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Artificial Intelligence Adoption for Green Innovation: A Systematic Review and Future Research Agenda

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☐ **I have not used any AI-based tools.**

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Abstract

Artificial intelligence (AI) is increasingly recognized as an influential enabler of green innovation through its potential to improve resource efficiency, environmental monitoring, and sustainability-oriented decision-making. Despite growing scholarly interest, research on AI adoption for green innovation remains fragmented and lacks a unified analytical structure integrating technological, organizational, and environmental conditions. This study addresses this gap through a systematic literature review guided by the Technology–Organization–Environment (TOE) framework. Using the Scopus database, 44 peer-reviewed journal articles published between 2020 and 2026 were systematically selected through a rigorous multi-stage screening process. Thematic analysis served as the primary analytical method, supported by bibliometric techniques including keyword co-occurrence analysis and thematic mapping using VOSviewer and Biblioshiny. The findings indicate that AI adoption for green innovation is shaped by interdependent conditions rather than isolated factors. Technological enablers include digital infrastructure, AI capability, cloud computing, and data analytics, while implementation cost, integration complexity, and data security concerns act as key barriers. Organizational factors, including leadership commitment, capability development, knowledge integration, and cross-functional coordination, strongly influence adoption effectiveness. Environmental conditions, including regulatory frameworks, institutional quality, and competitive pressure, shape the likelihood and depth of green innovation outcomes. The synthesis identifies three core arguments: technological readiness is necessary but insufficient; the organizational context is the active translating system converting technological potential into sustainability outcomes; and the environmental context determines adoption quality, distinguishing substantive green innovation from symbolic compliance. Two interaction effects underpin these arguments: the capability-technology complementarity and the institutional amplification effect. The study contributes by advancing the TOE framework through a more dynamic and integrative interpretation of AI adoption for green innovation. It provides managerial and policy implications and proposes a future research agenda emphasizing longitudinal, configurational, and context-sensitive investigation of AI-enabled sustainability transformation.

Keywords: Artificial Intelligence, Green Innovation, AI Adoption, Technology-Organization-Environment Framework, Sustainability

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1 Introduction

This chapter introduces the background, research gap, research questions, scope, and overall structure of the thesis. It first outlines the growing relevance of AI and green innovation in organizational contexts. It then identifies the main limitations in existing research and explains why an SLR is needed. Finally, the chapter presents the research questions and describes the structure of the thesis.

1.1 Background and Context

Artificial Intelligence (AI) refers to the idea of developing and implementing intelligent machines or software that function by identifying and adapting to their environments, thereby facilitating the exploration and analysis of extensive amounts of data (Sander et al. 2021, 1). AI has rapidly evolved into a foundational technological capability that is reshaping organizational processes, innovation strategies, and competitive dynamics across industries (Ma et al. 2025, 1-2; Mansour et al. 2025, 3). Advances in machine learning, data analytics, and intelligent systems have enabled organizations to process large volumes of data, automate decision-making, and enhance operational efficiency. As a result, AI is increasingly viewed not merely as a technological tool but as a strategic enabler of organizational transformation and long-term value creation (Gao, Liu & Yang 2025, 1).

Parallel to these technological developments, organizations are facing growing pressure to address environmental and sustainability challenges. Climate change, resource scarcity, and increasing regulatory demands have compelled firms to integrate sustainability into their core strategic agendas (Abdulmuhsin et al. 2024, 204-205). In this context, green innovation has emerged as a critical mechanism through which organizations can reduce environmental impact while maintaining economic performance. Green innovation encompasses the development and implementation of environmentally friendly products, processes, and practices, including energy-efficient production, waste reduction, and circular economy initiatives. (Ahmed et al. 2026, 23)

The intersection of AI and green innovation represents a particularly promising domain for achieving sustainable transformation. AI technologies can facilitate green innovation by optimizing resource allocation, enabling predictive maintenance, enhancing energy efficiency, and supporting environmentally informed decision-making (Feng et al. 2025 1-3). For example, AI-driven analytics can identify inefficiencies in production processes. Intelligent systems can optimize logistics and supply chains to reduce emissions and waste. Consequently, AI has the potential to significantly accelerate the transition toward more sustainable and environmentally responsible business models (Xu et al. 2024,1; Han & Mao 2024, 5335).

