengthen their capacity to navigate the changing market dynamics.

In this context, Profit which reflects the economic dimension goes beyond the usual financial metrics of profitability, cost efficiency, market share and sales revenue to include factors like economic and operational business impact on the society like job creation, fair wages, and economic stability (Chabowski, Mena and Gonzalez-Padron, 2011). The People aspect addresses the social dimension by emphasising the effect of the organisation's activities on its employees, customers and communities where it operates. Social sustainability considers safe working conditions, fair labour practices, impact organisation's activities on the local community as well as the organisation's involvement in addressing societal issues like human rights, education and health. Planet represents the environmental dimension of sustainability. This aspect has recently been the main focus of attention from academics and professionals alike (Seuring and Müller, 2008). The environmental dimension emphasises the effects of the organisation's activities on the environment. It considers the use and conservation of resources, minimising emissions, reducing waste and protecting ecosystems such as efforts to reduce carbon footprints, use sustainable materials, and manage waste responsibly.

4.4.2 Conceptual Model

Building on emerging literature at the intersection of AI and I4.0T and sustainability and informed by the Dynamic Capabilities and Triple Bottom Line theories, this study presents the research model illustrated in Figure 4.1.

The model proposes that:

- AI and I4.0T assimilation, the process by which technologies fully integrated, routinised and embedded into organisational processes, directly influences supply chain sustainability performance.
- This relationship is mediated by two core internal capabilities, namely:
    - Technological capability, referring to the firm's capacity to implement, adapt, and scale digital tools.
    - Organisational agility, referring to the firm's ability to sense, respond to and recover from change.

Through the incorporation of these elements, the model accounts for both direct and indirect pathways linking AI and I4.0T assimilation to sustainability outcomes. By focusing on the depth of integration rather than initial adoption, it highlights how technological and organisational capabilities shape the potential for sustained, long-term improvements in supply chain sustainability performance. Figure 4.1 illustrates the conceptual model

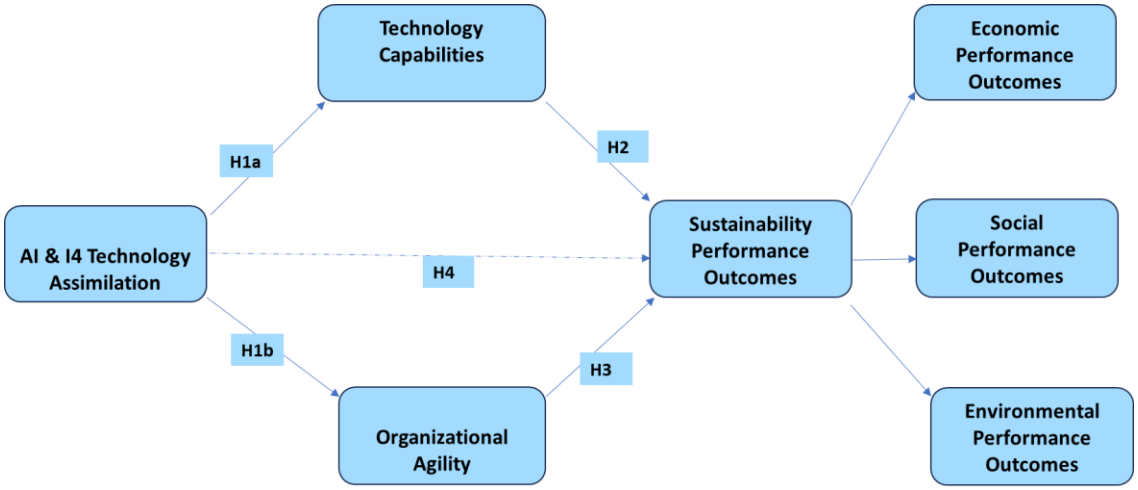

Figure 4.1 Conceptual Model

4.4.3 Hypothesis Development

4.4.3.1 Technology Assimilation in Supply Chains

Fichman and Kemerer (1999) draw attention to the distinction between *diffusion* and *assimilation*, stating that while diffusion considers the spread of technology across the organisation, assimilation applies to a wider scope covering the initial awareness and knowledge of the technology to adoption, integration and full utilisation. Technology assimilation generally encompasses the process by which organisations adopt, implement and embed advanced technologies into their operations, processes and routines (Purvis, Sambamurthy and Zmud, 2001). AI and I4.0T assimilation involve their effective integration into organisational processes, workflows and decision-making structures. The adoption and assimilation of digital tools should align with organisational capabilities, routines and long-term strategic goals. Going beyond mere adoption, assimilation encompasses the complete integration into organisational processes (Zhu *et al.*, 2006). Gallivan (2001) notes that infusion and routinisation differentiate assimilation from adoption as evidenced in range and scope of utilisation in the organisation. Again, digital transformation driven by AI and I4.0T is achieved through an iterative process where organisations reorganise their processes, resources and capabilities (Vial, 2019). Significant performance improvements are only achieved when AI

and I4.0 tools are embedded into organisational strategy, decision-making and core operations (Martinez-Caro *et al.*, 2020). Effective assimilation of these digital tools fuel intelligent automation, enables predictive maintenance and enhance supply chain optimisation. AI and I4.0T provides opportunities for supply chains to improve communication, acquire and transmit data that enables effective decision-making, enhancing supply chain performance through internal integration of its processes and integration externally with vendors and customers (Ben-Daya, Hassini and Bahroun, 2019).

The assimilation of AI and I4.0T is essential for building technological capabilities within organisations. As organisations increasingly integrate these tools into their operations, they invest in technical expertise, upgrade infrastructure and develop innovation competencies. Again, the complexity and interconnectedness of AI and I4.0T systems require the development of new skills in areas such as data analytics, system integration and technology management. Previous research provides evidence of this link as Wamba *et al.* (2017) show that adopting Big Data Analytics significantly enhances firms' technological competencies while Ghobakhloo (2020) argues that I4.0T can contribute to bridging the skill gap and establish a foundation for advanced capabilities that enable digital transformation. Similarly, assimilating AI requires the purposeful orchestration of AI resources like data, knowledge, algorithms and information systems that organisations need to build expertise in machine learning, data science and algorithmic thinking (Peretz-Andersson *et al.*, 2024). These competencies are not only key to expanding the organisation's technological capability but also vital for achieving sustained improvements in supply chain sustainability performance, therefore this study hypothesises the following:

H1a: AI and I4.0T assimilation positively influences Technological capability

The assimilation of AI and I4.0T strengthens organisational agility by enabling real-time data processing, predictive analytics and automated decision-making. These technologies

enable organisations detect market shifts earlier, process information more effectively and respond to environmental uncertainties with greater speed and accuracy. Both empirical and review studies confirm this relationship. For instance, Mrugalska and Ahmed (2021) find that technologies such as smart manufacturing, IoT, cyber-physical systems, Big Data Analytics, and cloud computing significantly enhance various forms of organisational agility. Similarly, in a case study of Smart and Agile Manufacturing Framework, Jadoon *et al.* (2020) demonstrate how combining traceability mechanisms, smart manufacturing and agile principles in automotive operations leads to increased flexibility, adaptability to changing customer feedback and improved responsiveness. Further, Lu (2017) argues that I4.0T especially, IoT and Big Data Analytics, foster unprecedented levels of operational flexibility and responsiveness. Likewise, AI applications such as machine learning and predictive analytics allow organisations anticipate market trends and adjust strategies proactively rather than reactively. Automation further contributes to agility by shortening decision-making and execution cycles. For example, smart manufacturing systems can automatically modify production settings in response to demand fluctuations or supply chain disruptions, allowing organisations to adapt with minimal delay (Fragapane *et al.*, 2022; Oluyisola *et al.*, 2022). Taken together, the above arguments support the following hypothesis:

H1b: The assimilation of AI and I4.0T positively influences Organisational agility

4.4.3.2 Sustainability Performance Outcomes

The debate on whether adopting new technologies improves organisational performance has been ongoing for some time (Brynjolfsson, 1993). Despite the efficiency, smarter decisions, and new ways of working promised by AI and I4.0T digital tools, the evidence suggests the relationship is far more complex and that simply adopting technology is rarely enough (Olan *et al.*, 2022). What matters is assimilating by how well these technologies are embedded into processes, culture and strategy (Zhu *et al.*, 2006). Studies show that

assimilation matters because organisations gain most when technology is absorbed and not just adopted (Martinez-Caro *et al.*, 2020). Similarly, earlier work by Fichman (2001) identified assimilation as a factor in the success of business-to-business (B2B) platforms, showing that full diffusion and routine use are necessary for organisations to reap the rewards of the technology. Furthermore, assimilation makes the difference because it links technology to capabilities such as agility, innovation and learning which are hard for competitors to copy (Cohen and Levinthal, 1990; Martinez-Caro *et al.*, 2020).

Similarly, studies show that without full integration, initiatives such as AI-powered sustainability improvements remain fragmented and under-utilize (Fosso Wamba *et al.*, 2022). Sustainability outcomes are a central measure of the value derived from assimilating AI and I4.0T into supply chains. These outcomes are typically assessed across the triple bottom line (TBL): environmental, economic, and social dimensions. From an environmental standpoint, the integration of AI and related digital tools has been linked to improved emissions tracking, better energy use optimisation and enhanced waste management (Bai *et al.*, 2020). Kamble, Gunasekaran and Gawankar (2018) highlight how organisations that deploy I4.0T can reduce resource consumption. These effects are often amplified when digital technologies are combined, such as using IoT sensors with AI-based analytics to detect inefficiencies in real time. Economic outcomes on the other hand are particularly related to operational efficiency and cost savings, and are well-documented (Dalenogare *et al.*, 2018). For instance, Ghobakhloo *et al.* (2021) point out that supplier selection, inventory optimisation, and predictive maintenance are all processes that benefit from AI and I4.0T adoption. A monotonous and repetitive tasks are taken over by AI and I4.0T systems, employee wellbeing and motivation linked to workplace safety and human learning through human- machine interaction are some of the identified social sustainability performance outcomes (Bai *et al.*,

2020; Müller, Kiel and Voigt, 2018). On the strength of the foregoing the following hypothesis is therefore proposed:

H4: AI and I40 technologies assimilation positively influences sustainability performance

4.4.3.3 Mediating Effect through Technological Capabilities and Organisational Agility

In this study, technological capabilities are viewed as the organisation's ability to deploy, manage and continuously upgrade AI and I4.0T effectively while organisational agility is the organisation's ability to sense changes in the environment and respond rapidly through flexible and adaptable decision-making and processes (Overby, Bharadwaj and Sambamurthy, 2006; Tallon and Pinsonneault, 2011). This study considers technological capability and organisational agility as dynamic capabilities. According to Felsberger and Reiner (2020) the influence of AI and I4.0T across economic, social and environmental sustainability dimensions is mediated by the reconciliation of dynamic capabilities. This suggests that technological capabilities and organisational agility act as key enablers in the technology-sustainability relationship.

4.4.3.3.1 Technological Capabilities

In today's dynamic business landscape, organisations must be proficient at identifying, developing and accessing technological opportunities. They need to capture value from these opportunities by continuously renewing and transforming their organisational routines (Ellström *et al.*, 2021). The successful integration of these technologies and their impact on performance depends more on technological capability rather than on the technologies themselves (Bhatt and Grover, 2005). To derive value from the new technologies or algorithms, organisations require technological expertise and competencies to understand these tools effectively. Since technologies are often tacit and not easily replicated or transferred between organisations, the transfer process focuses on learning and developing unique competencies (Handoko, Nursanti and Harmanto, 2016). An organisation's distinct competencies include the

abilities, procedures, technologies and processes that facilitate differentiation and provide a competitive advantage because they are typically difficult for competitors to replicate. Technological capabilities have been recognised as one of the distinct competencies that can enhance organisational performance (Coombs and Bierly III, 2006). Mikalef *et al.* (2020) describe IT enabled capabilities as a "firm's ability to leverage its IT resources and IT competencies, in combination with other organisational resources and capabilities, in order to address rapidly changing business environments". These capabilities include those shaped by technology and those that influence how technology is utilised to create a competitive edge and improve organisational performance (McLaughlin, 2017). Additionally, Archibugi and Coco (2004) argue that the economic and societal impact of various waves of technological innovation is amplified by an organisation's technological capabilities, which enable successful integration. Besides, the study by Bharadwaj (2000) provides empirical evidence that technological capabilities have positive impacts on organisational performance. On the strength of the above, this study proposes that:

H2: Technological capabilities mediate the relationship between AI and I4.0T assimilation and sustainability outcomes

4.4.3.3.2 Organisational Agility

The constant change in contemporary business environment is fast becoming the new normal (Desalegn *et al.*, 2024). As the frequency of sustainability changes become more significant and the customer demands increasingly dynamic, achieving superior business performance constitutes a critical objective for organisations. Specific organisational capabilities could enable them exploit these changes and turn them into opportunities by responding appropriately to the rapidly changing conditions in the environment. Hatzijordanou, Bohn and Terzidis (2019) identify agility as a key capability that enables the quick exploitation of business opportunities. Agility in the context of business was initially expressed by Brown

and Agnew (1982) as ‘’the capacity to react quickly to rapidly changing circumstances’’. Since then, organisational agility has been viewed from various perspectives by different authors as presented in existing literature. Meade and Sarkis (1999) conceptualize it as a paradigm while Zhang and Sharifi (2007) consider agility as a ‘manufacturing strategy’ although the more common approach conceptualizes it as a capability. According to Sherehiy, Karwowski and Layer (2007), the concept of organisational agility is based on the related concepts of adaptability and flexibility which stems from the performance characteristics of agile organisations. Tallon and Pinsonneault (2011) assert that organisational agility is the organisation’s ability to rapidly change or adapt in response to changes. The literature commonly highlights three connected forms of agility: *operational agility,* which signifies how easily and quickly an organisation can adjust its internal processes to meet changing condition (Tallon, 2008) *customer* a*gility*, reflects how well an organisation can respond to market shifts by updating its offerings and internal activities to retain and deliver added value to customers (Lu and Ramamurthy, 2011) and *partnering agility* which involves making effective use of resources and relationships with external stakeholders such as suppliers, contract manufacturers, logistics partners and distributors, through collaboration and alliances (Felipe *et al.*, 2020)

The implementation and assimilation of AI and I4.0T allows organisations make necessary changes to management approaches and develop new capabilities to perform in this dynamic environment, making them flexible and agile in responding to rapidly changing conditions with real-time planning and control (Ghadge *et al.*, 2020). Ciampi *et al.* (2022) conclude that digitalisation and agility have a reciprocal effect on each other. As firms digitalise operations, they tend to become more agile in how they respond to disruptions, shifts in demand, and sustainability pressures. Further, Overby, Bharadwaj and Sambamurthy (2006) confirm that an organisation’s agility is impacted by the level of investments in information technologies,

serving as a foundation for agility (Sambamurthy, Bharadwaj and Grover, 2003). When viewed across the sustainability dimensions, to navigate changes in the economic (i.e. costs, resources, productivity, product complexity), social aspects (customers' demands, changing markets and organisational cultures), and environmental dimensions (waste management, resource consumption, and impact on climate) of contemporary business environment, organisations need to be agile and build considerable resilience, organisational capabilities and flexibility that allow for rapid responses to these challenges (Ben-Daya, Hassini and Bahroun, 2019). Extending this perspective to the adoption of AI and I4.0T, organisational agility can be considered as an essential mechanism that turns these advanced technologies into sustained improvements in supply chain sustainability performance. Based on the above discussion, the following hypothesis is proposed:

H3: Organisational agility mediates the relationship between the assimilation of AI and I4.0T and supply chain sustainability performance.

4.5 Methodology

4.5.1 Research Process

Leedy and Ormrod (2015) explain that research goes beyond gathering or summarizing information. It is a systematic and repeatable process of collecting, analysing, and interpreting data to generate new insights and a deeper understanding of a phenomenon. The research methodology provides the structure needed to carry out a study, address the research questions, and meet the study's objectives. This chapter outlines the methodological steps taken to investigate the influence of AI and I4.0T adoption and assimilation on sustainability performance through the mediation of organisational agility and technological capability. Guided by Saunders et al.'s (2019) research onion model, this chapter presents the philosophical foundations, research strategy and design, data collection methods, and analytical procedures used in this study. Figure 4.2 illustrates the research design process.

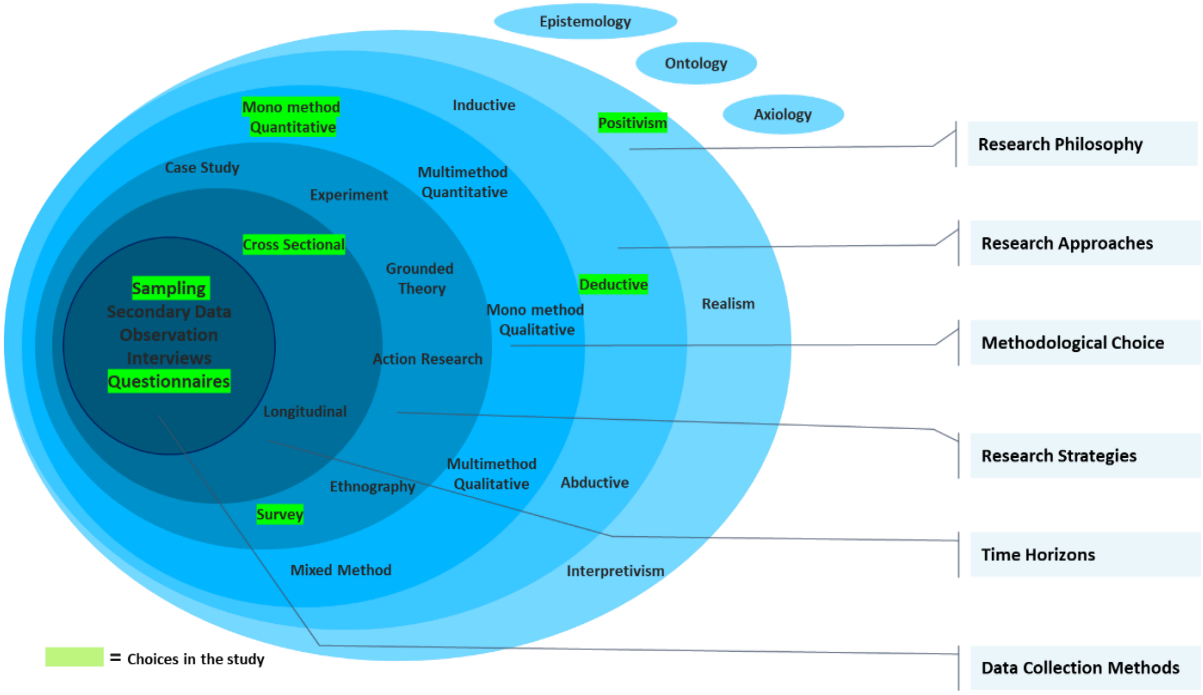

Figure 4.2 Research Process Onion (Adapted from Saunders et al 2019)

4.5.1.1 Research Philosophy

With multiple philosophical approaches available in research, Holden and Lynch (2004) advise that ideally, the researcher's philosophical perspective and the social science phenomenon under examination should guide the choice of methodology rather than by a rigid attachment to methodology. As such, to comprehensively address the primary research question, this study adopts a quantitative approach. This approach enables the statistical analysis of the various relationships between AI and I4.0T adoption and assimilation, technological capability, organisational agility and sustainability performance outcomes. In line with the quantitative approach, a positivist paradigm and objective epistemology is adopted to discover knowledge about AI and I4.0T assimilation on sustainability performance outcomes impartially and objectively. The positivist paradigm asserts that reality exists independently of human perception and can be objectively measured (Alharahsheh and Pius, 2020; Scotland, 2012). This viewpoint is particularly relevant to technology adoption and assimilation, as organisational decisions can be quantified and examined through observable behaviours and measurable results. Positivism is suitable for this study as it enables an objective assessment of

the impact AI and I4.0T assimilation on sustainability performance outcomes and the identification of the mediating effect of organisational agility and technological capability through statistical techniques. This philosophical approach is in accord with the study's quantitative emphasis and supports the use of structured data collection and statistical analysis methods. Orlikowski and Baroudi (1991) and Alavi and Carlson (1992) indicate that positivism is in line with the approach of the broader information systems field, where it is the dominant philosophical stance.

4.5.1.2 Research Approaches

A deductive research approach enables the movement from theory to empirical testing (Saunders, Lewis and Thornhill, 2009). With the extant theories on technology adoption and assimilation, dynamic capabilities and sustainability there is a considerable theoretical base that provide a solid foundation for hypothesis development. This approach begins with existing theoretical frameworks: Dynamic Capabilities theory, The Triple bottom-line Sustainability theory, to develop testable hypotheses about technology assimilation and sustainability performance outcomes. This approach contributes to the validation and refinement of existing models by enabling the study to test established theories of Dynamic Capability and Triple bottom line in a new context of mediation.

4.5.1.3 Methodological choices

Researchers have the choice of collecting the data for studies in two general forms as either quantitative or qualitative. The focus for quantitative research is on amounts or quantities of one or more variables of interest. These variables are measured numerically through methods such as tests, questionnaires or rating scales. By contrast, qualitative research seeks to explore perspectives and contexts by examining attributes and meanings which cannot be easily reduced to numbers. This study employs a mono-method quantitative design, using a single data collection technique followed by statistical analysis (Saunders, Lewis and Thornhill,

2009). This choice aligns with the research objectives of identifying and measuring relationships between AI and I4.0T adoption and assimilation and sustainability performance outcome mediated by organisational agility and technology capability.

4.5.1.4 Research strategies

The study selected a survey strategy as the primary research method to enable systematic data collection from a large sample of organisations. Survey research involves collecting data from a sample representing the population of interest and is characteristically quantitative, structured, with standardised information defining and describing the variables (Malhotra and Grover, 1998). This choice offers the flexibility of different methods of recruiting participants and collecting data with a variety of instrumentation methods (Ponto, 2015). Surveys are a common form of data collection in social sciences and are particularly suitable for examining relationships between variables. They allow for statistical generalisation of findings to the broader population. The survey strategy has a major advantage of offering the potential to collect vast amount of data with minimal expense of time, effort, or money (Melnyk *et al.*, 2012). This study took the advantage offered by survey to systematically collect data from a large sample that will enable statistical generalisation. Moreover, Choudrie and Dwivedi (2005) observed that surveys were one of the more predominantly used methods for studying technology adoption.

Regardless of the advantages, this study acknowledges that respondents may not always provide thoughtful responses to the survey questions and may agree or disagree with items regardless of the content or attempt to follow the herd or be deviant.

4.5.1.5 Time Horizons

Adopting a cross-sectional design this study collected data at a single point in time to provide a snapshot of current patterns of technology assimilation, levels of organisational agility and technological capability and sustainability performance status. While longitudinal

studies could provide insights into adoption and assimilation processes over time, resource constraints and the study's aim to identify the correlations among these factors within the population makes a cross-sectional design a valid choice.

4.5.1.6 Data collection Techniques

4.5.1.6.1 Sampling and Sample Size

It may be unrealistic to expect to collect data from the entire population of registered business organisations in Nigeria, as it is very unlikely all companies, will respond even if they were all contacted. However, a subset of the population can provide reliable insights into the larger group (Malhotra and Birks, 2007). The associated challenges of gathering data from the entire population, which are usually unfeasible or excessively demanding in terms of time, financial resources and other human capital, are addressed by sampling (Forza, 2002). Sampling enables quicker and cost-effective collection of data while enhancing the accuracy of the study's results (Cooper, Schindler and Sun, 2003). After considering both theoretical and practical implications of the two primary categories of sampling methods (*probability* and *non-probability)*, the study opted for random probability sampling. As this sampling method is based on random selection of participants, all members of the population have equal chance of selection (Babbie, 2020). Also, this sampling process is representative and reduces the risk of bias while increasing the generalisability to the target population sampling. However, some of the survey participants were also recruited by referral.