Despite this potential, the adoption of AI for green innovation remains uneven and complex (Mansour et al. 2025, 4; Youssef 2025, 15-16). Organizations must navigate a range of technological, organizational, environmental and social challenges when integrating AI into sustainability-oriented innovation processes (Florek-Paszkowska, Ujwary-Gil 2025, 117). These challenges include issues related to technological readiness, data availability, financial investment, regulatory uncertainty, and organizational capabilities (Youssef 2025, 24; Boonmee, 2025, 2). At the same time, various enabling conditions such as managerial support, digital infrastructure, and external stakeholder pressure can facilitate adoption. Understanding these factors is essential for advancing both academic knowledge and practical implementation. (Abdelfattah et al. 2024, 155; Sanders et al. 2021,1; Qalati & Siddiqui 2025, 11)

1.2 Research Gap

While the literature on AI adoption and green innovation has grown substantially in recent years, the intersection of these domains remains conceptually dispersed and insufficiently synthesized (Qalati & Siddiqui 2025, 1). First, a significant body of research has examined AI adoption within organizational contexts, focusing on factors such as technological readiness, organizational capabilities, and environmental pressures. These studies have provided valuable insights into how organizations implement AI to enhance efficiency, decision-making, and performance (Qalati & Siddiqui 2025, 2-3; Feng et al. 2024, 3). However, this stream of literature predominantly addresses AI adoption in general contexts, often overlooking sustainability-oriented applications and the specific requirements of green innovation processes.

Second, the literature on green innovation has extensively explored the drivers and barriers of environmentally sustainable practices. Researchers emphasize the roles of regulatory frameworks, stakeholder pressures, and organizational commitment. These studies demonstrate that green innovation contributes to improved environmental performance and, in many cases, enhanced competitive advantage (Boonmee et al. 2025, 6-7; Haq et al. 2025, 1). Nevertheless, this body of work has traditionally focused on conventional innovation systems, with limited attention to the role of advanced digital technologies such as AI in enabling green innovation.

Third, existing research on AI-enabled green innovation draws on a diverse range of theoretical perspectives across innovation, sustainability, organizational, and technology adoption literature (Ji & Tian 2026; Mansour et al. 2025; Wang et al. 2023; Liu et al. 2025). This theoretical diversity reflects the interdisciplinary nature of research related to AI, digital transformation, green innovation, ESG, and sustainable innovation.

A substantial portion of the literature is grounded in resource- and capability-oriented perspectives, particularly the Resource-Based View (RBV), Dynamic Capabilities Theory (DCT), and the Knowledge-Based View (KBV). These perspectives emphasize organizational resources, capability development, and knowledge integration as drivers of innovation and competitive advantage. Related approaches, including Knowledge Management Theory (KMT), Human Capital Theory (HCT), and the Natural Resource-Based View (NRBV), further extend this discussion toward sustainability-oriented capability development (Abdulmuhsin et al. 2024; Hasan 2026; Mansour et al. 2025; Pu 2025). Other studies adopt institutional, innovation, and technology adoption perspectives, including Institutional Theory (IT), Diffusion of Innovation Theory (DIT), the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), and Task–Technology Fit (TTF) (Zhao & Liu 2025; Florek-Paszkowska & Ujwary-Gil 2025; Popa et al. 2025; Lin 2025; Sabat & Bhattacharyya 2025). Additional contributions also emerge from behavioral and systems-oriented approaches such as Social Cognitive Theory (SCT), Systems Theory (ST), and the Theory of Planned Behaviour (TPB) (Crocco et al. 2025; Boonmee et al. 2025; Raza et al. 2025)

Existing studies adopting the TOE framework often focus on specific organizational or industrial contexts. For example, Shaik (2024) applies the TOE framework to AI-driven strategic business models but limits the analysis to small and medium-sized enterprises (SMEs). In contrast, the present study adopts a broader organizational perspective by examining AI adoption for green innovation across diverse organizational settings. The study further uses the TOE framework as an integrative analytical lens to systematically identify and synthesize the technological, organizational, and environmental factors influencing adoption. In doing so, it aims to address the conceptual inconsistency and limited synthesis evident in the existing literature.

Fourth, existing studies linking digital technologies with sustainability often adopt diverse and context-specific perspectives (Ji & Tian 2026, 1; Abdulmuhsin et al. 2024, 204; Gandía et al. 2024, 6). Many studies focus on particular industries, including manufacturing, banking, agriculture, high-technology firms, and the oil and gas sector. Other studies examine specific organizational contexts, such as listed companies across different countries or small and medium-sized enterprises (SMEs). Research also addresses particular functional areas, including human resource management and entrepreneurship (Larbi-Siaw et al. 2022; Siddik et al. 2025; Raza et al. 2025; Feng et al. 2024; Abdulmuhsin et al. 2024; Noronha & Vaz 2020).

In addition, the literature explores a wide range of sustainability-related themes, including environmental protection law, digital transformation, robotics, automation, smart solutions, ESG performance, carbon emissions, and open innovation (Lia et al. 2025; Florek-Paszkowska & Ujwary-Gil 2025; Wang et al. 2023; Almusharraf 2025; Sabat & Bhattacharyya 2025; Dhar & Sarkar 2025; Cassânego 2025). While this diversity reflects the interdisciplinary nature of the field, it also contributes to conceptual inconsistency. Existing studies frequently emphasize isolated contexts, sectors, or themes rather than developing an integrated understanding of AI adoption for green innovation across organizational settings.

Fifth, existing research differs considerably in both its units of analysis and methodological orientation. Some studies focus on managers and decision-makers at different organizational levels, while others adopt SLR approaches or develop conceptual frameworks. There is also increasing scholarly interest in examining sustainability through the lens of the Sustainable Development Goals (SDGs) (Qalati & Siddiqui 2025; Gandía et al. 2024; Freihat et al. 2025; Naqbi et al. 2025; Saiyed et al. 2025; Yi et al. 2025; Dzhereleiko et al. 2024).

Although this diversity reflects the interdisciplinary and evolving nature of the field, it also creates challenges for theoretical integration and the accumulation of coherent knowledge. This limited integration is particularly evident in research on AI-enabled green innovation. Existing studies differ substantially in their conceptualizations, methodological approaches, and focal variables. Consequently, the development of a more unified and integrative research agenda remains limited.

Sixth, a critical limitation of the existing literature is the absence of a consolidated framework that systematically identifies and categorizes the factors influencing AI adoption for green innovation. Current studies tend to examine these factors in isolation rather than integrating them into a unified structure (Lin 2025, 473; Teplova et al. 2023, 1; Boonmee et al. 2025, 8-9). For example:

Technological factors are frequently highlighted. These include digital or technological infrastructure, as well as issues related to data privacy and security. Other concerns include intrinsic inefficiencies and the length or complexity of R&D cycles (Arshed et al. 2026; Yi et al. 2025; Han & Mao 2024; Popa et al. 2025; Naqbi et al. 2025; Hussain et al. 2024; Crocco et al. 2025).

Economic and financial factors also receive considerable attention. These include high initial investment costs, financial constraints, profitability concerns, and the underutilization of available resources (Sabat & Bhattacharyya 2025; Xu et al. 2024; Wang et al. 2023; Ma et al. 2025; Shaik 2024; Duong 2025; Sanders et al. 2021; Benalcázar et al. 2025; Haq et al. 2025).

Organizational factors are another crucial dimension. These include resistance to change, organizational readiness, institutional weaknesses, workforce skill limitations, and concerns related to job security. Cultural relevance within organizations is also discussed in some studies (Boonmee et al. 2025; Dhar & Sarkar 2025; Raza et al. 2026; Hamza & Karadas 2025; Haq et al. 2025; Mansour et al. 2025; Siddik et al. 2025; Lin 2025).

Environmental and external factors further shape AI adoption. These include government policies, market conditions such as competition and turbulence, and broader external pressures and uncertainties (Shaik 2024; Zhao & Liu 2025; Larbi-Siaw et al. 2022; Feng et al. 2024; Freihat et al. 2025; Liu et al. 2025).

Despite the identification of diverse technological, organizational, financial, and environmental factors, prior studies rarely integrate these conditions into a coherent framework explaining the adoption of AI for green innovation. As a result, there is limited understanding of how these factors interact and collectively influence organizational adoption under different contextual conditions. Existing research frequently examines adoption-related factors in isolation, limiting broader theoretical integration.

Furthermore, the literature lacks a systematic synthesis that clearly distinguishes between facilitating and constraining factors shaping the adoption of AI for green innovation. Although some studies address drivers and barriers, they often do so within narrow empirical or sector-specific contexts, limiting the broader applicability of findings (Duong 2025; Zhao & Liu 2025; Florek-Paszkowska & Ujwary-Gil 2025; Hasan 2026; Youssef 2025; Boonmee et al. 2025). This creates challenges for understanding the broader dynamics influencing organizational adoption.