In terms of sample size, there still remains varying opinions on what the sample size should be, especially when using structural equation modelling (SEM). Costello and Osborne (2005) suggest that rigid rules regarding sample size for factor analysis have become less common. Similarly, Bagozzi (2010) noted that the rules of thumb concerning sample size can be quite arbitrary while Iacobucci (2009) regards the requirement for sample sizes greater than 200 as "simplistic "and further asserts that "samples of 50 to 100 can be plenty." In line with

Bagozzi (2010) recommendation of a sample size above 100 and Iacobucci (2009) further advises that where the measurement has at least three indicators per factor and has achieved good reliabilities with the structural paths that are not overly complex, samples size of 50 or 100 can be utilised. Therefore, the study considered the sample size of 196 adequate for the planned analyses.

4.5.1.6.2 Measurement and Operationalisation

The credibility of research findings rests on the foundation of replicability. Replication is a crucial aspect of research that instils confidence in the reliability and generalisability of findings by allowing for their verification and validation (Viera, 2025). The success of replication relies heavily on the accurate measurement and operationalisation of research constructs. Proper measurement and operationalisation of variables are essential, as they enable the achievement of research aims and objectives. Measurement involves using specified rules to determine the characteristics or attributes of objects by assigning values such as numbers or symbols to them (Allanson and Notar, 2020).

The study operationalised the abstract concepts of assimilation, organisational agility, technological capability and sustainability performance into measurable observations. To aid empirical observation, specific measures that are accurate representations of technology assimilation, technological capability, organisational agility and sustainability performance were developed. Recognising the assertion of Bhandari (2023) that operationalisation can at times be reductive, causing a lack of universality due to underdetermination MacKenzie, Podsakoff and Podsakoff (2011) six stage approach formed the guide for the operationalisation and development of measurement scale in this study. Further, following the recommendation of Bryman and Bell (2007), this study considered representation of technology assimilation, technological capability, organisational agility and sustainability performance in earlier literature to develop the conceptual definition of the construct and also selected measurement

scales that had been previously validated in earlier research to assess its model constructs. Items TAS1-TAS5, used to measure AI and I4.0T assimilation, were adapted from Wamba (2022) and Liu *et al.* (2016). Technology assimilation is operationalised following (Chatterjee, Grewal and Sambamurthy, 2002) at the routinisation and infusion stages, capturing the extent to which AI and I4.0T are embedded in workflows, decision routines, and organisational processes. It is measured using five frequency-based items (Never = 1 to Always = 5) reflecting use across business processes, functional areas, strategic decision-making, operations, and management practices. They are as follows:

TA1*: AI and/or I4.0T tools are used across the organisation's business processes;*

TA2*: AI and/or I4.0T tools are used in many functional areas;*

TA3*: AI and/or I4.0T tools are used for strategic decision-making across many functional areas;*

TA4*: AI and/or I4.0T tools are used for business operations across many functional areas; and* ***TA5****: AI and/or I4.0T tools are used for management practices including workflow organisation and performance tracking across many functional areas.*

While Dynamic Capabilities Theory conceptualises assimilation as deep institutionalisation within organisational routines, the measures primarily capture observable breadth and frequency of use. This reflects a theoretically grounded choice consistent with prior studies (Liang *et al.*, 2007). This study acknowledges this as a limitation inherent in survey-based measurement, where behavioural indicators provide the most accessible proxy for assimilation. Deeper institutionalisation may require longitudinal or qualitative approaches to capture more fully.

To evaluate the mediating roles of technological capability and organisational agility on the relationship between AI and I4.0T assimilation and sustainability performance, the scale for technological capability (TA) comprised seven items drawn from Wang *et al.* (2006) and Salisu and Abu Bakar (2019) while the organisational agility (OA) scale was based on items

from Tallon and Pinsonneault (2011). Finally, sustainability performance outcomes (SUS) were measured across the three sustainability dimensions of economic (ECS), social (SOS), and environmental (ENS) using items from the research by Harun, Hogset and Mwesiumo (2023). Table C1, Appendix C presents the full details of the measurement scales for all constructs.

4.5.1.7 Data Collection Procedure

4.5.1.7.1 Questionnaire

The choice for online questionnaire for primary data collection method is based on ease and flexibility provided for data collection used to evaluate the hypothesised relationships between technology assimilation, technological capabilities, organisational agility and sustainability performance outcomes and assess the boundaries of conceptual model's validity (Forza, 2002). With the questionnaire, the study ensured anonymity and minimised interviewer bias. This enhances overall validity and reliability while providing a cost-effective solution that allows for relatively simple data collection process that can be completed at users' convenience (Jere and Ngidi, 2020; Wu, Zhao and Fils-Aime, 2022). The questionnaire used multiple item 5-point Likert scale with a minimum of five responses per scale to ensure that a wide range of views are captured (Gehlbach and Artino Jr, 2018). The question types were varied in order to minimise the acquiescence bias common with the 'agree to disagree' type question (Suárez Álvarez *et al.*, 2018).

4.5.1.7.2 Pilot Testing

A pre-testing of the questionnaire was conducted to test the quality and appropriateness of the questionnaire instrument items and ensure its validity (Hair, 2009). The study adopted Forza (2002) suggestion for pilot testing by sharing the draft of the questionnaire across three distinct groups: academic (2), supply chain industry experts (2) and target respondents (2). The academics helped evaluate whether the questionnaire meets the study's objectives while supply chain industry experts helped to identify and eliminate questions that might reveal knowledge

gap in specific areas. Target respondents pilot offered feedback on all aspects that may influence the responses and the answers provided by the targeted respondents. The study incorporated the suggestion given to simplify and improve the clarity of the final questionnaire.

The Qualtrics online survey, published on 8 September 2024 and closed on 11 April 2025, was used for data collection. Although the survey went live early in September, the study faced a slow response rate, which made it necessary to keep the questionnaire open for an extended period. Participants were recruited from the Chartered Institute of Procurement and Supply (CIPS) Nigeria members database, LinkedIn.com database and author's professional contacts. These sources provided a unique avenue to engage a diverse range of respondents characterised by varying job titles, educational backgrounds, and geographical locations across Nigeria (Nguyen, Nguyen and Dang, 2022).

4.5.1.7.3 Integrated Survey Design

Data for this study and the adoption readiness study in Chapter 3 were collected using a single integrated survey administered to the same respondent pool between 8 September 2024 and 17 January 2025. This design reduced respondent burden and improved response rates, while reflecting the coexistence of adoption and assimilation in practice, where organisations simultaneously adopt some AI and I4.0T applications while assimilating others. This approach has implications. First. the models in Chapters 3 and 4 represent separate analytical frameworks applied to the same dataset. Again, the single-source, cross-sectional design increases exposure to common method bias. Although procedural and statistical controls were applied, this risk cannot be fully eliminated. However, the observed non-uniform patterns such as asymmetric mediation and differential capability effects, are not consistent with uniform method inflation. Third, the distinction between adoption readiness and assimilation is theoretical rather than temporal, as both were measured simultaneously. Longitudinal designs are needed to establish temporal ordering.

Participants were required to hold managerial positions or higher. This criterion is vital because individuals at this level, by virtue of their position, have the necessary knowledge and or are involved in the decision and implementation of organisational change processes such as AI and I4.0T adoption and assimilation. Invitations to participate in the online survey were distributed to 454 prospective participants using the Qualtrics platform as follows: 318 via LinkedIn, 109 through direct emails, and 27 by email forwards. Of the 342 responses received, 196 were deemed valid for data analysis after excluding duplicates, spurious entries and outliers.

4.5.2 Data Analysis Technique and Procedure

Data collected from the online survey was analysed using SPSS 28.0 and AMOS 26.0 software packages. Some key analysis carried out include the examination of the sample characteristics and the distribution of the variables, assessment of the internal consistency of the factor analysis both exploratory and confirmatory, structural equation modelling and mediation analysis,

4.6 Analysis and Findings

4.6.1 Preliminary Analysis

The purpose of the preliminary analyses is to ensure reduction of errors in model estimation prior to conducting structural equation modelling. It involves data screening, analysis of descriptives, factor analysis and reliability test.

4.6.1.1 Data Screening

Regardless, of the advantages of questionnaire data collection, it is well known that respondents may not always provide thoughtful responses to the survey questions and may agree or disagree with items regardless of the content or attempt to follow the herd or be deviant (DeSimone, Harms and DeSimone, 2015). This study considered a thorough review of data before the main analyses as fundamental to providing a foundation for the integrity of the

inferential statistics and reliable research analysis outcomes (Tabachnick and Fidell, 2013). As data quality can compromise the integrity of data analysis, the study ensured the suitability for analysis by screening collected data to address errors, inconsistencies and missing values. The following section outlines the preliminary analyses conducted to prepare the dataset.

4.6.1.1.1 Missing data Analysis

Missing data can arise from respondents failing to complete the survey, missing some sections of the survey. Little (2024) described missing data as a 'thorny problem in the statistical analysis' especially as missing data is usually not the principal focus in the development of data analysis procedures (Schafer and Graham, 2002). Missing data can add ambiguity and bias, reduce statistical power distort the validity of analysis results and lead to invalid conclusion. The main concern with missing data is how much is missing and in what pattern. It is less problematic when missing data do not exceed 5% and follows a random pattern. The results of Little's MCAR test (Little, 1988) carried out to determine whether the values were missing completely at random was not significant (χ^2 =831.582; df= 742 p = .012), suggesting that values were missing entirely at chance.

Missing data can be handled by deletion or imputation of estimated value (Tabachnick and Fidell, 2007). The study opted for imputation to limit the estimation of biased parameters and to preserve the sample size. The two most common imputation approaches are the Regression Based Imputation (RBI) and the Expectation Maximization (EM) algorithm. Both methods have different approaches, advantages and limitation. A comparison of the means from EM and RBI imputation results showed not much difference, however, this study opted for EM as it is considered better suited to handle models with latent variables (Malan *et al.*, 2020). Figure 4.3 presents the missing data comparison chart.

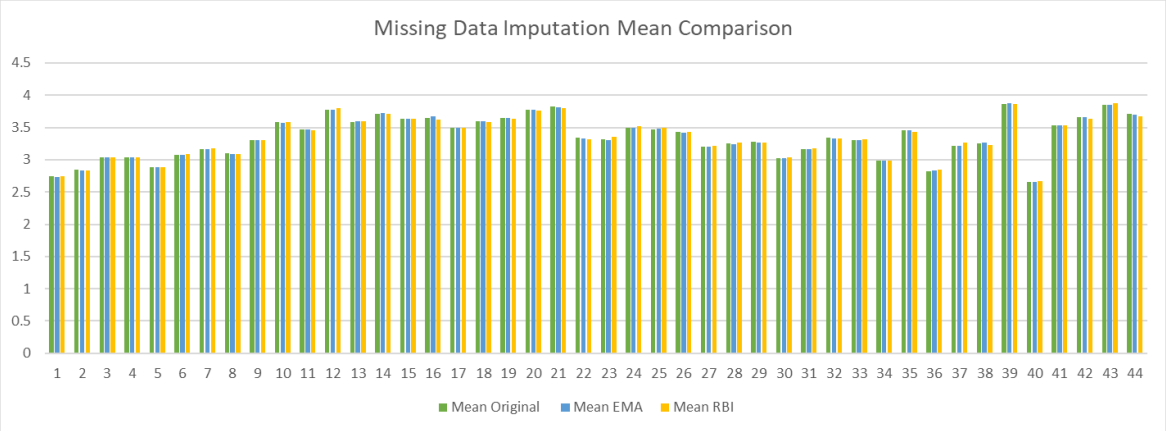

Figure 4.3 Missing Data Imputation Chart

4.6.1.1.2 Normality

As normality is a requirement for using parametric tests, the study conducted a normality assessment as part of the preliminary data checks. Using the Kolmogorov-Smirnov and Shapiro-Wilk tests the study performed normality tests on all observed variables. The Kolmogorov-Smirnov values (0.155 - 0.270) and Shapiro-Wilk values (0.855 - 0.924) indicated some level of deviations from normality. This outcome is not entirely unexpected being that Likert scale data are ordinal, naturally bounded and prone to violation of normality assumption (Field, 2018). Moreover, normality tests tend to be sensitive in samples larger than 30 (Kline, 2016). However, as the descriptive statistics, skewness and kurtosis, suggest the distributions are not severely non-normal. Using common guidelines of skewness between -2 and +2 and kurtosis between -7 and +7 (George and Mallery, 2010; Kline, 2016), all items fall comfortably within acceptable limits. Skewness ranged from -0.873 to 0.236, and kurtosis from -1.233 to 0.635, indicating no meaningful departure from normality.

Although the study observed some deviations from normality, SEM in AMOS can handle non-normal data through robust estimation and bootstrapped standard errors (Byrne, 2016; Bentler and Chou, 1987). Bootstrapping improves reliability by resampling the dataset to generate stable standard errors and confidence intervals (Efron and Tibshirani, 1994). Norman (2010) also notes that Likert-scale data can still be used in parametric analyses and

SEM, especially when supported by an adequate sample size, which helps offset normality issues (Hair *et al.*, 2019). Therefore, the study deemed the data suitable for SEM with no data transformation required.

4.6.1.1.3 Outliers

There are several definitions of outliers. Hawkins (1980) described an outlier as an observation that "deviates so much from other observations as to arouse suspicions that it was generated by a different mechanism". It has also been referred to as ''an observation (or subset of observations) which appears to be inconsistent with the remainder of that set of data'' (Barnett and Lewis, 1994). Irrespective of the definition, outliers can be detrimental to statistical analysis (Osborne and Overbay, 2004). Determining which data points are outliers can sometimes be subjective as in case of Likert scale data where the extreme response may represent genuine responses rather than spurious entries (Lewis, 2015). Some researchers have even suggested that outliers do not really exist in Likert scales (Gaskin, 2021b).

A visual evaluation for outliers conducted using boxplots and histograms revealed three outliers which were excluded. In addition, Mahalanobis distance calculated in SPSS flagged 16 cases. Further inspection of these cases showed no inconsistencies, contradictory responses or evidence of too quick or inattentive answering (Meade and Craig, 2012). The study considered these as valid responses indicating the respondents' perspective and were included to maintain the representativeness of the dataset (Osborne and Overbay, 2004).

4.6.1.1.4 Multicollinearity

Multicollinearity occurs when two or more independent variables are highly correlated. This blurs the individual effects of the independent variables, making it difficult to assess which variable is driving the effect (Farrar and Glauber, 1967). Multicollinearity increases the variances and standard errors of the regression coefficient estimates which affects the reliability of the statistical significance of the coefficients (Kim, 2019). As the main purpose of linear

regression analysis is not to assess interdependence, it is therefore important to ensure that data meets the multicollinearity assumption (Daoud, 2017).

There are several methods for testing for multicollinearity including: Tolerance, Variance Inflated Factor (VIF), Condition Index (CI), Correlation Analysis, Eigenvalues and Cooks Distance. This study considered Tolerance and VIF as they are closely related. Tolerance as an indicator of multicollinearity is estimated using the formula $\boldsymbol{1 - R^2}$, where $\boldsymbol{R^2}$ represents the coefficient of determination. This calculates the amount of variance in one independent variable not explained by the other independent variables. There is significant issue of multicollinearity where tolerance is less than 0.1 (Tabachnick and Fidell, 2013). On the other hand, Variance Inflated Factor (VIF) is the reciprocal of Tolerance and is calculated as $\mathbf{1/ (1 - R^2)}$. VIF indicates how much variance is inflated for each of the independent variables in a multiple regression model. Various acceptable thresholds for VIF have been proposed including a value of five (5) recommended by Rogerson (2019) and four (4) by Pan and Jackson (2008). However, it is generally accepted that a VIF above ten (10) is high and indicates severe multicollinearity (Hair *et al.*, 1995). This study adopts a VIF threshold of 10 because this corresponds with the tolerance threshold of 0.1.

The collinearity diagnostics results presented in Table C2, Appendix C shows no multicollinearity issues in the study's data as all values are well within the acceptable thresholds for: Tolerance at greater than 0.1(0.723, 0.452 and 0.499); Variance Inflated Factor values less than 10 (1.383, 2.211 and 2.005)

4.6.1.1.5 Common Method Bias

The study recognised the threat of common method bias considering that data on both dependent and independent variables were collected at the same time using the same instrument (Kock, Berbekova and Assaf, 2021). Method bias could influence the parameter estimates by inflating, and some cases deflating the relationships between variables (MacKenzie and

Podsakoff, 2012). This poses a risk to the validity of the research findings. Although there are varying views on the extent of bias caused by common method variance, this study considered it important and took cognizance of risk of bias both in design of the survey instruments and statistical control. In terms of design, firstly, the survey instructions were clear, avoiding technical jargons, abbreviations and ambiguous words, while ensuring anonymity of responses. Secondly, the independent and dependent variables were separated and a mix of different scale formats including reverse worded questions were used to collect the data (Kock, Berbekova and Assaf, 2021; Podsakoff *et al.*, 2003b; Podsakoff, MacKenzie and Podsakoff, 2012). Likewise, having collected data, statistical measures were also employed to evaluate common method bias. Herman's single factor test is one of the statistical controls employed to assess common method bias using SPSS. The test entails employing an unrotated solution exploratory factor analysis with extraction fixed for one factor. Where all the measured items loading on one factor accounts for more than 50% of the variance, common method bias exists (Podsakoff, MacKenzie and Podsakoff, 2012). In this study, the highest value of variance accounted for by a single factor equals 39.76%, indicating that common method bias is not present. Details of the results for the single factors test are provided in Table C3 Appendix C

4.6.1.2 Demographics of Participants

The sample consists of decision makers from various organisational levels, including executive leadership (CEOs and Managing Directors, 7.1%) and business owners (7.1%). Senior management roles are well represented, with 24.5% identified as Senior Managers or Principal Specialists and 28.1% as Managers or Senior Specialists. The findings reveal a highly experienced leadership sample, as most respondents (41.3%) have 16-20 years of experience within their organisations, with only 8.7% having less than 5 years of experience. The respondent base primarily consists of mature professionals, with 46.2% in the 56-65 age range and 29.1% aged 46-55. Again, the sample showed a prevalence of larger, more formalized

business structures, with Private Limited Companies (Ltd) and Public Limited Companies (Plc) representing 47.4% and 21.9% of the responses, respectively. Furthermore, a significant majority of businesses (75.5%) report generating over N100 million in annual turnover highlighting a sample predominantly made up of high revenue generating enterprises with strong representation across various industries, particularly within traditional sectors. The top four sectors (Oil & Gas, Consumer Goods, Healthcare/Pharmaceuticals and Telecommunication account for 57.2% of the total sample. The 5% response as 'Others' included responses such as 'Renewable Energy', 'Paint manufacturing', 'Justice', and 'International Development'. Table 4.1 gives an overview of the demographic characteristics of the participants.

Table 4.1 Demographics of participants

Job Level	N	%
Owner	14	7.1
CEO/MD	14	7.1
Vice President	7	3.6
Chief-Level Officer	12	6.1
Director	23	11.7
Associate/Deputy Director	12	6.1
Senior Manager/Principal Specialist	48	24.5
Manager/Senior Specialist	55	28.1
Other	11	5.6
Total	**196**	**100**

Ownership type	N	%
Sole proprietorship	10	5.1
Partnership	10	5.1
Private limited company (Ltd)	93	47.4
Public limited company (Plc)	43	21.9
Partnership (other)	3	1.5
Subsidiary of a Multinational Corporation	28	14.3
Other (Please state)	9	4.6
Total	**196**	**100**

Age	N	%
Below 25 years	2	1.0
25–35 years	1	0.5
36–45 years	20	10.2
46–55 years	56	28.6
56–65 years	84	42.9
Above 65 years	30	15.3
Prefer not to say	3	1.5
Total	**196**	**100**

Experience in Company	N	%
Less than 12 months	8	4.1
1 to 5 years	9	4.6
6 to 10 years	36	18.4
11 to 15 years	40	20.4
16 to 20 years	81	41.3
More than 20 years	22	11.2
Total	**196**	**100**

Business Age	N	%
Less than 5 years	93	47.4
5–10 years	37	18.9
10–15 years	23	11.7
15–20 years	29	14.8
More than 20 years	14	7.1
Total	196	100

Turnover	N	%
Below ₦10 million	6	3.1
₦10 million – ₦25 million	7	3.6
Above ₦25 million but below ₦100 million	35	17.9
Above ₦100 million	148	75.5
Total	196	100

Sector	N	%
Agriculture / Agro-Business	9	4.6
Consumer Goods	27	13.8
Financial Services	13	6.6
Professional Services	15	7.7
Healthcare / Pharmaceuticals	26	13.3
Telecommunications	25	12.8
Oil & Gas	34	17.3
Power & Energy	11	5.6
Information Communication & Technology (ICT)	7	3.6
Construction / Real Estate	6	3.1
Retail Services	7	3.6
Food & Hospitality	7	3.6
Other	9	4.6
Total	**196**	**100**

4.6.1.3 Exploratory factor analysis (EFA)

Exploratory factor analysis (EFA) is a descriptive data technique used in identifying the suitable number of common factors, as well as determining which observed variables are valid indicators of the different latent dimensions (Brown and Moore, 2012). To ascertain the underlying constructs and possibly reduce variables, the study carried out an EFA using the principal axis factoring (PAF) and varimax rotation. This choice was based on Fabrigar *et al.* (1999) recommendation for of PAF where there are questions of data normality. Moreover, PAF

limits the inflation of estimates of variance because it only analyses shared variance (Costello and Osborne, 2005). The minimum factor loading criteria was set to 0.50.

The results of the assessment of communality of the scale, which indicates the amount of variance in each dimension, show that all communalities were over 0.50, ensuring acceptable level of explanation. The study recognised the importance of also checking that there are meaningful latent factors contained within the data. This involves weighing the overall significance of the correlation matrix using Bartlett's Test of Sphericity. This test provides a measure of the statistical probability that the correlation matrix has significant correlations among some of its components. The results were significant, $x2(n = 595) = 6331.542(p < 0.001)$, indicating its suitability for factor analysis. Using a further measure of sampling adequacy (MSA), the Kaiser-Meyer-Olkin (KMO) test, the study checked if the partial correlations within the data are close enough to zero to suggest that there is at least one latent factor underlying the research variables. Usually, data with MSA values above 0.800 are considered appropriate for factor analysis. The study's KMO result of 0.921 indicated the appropriateness of the data for factor analysis. Finally, the factor solution derived from this analysis yielded six factors for the scale, which accounted for 67.601% of the variation in the data. As EFA is considered an iterative process involving the removal of redundant items within a developing measure (Rattray and Jones, 2007) and involves removal of variables with weak loadings or failing to load above 0·50 on any factor, therefore item SOP1 which failed to significantly load on any dimension was removed from further analysis in the initial EFA.

The EFA was subsequently repeated without the excluded items. The results of this new analysis confirmed the six-dimensional structure theoretically defined in the research. The Bartlett's Test of sphericity confirmed significance, the Kaiser-Meyer-Olkin MSA had a value of 0.919 with all communalities over the required value of 0.500. As shown in Table C4 the six factors explained a total of 73.282% of the variance among the items in the study. The six

factors identified as part of this EFA aligned with the theoretical proposition in this research. Factor 1 includes items TA1 to TA5, referring to Technology Assimilation (TAS), Factor 2 gathers items TC1 to TC7, which represents Technological Capability (TC), Factor 3 with items OA1 to OA7 denotes Organisational Agility (OA). Finally, Factor 4, 5 and 6 denotes the sustainability performance outcomes and includes items ECP1 to ECP4, SOP2 to SOP4 and ENP1 to ENP4 denoting Economic, Social and Environmental dimensions respectively. The results of the KMO & Bartlett's Test and the Factor Loadings are presented in Tables 4.2 and 4.3 respectively.