Another important limitation concerns the limited mapping of the intellectual structure of this emerging research domain. Understanding dominant themes, publication trends, and research clusters is important for identifying the development of the field and recognizing underexplored research areas. However, such bibliometric insights remain limited within the existing literature on AI adoption for green innovation.

Overall, these limitations highlight the need for a systematic and integrative review that synthesizes existing research and develops a structured understanding of the factors shaping the adoption of AI for green innovation in organizations. In response to this gap, the present study conducts an SLR to identify, categorize, and synthesize the influencing factors associated with organizational adoption. The study also maps the intellectual structure of the field and proposes directions for future research.

1.3 Research Questions

Building on the identified research gap, this study is guided by the following overarching research question:

> *What factors shape the adoption of AI for green innovation in organizations?*

By facilitating a comprehensive understanding of this overarching question, the study addresses the following sub-research questions:

> RQ1. What specific factors influence the adoption of AI for green innovation in organizations?
>
> RQ2. How do these factors facilitate or hinder the adoption of AI for green innovation under different contextual conditions?
>
> RQ3. What future research directions emerge from the synthesis of existing studies?

This study focuses on the organizational-level adoption of AI. It emphasizes how adoption occurs within firms rather than at the individual or consumer level (Boonmee et al. 2025, 7; Haq et al. 2025, 11-12). The study specifically examines the use of AI for green innovation. It explores what factors shape the adoption of AI for green innovation in organizations (Hamza & Karadas 2025, 1; Dhar & Sarkar 2025, 1).

The study adopts an SLR methodology based on peer-reviewed journal articles indexed in Scopus. To ensure quality and relevance, only English-language publications within selected subject areas such as business, management, accounting, economics, and social sciences are included.

While this approach enables a comprehensive synthesis of high-quality research, it also introduces certain limitations. The reliance on specific databases and selection criteria may exclude relevant studies published in other outlets. Additionally, the findings are dependent on the scope and quality of existing literature.

This thesis is organized as follows. Chapter 2 presents the theoretical background and conceptual foundations, including key concepts related to AI, green innovation, and technology adoption. Chapter 3 outlines the research methodology, detailing the SLR process and bibliometric analysis. Chapter 4 presents the findings, including both descriptive and analytical in the process of identification and categorization of influencing factors and the mapping of the intellectual structure of the field. Chapter 5 outlines the conclusion, including contributions, implications, limitations, and future research directions. Finally, Chapter 6 concludes the thesis by summarizing key insights.

2 Theoretical Background and Conceptual Foundations

2.1 AI in Organizational Contexts

AI has become a central component of contemporary organizational transformation, enabling firms to process complex data, automate operations, and enhance strategic decision-making (Zhao & Liu 2025, 3). In addition, being regarded as widely accepted by the industry, AI has brought about the development of new employee and organizational research streams (Aleem et al. 2023, 3). Digital transformation continues to reshape organizations and markets. Within this context, AI is increasingly recognized as a critical driver of sustainable innovation. It also supports entrepreneurial resilience and strengthens organizational competitiveness in the global economy. For example, AI technology possesses the potential to revolutionize domains like data analytics and automation (Boonmee et al. 2025, 1-2). In extended terms, AI refers to a group of technologies designed to enable machines and systems to perform tasks that normally require human intelligence. This includes learning, reasoning, pattern recognition, and problem-solving (Housheya & Atikbay 2025, 6; Chowdhury et al. 2022, 33; Teece 2007,1319)

In organizational contexts, AI surrounds a wide variety of applications, including machine learning algorithms, natural language processing, computer vision, Intelligent data analysis, deep learning, business intelligence, image understanding, identity verification, biometrics, voice recognition, investment decision aid and intelligent decision-support systems (Chowdhury et al. 2022, 33; Chen & Hao 2022,1757; Pu 2025, 8). These technologies allow organizations to extract insights from large datasets, predict future trends, and optimize operational processes (Larbi-Siaw et al. 2022, 12). For example, machine learning models can analyse historical data in forecasting the pattern of demand, while intelligent systems can automate routine tasks, thereby improving efficiency and reducing human error.

AI offers novel opportunities for productivity, eco-friendly solutions, and insightful predictions across industries (Abuzaid, 2024, 1). Since AI was first used in rule-based systems, researchers have documented the gradual improvements. Continuous advancements have enabled AI to become a disruptive force. It is now reshaping business dynamics and competitive strategies (Floridi et al. 2024, 185). Businesses with comprehensive AI capabilities, such as learning, seizing, sensing, integrating stakeholders, and transforming, are more likely to generate outcomes that are innovative and sustainable. (Siddiqui & Qalati 2025, 8–9)

The adoption of AI in organizations is often driven by the need to enhance competitiveness and adapt to rapidly changing environments (Abuzaid 2024, 1). AI enables firms to develop dynamic capabilities by facilitating faster decision-making, improving resource allocation, and supporting innovation processes (Pu 2025, 2). Moreover, AI plays a critical role in enabling digital transformation. Furthermore, it allows organizations to integrate data-driven insights into their managerial and policy-setting activities (Youssef 2025, 1)

Despite its potential benefits, the adoption of AI is associated with several challenges (Naqbi et al. 2025, 15). These include technological prospects such as the lack of adequate digital or technological infrastructure and concerns related to data privacy (Arshed et al. 2026; Yi, Zhang & Ding 2025; Han & Mao 2024; Youssef 2025; Hasan 2026; Saiyed et al. 2025; Popa et al. 2025; Naqbi et al. 2025).

Economic and resource-related challenges are also significant. High initial investment costs, financial constraints, and the underutilization of available resources are frequently identified as key obstacles (Sabat & Bhattacharyya 2025; Xu et al. 2024; Florek-Paszkowska & Ujwary-Gil 2025; Ma et al. 2025; Shaik 2024; Duong 2025; Sanders et al. 2021; Arshed et al. 2026; Benalcázar et al. 2025; Haq et al. 2025).

Organizational barriers further complicate adoption processes. These include resistance to change, low-skilled workers, and issues related to organizational readiness and institutional weaknesses. The length and complexity of R&D cycles also contribute to these challenges (Raza et al. 2025; Boonmee et al. 2025; Almusharraf 2025; Florek-Paszkowska & Ujwary-Gil 2025; Dhar & Sarkar 2025; Raza et al. 2026; Hamza & Karadas 2025; Haq et al. 2025; Mansour et al. 2025; Crocco et al. 2025).

Moreover, diversified External pressures additionally influence AI adoption. These include broader environmental and market-related factors that shape organizational decision-making (Feng et al. 2024; Freihat et al. 2025). Furthermore, the complexity of AI technologies can itself act as a barrier to adoption. This is particularly relevant for small and medium-sized enterprises (SMEs), which frequently operate under resource constraints. These challenges collectively highlight the importance of understanding the factors influencing AI adoption within organizational contexts (Boonmee et al. 2025, 13–14).

2.1.1 Green Innovation and Sustainability

In response to human activity and irresponsible economic expansion, climate change has become a major global issue in recent decades. The environment has been severely affected by industrial growth, fast urbanization, and increased resource use. These factors have resulted in ecological degradation, biodiversity loss, and the depletion of natural resources (Quito et al. 2023, 1529). Green innovation has become a crucial strategy for addressing environmental challenges and advancing sustainable development (Liu et al. 2025, 1). It refers to the progress and implementation of products, processes, and practices that reduce environmental impact while encouraging or improving economic performance (Freihat et al. 2025, 5-6). Green innovation/eco-innovation encompasses a wide range of activities, including eco-friendly product design, energy-efficient production processes, waste minimization, ensuring long term economic viability, reducing environmental impacts, Social growth, responsible business practices, promotion of ethics, and the adoption of renewable energy technologies (Pu 2025, 1; Freihat et al. 2025, 6)

From a strategic perspective, green innovation is increasingly viewed as a source of competitive advantage (Freihat et al. 2025, 5). Organizations that adopt environmentally sustainable practices can improve their reputation, comply with regulatory requirements, and meet the growing demand for sustainable products and services (Siddik et al. 2025, 1269). Moreover, green innovation can contribute to cost reduction through improved resource efficiency and lower levels of waste (Freihat et al. 2025, 12).

The drivers of green innovation are multifaceted and include AI, regulatory pressures, market demand, financial markets perception, value green innovation initiatives, and organizational commitment to sustainability (Feng et al. 2024, 8). Governments play a significant role by implementing policies and regulations that encourage environmentally responsible practices (Abdelfattah et al. 2024, 155). At the same time, consumers and investors are increasingly prioritizing sustainability, creating market incentives for organizations to adopt green innovation.