Table 4.2 KMO and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.919
Bartlett's Test of Sphericity	Approx. Chi-Square	5694.133
	df	435
	Sig.	<.001

Table 4.3 Factor Matrix

Rotated Factor Matrixa						
	Factor					
	1	2	3	4	5	6
TA1	0.821					
TA2	0.842					
TA3	0.766					
TA4	0.857					
TA5	0.801					
TC1		0.61				
TC2		0.766				
TC3		0.658				
TC4		0.71				
TC5		0.699				
TC6		0.639				
TC7		0.574				
OA1			0.647			
OA2			0.638			
OA3			0.623			
OA4			0.709			
OA5			0.642			
OA6			0.651			
OA7			0.777			
ECP1					0.646	
ECP2					0.745	
ECP3					0.71	
ECP4					0.657	
SOP2						0.711
SOP3						0.687
SOP4						0.653
ENP1				0.716		
ENP2				0.842		
ENP3				0.804		
ENP4				0.793		
Extraction Method: Principal Axis Factoring.						
Rotation Method: Varimax with Kaiser Normalization.						
a Rotation converged in 7 iterations.						

4.6.1.4 Reliability

After confirming the factor structure, an assessment of the internal consistency reliability of the measurement scales was assessed for the constructs Technology Assimilation (TAS), Technological Capability (TC), Organisational Agility (OA), and Economic sustainability performance (ECP), Social sustainability performance (SOP) and Environmental sustainability performance. Cronbach's Alpha (CA) was used to assess reliability by estimating how consistently the items in a scale measure the underlying constructs. A Cronbach's Alpha of 0.70 or higher indicates acceptable reliability (Nunnally and Bernstein, 1994; Hair *et al.*, 2019). All items showed corrected total correlations above the 0.50 threshold, indicating good discrimination. No item removal would have improved alpha values. Overall, the scales

demonstrated acceptable to excellent internal consistency. These results justify the use of the items as composite measures in subsequent analyses, including structural equation modelling. Table 4.4 reports the results of the reliability test.

Table 4.4 Construct Reliability

Construct	No of Items	Cronbach's α	Factor Correlations	Communalities	Overall Status
TA	5	0.949	0.737-0.838	0.723-0.888	**Excellent**
TC	7	0.92	0.531-0.710	0.568-0.747	**Very Good**
OA	7	0.91	0.529-0.700	0.548-0.744	**Very Good**
ECP	4	0.935	0.744-0.810	0.746-0.849	**Excellent**
SOP	3	0.943	0.828-0.836	0.835-0.844	**Excellent**
ENP	4	0.924	0.676-0.786	0.637-0.793	**Excellent**

4.6.2 Measurement Model

Having defined the data structure with EFA, a Confirmatory Factor Analysis (CFA) was conducted to confirm the factor structure of the observed variables in order to ascertain whether the hypothesised relationships between the observed variables and their latent constructs exists (Statistics-Solutions, 2025). According to Brown and Moore (2012) whereas EFA is exploratory and descriptive and is at the initial stages of scale development and construct validation, CFA uses predefined number of factors in a model which is based on a conceptual framework that informs its specification and assessment to determine its ability to accurately reproduce the sample covariance matrix of the observed variables.

Confirmatory factor analysis was conducted with AMOS ver.28 to determine the evaluate the influence of AI and I4.0T adoption and assimilation on sustainability performance outcomes. The study hypothesised six (6) latent factors namely Technology Assimilation (TAS), Technological Capability (TC), Organisational Agility (OA), Economic Sustainability Performance (ECP) Social Sustainability Performance (SOP) and Environmental Sustainability Performance (ENP). Maximum Likelihood which is one of the more widely used estimation methods was chosen for the estimation of the model parameters and depicted in Fig. 4.4.

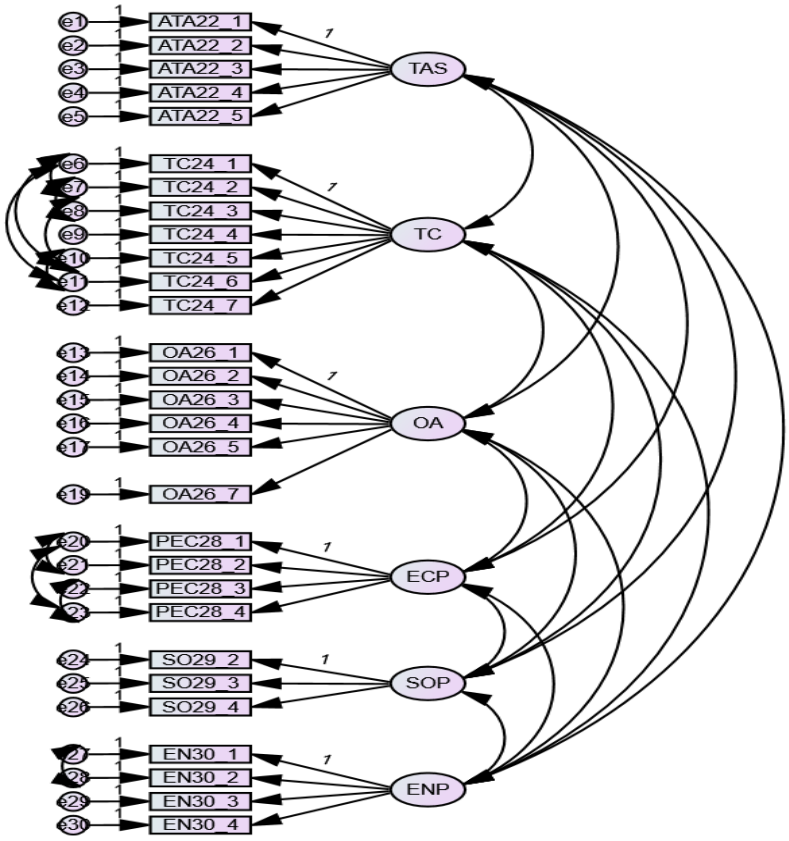

Figure 4.4 CFA Model (Fit indices: X^2: 613.842; df: 352; CFI:0.951; SRMR:0.045; RMSEA:0.062)

Following recommendations in literature (Bollen, 1989; Fan, Thompson and Wang, 1999; Hu and Bentler, 1999; Schumacker and Lomax, 2004) model fit in the CFA was assessed using indices from all three categories of fit measures. The criteria applied were: RMSEA ≤ 0.06 (90% CI ≤ 0.06), SRMR ≤ 0.08, CFI ≥ 0.95, and TLI ≥ 0.90 (Hu and Bentler, 1999; Byrne, 2016; Schumacker and Lomax, 2004). In addition, the chi-square/df ratio ≤ 3 rule recommended by Kline (2016) was applied. The six-factor model (Technology Assimilation, Technological Capability, Organisational Agility, Economic Sustainability Performance, Social Sustainability Performance and Environmental Sustainability Performance) exhibited good fit for the data: CMIN/df = 1.744, RMSEA = 0.062, CFI = 0.951, and TLI = 0.944. Here are the results presented in Table 4.5

Table 4.5 Model fit Indices

Measure	Estimate	Threshold	Interpretation	Source
CMIN	613.842	--	--	
DF	352	--	--	
CMIN/DF	1.744	Between 1 and 3	Excellent	Hu and Bentler (1999)
CFI	0.951	>0.95	Excellent	Schumacker and Lomax (2004), Hu and Bentler (1999)
SRMR	0.045	<0.08	Excellent	Hu and Bentler (1999)
RMSEA	0.062	<0.06	Acceptable	Hu and Bentler (1999)
Tucker Lewis	0.944	>0.90	Excellent	Schumacker and Lomax (2004); Bryne (1991)

Following the confirmation of model fit, internal reliability and convergent validity of the measurement model were assessed prior to testing the structural relationships (Bagozzi and Yi, 1991) Discriminant validity was then examined to ensure that the constructs were distinct from one another. Together, these assessments established the adequacy of the measurement model before evaluating the structural relationships. Details of these tests are presented in the following sub-sections.

4.6.2.1 Construct Reliability

The term "*Consistency*" encapsulates the core concept of reliability. Reliability reflects the consistency of a measure. As Straub, Boudreau and Gefen (2004) note , construct reliability evaluates how consistently a variable or group of variables captures what it is intended to measure. In this study, reliability was evaluated using Cronbach's Alpha and Composite Reliability. Cronbach's Alpha was computed in SPSS, while Composite Reliability was assessed in AMOS. Both measures were interpreted using the commonly accepted threshold of 0.70 as recommended by Nunnally and Bernstein (1994) and Hair *et al.* (2010) as acceptable reliability.

The Cronbach Alpha for each construct in the study was well within the required threshold of 0.70 and above as reported earlier. The composite reliabilities were also above recommended benchmark of 0.70 as the values ranged from 0.90 to 0. 945. With these results,

construct reliability was established for each construct in the study. Table 4.6 shows the Construct Reliability results.

Table 4.6 Construct Reliability

Construct	No of Items	Cronbach's Alpha	Composite Reliability
TAS	5	0.949	0.945
TC	7	0.92	0.917
OA	7	0.91	0.905
ECP	4	0.935	0.927
SOP	3	0.943	0.945
ENP	4	0.924	0.917

4.6.2.2 Validity

Validity relates to the extent to which the observed measures accurately reflect the latent constructs under investigation and the extent to which those constructs are interrelated within the model. Validity is important to reduce the potential biases from sample peculiarities or measurement inaccuracies, thereby guaranteeing that the findings are both statistically significant and meaningful. The validity of the measurement model was evaluated through convergent and discriminant validity analyses ensuring that the latent constructs are measured correctly and can be effectively utilised in the following structural analysis.

Regarding convergent validity, Bagozzi (1981) explained the idea of convergence in measurement stating that "measures of the same construct should be highly intercorrelated among themselves and uniform in the pattern of intercorrelations". Convergent validity evaluates the extent to which the various items measuring a construct that theoretically should be related are in fact related (Gefen and Straub, 2000). This helps in eliminating redundant indicators and ensures one-dimensionality of multiple items constructs (Bollen, 1989). The study assessed convergent validity using Average Variance Extracted (AVE) by taking the sum of squares of the factor loadings and dividing it by the number of items in the unobserved latent variable. The AVE indicates how much of the indicators' variance can be explained by the latent

unobserved variable. To establish convergent validity, Hair *et al.* (2019) states that the: (a) Average Variance Extracted (AVE) for each construct should be greater than 0.50. This indicates that more than half of the variance in observed variables is captured by the latent construct (Fornell and Larcker, 1981) and (b) Composite Reliability (CR) is higher than 0.70. This reflects satisfactory internal consistency (Hair *et al.*, 2019). As presented in Table 3.7 the study's constructs exceed the minimum thresholds for both AVE and CR, thus confirming convergent validity of the measurement model.

Discriminant validity on the other hand, refers to the extent to which factors are distinct and uncorrelated (Hair *et al.*, 2019). It suggests that variables should show a stronger relationship with their respective factor than with any other factor (Gaskin, 2021c). Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio of correlations, the two commonly used methods, were employed in the study to assess discriminant validity. According to Fornell and Larcker (1981), to achieve discriminant validity, the square root of the AVE for each construct should be greater than its correlations with any other construct. This ensures that the construct shares more variance with its own indicators than with others. From the results presented in Table 4.8, all constructs met this condition except the TC-OA relationship that fell short of this requirement. The absolute value of their corelation (0.791) is higher than the square root of AVE (0.783). However, Henseler, Ringle and Sarstedt (2014) and Rönkkö and Evermann (2013) have questioned the Fornell and Larcker criterion's capturing of discriminant validity and criticised it for not being effective under certain circumstances. Consequently, Henseler, Ringle and Sarstedt (2014) introduced the HTMT ratio as an alternative measure to better assess discriminant validity. HTMT is the mean of the item correlations across constructs relative to the mean of the item correlations within the same construct (Henseler, Ringle and Sarstedt, 2014). A commonly accepted threshold for HTMT is

0.85. In this study, all HTMT values as shown in Table 4.8 were below that threshold, indicating that discriminant validity is not violated.

Table 4.7 Construct validity

CONSTRUCT	CR	AVE	TAS	TC	OA	ECP	SOP	ENP
TAS	0.945	0.776	***0.881***					
TC	0.917	0.613	0.542	**0.783**				
OA	0.905	0.581	0.486	0.791	**0.762**			
ECP	0.927	0.761	0.663	0.611	0.596	**0.872**		
SOP	0.945	0.852	0.500	0.605	0.589	0.700	**0.923**	
ENP	0.917	0.735	0.453	0.517	0.488	0.563	0.713	**0.857**

TAS = Technology Assimilation, TC = Technology Capability; OA = Organisational Agility; ECP = Economic Sustainability Performance; SOP = Social Sustainability Performance; ENP = Environmental Sustainability Performance; CR = Composite Relaiability; AVE = Average Variance Extracted; Diagonal values in bold are the square roots of AVE per construct while off diagonal values are the corelations of the variables

Table 4.8 HTMT Ratio Analysis

HTMT ANALYSIS						
CONSTRCT	**ENP**	**SOP**	**ECP**	**OA**	**TC**	**TAS**
ENP						
SOP	0.693					
ECP	0.588	0.697				
OA	0.479	0.581	0.547			
TC	0.499	0.580	0.595	0.781		
TAS	0.455	0.504	0.632	0.496	0.54	

4.6.3 Structural Model

The structural model assessed the relationships between AI and I4.0T assimilation and sustainability performance outcomes and the mediating influence of technological capability and organisational agility. The model did not show good overall fit, with the following fit indices: CMIN = 803.527; df = 356; CMIN/df = 2.257, RMSEA = 0.080, CFI = 0.917, and TLI = 0.944, SRMR = 0.133. An image of the structural model is presented in Figure 4.5

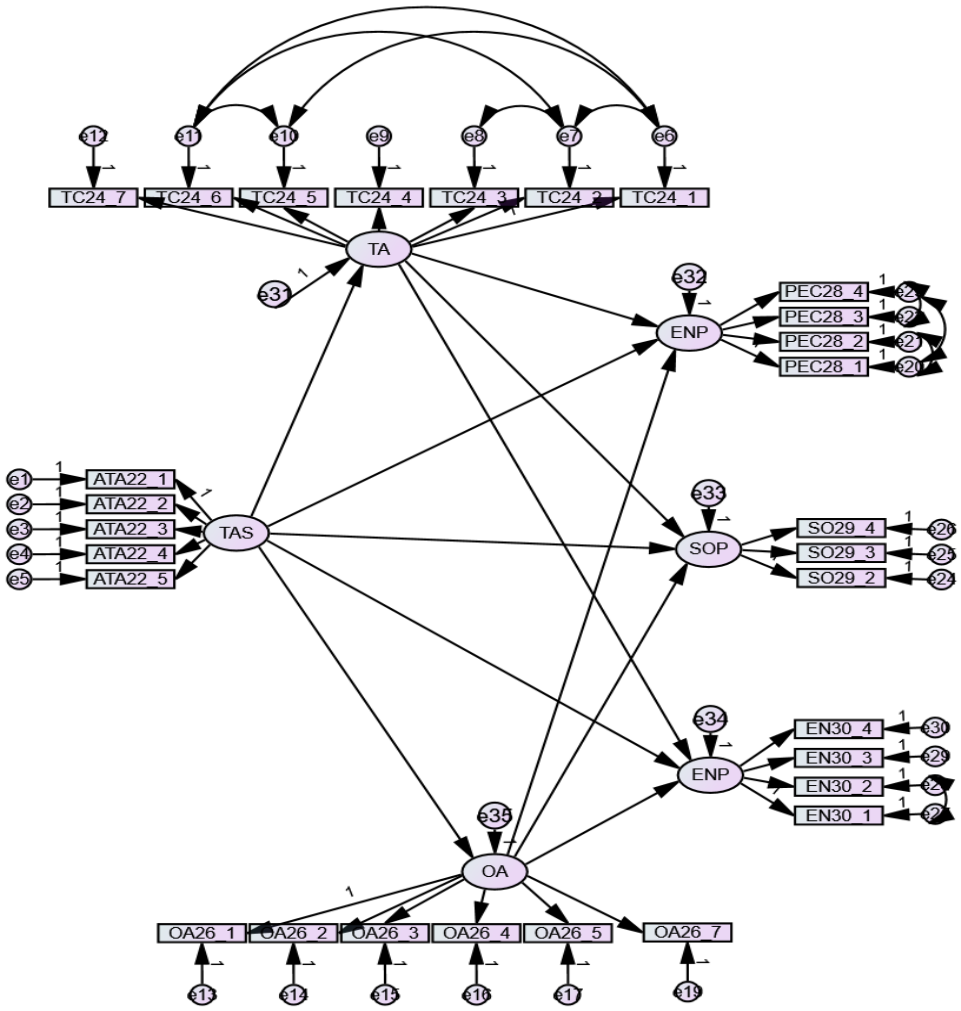

Figure 4.5 Structural Model

However, all paths are statistically significant with $p < 0.05$ as well as many highly significant paths with $p<0.001$. The strongest relationships were between Technology Assimilation and both Technological Capability (TAS → TA, $\beta = 0.507$) and Organisational Agility (TAS → OA, $\beta = 0.337$) suggesting Technology Assimilation significantly explains both Technological Capability and Organisational Agility and is influential in shaping both constructs. These in turn influence the sustainability performance outcomes with significant paths as seen in the regression weight presented in Table 4.9

Table 4.9 Regression Weights

			Estimate	S.E.	C.R.	P	Label
TA	<---	TAS	0.507	0.07	7.294	***	
OA	<---	TAS	0.337	0.051	6.658	***	
ECP	<---	TA	0.269	0.071	3.774	***	
SOP	<---	TA	0.297	0.084	3.539	***	
ENP	<---	TA	0.209	0.068	3.07	0.002	
ENP	<---	OA	0.212	0.085	2.503	0.012	
SOP	<---	OA	0.413	0.107	3.866	***	
ECP	<---	OA	0.242	0.088	2.745	0.006	
ECP	<---	TAS	0.365	0.069	5.273	***	
SOP	<---	TAS	0.208	0.08	2.621	0.009	
ENP	<---	TAS	0.157	0.064	2.439	0.015	

Significance of Estimate *** p < .001; ** p < .01; * p < .05.

4.6.3.1 Higher Order Construct Justification

The study considered a higher order factor structure to reflect the conceptual nature of sustainability as a multidimensional construct with the aim of enhancing model clarity, parsimony and interpretability (Sarstedt *et al.*, 2019). The high intercorrelations as seen from earlier reported HTMT values (Table 3.9) suggests that some of the lower order constructs reflect broader latent dimensions. As such higher order construct can improve model fit by reducing the number of paths in the structure model. This enhances the degrees of freedom and makes interpretation less cumbersome (Hair *et al.*, 2021). Using higher order, the study was able to reflect the hierarchical structure of the Triple Bottom Line theoretical framework by modelling abstract and multidimensional constructs of sustainability more parsimoniously (Jarvis, MacKenzie and Podsakoff, 2003). Besides, theoretically, economic, social and environment are conceptualised as facets of the broader concept of sustainability. Therefore, economic, social and environmental sustainability performance outcomes can be modelled as second order factors reflecting sustainability performance outcomes.

4.6.3.2 Higher Order Confirmatory Factor Analysis

The Higher Order Confirmatory Factor Analysis results reflected improvements across all indices (Chi-square value = 633.651; df: 358; CFI:0.949; SRMR:0.051; RMSEA:0.063).

The model fit now falls within acceptable to good range across all indices. This indicates that the higher order model is much more appropriate than the initial model as it shows a better fit with the data and aligns with theory. Figure 4.6 presents the Higher Order CFA.

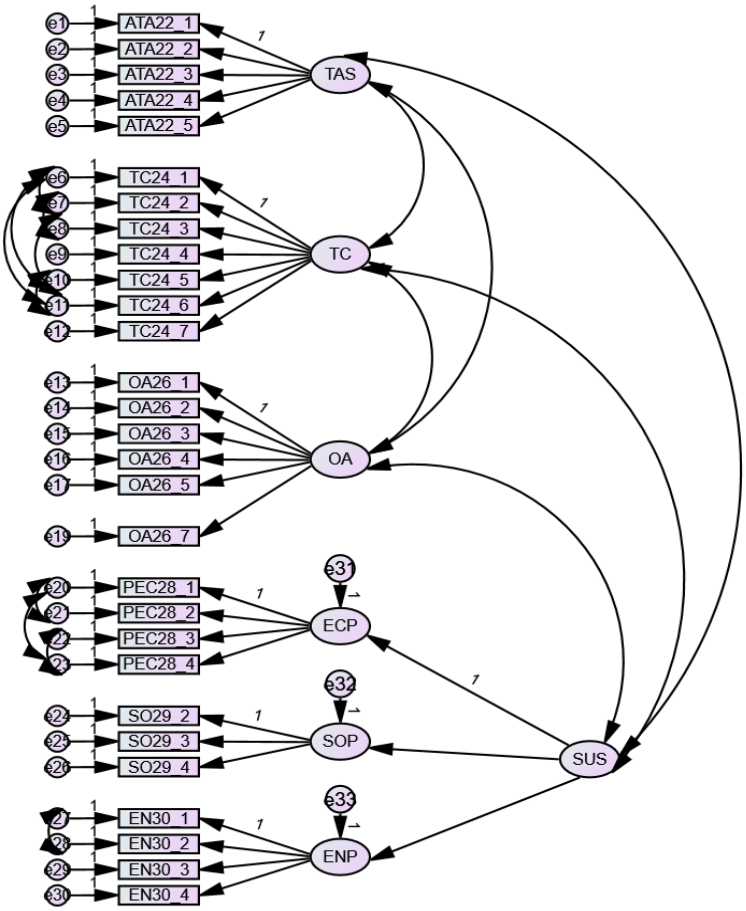

Figure 4.6 Higher order CFA

The construct reliability and validity for the higher order model followed a two -step process by assessing the reliability of the lower orders ECP, SOP and ENP using Cronbach's Alpha and composite reliability and then the composite reliability of the higher order. As reported earlier, ECP, SOP and ENP constructs were well above the benchmark for both Cronbach's Alpha and composite reliability. For the higher order, the composite reliabilities

show Sustainability Performance outcomes (SUS) = 0.862, Technology Assimilation = 0.949, Technological Capability = 0.916 and Organisational Agility = 0.907.

Convergent validity of the higher order model estimated using AVE had values above the threshold value of 0.50 indicating the required convergent validity (Fornell and Larcker, 1981). The discriminant validity assessment using Fornell and Larcker Criterion and Heterotrait-Monotrait (HTMT) Ratio both fell within the required thresholds. Table 4.10 reports the construct reliability, convergent and discriminant validity for the higher order CFA model.