However, the implementation of green innovation presents several challenges. These include high initial investment costs and technological or institutional uncertainties (Ji & Tian 2026, 2; Pu 2025, 2). Market-related challenges are also significant. These include market turbulence and competitive pressures that influence organizational decision-making (Larbi-Siaw et al. 2022, 4; Zhao & Liu 2025, 4). Organizational challenges further complicate implementation. These include the need for organizational change and the alignment of internal processes with sustainability vision (Qalati & Siddiqui 2025, 2). In addition, firms may face difficulties in integrating sustainability into their existing business models and operational processes (Youssef 2025, 4). These challenges highlight the importance of identifying the key factors that influence the adoption of green innovation within organizational contexts.

2.1.2 AI-Enabled Green Innovation

The integration of AI and green innovation represents a transformative approach to achieving sustainability goals (Youssef 2025, 1). AI technologies enhance organizational capabilities by enabling more efficient resource optimization and supporting increased research and development initiatives (Zhao & Liu 2025, 2; Xu et al. 2024). They also contribute to reducing environmental impacts and strengthening the human and knowledge base within organizations (Liu et al. 2025; Ji & Tian 2026, 12). In addition, AI supports the development of competitive advantage and facilitates digital collaboration and innovation processes (Abdelfattah et al. 2024, 165; Florek-Paszkowska & Ujwary-Gil 2025, 126).

One of the key ways in which AI enables green innovation is through data-driven decision-making. AI systems can analyse extensive volumes of environmental and operational data to identify inefficiencies and recommend sustainable alternatives (Pu 2025, 3-4). For example, AI can be used to optimize energy consumption in manufacturing processes, reducing supply chain wastage, and improving the efficiency of transportation systems (Chin et al., 2022; X. Liu et al., 2023)

AI plays a critical role in supporting the transition toward circular economy models (Florek-Paszkowska & Ujwary-Gil 2025, 130–131). AI enables real-time monitoring and predictive analytics. These capabilities allow organizations to design systems that minimize waste, optimize resource utilization, and reduce environmental impacts (Ahmed et al. 2026, 23). AI also supports operational practices such as recycling and reuse. AI-driven platforms can facilitate more efficient material recovery and circulation, thereby reducing the environmental impact of production processes (Freihat et al. 2025, 14). In addition, AI contributes to sustainable product design. By analyzing customer preferences alongside environmental data, organizations can develop products that are both environmentally sustainable and economically viable (Florek-Paszkowska & Ujwary-Gil 2025, 125). This integration of sustainability and innovation is essential for achieving long-term competitive advantage.

Despite these benefits, the adoption of AI for green innovation remains at an early stage. Organizations encounter several challenges in integrating AI into sustainability initiatives. These include technological complexity, lack of expertise, and organizational resistance (Shaik et al. 2024, 2737; Hussain et al. 2024, 4389; Boonmee et al. 2025, 7). In addition, aligning AI strategies with sustainability focus requires careful planning and coordination. These challenges emphasize the need for a systematic understanding of the factors influencing AI adoption for green innovation.

2.2 Technology Adoption in Organizations through the TOE framework

2.2.1 Technology Adoption in Organizations

Technology adoption in organizations refers to the process by which firms decide to implement and use new technologies to upgrade their operations and performance. This process involves multiple stages, including awareness, evaluation, adoption, implementation, and diffusion (Miranda et al. 2016, 49-50)

At the organizational level, technology adoption is impacted by an amalgamation of internal and external factors (Damanpour et al. 2018, 713). Internal factors include organizational resources, capabilities, leadership support, and strategic orientation. External factors include market competition, regulatory requirements, and technological trends (Kahpi et al. 2026, 2225)

The adoption of advanced technologies such as AI is particularly complex. It requires significant changes in organizational processes and structures that encourage ongoing competition and implement cost-effective, efficient, and productive strategies (Puklavec et al. 2018, 238-239). Organizations must invest in infrastructure, develop technical expertise, compatibility, and align their strategies with technological capabilities (Youssef 2025, 3). In addition, the successful implementation of technology depends on the ability of organizations to manage change, comply with regulatory policies, management support, and overcome resistance (Youssef et al. 2025, 8)

Understanding the factors that motivate technology adoption is essential for explaining why some organizations successfully implement new technologies while others do not. This understanding is particularly meaningful in the context of AI adoption for green innovation, where multiple dimensions of influence interact.

2.2.2 The TOE Framework

2.2.2.1 Overview of TOE

The TOE framework provides a comprehensive model for analysing the factors influencing technology adoption at the organizational level (Baker 2012). Originally developed by Tornatzky and Fleischer, the TOE framework (Tornatzky & Fleischer 1990) identifies three key contexts that shape adoption decisions: technological, organizational, and environmental (Tornatzky & Fleischer 1990; Baker 2012, 232)

The technological context: It refers to the internal and external technological resources available to an organization that create opportunities for innovation, adaptation, and organizational transformation (Baker 2012, 232; Shaik et al. 2024, 2734). It identifies the technological infrastructure, enabling factors, and characteristics of a technology that influence an organization's decision to adopt systems such as AI. These technologies are often adopted to achieve strategic goals, including carbon neutrality and sustainability improvement (Shaik et al. 2024, 2734). This distinction is vital because a firm's existing technological base shapes its capacity to change, while emerging technologies indicate what may be possible in the future (Collins & Hage et al. 1988, 534).

At the initial stage, an organization's existing technologies shape both the scope and pace of technological change (Amini & Javid 2023, 1221). These technologies promote interconnection, meaning that future adoption decisions are often constrained or enabled by prior technological investments. Successful adoption is closely associated with the availability of robust digital infrastructure and high-quality data resources. It is also influenced by the perceived usefulness of AI in enhancing energy efficiency and sustainability performance (Abdelfattah et al. 2024, 155). Organizations with adaptable, scalable, and well-integrated systems are better positioned to absorb and implement innovations. In contrast, rigid or slow-responding organizational structures may limit adoption potential (Collins & Hage et al. 1988, 524).

A more profound understanding of the technological prospect emerges while considering the nature of technological change. Innovations can be categorized into incremental, synthetic, and discontinuous types. Incremental innovations involve minor improvements to existing technologies and typically require minimal adjustment, making them relatively low-risk. Synthetic innovations represent a moderate level of change, as they recombine existing technologies in novel ways and require coordination across organizational functions. In contrast, discontinuous or radical innovations introduce fundamental shifts that can transform technologies, processes, and even industry structures. (Amini & Javid 2023, 1221-1222; Baker 2012, 232)

The type of innovation undertaking directly influences the speed and complexity of adoption decisions (Florek-Paszkowska & Ujwary-Gil 2025, 119). In a situation characterized by incremental or synthetic change, firms can adopt technologies in a gradual and controlled manner (Baker 2012, 232). However, when discontinuous innovations dominate, organizations must respond rapidly to avoid losing competitive advantage (Gandía et al. 2023, 3). This urgency is further shaped by whether innovations are competence-enhancing or competence-destroying. Competence-enhancing innovations allow firms to build upon existing knowledge and capabilities, facilitating smoother transitions. In contrast, competence-destroying innovations render established expertise obsolete and often require substantial restructuring and capability development. (Tushman & Anderson 1986, 443)

Beyond technological comprehension and its type of adoption, a few crucial technological factors are derived in the process of adopting the TOE. Some of these factors are characteristics of technology, availability, infrastructure, complexity, compatibility, technology readiness, competitive pressure, speed, cost effectiveness, relative advantages, data security, perceived benefits, and technology diffusion process (Baker 2012, 236; Prakash 2025, 86; Amini & Javid 2023, 1217). An organization's capability to evaluate and integrate these technological dimensions shapes its capacity to adopt and utilize new technologies for sustained competitive advantage (Hasan 2026, 5)

The organizational context: It represents the central internal environment in which technological potential is interpreted, implemented, and transformed into meaningful organizational outcomes. In other words, organizational factors demonstrate the internal characteristics and resources of an organization (Baker 2012, 433; Shaik et al. 2024, 2734). A vital element of the organizational perspective is the prevalence of linking systems. These systems promote integration across different units within the organization. (Abdulmuhsin 2026, 209). This mechanism operates through both formal and informal structures. Formal systems include cross-functional teams. These teams enable coordination across departments and support collaborative decision-making. Informal systems include roles such as product champions, boundary spanners, and gatekeepers (Baker 2012, 4330). These roles assist in bridging internal and external knowledge flows. Collectively, these integrations facilitate effective communication within the organization. They also support knowledge sharing and reduce structural complexity. (Abdulmuhsin 2026, 212)

Organizational structure also plays a significant role in innovation (Wang et al. 2023, 1). Organizational structure can be evaluated based on the extent to which decision-making authority is decentralized within the organization. Decentralized structures support the innovation stage. This strategy enhances boundary scanning and increases awareness of business, alongside encouraging flexibility and idea generation. In addition, a decentralized structure allows organizations to respond more effectively to change. However, Centralized structures are more suitable for implementation. They provide control and coordination during execution (Amini & Javid 2023, 1221-122, 1229).