Table 4.10 Reliability & Validity

CONSTRUCT	CR	AVE	SUS	TAS	TC	OA
SUS	0.862	0.677	***0.823***			
TAS	0.949	0.790	0.664	***0.889***		
TC	0.916	0.610	0.71	0.562	***0.781***	
OA	0.907	0.622	0.674	0.501	0.806	***0.789***

SUS = Sustainability Performance;TAS = Technology Assimilation, TC = Technology Capability; OA = Organisational Agility; CR = Composite Relaiability; AVE = Average Variance Extracted; Diagonal values in bold are the square roots of AVE per construct while off diagonal values are the corelations of the variables

4.6.3.3 Higher Order Structural Model

The structural model was developed to examine the effect of AI and I4.0T assimilation (TAS) on sustainability performance outcomes (SUS) with technological capability (TA) and organisational agility (OA) as mediators. Sustainability performance outcomes were modelled as a higher order construct comprising economic (ECP), social (SOP) and environmental (EN) sustainability. The model was estimated using maximum likelihood in AMOS, with bootstrapping 5,000 samples and 95% confidence interval enabled for testing the indirect effects. This mediation model demonstrated reasonably acceptable fit indices (CMIN = 700.915, CMIN/DF = 1.958, CFI = 0.936, TLI = 0.928, RMSEA = 0.070) except SRMR with above the threshold value of 0.118. The structural model is illustrated in Figure 4.7

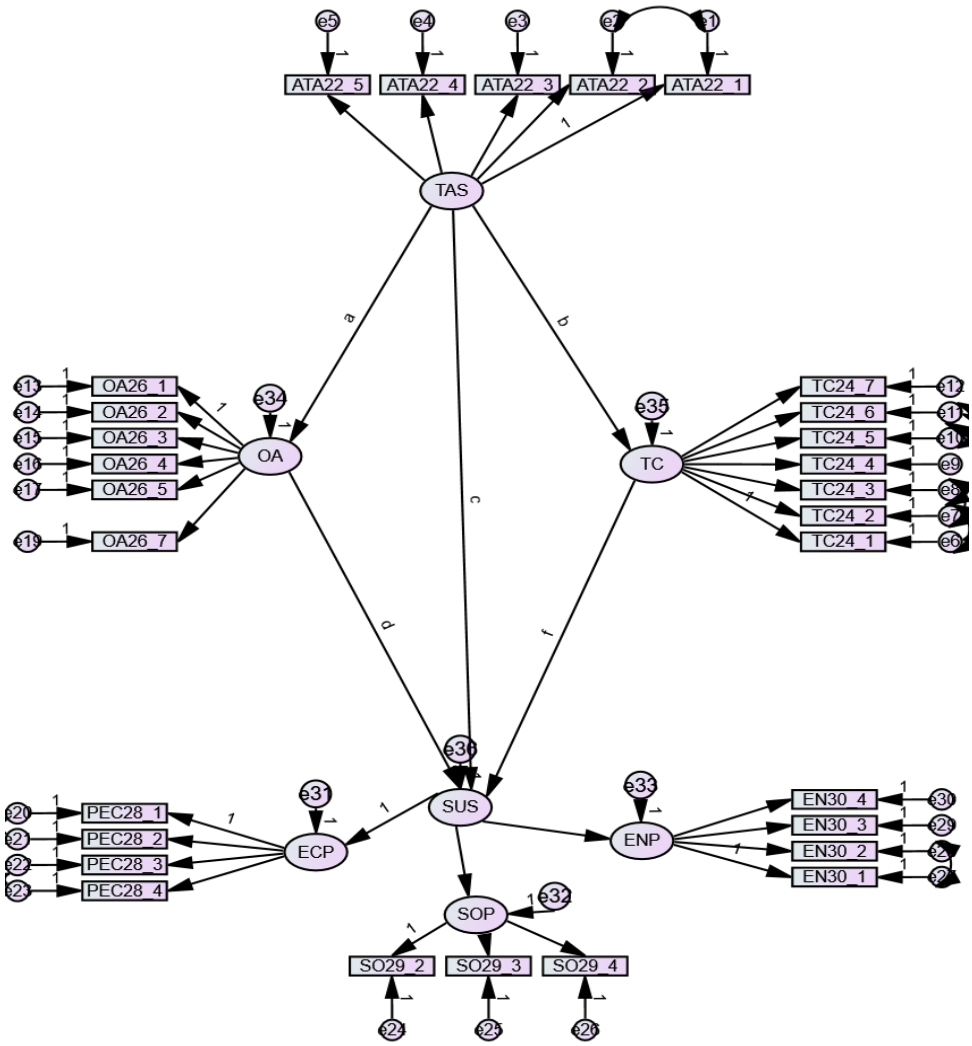

Figure 4.7 Higher Order Model

These results confirm that technology assimilation directly influences both technological capability (TA) and organisational agility (OA) supporting H1a and H1b and as the structural paths among these constructs were all significant (TAS > OA 0.353 $p < .001$; TAS > TC 0.353 $p < .001$) In addition, technological capability (TA) and organisational agility (OA) independently predict sustainability performance outcomes (TC > SUS 0.241, $p < .001$; OA > SUS 0.278, $p < .001$) supporting H5 and H6. H7 is also supported as shown in the significant direct effect of technology assimilation on sustainability performance outcomes (TAS > SUS 0.264; $p < .001$). This suggests both partial mediation and direct influence. Table 4.11 summarizes the standardized estimates.

Table 4.11 Higher Order Regression Weight Estimates

Path	Estimate	S.E.	C.R.	p-value
OA ← TAS	0.353	0.053	6.644	***
TC ← TAS	0.536	0.073	7.307	***
SUS ← TAS	0.264	0.063	4.208	***
SUS ← OA	0.278	0.078	3.559	***
SUS ← TC	0.241	0.062	3.868	***

Significance of Estimate *** p < .001; ** p < .01; * p < .05.

4.6.4 Mediation Analysis

The study assessed the mediating role of Technological Capability (TC) and Organisational Agility (OA) on the relationship between Technology Assimilation (TAS) and Sustainability performance outcomes (SUS). The results revealed a significant indirect effect of TAS on SUS through OA (b = 0.095, t = 1.792, p = 0.039) supporting H3. The mediation analysis also found a significant mediating role of TC on the relationship between TAS and SUS (b = 0.126, t = 2.377, p = 0.011), supporting H2. Furthermore, the direct effect of TAS on SUS in the presence of the mediators was also found significant (b = 0.256, p = 0.000) supporting H4. This indicates that both TC and OA partially mediate the relationship between TAS and SUS. Mediation analysis summary is presented in Table 4.12.

Table 4.12 Mediation Analysis

Relationship	Direct Effect	Indirect Effect	VAF(%)	Direct Effect:Indirect Effect	Effect Size	Confidence Interval		P-value	Conclusion
						Lower	Upper		
TAS > OA > SUS		0.095	19.92	0.37	Small	0.004	0.212	0.039	Partial Mediation
TAS > TC > SUS		0.126	26.42	0.49	Small-Medium	0.03	0.244	0.011	Partial Mediation
TAS > SUS	0.256		53.67		Medium			0	Significant Direct Effect
Total Effect (Direct effect + Indirect effect (OA + TC)		0.477							

The total effect of TAS on SUS is 0.477, with OA accounting for 19.9%, TC 26.4%, and the direct effect 53.7%. This confirms that TAS retains a strong independent influence alongside

both mediators. Based on Cohen (2013), OA represents a small effect, while TC approaches medium magnitude. Relative to the direct effect, OA is 37% as large and TC 49%, reinforcing TC as the stronger pathway. The OA effect, while significant, is modest, suggesting agility functions as a supporting mechanism rather than a primary driver. For decision-makers, this implies that while agility development adds value, it should be pursued as part of a broader capability strategy, particularly given the stronger and more reliable contribution of TC. However, small effects may still be meaningful, For instance, in high-stakes contexts even modest improvements can generate meaningful impact across systems (Prentice and Miller, 2016). Similarly, small effects may accumulate across supply chain networks, producing substantial aggregate value (Abelson, 1985). However, organisations must weigh it against the cost and complexity of developing organisational agility, which may limit its standalone justification despite its supporting role.

4.7 Discussion

Although AI and I4.0T hold strong theoretical potential to enhance sustainability performance, empirical evidence shows a persistent implementation gap. Brynjolfsson's (1993) study on IT investments highlighted the "productivity paradox," which also appears in sustainability contexts, where technology adoption does not automatically translate to improved sustainability outcomes. Similarly, Müller, Kiel and Voigt (2018) and Frank, Dalenogare and Ayala (2019) report that with adoption often being partial or fragmented, the expected environmental and operational gains remain limited. While digital technologies such as AI and I4.0T can support stronger sustainability outcomes, their impact depends on how well they are embedded within organisational processes such as supply chain practices that prioritise sustainability (Patrucco *et al.*, 2025). However, assimilating these technologies into core operations can sometimes generate organisational friction and uneven benefits which make it difficult to translate potential into tangible sustainability gains. This study addresses

these challenges by empirically examining how the assimilation of AI and I4.0T affects sustainability performance outcomes. It investigates the mediating roles of technological capability and organisational agility as key mechanisms that enable organisations to convert technological potential into operational, economic, and environmental value.

4.7.1 Overview of Model Performance and Measurement Model Assessment

The measurement model was evaluated for reliability, convergent validity, and discriminant validity. All constructs exhibit strong psychometric properties. These results confirm the constructs in the model as valid and reliable representations of the theoretical concepts of technology assimilation, technological capability, organisational agility and sustainability.

Likewise, the structural model examined the hypothesised relationships among technology assimilation, organisational agility, technological capability and sustainability performance outcomes and its economic, environmental and social sub-dimensions. All path coefficients are statistically significant, supporting the hypothesis that AI and I4.0T assimilation positively influences organisational agility and technological capability, which in turn impact sustainability outcomes. Furthermore, the structural equation model analysis reveal significant relationships between technology assimilation and sustainability performance outcomes, mediated through technological capability and organisational agility. The final mediation model demonstrates acceptable fit indices (CMIN/DF = 2.049, CFI = 0.930, RMSEA = 0.073). The model positions sustainability as a higher-order construct measured through economic, social, and environmental sustainability performance dimensions. However, there are model limitations related to fit indices that require close attention and improvement for optimal specification in future studies. Although the model demonstrates acceptable fit, the SRMR value (0.119) exceeds optimal thresholds.

Finally, a bootstrapping procedure with 2,000 samples was conducted to assess the mediating roles of organisational agility and technological capability in the relationship between AI and I4.0T assimilation and sustainability performance outcomes. The significant indirect paths confirm organisational agility and technological capability partially mediate the relationship between AI and I4.0T assimilation and sustainability performance outcomes. The direct effect of AI and I4.0T assimilation on sustainability performance outcomes remain significant, indicating partial rather than full mediation. The total indirect effect (0.221) suggests that technological capability and organisational agility together provide meaningful mediation between technology assimilation and sustainability performance.

4.7.2 Empirical insights

4.7.2.1 How does the assimilation of AI and I4.0T influence supply chain sustainability performance?

The results reveal both significant direct and indirect pathways from technology assimilation to sustainability performance supporting the primary research objective. The strong and positive influence on supply chain sustainability performance is consistent with earlier work suggesting that organisations gain most from digital technologies when they move beyond adoption and embed these tools into their routine processes (Liu *et al.*, 2013; Mu, Kirsch and Butler, 2015). This confirms the argument that the true value of digital transformation emerges when technologies are embedded deeply enough to influence behaviour and decision-making (Peppard and Ward, 2016; Wamba, 2022). Therefore, improved economic, environmental and social performance are associated with the successful integration of AI and I4.0T into organisation's workflows, decision structures and operational routines (Chatterjee, Grewal and Sambamurthy, 2002). Also, this positive direct relationship reinforces earlier claims that digital technologies can enhance transparency, resource efficiency and overall sustainability across the supply chain (Dubey *et al.*, 2017; Bag *et al.*, 2020).

Regarding indirect effects, the significant result reinforces the critical role of assimilation. The substantial indirect effects through organisational agility and technological capability confirms that adoption on its own is not sufficient; how organisations absorb, adapt and apply new technologies is also of great importance. Furthermore, organisations benefit from technology assimilation, particularly when paired with the right internal mechanisms. This mediation results agree with dynamic capabilities view that argues that how well organisations can integrate, reconfigure and deploy resources effectively in changing environments shapes their performance (Teece, Pisano and Shuen, 1997). Again, earlier studies show that through support of data analytics, automation and integration, technological capability act as a key mechanism through which digital tools such as AI and I4.0T improve performance (Baryannis *et al.*, 2019). At the same time, organisational agility helps organisations respond quickly to disruptions and sustainability pressures and supports previous arguments that agility enables organisations to adapt to market expectations and shifting sustainability requirements (Mrugalska and Ahmed, 2021; Kumkale, 2022). Therefore, assimilation improves sustainability not just because the technology exists, but because organisations develop the technological capabilities and organisational agility needed to use digital tools productively.

A key finding is that assimilation has a stronger relationship with social sustainability than with environmental sustainability, with social performance showing the strongest loading on the higher-order sustainability construct. This contrasts with dominant literature, which positions environmental sustainability as the primary outcome of AI and I4.0T adoption in supply chains (Agrawal and Narain, 2023; Nishant, Kennedy and Corbett, 2020; Bag *et al.*, 2020). In the Nigerian context, three structural mechanisms help explain this inversion. First, high informal labour participation, youth unemployment, and concerns over job displacement and fairness make social sustainability more immediate and salient for managers than

environmental outcomes (International Labour Organization ILO, 2022; Ojubanire *et al.*, 2024; Steinmueller, 2001). Furthermore, AI and I4.0T assimilation produces visible social effects in work organisation, skills requirements and workforce interaction. Second, weak environmental reporting and monitoring frameworks reduce the visibility and measurability of environmental gains relative to directly observable social changes. Third, infrastructure constraints enable "leapfrogging" effects, where AI and I4.0T generate immediate social benefits such as improved inclusion, coordination and supplier connectivity without requiring equivalent environmental infrastructure. Collectively, these mechanisms suggest that the environmental dominance in prior literature may reflect developed-economy bias, while in Nigeria social sustainability emerges as the more immediate and salient outcome of digital assimilation.

4.7.2.2 What roles do technological capability and organisational agility play as mediators?

The findings show that both technological capability and organisational agility play strong and significant mediating roles in enhancing the impact of AI and I4.0T assimilation on sustainability. This confirms the general view that technology alone does not create value but it needs to be supported by organisational capabilities embedded in its routines (Peppard and Ward, 2016).

In terms of technological capabilities, they transform raw technological resources into operational capabilities such as data analytics capability, process automation capability and integration capability. This enables organisations to extract value from AI and I4.0T investments beyond just adoption. These results extend the literature by showing that technological capability provides a more direct pathway from assimilation although it has a weaker relationship with sustainability performance despite its stronger indirect effect. This supports the idea that having advanced technological resources does not automatically ensure

sustainability gains, especially as sustainability targets require cross-functional alignment that goes beyond technical proficiency. Furthermore, the findings reinforce earlier arguments that digital technologies become productive when organisations develop expertise to exploit them by building intangibles including business processes, managerial experience and skilled workers (Brynjolfsson, Rock and Syverson, 2021).

Organisational agility, on the other hand, demonstrates a different but equally influential role. Organisational agility, which includes market sensing agility, operational adjustment agility and network reconfiguration agility, enables organisations respond quickly to sustainability challenges and opportunities. It also provides the flexibility needed to manage tensions and paradoxes effectively. Although assimilation has a weaker direct association with organisational agility than with technological capability, organisational agility shows a stronger direct relationship with sustainability performance. This finding is consistent with literature emphasising the importance of organisational agility in navigating uncertainty, responding to shifting market conditions and addressing emerging sustainability pressures (Tallon and Pinsonneault, 2011; Overby, Bharadwaj and Sambamurthy, 2006). These results could be taken to mean that organisational agility becomes especially valuable in the context of sustainability related change, where responsiveness, rapid adjustment and flexibility are more significant than technical sophistication alone.

4.7.2.3 What paradoxes emerge during assimilation?

The study identifies three paradoxes that help explain why digital transformation may not always lead to the sustainability outcomes organisations expect. These paradoxes echo earlier work by work Smith and Lewis (2011) on organisational tensions in technology implementation and extends it within the context of AI and I4.0T.

a. Adoption vs. Application Paradox

The first paradox reflects the disconnect between acquiring technological capability and effectively applying it to achieve sustainability outcomes. While technological capability, often more readily developed through AI and I4.0T assimilation, the findings indicate that organisational agility plays a more critical role in translating these capabilities into sustainability gains. This paradox constitutes a theoretical contribution to the Dynamic Capabilities perspective by establishing a boundary condition: the positive effect of technological capability on sustainability outcomes is contingent on the level of organisational agility. In the absence of sufficient agility, investments in advanced technologies may yield limited impact despite high levels of adoption.(Bharadwaj, 2000). This helps explain why organisations with sophisticated digital systems may still struggle to achieve measurable sustainability improvements. Future research can operationalise this paradox by modelling organisational agility as a moderating variable in the relationship between technological capability and sustainability outcomes, or by testing an interaction effect between capability and agility to capture conditional or diminishing returns.

b. Complexity vs. Capability Paradox

The second paradox highlights the tension between increasing technological complexity and the organisation's ability to manage it effectively. While advanced AI and I4.0T systems enhance data availability and decision-making potential, the findings suggest that greater complexity does not automatically lead to improved sustainability outcomes and may, in some cases, impede them (Sambamurthy, Bharadwaj and Grover, 2003). This introduces a boundary condition to the assumed positive relationship between digital assimilation and environmental performance where sustainability gains may weaken or reverse when increased efficiency leads to higher resource utilisation or when organisational capabilities are insufficient to manage complexity. This aligns with the notion of an environmental rebound effect, where efficiency improvements stimulate additional consumption or scale expansion.

Future studies can operationalise this paradox by incorporating production scale, demand growth, or resource utilisation intensity as moderating variables, or by testing non-linear relationships between digital assimilation and environmental performance.

c. Speed vs. Strategy Paradox

The third paradox captures the trade-off between rapid technology adoption and the depth of integration required to realise sustainability benefits. The findings suggest that accelerated adoption, particularly in pursuit of environmental goals, may outpace organisational readiness and result in fragmented implementation. This defines a boundary condition on the adoption-assimilation-performance pathway in which the positive impact of adoption on sustainability outcomes depends on the depth of assimilation achieved. Without sufficient integration, early gains may be superficial or uneven across sustainability dimensions. This paradox can be operationalised by modelling assimilation depth as a moderating variable between adoption and sustainability outcomes, or by introducing an interaction term between adoption speed and integration depth to assess how rapid adoption influences long-term performance.

Despite the widely accepted positive impact of AI and I4.0T on performance across sustainability dimensions (Bai *et al.*, 2020), organisations struggle to achieve measurable advances in sustainability with actual results often falling short of expectations. The mediation findings provide an empirical answer to the productivity paradox in the sustainability context of why technology adoption often fails to deliver expected outcomes. Assimilation accounts for 53.7% of the total effect on sustainability performance while the remaining 46.3% depends on complementary capability development. Organisations that do not strengthen technological capability and organisational agility therefore forgo a substantial share of potential benefits. Rather than resolving the paradox, the findings confirm that adoption without capability

development predictably underperforms. It simultaneously extends the paradox into the sustainability domain by identifying the mechanisms through which this gap occurs. Technological capability provides the integration pathway through which systems are effectively embedded, while organisational agility provides the adaptive pathway that enables alignment with sustainability objectives. Together, these findings demonstrate that the sustainability productivity gap is fundamentally a capability gap rather than a technology gap, and that value realisation depends on organisational transformation alongside technological assimilation (Brynjolfsson and Hitt, 2000; Teece, 2018)

4.8 Conclusion

This study looks beyond mere adoption to evaluate assimilation, focusing on how the integration of AI and I4.0T within organisational processes impacts sustainability outcomes. Through the Dynamic Capabilities Theory lens, it explores the mediating roles of technological capability and organisational agility in linking assimilation to performance outcomes across the environmental, social and economic dimensions of sustainability. The study develops and empirically tests a model linking technology assimilation to sustainability outcomes through the mediating roles of technological capability and organisational agility using data from participants in Nigeria. It extends the Dynamic Capabilities theory to AI and I4.0T context and confirms that although assimilation enhances sustainability, it does so through the development of adaptive capabilities such as reconfiguration of processes, continuous learning and responsiveness to sustainability changes. The findings further emphasise the dynamic and evolving nature of AI and I4.0T. Additionally, the Nigerian context provides data and findings from the perspective of an often-underrepresented emerging economy perspective thereby contributing new insights to global theories.

4.8.1 Theoretical contribution

This study has gone some way towards enhancing the theoretical understanding of digital transformation for sustainability by examining how organisations adopt and assimilate AI and I4.0T and how these processes translate into measurable sustainability outcomes. The findings from this study make several contributions to the current literature. Broadly, it advances dynamic capabilities theory, extends technology adoption and assimilation perspectives, brings the paradox lens into sustainability and the AI and I4.0T context while providing an emerging economy perspective by focusing on Nigerian businesses. The following discussions further illustrates the theoretical contributions in more detail.

First, a key contribution of the study is in the advancing of Dynamic Capabilities theory through dual mediation. It demonstrates how technological capability and organisational agility function as dual mediators between AI and I4.0T assimilation and sustainability performance outcomes. The findings reveal that assimilation strengthens technological capability and organisational agility, two distinct but complementary internal mechanisms that do not operate in isolation. When both are strong, they create a multiplicative effect, reinforce each other and amplify sustainability benefits. Furthermore, this dual mediation model enriches dynamic capabilities theory by highlighting that different dynamic capabilities carry different weights depending on the performance outcome examined. Organisational agility shows a stronger relationship with sustainability impact once established even though technological capability offers a clear pathway for translating assimilation into operational improvements. This distinction adds new insight to ongoing discussion about which capabilities matter most in digital transformation. It shows that technology focused capabilities alone are insufficient. Instead, the more adaptive and behavioural qualities related to organisational agility become essential for turning technological investments into sustainability performance gains.

Again, the stronger assimilation-to-technological capability path relative to organisational agility, indicates a clear tendency for technical competencies to develop more readily and to underpin the emergence of adaptive capabilities. While this pattern suggests a sequential development logic, the model employs parallel mediation rather than a formally specified sequential design. A definitive test of sequencing would require modelling technological capability as a predictor of organisational agility within the mediation chain, though not undertaken here. Nevertheless, the strength differential provides a theoretically grounded basis for proposing capability sequencing as a meaningful extension to Dynamic Capabilities Theory. Within the scope of the current model, the findings robustly establish that assimilation strengthens both technological capability and organisational agility as distinct pathways, while demonstrating that these capabilities do not develop uniformly. This contributes important empirical nuance to Dynamic Capacity theory by showing that capability development following technology assimilation is uneven rather than simultaneous.

Furthermore, this study adds to the growing conversation on the paradox perspective in sustainability. By bringing this viewpoint into the AI and I4.0T context, the study reveals that digital transformation often brings competing demands, hidden tensions, and unexpected outcomes that shape organisational actions and impact sustainability. For example, organisations with high technology readiness may adopt AI and I4.0T quickly, yet this early advantage can reduce the motivation to develop deeper dynamic capabilities. This suggests that conditions that support rapid adoption can simultaneously constrain the development of deeper dynamic capabilities when organisations rely so much on existing strengths. This paradox illustrates how early advantages in readiness may limit long-term sustainability impact if organisations fail to develop the agility required to reconfigure and adapt their processes in line with continued digital transformations and sustainability changes.

In addition, this research also expands supply chain theories through an emerging country perspective by focusing on Nigeria. Most supply chain theories originate from developed economies where digital infrastructure is mature, regulatory environments stable and organisational capabilities well established. These limits understanding of how these theories hold in more complex conditions such as fragmented supply chains, uneven infrastructure, limited digital access and regulatory inconsistencies. The study setting therefore offers a unique setting for evaluating AI and I4.0T adoption and assimilation because it serves as a critical testing ground for understanding how AI and I4.0Ts diffuse under resource constraints and institutional uncertainty. The Nigerian context also contributes perspectives largely underrepresented in literature on technology adoption and sustainability. These insights help broaden existing theories by adding perspectives from the Global South for a more balanced conversation.

Finally, the thesis strengthens sustainability theory by empirically modelling sustainability as a higher-order construct. The empirically supported conceptualisation of sustainability as a higher order construct measured through economic, social and environmental dimensions gives a more nuanced view of how internal processes translate technological inputs into sustainability outcomes. The results show that AI and I4.0T assimilation does not influence these dimensions equally. The differential loadings across dimensions demonstrate that organisations may experience stronger impacts in certain areas when integrating advanced technologies. This challenges one dimensional focus and supports the development of more balanced sustainability strategies that address economic, social and environmental outcomes simultaneously.

4.8.2 Practical Implication

The results of this study have clear implications for managers, technology leaders, and policymakers. The following points elaborate practical actions and priorities.

First, organisations should treat AI and I4.0T adoption as important but not sufficient by separating acquisition from assimilation. Managers should view investments in technology as the start of the digital transformation process and not the end. Initiatives targeted at developing technological capability including analytics, automation, integration and organisational agility for sensing, rapid decision-making and network reconfiguration must follow the acquisition and deployment of these digital tools. Moreover, considering that assimilation more readily impacts technological capability than organisational agility, organisations should plan for staged development. They should enhance their technical foundations by strengthening data platforms, integration, automation and then invest in strategies to foster agility through cross-functional teams, decentralised decision making and experimentation processes.

Again, with that organisational agility strongly predicting sustainability performance, organisations should prioritise organisational agility as a core sustainability enabler. In this regard they can invest in adaptive structures with practices and routines that enhance rapid sensing and response through market intelligence systems, flexible resource allocation, modular processes and supplier network flexibility.

Further, managers should manage paradoxes in implementation by acknowledging and planning for tensions and contradictions. By recognising the trade-offs, they can design interventions that address them rather than assume technology will resolve tensions automatically. Additionally, they can embed paradox sensitive governance to create governance structures that monitor the unintended consequences of technology like energy consumption, workforce impacts, increased process complexity and provide timely corrective actions.

Besides, organisations need to look beyond spending on infrastructure to strengthening mediating mechanisms by focusing on capability development, not only hardware. Digital literacy, data governance and analytics skills are essential for converting tools into

sustainability outcomes. Therefore, organisational policies and investments must go beyond funding devices and platforms to supporting human capital, managerial skills and process redesign.

Additionally, the varying sustainability dimension loadings suggest that organisations should adopt a comprehensive sustainability approach by designing for environmental, social and economic outcomes. Organisations should set integrated sustainability targets that require cross-functional coordination rather than siloed environmental initiatives. Metrics that capture multi-dimensional impacts could improve sustainability performance measurement and reporting. This enables better alignment of AI and I4.0T initiatives with sustainability goals.

Again, the study's findings highlight the role of policy in enabling organisations to move from adoption to impact. In Nigeria, where infrastructure, capacity and institutional support vary widely, policy support can accelerate meaningful digitalisation for sustainability by addressing infrastructure gaps, limited digital skills and resource constraints. Governments and regulators can accelerate positive outcomes by funding digital infrastructure, supporting public-private training partnerships, providing targeted incentives for capacity building and clarifying AI data governance to build trust. Finally, the findings hold broader relevance for other developing countries in sub-Saharan Africa and perhaps South Asia and Latin America due to similar institutional and infrastructural characteristics. Here, policies that combine infrastructure, incentives, skills and governance will be more effective than those that focus narrowly on procurement. Therefore, governments and organisations in these regions must intentionally design capability and agility development into digital strategies to achieve sustainability outcomes.

4.8.3 Limitations

The limitations identified in the study open useful avenues for further academic investigation. The integrated survey design shared with Chapter 3 presents a notable limitation.

As both chapters draw on the same respondent pool, the structural models are not statistically independent and the findings should be interpreted as covariance patterns rather than independently corroborated evidence. A further limitation relates to the single-source, cross-sectional design which increases exposure to common method bias. Although procedural and statistical controls were applied, this risk cannot be fully eliminated. Future research using multi-source, longitudinal designs that separate the measurement of adoption readiness, assimilation and sustainability over time would provide a stronger test of the proposed relationships.

Furthermore, sampling considerations of the study also introduce limitations. Although the sample size was sufficient for the analysis, a larger sample could increase statistical power and offer opportunity for more detailed subgroup analysis. Again, even with the responses coming from organisations of varying size, smaller firms appear under-represented. This may influence how well the findings reflect the realities of micro and small enterprises that often face distinct resource constraints. The sample also comprised mainly privately limited companies (Ltd), with fewer public listed companies (Plc), foreign-owned or multinational (MNC) subsidiaries represented. Ownership structure often shapes technology investment decisions, capability development and managerial priorities. Therefore, the limited variation may affect the breadth of insights. Similarly, sectoral diversity, although present, was uneven and so limits the ability to compare the mediation effects across different industries.

Finally, the study relied on self-reported organisational data, which may introduce response bias. Participants may have provided socially desirable answers or overestimated the maturity of their technology assimilation and sustainability practices. While this was mitigated by separating independent and dependent variables, using a mix of different validated scale formats including reverse worded questions, assuring confidentiality and as well as applying statistical methods after data collection, the potential for subjective bias remains.

Taken together, these limitations do not undermine the core findings but highlight opportunities for future research to apply more diverse samples, extended periods, and mixed-method designs to deepen and validate the insights generated by this study.

4.8.4 Recommendations for Future Research

There are a few areas that provide opportunities to extend the research findings.

First, considering the complex relationship between AI and I4.0T assimilation and sustainability outcomes, future studies could modify the conceptual framework to create a circular rather than linear relationship by incorporating feedback mechanisms. With this, sustainability outcomes become strategic drivers that could influence deeper assimilation and future technology adoption decisions. This offers a positive reinforcement cycle of learning and capacity development from experience and potentially establish industry benchmarks that can act as mimetic pressures on other supply chain actors to adopt AI and I4.0Ts.

Secondly, subsequent research could benefit from applying longitudinal designs to clarify the sequence of relationships in the dual mediation model, particularly the development of technological capability and organisational agility over time. Exploring how these two mediators interact may uncover synergistic effects that enhance sustainability performance.

Thirdly, developing separate models for economic, social and environmental sustainability outcomes could help identify distinct mediation pathways specific to each dimension. Additionally, mediators, such as organisational learning capability, innovation capacity or change management effectiveness, could also be considered in future studies to extend the current framework. Alternatively, investigating moderating factors such as industry context, organisational size or environmental dynamism may reveal conditions that influence the strength of mediation effects.

Fourthly, alternative research strategies and methods such as qualitative methods, including case studies or interviews could deepen understanding of the processes through which technology assimilation shapes sustainability outcomes. These methods can provide richer insight into managerial decision making, organisational routines and contextual influences that may be difficult to capture through quantitative designs.

Fifthly, a multi-level research focus offers another valuable direction. Studying relationships at the individual, team and organisational levels could help clarify how digital skills, collaborative behaviours and strategic processes could jointly influence capability development and sustainability outcomes.

Finally, applying and testing the model across different industries, organisational types and cultural settings would help determine its broader relevance. Comparative studies across emerging and developed economies, including contexts with varying infrastructure and institutional conditions, would further strengthen the robustness and generalisability of the framework.

Chapter 5 Conclusion

5.1 Introduction

The objectives of this study are shaped by the rapid advancement of digital technologies, alongside growing sustainability pressures in supply chains. Although the research on the digitalisation of supply chains and sustainability has expanded, key theoretical and empirical gaps remain. Existing theories do not adequately capture the autonomous, adaptive, and learning characteristics of AI and I4.0T, often treating them as static tools rather than dynamic actors shaping organisational processes and outcomes (Hendriksen, 2023). Again, the literature gives limited attention to the socio-technical integration required for effective deployment, particularly the roles of human readiness and organisational culture (Wang et al., 2025). Consequently, the mechanisms linking enabling conditions to adoption, especially the mediating role of the Technology Readiness Index, remain insufficiently explained. Furthermore, sustainability discussions largely focus on economic and environmental outcomes, with social dimensions such as labour inclusion, ethical implications, employment practices and equity (Shamsuddoha *et al.*, 2025; Whittlestone *et al.*, 2019; Muldoon *et al.*, 2025). Empirical evidence connecting digital assimilation to sustainability performance also remains limited, particularly regarding the roles of technological capability and organisational agility in translating digital investments into outcomes (Abdul Wahab and Radmehr, 2024). Furthermore, the dominance of developed-economy studies restricts understanding of how contextual factors shape these relationships in emerging economies such as Nigeria. These gaps collectively point to a fragmented understanding of how digitalisation drives sustainable supply chain performance. This study addresses this limitation by examining how AI and I4.0T adoption and assimilation translate into sustainability outcomes, with a focus on technology readiness, technological capability, and organisational agility.

5.2 Justification for Multi Paper Design

The complexity of digital transformation in supply chains and its implications for sustainability performance informed the adoption of a multi-paper research design. Examining how AI and I4.0T influence sustainability outcomes, and how the TRI, organisational agility, and technological capabilities mediate the transition from adoption to impact, requires a sequential and multi-layered approach. This structure aligns with methodological guidance suggesting that multi-study designs are well suited to research that spans multiple levels of analysis and integrates conceptual development with empirical investigation (Sandberg and Alvesson, 2011)

The thesis is structured across three interrelated studies. The first study is a systematic literature review that responds to the fragmented nature of literature linking AI, I4.0T and supply chain sustainability (Tortorella, Giglio and Van Dun, 2019). Using a transparent and reproducible methodology, it consolidates existing knowledge and establishes a theoretical foundation for the thesis (Snyder, 2019). Following Sandberg and Alvesson's (2011) gap spotting approach, it clarifies what is known and identifies underexplored areas, thereby shaping the direction of the empirical studies. The second study examines technology adoption through the TOE framework, with a specific focus on TRI as a mediating construct. While prior research has largely treated readiness as a contextual background condition, this study positions TRI as an active mechanism shaping adoption outcomes (Blut and Wang, 2019). It empirically explores how inhibitors and motivators within TRI influence technological, organisational, and environmental factors, extending TOE theory by emphasising socio-technical readiness as a determinant of AI and I4.0T adoption rather than merely infrastructural availability. The third study shifts the focus from adoption to assimilation, investigating how technological capability and organisational agility enable the conversion of adoption into sustainability performance outcomes. Grounded in dynamic capability theory, it explains how firms reconfigure resources

and processes to generate value from digital technologies. In doing so, it engages in theoretical problematisation (Sandberg and Alvesson, 2011) by challenging assumptions within dynamic capability theory regarding the role of technology in delivering sustainability benefits beyond operational efficiency. Taken together, the three studies establish a sequential analytical pathway from digitalisation to sustainability outcomes, tracing progression from adoption to assimilation. This structure provides theoretical depth, empirical robustness, and contextual relevance, offering a comprehensive explanation of how AI and I4.0T contribute to supply chain sustainability performance.

The CIMO framework extended through a CIMO-Symphony Orchestra perspective in Chapter 2, strengthens this integration by highlighting how multiple mechanisms operate in concert rather than in isolation. Within this structure, contextual conditions such as infrastructural constraints, institutional instability, and collectivist cultural norms (identified in the Nigerian context) shape the feasibility of AI and I4.0T adoption (Context-Overture). The TOE factors in Chapter 3 represent the Intervention-Ensemble, capturing the configuration of technological, organisational, and environmental elements influencing adoption. TRI functions as the Mechanism-Conductor, explaining how readiness mediates the translation of these conditions into adoption behaviour. Finally, the triple bottom line outcomes in Chapter 4 correspond to the Outcome-Finale, demonstrating that sustainability performance emerges only through the effective integration of these interconnected elements. Together, this integrated framework reinforces the thesis contribution by explaining not only whether AI and I4.0T improve sustainability performance, but how and under what conditions these outcomes are realised.

5.3 Summary of Key findings

This section integrates the key insights from the three empirical studies and discusses their collective contribution to understanding how AI and I4.0T influence supply chain

sustainability. It synthesises the results offers a coherent explanation of the relationships between technology adoption, assimilation, and sustainability outcomes. Across the three studies, the findings highlight that digital transformation in supply chains is a multi-stage and conditional process, shaped by organisational readiness, adoption determinants, and post-adoption capabilities. This provides the basis for a broader interpretation of how and under what conditions AI and I4.0T generate sustainability value. Table 5.1 summarises the linkages from concept to adoption through assimilation to outcome and discussed in details in the following sections.

Table 5.1 Summary of Findings

Paper 1 Findings	Gap Identified	Empirical or Theoretical Advancement	Addressed By
Under theorisation in the context of digital adoption	Limited understanding of contextual factors enabling AI&I4.0T adoption	Extends TOE framework to show how Technology Readiness Index motivates or inhibits adoption	**Chapter 3**
Lack of sociotechnical view of adoption	Over reliance on technical and managerial models	Introduces sociotechnical mediators: - TRI within TOE framework - Technological Capability and Organisational Agility in Dynamic Capabilities Theory	**Chapter 3 & 4**
Limited Global South Context	Few empirical studies from emerging markets. Existing theories and technologies developed from Global North perspective	Expands study to underrepresented contexts by focusing on Nigeria	**Chapter 3&4**
Under theorisation of AI and I4.0T capabilities	Existing theories (e.g. Agency, Stakeholder) fail to capture autonomy, adaptability and learning	Draws on Dynamic Capabilities Theory to explain how organisations absorb and leverage AI &I4.0T for sustainability	**Chapter 4**
Limited focus on social sustainability	Emphasis on economic and environmental metrics	Incorporates social sustainability for balanced sustainability performance outcomes	**Paper 3**

5.3.1 Chapter 2: AI Powered supply chain and Sustainability Performance

Chapter 2 establishes the conceptual foundation of the thesis by synthesising existing literature on AI and I4.0T in supply chains and their implications for sustainability. It highlights that while prior research largely emphasises efficiency, visibility, and environmental benefits, it gives limited attention to social sustainability and unintended consequences. The review also identifies important gaps in existing supply chain theories, particularly their limited ability to account for AI's evolving, autonomous, and socio-technical characteristics. These insights provide the basis for the thesis's central argument that understanding sustainability outcomes requires moving beyond adoption-focused perspectives toward a more integrated, process-oriented view.

5.3.2 Chapter 3: TOE adoption factors and the mediating role of Technology Readiness Index

Building on the conceptual gaps identified in Chapter 2, Chapter 3 empirically examines the determinants of AI and I4.0T adoption by extending the TOE framework through the inclusion of the Technology Readiness Index as a mediating mechanism. The findings show that adoption is shaped not only by technological, organisational, and environmental conditions but also by underlying psychological and attitudinal readiness. This shifts the explanation of adoption from a purely structural perspective to one that incorporates human and organisational readiness, thereby establishing adoption as a conditional and multi-level process that sets the stage for subsequent assimilation and outcomes.

5.3.3 Chapter 4: Translating post adoption assimilation to sustainability outcomes through dynamic capabilities

Extending the focus from adoption to post-adoption processes, Chapter 4 examines how AI and I4.0T assimilation translates into sustainability outcomes through the mediating roles of technological capability and organisational agility. The findings demonstrate that

sustainability benefits are realised not through adoption alone but through the organisation's ability to integrate, adapt, and apply these technologies effectively. This reinforces the thesis's process-based perspective by showing that the relationship between assimilation and sustainability outcomes is conditional and shaped by capability development. The paper also highlights the presence of underlying tensions, further supporting the need for a non-linear understanding of digital transformation in supply chains.

Overall, the findings of this thesis present a structured and progressive understanding of digital transformation in supply chains, moving from conceptual foundations to adoption mechanisms and finally to post-adoption outcomes. When viewed collectively, the results demonstrate that sustainability benefits from AI and I4.0T are not automatic but depend on a sequence of enabling conditions across different stages of the transformation process. This reinforces the central argument of the thesis that digitalisation should be understood as a conditional, multi-level process rather than a linear pathway. The following section outlines the theoretical, methodological, and practical contributions arising from these integrated findings.

5.4 Theoretical Contributions

This thesis makes important theoretical contributions by developing a more nuanced and integrated understanding of AI and I4.0T adoption and assimilation within organisations and how they shape supply chain sustainability performance.

5.4.1 Overall Contribution of the Research

Taken as a whole, this thesis empirically demonstrates and theoretically substantiates its central claim that digital transformation for sustainability is a contingent, sequentially mediated process in which each transition is governed by a distinct organisational mechanism that the preceding stage neither guarantees nor automatically activates. While prior research has examined readiness, adoption, capabilities and sustainability outcomes separately, these relationships have not been modelled as an integrated sequence.

The study identifies two critical transition gaps. First, favourable TOE conditions do not lead to adoption without TRI motivator activation. Second, assimilation does not translate into sustainability outcomes without technological capability and organisational agility. Together, these findings show that a substantial share of the total effect is contingent on intermediate mechanisms rather than direct progression across stages.

Across the three stages, distinct theoretical lenses explain each transition: TOE-TRI explains the move from conditions to adoption, organisational learning and institutional diffusion explain the shift from adoption to assimilation, and Dynamic Capabilities Theory explains how assimilation converts into sustainability performance through technological capability and organisational agility. The combined evidence validates that each stage is governed by a different mechanism operating at a specific transition point.

The cumulative insight is that the sustainability productivity paradox is not a technology failure but a sequenced mediation failure. By modelling and testing all transitions within a single integrated framework, the thesis shows that sustainability-oriented digital transformation depends on staged organisational investments in readiness, capability development and agility, with breakdown at any stage limiting realised sustainability outcomes.

5.4.2 Theoretical Implications

5.4.2.1 Extension of the TOE Framework and Dynamic Capabilities Theory

This thesis significantly advances existing theories by extending both the Technology-Organisation-Environment framework and Dynamic Capabilities Theory in the following ways

TOE Framework: The study enhances TOE's explanatory strength by positioning technology readiness index as a mediating factor that connects the potential adoption predicted by TOE factors to actual adoption. This perspective goes beyond identifying adoption determinants to explaining the mechanisms through which adoption potentials lead to tangible integration and use of AI and I4.0Ts.

Dynamic Capabilities Theory: The thesis expands the application of Dynamic Capabilities Theory by identifying technological capability and organisational agility as critical mechanisms linking technology assimilation to sustainability performance. In the rapidly evolving landscape of AI and I4.0Ts, traditional static capabilities become insufficient. Dynamic Capabilities Theory becomes particularly valuable lens for understanding how organisations transform technological investments into long-term sustainability performance because it emphasises an organisation's ability to sense, seize and reconfigure resources and capabilities to adapt to changing environments. This highlights that achieving sustainability through digital transformation is not only about owning technology but about continuously adapting and reconfiguring capabilities in response to evolving sustainability challenges.

5.4.2.2 Comprehensive Integrated Framework for Digitalisation and Sustainability

The research offers a novel integrated framework that unites the strengths of TOE and Dynamic Capabilities Theory to capture the full trajectory of digital transformation for sustainability. While TOE explains why organisations adopt technologies, it typically stops at the adoption decision and fails to predict implementation success or subsequent impacts. On the other hand, Dynamic Capabilities Theory explains how capabilities enable effective use of technology but assumes adoption as a given. By integrating these perspectives into a sequential model of digital transformation for sustainability, this thesis offers greater theoretical clarity, emphasising the roles of TOE factors and TRI in understanding AI and I4.0T adoption and establishes the significance of dynamic capabilities for achieving desired sustainability performance outcomes across all three dimensions. This model also reveals how dynamic capabilities and TOE factors interact synergistically, suggesting that their combined strength amplifies sustainability outcomes. This theoretical synthesis provides a more complete understanding of how AI and I4.0Ts influence sustainability across environmental, economic, and social dimensions. Furthermore, by examining how TOE and dynamic capabilities

mediating factors interact and potentially create a multiplicative effect when both are strong, this research represents a novel theoretical development in understanding the complex technology-sustainability relationship

5.4.2.3 Insights from the Paradox Perspective on Sustainability

A central theoretical contribution of this thesis lies in the identification and formalisation of three interrelated paradoxes that shape the relationship between AI and I4.0T assimilation and sustainability outcomes. Rather than assuming a linear and uniformly positive effect, the findings demonstrate that the assimilation-sustainability relationship within the proposed mediation model is inherently conditional and characterised by tensions. Specifically, these paradoxes establish important boundary conditions on the mediation pathways linking assimilation to sustainability outcomes through technological capability and organisational agility. This relationship is conditional rather than uniform, as the effects of assimilation on sustainability outcomes depend on how technological capability and organisational agility interact. In addition, the findings indicate that improvements in environmental performance arising from AI and I4.0T assimilation may be offset under certain conditions, reflecting rebound effects associated with increased efficiency and scale. Furthermore, rapid technology adoption, even when enabled by high levels of technology readiness, may limit the depth of assimilation required to achieve sustained sustainability outcomes. By articulating these conditions, the thesis extends existing frameworks such as the TOE framework and the Dynamic Capabilities perspective by introducing non-linear and conditional relationships into the adoption-assimilation-sustainability pathway. In doing so, it reframes digital transformation in supply chains as a process shaped by interacting tensions, offering a more precise explanation of how and when AI and I4.0T contribute to sustainability across economic, environmental, and social dimensions.

5.4.2.4 Revisiting Conventional Supply Chain Theories

This work contributes to existing knowledge by revealing the growing necessity to revisit the application of existing supply chain theories considering increased AI and I4.0T adoption. The heightened significance of data, coupled with the increasing autonomy, learning ability and complexity of AI and I4.0Ts challenge some of the fundamental assumptions of established theories, while the empirical findings and theoretical analysis in Chapter 2 indicate specific areas requiring theoretical refinement. The thesis identifies concrete proposition-level modifications for future development. In relation to Agency Theory, which assumes human principals and agents governed through monitoring, incentives and contracts, the evidence suggests a shift toward hybrid principal-agent-algorithm systems. Here, accountability becomes distributed across human decision-makers and the developers and auditors of autonomous systems, requiring algorithmic transparency and explainability alongside conventional governance mechanisms. For Stakeholder Theory, which assumes managerial balancing of competing human interests through moral reasoning, the findings indicate the need to incorporate algorithmic accountability structures. In AI-enabled supply chains, systems optimised for narrow objectives can unintentionally marginalise stakeholders not represented in optimisation functions, requiring governance that extends beyond managerial discretion. These propositions do not represent full theoretical revisions but specify the assumption-level changes implied by the evidence, providing a clear agenda for future formal theoretical development and empirical testing.

5.4.2.5 Developing Country Perspective

The Nigerian context extends the theoretical contribution of this study beyond empirical novelty by revealing clear boundary conditions for TOE, TRI and DCT that are not evident in developed-economy settings. Existing literature mostly assumes stable regulatory environments, mature digital infrastructure and well-developed organisational capabilities,

which limits explanatory power in settings characterised by fragmented supply chains, infrastructure deficits, restricted digital access and institutional uncertainty. Nigeria therefore serves as a critical context for examining AI and I4.0T adoption and assimilation under structural constraint. Across the analysis, five key divergences from established theory emerge. First, the TRI inhibitor pathway is largely non-significant, suggesting a dominance of structural constraints where infrastructural and institutional constraints suppress expected psychological barriers to adoption. Second, TOE conditions do not lead to adoption unless reinforced by TRI motivators, indicating a conditional relationship in which structural uncertainty shapes psychological engagement. Third, organisational culture emerges as the strongest predictor of readiness, outweighing technology-attribute effects and highlighting a cultural boundary condition where collective norms shape technology attitudes more strongly than technical factors. Fourth, external support primarily strengthens motivators rather than reducing inhibitors, implying that in high-uncertainty contexts policy and institutional support function as signalling effects rather than direct barrier removal. Fifth, early-stage assimilation already produces measurable sustainability outcomes, indicating that limited initial capabilities can still generate disproportionate gains compared with expectations in dynamic capability theory. Overall, these findings show that TOE, TRI and DCT are not universally stable but are shaped by structural, cultural and institutional environments. The Nigerian context therefore not only extends prior research geographically but also re-specifies the boundary conditions under which these theories operate, strengthening their external validity while identifying where contextual recalibration is required.

5.5 Practical and Managerial Implications:

The findings of this study will be of interest to a wide range of professionals including managers, sustainability officers and supply chain leaders

For managers, the findings suggest that they must evaluate their organisation's technology readiness before investing in AI and I4.0T. Managers run the risk of adoption failures where they embark on AI and I4.0T initiatives without cultural alignment. Considering that the findings reveals that organisational culture strongly shapes technology adoption both as a direct influence and through factors like technology readiness, managers should pursue cultural transformation to support innovation. Mangers should therefore focus on efforts that transform culture to encourage innovation, risk-taking, and receptiveness to new technologies. Similarly, managers must bear in mind that adopting so called universal models without adapting them to local cultural realities can lead to incomplete or misleading conclusions about what drives or hinders technology adoption especially in developing countries. Again, the significant mediating role of motivators highlights the need to focus resource allocation strategy primarily on investing in boosting positive motivations instead of focusing solely on addressing barriers.

For supply chain leaders, when addressing the technology-sustainability gap, they must recognise that simply adopting AI and I4.0T or even its assimilation alone does not guarantee improved sustainability performance. Instead, organisations must actively strengthen the mechanisms that mediate this relationship by intentionally enhancing both technological capability and organisational agility and not just by increasing technology investments. Building agility and technological capability is crucial for turning technology investments into tangible outcomes. This involves: (a) developing technological capability that extends beyond technical infrastructure to include digital competencies and management skills; (b) fostering organisational agility through adaptive processes, flexible resource allocation, and responsive decision-making (c) creating synergies between technological capability and organisational agility to maximize sustainability impact.

For sustainability officers, the differing impacts across sustainability dimensions highlight the need for a comprehensive approach when evaluating digitalisation projects. Considering all three pillars, environmental, social, and economic, ensures more balanced and effective outcomes. This requires expanding sustainability goals beyond environmental factors to include social and economic considerations, developing measurement systems that reflect the complexity and multidimensionality of technology enabled sustainability practices and directing AI and I4.0T investments toward comprehensive strategies rather than focusing on a single dimension.

5.6 Implications for Policy makers

The study's empirical findings generate targeted policy implications with each implication directly grounded in specific results. The study's findings suggest a necessary shift in policy focus from enabling conditions to enabling deployment. Despite favourable TOE conditions, low adoption levels reveal a deployment gap rather than a technology deficit. Policy should therefore prioritise implementation support through technical assistance, adoption intermediaries and deployment-focused programmes, while maintaining targeted infrastructure investment for underserved segments like SMEs (Wong, 2025). The results further show that adoption is driven primarily by TRI motivators (optimism and innovativeness), not inhibitors. This challenges conventional skills policies centred on barrier reduction. More effective approaches should emphasise benefit demonstration, peer learning, public-sector exemplars and visible success cases. The strong influence of organisational culture reinforces the need for interventions that extend beyond individual skills development to include leadership capability, innovation culture and organisational change support. Financing mechanisms also require recalibration. With nearly half of sustainability outcomes dependant on capability development, technology acquisition alone underdelivers. Phased financing tied to capability development milestones would better ensure that investments translate into measurable

outcomes. External support is most effective when it activates motivation rather than reduces barriers. Innovation hubs should therefore prioritise peer demonstration and context-relevant success cases to build confidence and stimulate adoption. Similarly, regulatory frameworks should combine compliance with visible institutional endorsement. Alongside regulatory safeguards such as the Nigeria Data Protection Act (NDPA, 2023) mechanisms like regulatory test environments, fast-track approvals and public sector adoption initiatives can signal commitment and strengthen adoption incentives. Finally, the stronger impact of assimilation on social rather than environmental sustainability highlights the need for differentiated policy design. Technology adoption incentives are more effective for social outcomes, while environmental performance requires complementary regulatory instruments. Policymakers aligning Nigeria's Agenda 2050 and the African Union's Agenda 2063 sustainability targets with digital transformation strategies should therefore recognise that technology adoption does not deliver uniformly across sustainability dimensions. Strategies should be mapped to the specific sustainability dimensions they are best suited to deliver.

5.7 Limitations

While this study makes valuable contributions, it also has limitations, as do most studies. These limitations may open directions for future research.

First, studies in chapters 3 and 4 used self-administered questionnaires that measured both the independent and dependent variables for data collection. Relying on the same response method introduces the possibility of common method bias (Kock, Berbekova and Assaf, 2021). To address this, the thesis applied both procedural and statistical safeguards to strengthen the validity and reliability of the results. The survey design included varied item wording and scale directions, avoided complex or ambiguous phrasing, provided clear instructions, and kept questionnaires concise. Respondent anonymity was also maintained (Podsakoff *et al.*, 2003b).

On the statistical side, Harman's single-factor test was used to assess common method bias, and the results showed that a single factor accounted for less than 50% of the total variance.

Second, the cross-sectional design of this study limits causal inference. Because data were collected at a single point in time, it is difficult to fully establish causal links between TOE factors, technology readiness, and AI and I4.0 adoption, or to trace the sequential development of technological capability and organisational agility. Technology adoption is a gradual process, and cross-sectional data may not fully capture its temporal dynamics or feedback loops. For example, early adoption success may encourage further implementation, creating a reinforcing cycle not reflected in the current model. This design also restricts understanding of how identified paradoxes develop over time. Moreover, a longitudinal approach could reveal whether sustainability related relationships shift as assimilation progresses and whether capability development paradoxes persist or resolve. Besides, the rapidly evolving AI and I4.0T landscape could potentially limit the shelf life of specific findings, especially those related to related to technology characteristics. This is because what constitutes cutting-edge technology today might be commonplace in a few years, altering the dynamics of adoption decisions.

Finally, although Nigeria provides a good background for exploring how AI and I4.0T influence sustainability performance in supply chains, several contextual limitations may affect the scope, interpretation and generalisability of the findings. In Nigeria, adoption and assimilation of these technologies remain relatively new across most sectors even with evidence of increasing adoption. This means that the observed sustainability outcomes may just reflect early-stage adoption and capability development and incremental rather than transformational technological effects. Moreover, infrastructure and institutional limitations may limit organisations' ability to sustain technology use. This could influence observed outcomes by distorting the true relationship between technology assimilation and sustainability

performance. Again, Nigeria's unique business environment characterised by informality, weak institutional enforcement and macroeconomic volatility limits the direct transferability of findings to other contexts. While the study advances theoretical understanding of digital transformation in emerging markets, results may best be interpreted as context dependent or extensions of existing theories rather than universally generalisable.

5.8 Future Research Directions

There are a few areas that provide opportunities to extend the research findings.

Given the complex relationship between AI and I4.0T adoption and sustainability outcomes, future studies could refine the conceptual framework by incorporating feedback mechanisms that reflect a circular rather than linear relationship between AI and I4.0T adoption and sustainability outcomes. This would position sustainability outcomes not only as results but also as strategic drivers that shape deeper assimilation, future adoption decisions and positive reinforcement cycles of learning and capability building. It could also highlight the role of sustainability outcomes in setting benchmarks that create mimetic pressures for adoption across supply chains.

Similarly, this study could be repeated using longitudinal designs to move beyond the limitations of cross-sectional data. Longitudinal studies would allow clearer causal inference between TOE factors, technology readiness, and AI and I4.0T adoption, as well as the sequential development of technological capability and organisational agility. It could also capture the temporal dynamics and feedback loops inherent in technology adoption, such as reinforcing cycles from early implementation success and reveal how paradoxes evolve over time. They would also support multilevel analysis across individual, team, and organisational layers, providing deeper insights into how effects operate throughout the organisation.

Again, future research could also consider alternative methodological approaches. Qualitative methods such as case studies and interviews could provide richer insights into the mechanisms linking technology assimilation with sustainability outcomes. Mixed-method designs combining surveys with qualitative case studies would allow researchers to capture contextual factors influencing adoption decisions and better explain how TOE factors shape technology readiness.

Furthermore, the contextual limitations identified in this study also provide avenues for future research. For instance, future research could expand to multi-country studies across Africa or other emerging economies to compare adoption patterns, barriers and sustainability outcomes across countries with varying institutional and infrastructural characteristics to expand both theory and practice within comparable emerging market contexts. Besides, Nigeria's infrastructural challenges could provide opportunities to explore how organisations adapt and localise AI and I4.0T under challenging conditions such as energy unreliability, low internet connectivity and logistics inefficiencies (PWC, 2025). This could advance understanding of and contribute to literature on frugal innovation and context sensitive digital transformation models (Al-Omoush *et al.*, 2025; Nassani *et al.*, 2022).

5.9 Concluding statement

The literature often suggests that digital technologies will make supply chains more sustainable, promising greater visibility, efficiency, risk reduction and greener operations. Yet in practice, adoption is uneven, implementations fall short and sustainability benefits are limited. If the potential is so strong, why does it so often go unrealised, and under what conditions can adoption lead to genuine sustainability impact? This gap between promise and outcome motivates this thesis. The thesis provides a clear answer. Digital transformation for sustainability is a contingent, sequentially mediated process. Favourable conditions do not guarantee adoption without the activation of TRI motivators. Adoption does not guarantee

assimilation without strategic integration and organisational commitment. Assimilation does not guarantee sustainability outcomes without the development of technological capability and organisational agility. At each stage, a distinct organisational mechanism determines whether progress occurs. The sustainability productivity paradox is therefore capability gap rather than a technology gap.

This thesis contributes by modelling these transitions within a single integrated framework and showing that sustainability gains emerge only when adoption evolves into assimilation supported by readiness, capability, and agility. These findings open clear directions for future research. Longitudinal studies are needed to establish causal sequencing across stages, while sequential mediation designs can test whether technological capability development precedes and enables organisational agility. Comparative studies across emerging economies will help determine whether the boundary conditions identified here are context-specific or generalisable. Further work is also needed to operationalise hybrid human-AI capability structures, extending current theory to reflect increasing technological autonomy.

For practice, the implication is straightforward: adoption is not the endpoint. Technology investment creates potential, but real impact depends on readiness before adoption, capability development after adoption and sustained organisational agility. Without these, organisations risk capturing only a fraction of the sustainability benefits digitalisation can deliver.

Finally, the Nigerian context underscores the broader significance of this research. As AI and I4.0T diffuse rapidly across emerging economies, evidence to guide their sustainable integration remains limited. Nigeria, characterised by infrastructural constraints, institutional uncertainty, and rapid digital adoption, provides a critical setting for examining how these technologies function under real-world conditions. It highlights the environments in which

many organisations operate, repositioning the Global South as central to understanding how digital transformation shapes sustainability outcomes.

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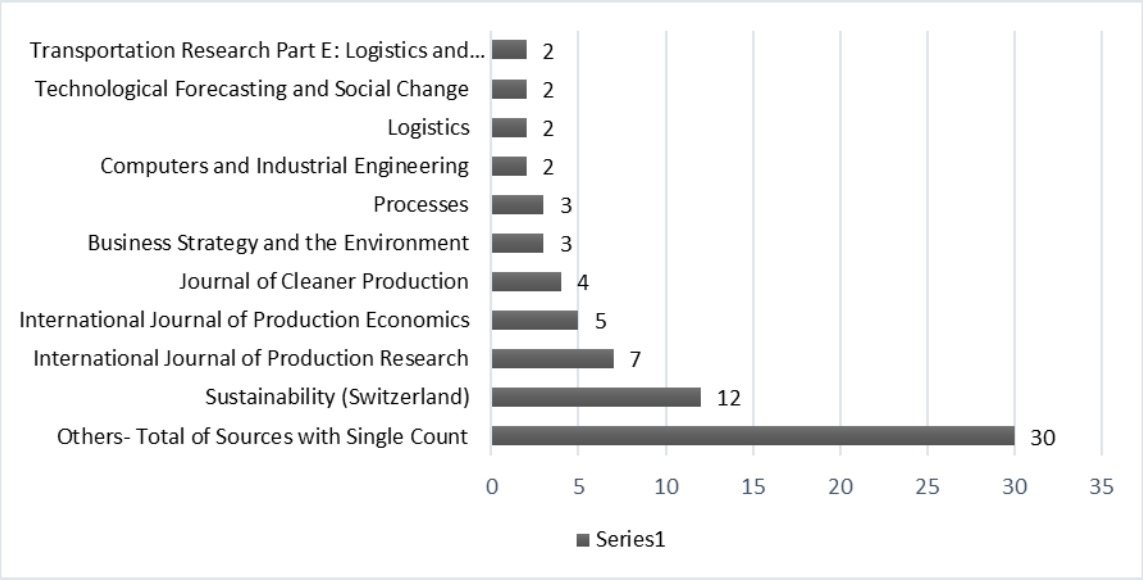
A APPENDIX A (Re: Chapter 2)



A.1 Figure A.1 Journals

A.2 Table A.1 Source Journals

Authors	Focus of Study	Sector	Methodology	Theory
(Ada *et al.*, 2021)	Barriers to circularity in food supply chain, I4.0 solutions	Food	Systematic Literature review	No Theoretical Lens
(Addou *et al.*, 2023)	BCT, IOT and ML for traceability and sustainability in food supply chain to track food, money and information	Food	Model proposed	No Theoretical Lens
(Agnusdei *et al.*, 2023)	The role of digitalisation as a driver of circularity in the agroindustry.	Agriculture	SWOT-ANP-ADAM approach	No Theoretical Lens
(Alavi, Tavana and Mina, 2021)	Circular economy and Supplier selection	Petrochemical	Case Study	No Theoretical Lens
(Aljabhan, 2023)	Supply chain risk management & application of AI based system	General	Case study	Plithogenic theory for SCRM
(Amentae and Gebresenbet, 2021)	The potential contribution of digitalisation of the food system to transition ton towards sustainable and resilient systems	Agro-Food	Integrative Literature review	No Theoretical Lens
(Apruzzese *et al.*, 2023)	New business models for Logistics	Transport & Logistics	GUEST methodology, Literature Review	No Theoretical Lens
(Arunmozhi *et al.*, 2022)	AI and Blockchain-based Smart Contracts for enhanced sustainable supply chain operations	Automotive	Case Study &Intervention Based Research	Business Process Re-engineering theory
(Asokan *et al.*, 2022)	Framework for exploring the adoption of Industry 4.0 technologies for improving SROP	General	View Point Paper &Narrative Review	No Theoretical Lens
(Bag *et al.*, 2020)	GSCM system product complexity and purchasing structure	Manufacturing Industry	Literature review/Case study	Systems Theory

(Bag and Pretorius, 2020)	Review the latest articles in Industry 4.0, sustainable manufacturing and circular economy	General	Literature Review	Institutional Theory/ Research Based View
(Bag *et al.*, 2023)	Suppliers' capability to examine the underlying limitations to adapting to CCA and DRR goals to combat the environmental crisis.	Garment Industry	Literature Review, Hypothesis testing & Structural Modelling	Institutional theory/Dynamic capability view
(Bai and Zhang, 2022)	Key ESG issues and the main ESG themes for companies in the power industry	Energy	Narrative	ESG
(Bai *et al.*, 2020)	Application and sustainability implications of Industry 4.0 technologies and a measures framework for sustainability based on the UN SDGs	General	Case Study	No Theoretical Lens
(Bechtsis *et al.*, 2022)	How data-centric Supply Chains be (re)designed and managed to support secure, resilient and sustainable ecosystems	General	Exploratory Literature Review	Transaction Cost Economics /Resource-Based View'
(Cannas *et al.*, 2023)	AI applications support of OSCM processes; identify benefits and barriers to implementation.	General	Case study	SCOR Model
(Carnerud *et al.*, 2020).	Trends in sustainability and digitalisation from the 1980s to date in Quality Management	General	Content Analysis	No Theoretical Lens
(Cataldo *et al.*, 2022)	Long term sustainability considerations in the supply chain in the construction sector	Construction	Exploratory Review	No Theoretical Lens
(Chauhan *et al.*, 2022)	The role of I4.0 technologies in the context of sustainable SCM	General	Systematic Literature review	No Theoretical Lens
(Damoah, Ayakwah and Tingbani, 2021)	AI-enhanced medical drone application in Ghana's healthcare supply chain and its contribution to SDGs	Medical supply chain	Case study	CSR
(Dhamija and Bag, 2020)	Review of research work on AI by top contributing universities, authors, keywords, funding sources, journals and citation statistics.	General	Systematic Literature review& Bibliometric analysis	No specific Theoretical Lens
(Di Vaio *et al.*, 2020)	The function of AI in agri-food industry and the role of stakeholders in its supply chain.	Agri-Food	Literature Review	No Theoretical Lens
(Dolgui *et al.*, 2020)	Blockchain oriented dynamic model and computational algorithm for smart contract design in the SC	Logistics Services	Modelling Methodology	Dynamic Control Theory
(Dubey *et al.*, 2020)	The role of Entrepreneurial orientation on the adoption BDA powered by AI (BDA-AI) and operational performance (	Manufacturing Industry	Empirical Research	Dynamic capabilities & Contingency theory
(Dumitrascu, Dumitrascu and Dobrotă, 2020)	Performance evaluation model linking relevant KPIs for every subsystem of the SCM to specific problems	Automotive	Case Study	No Theoretical Lens
(Elghaish *et al.*, 2022)	Relationship between I4.0digital technologies (e.g.	Construction	Systematic Literature Review	Conceptual framework developed

	BCT, IoT and AI) transition into a circular economy (CE) system			
(Espina-Romero and Guerrero-Alcedo, 2022)	The fields of study where digitalisation is most applied	General	Bibliometric Review	No Theoretical Lens
(Feng, Lai and Zhu, 2022)	The emergence and adoption of GSCI in digital-enabled I4.0	General	Literature Review	No Theoretical Lens
(Gebhardt *et al.*, 2021)	The intersection of the Circular economy, Supply Chain Collaboration, and I4.0.	General	Systematic Literature review	Resource based view
(Gong, 2023)	The outcomes of digital inclusiveness in overall SCM for the growth of retail and e-commerce-based platforms.	Retail E-commerce	Descriptive/ Explanatory study	No Theoretical Lens
(Hao and Demir, 2023).	Identification of three-dimensional triggers, linked to ESG, as well as technological inhibitors	General	Systematic Literature review	Environment, Social & Governance theory
(Hong *et al.*, 2021)	Current approaches for traceability in the value chain, and technologies essential for promoting the circular economy	Garment Industry	Literature Review	No Theoretical Lens
(Hu and Yao, 2023)	Effects AI, IoT, and BD on Supply Chain practices and the effects on environmental and sustainability results of SDGs	General	Case study	No Theoretical Lens
(Huang *et al.*, 2022),	Impact of AI on Service supply chain	Service Supply chain	Conceptual Paper	No Theoretical Lens
(Ivanov, 2023)	Three decision-making approaches that involve humans and artificial autonomous agents and determinants of the choice of a decision-making approach	General	Conceptual Paper	Agency Theory
(Kamal, Abdel-Gawad and Zaki, 2023)	The potential benefits and applications of integrating Neutrophil reasoning and ML in SCM	General	Narrative	Neutrosophic Theory
(Kamble *et al.*, 2022)	Digital twins application in manufacturing to combat sustainability challenges	Manufacturing Industry	Systematic Literature Review	No specific Theoretical Lens
(Kannan, 2018)	Important CSFs that contribute to success in attaining sustainability based on stakeholder theory	Garment Industry	Case study	Stakeholder Theory, CSF, 3BL
(Kar, Choudhary and Singh, 2022)	AI and sustainability focused on different use cases	General	Literature Review	No Theoretical Lens
(Kazancoglu *et al.*, 2021)	Circular economy in Dairy supply chain	Food- Dairy	Case study	No specific Theoretical Lens
(Krupitzer and Stein, 2021)	The concept of Food Informatics as a supportive discipline that subsumes the incorporation of information technology, mainly IoT and AI	Food	Systematic Mapping	No Theoretical Lens
(Kumar and Barua, 2021)	The sustainable dimensions and disruptive technologies in the Petroleum supply chain	Petroleum Sector	Literature Review and Content Analysis	Regret theory (RT)
(Kunkel *et al.*, 2022)	Digitalisation in the Electronics supply chain and its implications for	Electronics	Exploratory study	No Theoretical Lens

	sustainable supply chain collaboration			
(Lee and Mangalaraj, 2022)	Existing studies in BDA presenting a framework of from interdisciplinary perspectives.	General	Systematic Literature review	No Theoretical Lens
(Lee, 2021)	Product design and social sustainability of AI	General	Systematic Literature review	No Theoretical Lens
(Liu, Song and Liu, 2023)	A conceptual framework of I4.0 technologies-embedded SSCM,	General	Integrative Review	No Theoretical Lens
(Maghsoudi *et al.*, 2023)	A co-authorship network analysis of the relationships among AI applications in Sustainable Supply Chains	General	Social Network Analysis	No Theoretical Lens
(Min, 2010)	The various sub-fields of AI that are most suitable for solving practical problems relevant to SCM	General	Literature Review	No Theoretical Lens
(Mithas *et al.*, 2022)	AI and emerging technologies and their impact on sustainability	Construction, Transportation, Healthcare, Manufacturing, Agriculture, and Water.	Literature Review	Theory of Disruptive Innovation SACE & ADRIOT Frameworks
(Nayal *et al.*, 2021)	The relation among flexibility, AI–IoT adoption, and SC firm performance under the circular economy (CE) environment	Manufacturing Industry	Case Study	Resource Orchestration theory (ROT) and Dynamic Capability theory (DC
(Naz *et al.*, 2022)	Applications of AI in sustainable supply chains	General	Systematic Literature review	No Theoretical Lens
(Noman *et al.*, 2022)	Adoption and integration of Applied AI techniques in Circular Economy	General	Bibliometric Analysis and Systematic Literature Review	No Theoretical Lens
(Olan *et al.*, 2021).	Impact of AI in stimulating financial services for FDIs through supply chain network activities	Food and Drink	Conceptual Paper	Supply Chain Network Theory
(Onyeaka *et al.*, 2023)	The potential for AI to tackle food waste and enhance the circular economy	Food	Literature Review	No theoretical Lens
(Pournader *et al.*, 2021)	Artificial intelligence applications	General	Systematic Literature Review	No Theoretical Lens
(Raja Santhi and Muthuswamy, 2022)	The role of I4.0 technologies in addressing challenges associated with supply chain management	General	Narrative/Descriptive Review	No Theoretical Lens
(Rejeb and Appolloni, 2022)	Existing literature on the applications of Industry 4.0 technologies in Circular Procurement	General	Systematic Literature review	No Theoretical Lens
(Romagnoli *et al.*, 2023)	Enhancing the functionality of CSCs by adopting sustainable practices and digital technologies to increase performance	General	Conceptual Paper	No Theoretical Lens
(Rusch, Schöggl and Baumgartner, 2022)	Examples of DT applications in Sustainable Product management	General	Systematic Literature Review & Content analysis	Circular Economy theory
(Sharma *et al.*, 2022)	Trends, gaps, and research opportunities on artificial AI applications in supply chain management (SCM)	General	Systematic Literature review	Resource Dependency

(Tariq, 2023)	The role of AI in enabling sustainable supply chain management	General	Literature Review	No specific Theoretical Lens
(Tavana *et al.*, 2022)	Digital Transformation on Supply Chain Process Management	General	Narrative Literature review Bibliometric analysis	No specific Theoretical Lens
(Tirkolaee *et al.*, 2021)	Machine Learning in supplier management, and circular economy in SCM	General	Literature review	No Theoretical Lens
(Toorajipour *et al.*, 2021)	The most prevalent & potential AI techniques in SCM; current & potential AI-improved SCM subfields;	General	Systematic Literature review	No Theoretical Lens
(Trabucco and De Giovanni, 2021)	Adoption of Lean approaches for sustainability and resilience during a pandemic	Retailing, Electronics, Pharmaceutics and Agriculture	Case study	No Theoretical Lens
(Tsolakis *et al.*, 2022)	AI and BCT in supply chains for extending operations performance boundaries and fostering sustainable development and data monetisation	Food	Case Study	Systems dynamics
(Varriale *et al.*, 2023)	Identifying which technologies favour sustainable emerging practices considering the triple bottom line (3BL) perspective	General	Systematic Literature review	3BL
(Verma *et al.*, 2022)	Recycling plastics and plastic waste using AI and Blockchain Technology	Waste Management	Literature Review	No Theoretical Lens
(Wilson, Paschen and Pitt, 2021)	AI and its implications for reverse logistics within the circular economy (CE).	Transport	Conceptual Paper	No Theoretical Lens
(Wong *et al.*, 2021)	Technical design and technical sustainability, scalability and big data processing and analytics	Logistics Services	Case study	No Theoretical Lens
(Wu *et al.*, 2020)	Multi-partner classification model for the partner qualification and classification process	Electronics	Literature Review and Concept	No Theoretical Lens
(Zhang, Li and Peng, 2020)	Risk indicators that affect the quality and safety of fresh produce in transit	Food	Case Study	No specific Theoretical Lens

B APPENDIX B (Re: Chapter 3)

B.1 Table B.1

Theory	Survey Construct	Code	Question	Reference
TECHNOLOGY	TECHNOLOGY CHARACTERISTICS (TCQI)	TC1	AI and /or I4 technologies are easy to integrate with our organization's existing processes	Gutierrez, Boukrami and Lumsden (2015), Abdekhoda, Dehnad and Zarei (2019) Olivera et al. (2014)
		TC2	Our organization finds AI and /or I4 technologies easy to use and manageable	
		TC3	AI and /or I4 technologies compatible with our organization's managerial and operational needs	
		TC4	AI and /or I4 technologies is compatible with our organizations existing system	
		TC5	Our organization finds AI and /or I4 technologies complicated to use	
	RELATIVE ADVANTAGE (RAQI)	RA1	Adopting AI and /or I4 technologies provides competitive advantage to our organization	Gutierrez, Boukrami and Lumsden (2015), Abdekhoda, Dehnad and Zarei (2019) Olivera et al. (2014)
		RA2	AI and /or I4 technologies provides more benefits for our organization than our current infrastructure	
		RA3	Adopting AI and /or I4 technologies offers our organization new opportunities	
		RA4	Specific tasks can be performed quicker using AI and /or I4 technologies	
		RA5	Using AI and /or I4 technologies improves job performance across the organization.	
Theory	**Survey Construct**	**Code**	**Question**	**Reference**
ORGNIZATION	ORGANIZATIONAL RESOURCES (ORQI)	OR1	There are sufficient technological resources to implement AI and /or I4 technologies in our organization	Malik et al., (2021); Gutierrez, Boukrami and Lumsden (2015)
		OR2	Our organisation has the financial resources for AI and /or I4 technologies adoption	
		OR3	There is adequate training and education for our employees to adopt AI and /or I4 technologies	
		OR4	There are cognitive capabilities of IT human resources in our organization to support AI and /or I4 technologies adoption	
		OR5	The existing technology in our organization can support AI and /or I4 technologies implementation	
	ORGANIZATIONAL CULTURE (OCQI)	OC1	The adoption of AI and /or I4 technologies is in line with the vision and mission of our organization	Malik et al., (2021); Gutierrez, Boukrami and Lumsden (2015)
		OC2	The concept of AI and /or I4 technologies is in accordance with the culture and identity of our organization	
		OC3	AI and /or I4 technologies are consistent with our organization's current values and beliefs	
		OC4	Our management has an openness to implement change in our organization	
		OC5	Our top management considers AI and /or I4 technologies adoption as strategically important for the organization	
Theory	**Survey Construct**	**Code**	**Question**	**Reference**
ENVIRONMENT	COMPETITIVE PRESSURE (CPQI)	CP1	AI and /or I4 technologies will provide stronger competitive advantage for our organization	Gutierrez, Boukrami and Lumsden (2
		CP2	AI and /or I4 technologies would increase our organization's ability to outperform competition	
		CP3	AI and /or I4 technologies allow generation of higher profits for our organization	
		CP4	AI and /or I4 technologies is being implemented by a few of our competitors.	
		CP5	Our competitors that have implemented AI and /or I4 technologies are favourably perceived within our industry	
	EXTERNAL SUPPORT (ESQI)	ES1	There are third party service providers that provide technical support for effective use of AI and /or I4 technologies	Bhattacharya and Wamba (2018); Naeem et al.,(2024); Nguyen (2022)
		ES2	External funding agencies encourage adoption of AI and /or I4 technologies	
		ES3	Government policies encourage adopting new technology such as AI and /or I4 technologies	
		ES4	Government agencies provide the technical support, training, and funding to increase the adoption of AI and /or I4 technologies	
		ES5	There are some business laws to deal with the security and privacy concerns related to AI and /or I4 technologies	
Theory	**Survey Construct**	**Code**	**Question**	**Reference**
TECHNOLOGY READINESS	MOTIVATING FACTORS (MFQI)	MF1	The adoption of advanced technologies provides our organization with greater flexibility and operational freedom.	Tunmibi and Okuonghae (2023)
		MF2	Implementing new technologies enhances the overall productivity and efficiency of our organization.	
		MF3	Our organization is often consulted by other firms for advice on adopting and integrating new technologies.	
		MF4	We are typically early adopters of new technologies within our industry.	
		MF5	Our organization actively stays updated with the latest technological advancements relevant to our industry.	
	INHIBITING FACTORS (IFQI)	IF1	Technical support services often fail to explain technological solutions in a way that is comprehensible and practical for our organization.	Tunmibi and Okuonghae (2023)
		IF2	There are instances where we feel that certain technology systems are not user-friendly or practical for typical organizational use.	
		IF3	Our organization is concerned that an over-reliance on technology may compromise our ability to perform essential functions independently.	
		IF4	Excessive use of technology can sometimes lead to distractions that negatively impact our workforce's productivity.	
		IF5	The extensive use of technology may reduce personal interactions, thereby potentially lowering the quality of internal relationships within our organization.	

AI TECHNOLOGY ADOPTION

Survey Construct	Code	Level of Adoption	Level AI functions	Level of Adoption
AI TECHNOLOGY ADOPTION	A3i	Initial	Very limited or no Artificial Intelligence technology use by the organization or the organization has no immediate plans to use Artificial Intelligence technology	Neumann, Guirguis and Steiner (2022); Nagarajan (2024)
		Assessing	Exploring and discovery of suitable Artificial Intelligence technologies for the organization.	
		Determined	Artificial Intelligence technology Proof of Concept or Product/ solution testing stage; or Determination of infrastructure needed to further implement AI technology	
		Managed	AI Pilot programme; deployment of AI solution in some areas of the organization. Preparation of large-scale AI application in the organisation; All essential organisational structures are in place for the integration of AI;	
		Optimize	Full AI infrastructure is in place; Organization is ready for large-scale AI deployment; A significant portion of business choices are facilitated or made using AI	

I4.O TECHNOLOGY ADOPTION

Survey Construct	Code	Level of Adoption	Level I4.0 functions	Level of Adoption
I4.O TECHNOLOGY ADOPTION	A3ii	Initial	Very limited or no Industry 4.0 technology use by the organization or the organization has no immediate plans to use Industry 4.0 technologies	Neumann, Guirguis and Steiner (2022); Nagarajan (2024)
		Assessing	Exploring and discovery of suitable I4.0 technologies for the organization.	
		Determined	I4.0 technology Proof of Concept or Product/ solution testing stage; or Determination of infrastructure needed to further implement I4.0 technology	
		Managed	I4.0 Pilot programme; deployment of I4.0 solution in some areas of the organization. Preparation of large-scale I4.0 application in the organisation; All essential organisational structures are in place for the integration of I4.0 technology;	
		Optimize	Full I4.0 infrastructure is in place; Organization is ready for large-scale I4.0 technology deployment; A significant portion of business choices are facilitated or made using some I4.0 technology	

B.2 Table B.2 Skewness and Kurtosis

DESCRIPTIVE NORMALITY STATISTICS			
S/n	**Item**	**Skewness**	**Kurtosis**
1	QID10_B1_TC1	-0.756	-0.076
2	QID10_B1_TC2	-0.831	0.514
3	QID10_B1_TC3	-1.06	0.901
4	QID10_B1_TC4	-0.829	0.845
5	QID10_B1_TC5_R	-0.332	-0.777
6	QID13_B2_RA1	-1.641	3.198
7	QID13_B2_RA2	-1.231	1.696
8	QID13_B2_RA3	-1.612	2.705
9	QID13_B2_RA4	-2.318	7.005
10	QID13_B2_RA5	-1.785	4.337
11	QID14_B3_OR1	-0.341	-0.925
12	QID14_B3_OR2	-0.529	-0.611
13	QID14_B3_OR3	-0.145	-0.894
14	QID14_B3_OR4	-0.533	-0.219
15	QID14_B3_OR5	-0.512	-0.556
16	QID15_B4_OC1	-1.067	0.675
17	QID15_B4_OC2	-0.941	0.728
18	QID15_B4_OC3	-0.728	0.157
19	QID15_B4_OC4	-1.192	1.033
20	QID15_B4_OC5	-1.136	0.732
21	QID16_B5_CP1	-1.648	4.083
22	QID16_B5_CP2	-1.223	1.829
23	QID16_B5_CP3	-0.767	0.736
24	QID16_B5_CP4	-0.432	0.22
25	QID16_B5_CP5	-0.23	-0.377
26	QID17_B6_ES1	-0.214	-0.792
27	QID17_B6_ES2	-0.149	-0.117
28	QID17_B6_ES3	-0.095	-0.611
29	QID17_B6_ES4	0.037	-0.79
30	QID17_B6_ES5	-0.479	-0.485
31	QID19_C1_MF1	-1.151	2.054
32	QID19_C1_MF2	-1.614	4.433
33	QID19_C1_MF3	-0.025	-0.498
34	QID19_C1_MF4	-0.244	-0.815
35	QID19_C1_MF5	-0.698	-0.176
36	QID20_C2_IF1_R	-0.063	-0.589
37	QID20_C2_IF2_R	-0.503	0.004
38	QID20_C2_IF3_R	0.149	-0.835
39	QID20_C2_IF4_R	-0.01	-0.943
40	QID20_C2_IF5_R	0.286	-1.01

B.3 Table B.3 Kolmogorov-Smimova and Shapiro-Wilk Test of Normality

Tests of Normality						
	Kolmogorov-Smirnova			Shapiro-Wilk		
Variable	Statistic	df	Sig.	Statistic	df	Sig.
A3i:AI_ADP	0.221	192	<.001	0.887	192	<.001
A3ii: I40_ADP	0.218	192	<.001	0.889	192	<.001
B1_TC1	0.270	192	<.001	0.865	192	<.001
B1_TC2	0.289	192	<.001	0.858	192	<.001
B1_TC3	0.291	192	<.001	0.832	192	<.001
B1_TC4	0.305	192	<.001	0.844	192	<.001
B1_TC5R	0.213	192	<.001	0.904	192	<.001
B2_RA1	0.274	192	<.001	0.734	192	<.001
B2_RA2	0.242	192	<.001	0.801	192	<.001
B2_RA3	0.285	192	<.001	0.734	192	<.001
B2_RA4	0.346	192	<.001	0.632	192	<.001
B2_RA5	0.295	192	<.001	0.719	192	<.001
B3_OR1	0.235	192	<.001	0.895	192	<.001
B3_OR2	0.226	192	<.001	0.876	192	<.001
B3_OR3	0.200	192	<.001	0.909	192	<.001
B3_OR4	0.240	192	<.001	0.891	192	<.001
B3_OR5	0.239	192	<.001	0.887	192	<.001
B4_OC1	0.245	192	<.001	0.818	192	<.001
B4_OC2	0.269	192	<.001	0.844	192	<.001
B4_OC3	0.229	192	<.001	0.862	192	<.001
B4_OC4	0.256	192	<.001	0.784	192	<.001
B4_OC5	0.249	192	<.001	0.803	192	<.001
B5_CP1	0.294	192	<.001	0.709	192	<.001
B5_CP2	0.259	192	<.001	0.783	192	<.001
B5_CP3	0.224	192	<.001	0.833	192	<.001
B5_CP4	0.211	192	<.001	0.880	192	<.001
B5_CP5	0.200	192	<.001	0.897	192	<.001
B6_ES1	0.167	192	<.001	0.911	192	<.001
B6_ES2	0.223	192	<.001	0.900	192	<.001
B6_ES3	0.189	192	<.001	0.916	192	<.001
B6_ES4	0.199	192	<.001	0.900	192	<.001
B6_ES5	0.233	192	<.001	0.890	192	<.001
C1_MF1	0.274	192	<.001	0.798	192	<.001
C1_MF2	0.277	192	<.001	0.739	192	<.001
C1_MF3	0.188	192	<.001	0.923	192	<.001
C1_MF4	0.164	192	<.001	0.929	192	<.001
C1_MF5	0.226	192	<.001	0.882	192	<.001
C2_IF1R	0.170	192	<.001	0.920	192	<.001
C2_IF2R	0.262	192	<.001	0.887	192	<.001
C2_IF3R	0.174	192	<.001	0.921	192	<.001
C2_IF4R	0.149	192	<.001	0.930	192	<.001
C2_IF5R	0.225	192	<.001	0.901	192	<.001

a Lilliefors Significance Correction

B.4 Table B.4 Harman's single Factor Test

Total Variance Explained						
	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	12.346	29.396	29.396	11.706	27.872	27.872
2	3.604	8.581	37.977			
3	2.605	6.203	44.18			
4	1.87	4.452	48.633			
5	1.636	3.895	52.527			
6	1.493	3.554	56.081			
7	1.427	3.397	59.478			
8	1.364	3.248	62.726			
9	1.178	2.806	65.532			
10	1.132	2.695	68.227			
11	0.995	2.37	70.597			
12	0.932	2.219	72.816			
13	0.851	2.027	74.842			
14	0.796	1.896	76.738			
15	0.742	1.767	78.506			
16	0.642	1.528	80.033			
17	0.611	1.455	81.488			
18	0.574	1.367	82.855			
19	0.545	1.297	84.152			
20	0.52	1.238	85.39			
21	0.477	1.135	86.526			
22	0.472	1.124	87.65			
23	0.432	1.03	88.679			
24	0.415	0.988	89.667			
25	0.409	0.973	90.64			
26	0.376	0.894	91.534			
27	0.372	0.886	92.42			
28	0.325	0.773	93.193			
29	0.3	0.713	93.906			
30	0.293	0.699	94.605			
31	0.286	0.681	95.286			
32	0.253	0.602	95.889			
33	0.228	0.542	96.431			
34	0.218	0.518	96.949			
35	0.203	0.484	97.433			
36	0.196	0.467	97.901			
37	0.187	0.445	98.345			
38	0.171	0.406	98.751			
39	0.155	0.37	99.121			
40	0.131	0.312	99.432			
41	0.129	0.308	99.74			
42	0.109	0.26	100			

Extraction Method: Principal Axis Factoring.

B.5 Table B.5 Descriptive Statistics if Variables

VARIABLES DESCRIPTIVE STATISTICS								
Variables	**Valid**	**Missing**	**Mean**	**Median**	**Mode**	**Std. Deviation**	**Skewness**	**Kurtosis**
A3i:AI_ADP	192	0	2.76	2.00	2	1.336	0.328	-1.089
A3ii: I40_ADP	192	0	2.84	3.00	2	1.342	0.233	-1.183
B1_TC1	192	0	3.7	4.00	4	1.093	-0.764	-0.052
B1_TC2	192	0	3.71	4.00	4	0.974	-0.796	0.427
B1_TC3	192	0	3.88	4.00	4	1.008	-1.034	0.85
B1_TC4	192	0	3.77	4.00	4	0.98	-0.902	0.609
B1_TC5R	192	0	3.29	3.00	4	1.208	-0.237	-0.962
B2_RA1	192	0	4.28	4.00	5	0.921	-1.632	3.124
B2_RA2	192	0	4.09	4.00	5	0.96	-1.194	1.552
B2_RA3	192	0	4.28	5.00	5	0.957	-1.627	2.751
B2_RA4	192	0	4.5	5.00	5	0.793	-2.286	6.772
B2_RA5	192	0	4.36	5.00	5	0.827	-1.723	4.08
B3_OR1	192	0	3.29	4.00	4	1.219	-0.33	-0.937
B3_OR2	192	0	3.7	4.00	4	1.117	-0.541	-0.596
B3_OR3	192	0	3.14	3.00	4	1.147	-0.132	-0.892
B3_OR4	192	0	3.5	4.00	4	1.063	-0.544	-0.213
B3_OR5	192	0	3.64	4.00	4	1.106	-0.502	-0.607
B4_OC1	192	0	4.04	4.00	5	1.024	-1.055	0.641
B4_OC2	192	0	3.9	4.00	4	0.974	-0.911	0.657
B4_OC3	192	0	3.88	4.00	4	0.983	-0.73	0.161
B4_OC4	192	0	4.14	4.00	5	0.985	-1.249	1.182
B4_OC5	192	0	4.06	4.00	5	1.056	-1.143	0.73
B5_CP1	192	0	4.39	5.00	5	0.758	-1.675	4.193
B5_CP2	192	0	4.27	4.00	5	0.827	-1.261	2.036
B5_CP3	192	0	4.05	4.00	4	0.88	-0.799	0.711
B5_CP4	192	0	3.63	4.00	4	0.93	-0.425	0.193
B5_CP5	192	0	3.61	4.00	3	0.949	-0.201	-0.332
B6_ES1	192	0	3.26	3.00	3	1.19	-0.205	-0.777
B6_ES2	192	0	3.17	3.00	3	1.001	-0.162	-0.119
B6_ES3	192	0	3	3.00	3	1.11	-0.105	-0.63
B6_ES4	192	0	2.58	3.00	3	1.082	0.032	-0.832
B6_ES5	192	0	3.64	4.00	4	1.021	-0.444	-0.461
C1_MF1	192	0	4.36	4.00	5	0.748	-1.141	1.985
C1_MF2	192	0	4.4	4.54	5	0.734	-1.622	4.242
C1_MF3	192	0	3.03	3.00	3	1.152	-0.016	-0.563
C1_MF4	192	0	3.28	3.00	4	1.2	-0.158	-0.717
C1_MF5	192	0	3.63	4.00	4	1.159	-0.707	-0.203
C2_IF1R	192	0	2.96	3.00	3	1.018	-0.027	-0.551
C2_IF2R	192	0	2.41	2.00	2	0.977	0.536	-0.218
C2_IF3R	192	0	3.17	3.00	4	1.19	-0.142	-0.888
C2_IF4R	192	0	3.13	3.00	3	1.238	0.016	-0.905
C2_IF5R	192	0	2.74	2.00	2	1.294	0.372	-0.947

Key: AI_ADP = AI Adoption ; I40_ADP = I4.0 Adoption; TC =Technology Characteristcis; RA = Relative Advantage; OR = Organizational Resource; OC: Organizational Culture; CP = Competitive Pressure; ES =External Support; MF =Motivating factors; IH = Inhibiting Factors

C APPENDIX C (Re: Chapter 4)

C.1 Table C.1 Measurement Scale

Survey Construct	Code	Question	Reference
TECHNOLOGY ASSIMILATION	TAS1	AI and /or I4.0 technology tools are used across our organization's business processes	Wamba (2022); Liu et al (2016)
	TAS2	AI and /or I4.0 technology tools are used in many functional areas in our organization	
	TAS3	AI and /or I4.0 technology tools are used for strategic decision-making (e.g. market entry/exit, new product /service launch) across many functional areas in our organization.	
	TAS4	AI and /or I4.0 technology tools are used for business operations across many functional areas in our organization.	
	TAS5	AI and /or I4.0 technology tools are used for management practices (e.g. organizing workflow, performance tracking & reporting) across many functional areas in our organization.	
TECHNOLOGICAL CAPABILITY	TC1	Our organization is one of the technology innovation leaders in our industry	Wang et al., (2006); Salisu and Abu Bakar (2020)
	TC2	Our organization has a strong and competitive technology strategy	
	TC3	Our organization has strong abilities to integrate internal and external technological resources	
	TC4	Our organization has robust technological skills in various areas of operations	
	TC5	Our organization has the capacity to attract talented experts	
	TC6	Our organization has the capacity to retain talented experts	
	TC7	Our organization improves technical skills through continuous training programs	
ORGANIZATIONAL AGILITY	OA1	Responding to changes in aggregate consumer demand	Tallon and Pinsonneault (2011).
	OA2	Customizing a product or service to suit an individual customer.	
	OA3	Expanding into new regional or international markets.	
	OA4	Changing (expanding or reducing) the variety of products/services available for sale.	
	OA5	Adopting new technologies to produce better, faster and cheaper products and services.	
	OA6	Switching suppliers to avail of lower costs	
	OA7	Switching suppliers to avail of better product or service quality	
SUSTAINABILITY: ECONOMIC	ECP1	Our market share has improved following AI and/or I4.0 technology adoption	Harun and Mwesiumo (2023).
	ECP2	Our sales revenues have improved following AI and/or I4.0 technology adoption	
	ECP3	Our cost-effectiveness has improved following AI and/or I4.0 technology adoption	
	ECP4	Our overall profitability has improved following AI and/or I4.0 technology adoption	
SUSTAINABILITY: SOCIAL	SOP1	Our company's working conditions (e.g. employee benefits, occupational health & safety) has improved following AI and/or I4.0 technology adoption	Harun and Mwesiumo (2023).
	SOP2	The participation of our company in local community development has improved AI and/or I4.0 following technology adoption	
	SOP3	Our company contribution to community health and safety has improved following AI and/or I4.0 technology adoption	
	SOP4	The general welfare of our stakeholders has improved following AI and/or I4.0 technology adoption	
SUSTAINABILITY: ENVIRONMENTAL	ENP1	Our company's reduction in direct GHG emissions has increased following AI and/or I4.0 technology adoption.	Harun and Mwesiumo (2023).
	ENP2	Our material reuse and recycling has increased following AI and/or I4.0 technology adoption.	
	ENP3	Our company has improved in terms of waste reduction following AI and/or I4.0 technology adoption	
	ENP4	Our company has improved in terms of resource (e.g. water, energy etc) conservation following AI and/or I4.0 technology adoption.	

C.2 Table C.2 Multicollinearity

Coefficients							
Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
1 (Constant)	0.797	0.192		4.15	<.001		
ASSM_COMP	0.258	0.044	0.345	5.855	<.001	0.723	1.383
TC_COMP	0.245	0.064	0.287	3.852	<.001	0.452	2.211
OA_COMP	0.23	0.071	0.231	3.254	0.001	0.499	2.005

a Dependent Variable: SUSTAINABILITY

Key: ASSM_COMP = Assimilation Composite variable; TC_COMP = Technological Capability composite variabel; OA_COMP = Organizational Agility Composite variable

C.3 Table C.3 Single factor Test

Total Variance Explained

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**
1	15.287	41.316	41.316	14.712	39.763	39.763
2	3.023	8.17	49.486			
3	2.899	7.836	57.322			
4	1.672	4.518	61.84			
5	1.407	3.804	65.643			
6	1.208	3.264	68.908			
7	1.151	3.111	72.019			
8	0.932	2.52	74.539			
9	0.844	2.281	76.82			
10	0.761	2.058	78.878			
11	0.693	1.872	80.75			
12	0.659	1.781	82.531			
13	0.603	1.63	84.161			
14	0.512	1.383	85.543			
15	0.463	1.251	86.794			
16	0.426	1.152	87.946			
17	0.385	1.04	88.986			
18	0.364	0.984	89.97			
19	0.354	0.957	90.927			
20	0.326	0.882	91.809			
21	0.303	0.82	92.629			
22	0.285	0.769	93.398			
23	0.265	0.716	94.114			
24	0.246	0.664	94.778			
25	0.224	0.606	95.384			
26	0.216	0.583	95.967			
27	0.195	0.526	96.493			
28	0.189	0.51	97.003			
29	0.184	0.497	97.499			
30	0.158	0.428	97.927			
31	0.143	0.386	98.313			
32	0.131	0.354	98.667			
33	0.123	0.333	99			

34	0.111	0.299	99.299
35	0.1	0.27	99.569
36	0.087	0.234	99.803
37	0.073	0.197	100

Extraction Method: Maximum Likelihood.

C.4 Table C.4 Total Variance Explained

Total Variance Explained

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	14.74	46.062	46.062	14.48	45.25	45.25	4.534	14.169	14.169
2	2.959	9.248	55.309	2.68	8.376	53.626	4.419	13.81	27.979
3	2.544	7.949	63.258	2.324	7.263	60.89	4.295	13.422	41.401
4	1.637	5.116	68.374	1.382	4.319	65.209	3.746	11.707	53.108
5	1.324	4.137	72.511	1.081	3.378	68.587	2.837	8.866	61.974
6	1.067	3.334	75.845	0.805	2.514	71.101	1.972	6.163	68.137
7	0.89	2.78	78.625	0.698	2.181	73.282	1.646	5.145	73.282
8	0.751	2.345	80.97						
9	0.729	2.279	83.249						
10	0.606	1.893	85.142						
11	0.456	1.425	86.567						
12	0.434	1.357	87.923						
13	0.393	1.227	89.151						
14	0.363	1.134	90.285						
15	0.328	1.025	91.31						
16	0.313	0.977	92.287						
17	0.277	0.866	93.153						
18	0.247	0.772	93.925						
19	0.234	0.732	94.657						
20	0.205	0.642	95.298						
21	0.199	0.621	95.92						
22	0.182	0.57	96.49						
23	0.17	0.53	97.02						
24	0.151	0.472	97.492						
25	0.14	0.437	97.929						
26	0.129	0.404	98.333						
27	0.11	0.344	98.677						
28	0.104	0.325	99.002						
29	0.101	0.317	99.319						
30	0.085	0.267	99.586						
31	0.07	0.22	99.805						
32	0.062	0.195	100						

Extraction Method: Principal Axis Factoring.

D Survey Questionnaire

IMPACT OF ARTIFICIAL INTELLIGENCE & INDUSTRY 4.0 TECHNOLOGIES ON SUSTAINABILITY PERFORMANCE OUTCOMES.

Dear Prospective Participant,

I am a PhD student at University of Essex. I am currently collecting data for my PhD research on the adoption of Artificial intelligence (AI) & Industry 4.0 Technologies(I4T). The study intends to investigate the impact of these technologies on sustainability performance outcomes and the influence of technological capabilities and organizational agility on this relationship.

The insight from the outcome of the study is expected to highlight how improved agility, can help organizations in anticipating and responding to rapid, relentless, changing situations by leveraging Artificial Intelligence and/ or Industry 4.0 technologies.

Please note that this research has received ethical approval from the University of Essex Research and Ethics Committee. A questionnaire has been designed to collect information on the technological, organizational, and environmental motivators and inhibitors of AI and/or I4.0 technology adoption, technology readiness, technology assimilation, organizational agility, technological capability and related sustainability performance outcomes.

It should take about **20-25 minutes** of your time at the most to complete. Your responses will be treated in the strictest confidence and your personal information will not be disclosed to anyone. Your participation in this study is voluntary and you can withdraw from the study at any time.

If you would like to contribute to this study, please complete the consent form below to indicate your intent to participate.

Kind Regards,

Chinwe J. Okpeku
Essex Business School
University of Essex
Southend Campus; Essex SS1 1LW
E: co22155@essex.ac.uk

CONSENT FORM

Research Title: Impact of Artificial Intelligence & Industry 4.0 technologies on sustainability performance outcomes

Researcher: Chinwe J. Okpeku
Supervisor 1: Prof. Niraj Kumar
Supervisor 2: Dr. Young-Ah Kim

STATEMENT OF CONSENT	TICK
I confirm that I have read and understand the Information Sheet for the above study **"Impact of Artificial Intelligence & Industry 4 Technologies on Sustainability Performance Outcomes"**	
I understand that my participation is voluntary and that I am free to withdraw from the survey at any time without giving any reason and without penalty	
I understand that my fully anonymised data will be used for research publications, conferences and seminars.	
I understand that my responses will be kept confidential and anonymous and that my personal information will be kept securely	
I agree to take part in the above study	

If you give your consent to participate in this study, please click below to proceed with the questionnaire.

Name/Signature:

The Impact of Artificial Intelligence And /Or Industry 4.0 Technologies on Sustainability Performance Outcomes

DEFINITIONS:
For the purposes of this survey the following definitions have been adopted:

Artificial intelligence Artificial intelligence (AI) is a computational technology comprising a suite of information and communication technologies (ICTs) designed to mimic human intellect, able to infer patterns and draw conclusions from data, with the primary goals of enhancing productivity, improving efficiency, and driving business growth. AI technologies include Machine Learning, Natural Language Processing, Computer Vision, Speech recognition and Expert systems. Examples of everyday use case includes Smart Assistants (Siri & Alexa), Customer service/ Helpdesk Chatbots and platforms such as Microsoft Azure AI, SAP, Salesforce etc.

Industry 4.0: Industry 4.0 is defined as a period that emphasises digitization, network communication, automation technologies, and analytics. Industry 4 technologies include:

a) **Additive manufacturing (3D printing):** A manufacturing technology that creates three-dimensional (3D) solid objects using a series of additive or layered development frameworks. (E.g. Material extrusion, Sheet lamination; Binder jetting)
b) **Big data and Analytics**: The strategy of analysing large volumes of data used when traditional data mining and handling techniques cannot uncover the insights and meaning of the underlying data. (E.g. Route optimization tools, Demand forecasting tools, Inventory and warehouse management solutions, SAP Ariba Supply chain collaboration.
c) **Blockchain:** A distributed decentralized ledger and a digital system for recording transactions among multiple parties in a verifiable and tamperproof way. (E.g. holograms, QR codes, and other identifiers on drug packaging for verification using mobile applications and SMS-based platforms)
d) **Cloud Computing:** A technology that provides a variety of services online and allows for remote access to information that is kept elsewhere. (E.g. File storage - Google Drive, OneDrive, and iCloud; Data backups and archiving - Google Cloud Storage; Software testing and development - Azure DevOps, Google App Engine; Communication - Google Workspace, Microsoft Teams, Zoom; Social networking - Facebook, Twitter, LinkedIn, and Instagram. ECommerce - Shopify; Education - Google Classroom, Canvas, Coursera)
e) **Cyber-physical systems**: A technological computer system that links components and machines together in the manufacturing process via the exchange of data and instructions through physical processes, cyberspace, controlling, and sensing. (E.g. Smart grids and industrial controls, Smart HVAC equipment, Detection and surveillance systems).
f) **Internet of Things (IOT):** IoT allows for wireless communication between devices, computers, and sensors, making data available from any location. (E.g. IoT devices like Bluetooth Low Energy (BLE) beacons & sensors for locating items in storage, Real-time tracking of location of goods & shipments using GPS and IoT devices; sensors monitoring environmental factors of storage conditions.)

g) **Radio Frequency Identification (RFID):** Technologies that use wireless communication between an object (or tag) and interrogating device (or reader) to automatically track and identify such objects. (E.g. Asset tags, RFID-enabled POS systems, Access control RFID cards or key fobs, RFID-enabled waste management systems)

h) Robotic Process Automation (RPA): A form of business process automation that allows anyone to define a set of instructions for a robot or 'bot' to perform. The use of bots and chatbots to automate manual tasks such as component assembly, order processing, shipment tracking, production scheduling and monitoring, quality control & testing, Invoice processing, Payroll processing, Customer service inquiries.

i) **Simulation:** Technologies that use the computer for the imitation of a real-world process or system. (E.g. dynamic simulation.)

j) **Unmanned Aerial Vehicle (UAV):** An aircraft without a human pilot onboard. (E.g. Drones.)

SECTION A: BACKGROUND INFORMATION
Please indicate your answer to each question by either ticking the most appropriate option or writing in the space provided.

A1: What sector does your organization belong to?

1. Agriculture/ Agro-Business
2. Consumer Goods
3. Financial Services
4. Professional services
5. Healthcare/ Pharmaceuticals
6. Telecommunications
7. Oil & Gas
8. Power & Energy
9. Information Communication and Technology (ICT)
10. Construction/Real Estate
11. Retail Services
12. Food & Hospitality
13. Other

A2: Which of the following Artificial Intelligence (AI) and/or Industry (I4.0) technologies are currently in use in your organization? (Select all applicable)

- Additive manufacturing (3D printing) *(E.g. Material extrusion, Binder Jetting)*
- Artificial intelligence *(E.g. Cobots, SAP Business AI, Chatbots, Microsoft Azure AI)*
- Big data and analytics: *(E.g. Power BI; Google Analytics, Tableau, SAP Analytics)*
- Blockchain:*(E.g. Ethereum blockchain solutions)*
- Cloud Computing *(E.g. OneDrive, Microsoft Teams, Shopify, Microsoft Azure)*
- Cyber-physical systems *(E.g. Smart grids, Building management systems)*
- Internet of Things (IoT) *(E.g. Smart Electric and water meter, Asset Tracking)*
- Simulation *(E.g. AnyLogic Simulation Software)*
- Radio Frequency Identification (RFID) *(Asset Tags)*
- Robotic Process Automation (RPA) *(Software bots)*
- Unmanned Aerial vehicle (UAV) *(Drones)*
- Other (please specify)

A3: Please rate your organization's adoption level by selecting the appropriate level as relevant for Artificial Intelligence and/or Industry 4.0 Technology.

A3i: Please indicate the level of Artificial Intelligence adoption in your organization

Rank	**1**	**2**	**3**	**4**	**5**
Level of Adoption	Initial	Assessing	Determined	Managed	Optimise
Level AI functions	Very limited or no Artificial Intelligence technology use by the organization or the organization has	Exploring and discovery of suitable Artificial Intelligence technologies	Artificial Intelligence technology Proof of Concept or Product/ solution	AI Pilot programme; Deployment of AI solution in some areas of the organization.	Full AI infrastructure is in place; Organization is ready for large-scale AI

	no immediate plans to use Artificial Intelligence technology	for the organization.	testing stage; or Determination of infrastructure needed to further implement AI technology	Preparation of large-scale AI application in the organisation; All essential organisational structures are in place for the integration of AI;	deployment; A significant portion of business choices are facilitated or made using AI

A3ii: Please indicate the level of Industry 4.0 technologies (I4.0) adoption in your organization

Rank	**1**	**2**	**3**	**4**	**5**
Level of Adoption	Initial	Assessing	Determined	Managed	Optimise
Level I4.0 functions	Very limited or no Industry 4.0 technology use by the organization or the organization has no immediate plans to use Industry 4.0 technologies	Exploring and discovery of suitable I4.0 technologies for the organization.	I4.0 technology Proof of Concept or Product/ solution testing stage; or Determination of infrastructure needed to further implement I4.0 technology	I4.0 Pilot programme; Deployment of I4.0 solution in some areas of the organization. Preparation of large-scale I4.0 application in the organisation; All essential organisational structures are in place for the integration of I4.0 technology;	Full I4.0 infrastructure is in place; Organization is ready for large-scale I4.0 technology deployment; A significant portion of business choices are facilitated or made using some I4.0 technology.

SECTION B: TECHNOLOGICAL, ORGANIZATIONAL & ENVIRONMENTAL INFLUENCES OF TECHNOLOGY ADOPTION

In this section, please focus on the Technological, Organizational and Environmental factors that impact your organization's adoption of AI and /or I4.0 Technologies.

TECHNOLOGICAL

B1: To what extent do you agree or disagree with the following statements regarding the technological characteristics of AI and /or I4.0 technology adopted by your organization?

1 = Strongly disagree 2 = Disagree 3 = Neutral 4 = Agree 5 = Strongly Agree

- TC1 AI and /or I4.0 technologies are easy to integrate with our organization's existing processes.
- TC2 Our organization finds AI and /or I4 technologies easy to use and manageable.
- TC3 AI and /or I4.0 technologies compatible with our organization's managerial and operational needs.
- TC4 AI and /or I4.0 technologies is compatible with our organizations existing system.
- TC5 Our organization finds AI and /or I4.0 technologies complicated to use.

B2: To what extent do you agree or disagree with the following statements regarding the relative advantage provided by AI and /or I4.0 technology?

1 = Strongly disagree 2 = Disagree 3 = Neutral 4 = Agree 5 = Strongly Agree

- RA1 Adopting AI and /or I4.0 technologies provides competitive advantage to our organization.
- RA2 AI and /or I4.0 technologies provides more benefits for our organization than our current infrastructure.
- RA3 Adopting AI and /or I4.0 technologies offers our organization new opportunities.
- RA4 Specific tasks can be performed quicker using AI and /or I4.0 technologies.
- RA5 Using AI and /or I4.0 technologies improves job performance across the organization.

ORGANIZATIONAL

B3: To what extent do you agree or disagree with the following statements regarding your organization's resources available for AI and /or I4.0 technology adoption?

1 = Strongly disagree 2 = Disagree 3 = Neutral 4 = Agree 5 = Strongly Agree

- OR1 There are sufficient technological resources to implement AI and /or I4.0 technologies in our organization.
- OR2 Our organisation has the financial resources for AI and /or I4.0 technologies adoption.

- OR3 There is adequate training and education for our employees to adopt AI and /or I4.0 technologies.
- OR4 There are cognitive capabilities of IT human resources in our organization to support AI and /or I4.0 technologies adoption.
- OR5 The existing technology in our organization can support AI and /or I4.0 technologies implementation.

B4: **To what extent do you agree or disagree with the following statements regarding your organizational culture in the context of AI and /or I4.0 technology adoption?**

1 = Strongly disagree 2 = Disagree 3 = Neutral 4 = Agree 5 = Strongly Agree

- OC1 The adoption of AI and /or I4.0 technologies is in line with the vision and mission of our organization
- OC2 The concept of AI and /or I4.0 technologies is in accordance with the culture and identity of our organization.
- OC3 AI and /or I4.0 technologies are consistent with our organization's current values and beliefs.
- OC4 Our management has an openness to implement change in our organization.
- OC5 Our top management considers AI and /or I4.0 technologies adoption as strategically important for the organization.

ENVIRONMENTAL

B5: To what extent do you agree or disagree with the following statements regarding the competitive advantage AI and /or I4.0 technology adoption will provide for your organization

1 = Strongly disagree 2 = Disagree 3 = Neutral 4 = Agree 5 = Strongly Agree

- CP1 AI and /or I4.0 technologies will provide stronger competitive advantage for our organization
- CP2 AI and /or I4.0 technologies would increase our organization's ability to outperform competition
- CP3 AI and /or I4.0 technologies allow generation of higher profits for our organization
- CP4 AI and /or I4.0 technologies is being implemented by a few of our competitors.
- CP5 Our competitors that have implemented AI and /or I4.0 technologies are favourably perceived within our industry

B6: To what extent do you agree or disagree with the following statements regarding external support available to your organization for adopting AI and /or I4 technology

1 = Strongly disagree 2 = Disagree 3 = Neutral 4 = Agree 5 = Strongly Agree

- ES1 There are third-party service providers that provide free or affordable technical support for the effective use of AI and /or I4.0 technologies.
- ES2 External funding agencies encourage adoption of AI and /or I4 technologies.
- ES3 Government policies encourage adopting new technology such as AI and /or I4.0 technologies.
- ES4 Government agencies provide the technical support, training, and funding to increase the adoption of AI and /or I4.0 technologies.
- ES5 There are some business laws or other cyber protection laws to deal with the security and privacy concerns related to AI and /or I4.0 technologies.

SECTION C: TECHNOLOGY READINESS & AI AND /OR I4.0 TECHNOLOGY ADOPTION

In this section, the questions are related to technology readiness, focusing on inhibitors and motivators of your organization's readiness to adopt AI and /or I4.0 Technologies.

C1: Please indicate whether you agree or disagree with the following motivating factors influencing the readiness of AI and /or I4.0 technology adoption in your organization

1 = Strongly disagree 2 = Disagree 3 = Neutral 4 = Agree 5 = Strongly Agree

- MF1 The adoption of advanced technologies provides our organization with greater flexibility and operational freedom.
- MF2 Implementing new technologies enhances the overall productivity and efficiency of our organization.
- MF3 Our organization is often consulted by other firms for advice on adopting and integrating new technologies.
- MF4 We are typically early adopters of new technologies within our industry.
- MF5 Our organization actively stays updated with the latest technological advancements relevant to our industry.

C2: Please indicate whether you agree or disagree with the following inhibiting factors influencing readiness of AI and /or I4.0 technology adoption in your organization

1 = Strongly disagree 2 = Disagree 3 = Neutral 4 = Agree 5 = Strongly Agree

- IF1 Technical support services often fail to explain technological solutions in a way that is comprehensible or practical for our organization.
- IF2 There are instances where we feel that certain technology systems are not user-friendly for typical organizational use.
- IF3 Our organization is concerned that an over-reliance on technology may compromise our ability to perform essential functions independently.
- IF4 Excessive use of technology can sometimes lead to distractions that negatively impact our workforce's productivity.
- IF5 The extensive use of technology may reduce personal interactions, thereby potentially lowering the quality of internal relationships within our organization.

SECTION D: TECHNOLOGY ASSIMILATION

In this section, you should concentrate on how Artificial Intelligence and /or Industry 4.0 technology is incorporated into all aspects of work and procedures within your organization and used in your organization's routine operations.

D1: Please indicate how often AI and/or I4.0 technology is utilized in your organization for the following situations

1 = Never 2 = Rarely 3 = Sometimes 4 = Very Often 5 = Always

- TA1 AI and /or I4.0 technology tools are used across our organization’s business processes
- TA2 AI and /or I4.0 technology tools are used in many functional areas in our organization
- TA3 AI and /or I4.0 technology tools are used for strategic decision-making (e.g. market entry/exit, new product /service launch) across many functional areas in our organization.
- TA4 AI and /or I4.0 technology tools are used for business operations across many functional areas in our organization.
- TA5 AI and /or I4.0 technology tools are used for management practices (e.g. organizing workflow, performance tracking & reporting) across many functional areas in our organization.

SECTION E: TECHNOLOGICAL CAPABILITY

In this section, please focus on your organization’s ability to expand and utilize its core capabilities, effectively combine different streams of technologies and mobilize technological resources throughout the firm.

E1: Please indicate the extent to which you agree or disagree with the following statement your organizations technological capability

1 = Strongly disagree 2 = Disagree 3 = Neutral 4 = Agree 5 = Strongly Agree

- TC1 Our organization is one of the technology innovation leaders in our industry
- TC2 Our organization has a strong and competitive technology strategy
- TC3 Our organization has strong abilities to integrate internal and external technological resources
- TC4 Our organization has robust technological skills in various areas of operations
- TC5 Our organization has the capacity to attract talented experts
- TC6 Our organization has the capacity to retain talented experts
- TC7 Our organization improves technical skills through continuous training programs

SECTION F: ORGANIZATIONAL AGILITY

In this section, please focus on your organization's management of change and uncertainties in the business environment

F1: How will you rate the ease and speed of your organization in performing the following activities?

1 = Extremely inadequate 2 = Somewhat Inadequate 3 = Neither Adequate or Inadequate 4 = Somewhat Adequate 5 = Adequate

- OA1 Responding to changes in aggregate consumer demand.
- OA2 Customizing a product or service to suit an individual customer.
- OA3 Expanding into new regional or international markets.
- OA4 Changing (expanding or reducing) the variety of products/services available for sale.
- OA5 Adopting new technologies to produce better, faster and cheaper products and services.
- OA6 Switching suppliers to avail of lower costs
- OA7 Switching suppliers to avail of better product or service quality

SECTION G: PERFORMANCE OUTCOMES

In this section, please focus on your organization's performance outcomes following adoption of technology such as AI and/or I4.0 technology

G1: To what extent do you agree or disagree with the following statements regarding your organization's Economic performance outcome

1 = Strongly disagree 2 = Disagree 3 = Neutral 4 = Agree 5 = Strongly Agree

- ECP1 Our market share has improved following AI and/or I4.0 technology adoption
- ECP2 Our sales revenues have improved following AI and/or I4.0 technology adoption
- ECP3 Our cost-effectiveness has improved following AI and/or I4.0 technology adoption
- ECP4 Our overall profitability has improved following AI and/or I4.0 technology adoption

G2: To what extent do you agree or disagree with the following statements regarding your organization's social performance outcome

1 = Strongly disagree 2 = Disagree 3 = Neutral 4 = Agree 5 = Strongly Agree

- SOP1 Our company's working conditions (e.g. employee benefits, occupational health & safety) has improved following AI and/or I4.0 technology adoption
- SOP2 The participation of our company in local community development has improved AI and/or I4.0 following technology adoption
- SOP3 Our company contribution to community health and safety has improved following AI and/or I4.0 technology adoption
- SOP4 The general welfare of our stakeholders has improved following AI and/or I4.0 technology adoption

G3: To what extent do you agree or disagree with the following statements regarding your organization's Environmental performance outcome.

1 = Strongly disagree 2 = Disagree 3 = Neutral 4 = Agree 5 = Strongly Agree

- ENP1 Our company's reduction in direct GHG emissions has increased following AI and/or I4.0 technology adoption.
- ENP2 Our material reuse and recycling has increased following AI and/or I4.0 technology adoption.
- ENP3 Our company has improved in terms of water consumption following AI and/or I4.0 technology adoption.
- ENP4 Our company has improved in terms of waste reduction following AI and/or I4.0 technology adoption
- ENP5 Our company has improved in terms of energy consumption & conservation following AI and/or I4.0 technology adoption.

G4: To what extent to you agree to the following statement regarding unanticipated outcomes of AI and/or I4.0 technology adoption in your organization?

1= Strongly disagree 2= Agree 3= Neutral 4= Agree 5= Strongly agree

- UO1 Our organization has encountered some unintended consequence of technology adoption (Unintended consequences such as increased energy or primary resource consumption, increased electric/electronic waste)
- UO2 Technology adoption has provided our organization with unexpected benefits
- UO3 Technology adoption has produced some adverse result(s) (adverse results such as encryption facilitating bribery/illicit payments, multiple antivirus programs attempting to tag each other as malware; tools designed to manage workload which increase it)
- UO4 Our organization has not encountered any negative effect due to technology adoption

Please give a brief example of unforeseen Outcomes encountered by your organization due to adoption of AI and I4.0 Technologies

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SECTION H: DEMOGRAPHIC INFORMATION

H1: Which of the following best describes your age?

- Below 25 years
- 26 -35 years
- 36-45 years
- 46 -55 years
- 56 - 65 years
- Above 65 years
- Prefer not to say

H2: What is your job level in the organization

- Owner

- CEO/MD
- Vice President
- Chief -Level Officer
- Director
- Associate /Deputy Director
- Senior Manager/Principal Specialist
- Manager/ Senior Specialist
- Other

H3: How long have you worked for your organisation?

- Less than 12 months
- 1 to 5 years
- 6 to 10 years
- 11 to 15 years
- 16 to 20 years
- More than 20 years

H4: How many employees work in your organisation?

- 1-9 employees
- 10-49 employees
- 50-249 employees
- 250-500 employees
- More than 500 employees

H5: Please indicate the average turnover per annum of your organisation (in Nigerian Naira ~~₦~~)

- Below N10 million
- N10 million - N25 million
- Above N25 million but below N100 million
- Above N100 million

H6: How long has your organization been in business?

- Less than 5 years
- 5 - 10 years
- 10 -15 years
- 15 - 20 years
- More than 20 years

H7: Which of the following best describes your organizations ownership type

- Sole proprietorship
- Partnership
- Private limited company (Ltd)
- Public limited company (Plc)
- Partnership
- Subsidiary of a Multinational Corporation
- Other (Please state)

H8: Does you organization operate outside of Nigeria

- Yes
- No
- Which country _____

H9: Do you have any additional information regarding the study topic or comments related to the questionnaire which you would like to share:

- Yes
- No
- If yes, please state here_____

SECTION I: ADDITIONAL INFORMATION

Thank you for participating in my research study.

I1: If you would like to receive a summary of the findings of this study and would like to be included in future expansion of this study, please share your email address here: _____

I2: Would you be willing to pass along the name and contact information of any colleague/co-worker or industry practitioner(s) who may be interested in contributing to this study? We will make the potential participants aware that you are the source of the referral.

- Yes
- No
- Name(s) & Contact details _____

PILOT STUDY FEEDBACK QUESTIONNAIRE:

The Impact of Artificial Intelligence & Industry 4 Technologies on Sustainability Performance Outcomes

Thank you for taking the time to participate in the pilot study for my research. The aim of the pilot test is to ascertain the clarity of the survey questions and the suitability of the format. Your opinion on this survey will help me make improvements before the major study.

To help me make necessary adjustment, you can either include your comments directly on the respective survey item(s) using track and change or include your comments in the space provided within the feedback form. Alternatively, I am available, depending on your schedule, for a brief chat to go through your comments regarding the survey.

1. How long did it take you to complete the questionnaire?

- 5- 10 minutes
- 10 – 15 minutes
- 15 - 20 minutes
- 20 - 25 minutes
- More than 25 minutes

2. Are the questionnaire instructions clear?

- Yes
- No (Please specify here) _____

3. Are the questions easy to understand?

- Yes
- No (Please specify here) _____

4. Is there any difficulty in understanding the kind of answers expected, or in providing answers to the questions asked?

- Yes (Please specify here) _____
- No

5. Is the language used in the questionnaire free from jargon, slangs and abbreviations?

- Yes
- No (Please specify here) _____

6. Are the structure and design of the questionnaire logical?

- Yes
- No (Please specify here) _____

7. Is the length of the questionnaire appropriate?

- Yes
- No (Please specify here) _____

8. Are there any elements of the questionnaire, which you think should be changed, deleted or modified?

- Yes (Please specify here) _____
- No

9. Do you have any additional comments or suggestions to improve the questionnaire and response rate

- Yes
- No
- If yes, please specify here_____