Communication processes within the organization play a critical role in shaping innovation outcomes. They influence how information is shared, interpreted, and implemented across different levels of the firm (Abdulmuhsin et al. 2024, 221). Top management holds a central position in directing these processes. Leadership behaviour sets the tone for how innovation is perceived within the organization.

When leaders actively support change, they create a culture that is more receptive to innovation (Youssef 2025, 9; Boonmee et al. 2025, 10).

An organization's unique characteristics, structural configurations, and internal procedures influence its ability to successfully integrate complex technologies such as AI for sustainability purposes (Shaik et al. 2024, 2734). In addition to organizational structure, degree of control, and communication process, some crucial organizational factors influence the Sustainable AI adoption using the TOE framework. Some of these pointed in the literature are: formal & informal linking structures, communication process, slack, resources, size, managerial structure, learning capabilities, organizational culture, leadership style, top management support, organizational innovativeness, organizational readiness, centralization, complexity, interconnectedness, number of employees, attitude toward change, openness of system (Baker 2012, 236; Prakash 2025, 77; Amini & Javid 2023, 1221). The alignment of these organizational elements under TOE framework is essential for facilitating the effective adoption and implementation of AI-driven sustainability initiatives.

The environmental context: It represents external conditions that shape a firm's innovation behaviour in which an organization operates. It encompasses external factors such as industry structures, industry competitive pressures, vendor support, technological support infrastructure, market uncertainty and regulatory environment. (Baker 2012, 235; Amini & Javid 2023, 1222). Horani et al. 2023, 1058; Puklavec et al. 2018, 239).

Industry structure is a key determinant of innovation dynamics. High levels of competition motivate firms to adopt new technologies to maintain their competitive position. In addition, Dominant firms within the value chain can shape innovation outcomes. They may encourage or pressure their partners to adopt new practices and technologies (Zhao & Liu 2026, 4; Liu et al. 2025, 8).

The environmental context also includes the external physical and collaborative conditions that can support or restrict the spread and adoption of technology. Such as Collaborative networks and regional innovation clusters involving industry, academia, and public institutions can reduce the uncertainty and implementation costs associated with complex AI systems (Youssef 2025, 9). Moreover, the absence of such infrastructure may act as a major constraint that limits AI adoption, regardless of an organization's internal willingness or strategic intent (Haq et al. 2025, 11). Furthermore, a strong digital economy supports the flow of information and skilled talent, enabling organizations to absorb external knowledge and integrate AI systems within global value chains (Ma et al. 2025, 2).

The stage of the industry life cycle significantly influences innovation behaviour. Firms operating in rapidly growing industries are generally more inclined to engage in innovation activities. In contrast, innovation patterns in mature or declining industries are more varied. Some firms focus on improving efficiency or diversifying into new areas. Others limit innovation efforts to reduce costs and manage uncertainty (Mansour et al.2026,7; Tornatzky and Fleischer 1990).

Technological support infrastructure represents a key driver of innovation. The availability of skilled labour, consultants, and technology service providers can strengthen an organization's capacity to adopt and implement new technologies (Youssef 2025, 13). At the same time, high labour costs can influence firm behaviour. They encourage firms to adopt labour-saving technologies (Almusharraf 2025, 1).

Government regulation strongly influences innovation. Regulations can encourage innovation by setting new standards. For example, environmental rules may require firms to adopt cleaner technologies. However, strict safety, testing, and licensing rules can increase costs (Abdelfattah et al. 2024, 156-157). They may also slow down innovation. Privacy regulations can create additional barriers. They may limit technological development in certain sectors (Florek-Paszkowska , Ujwary-Gil 2025, 127)

The environmental context within the TOE framework emphasizes the role of external forces in shaping innovation and technology adoption. Factors such as industry dynamics, resource availability, and regulatory conditions influence firm behaviour. These factors create both opportunities and constraints for organizations (Shaik et al. 2024, 2734; Youssef 2025, 1).

2.2.2.2 Applying the TOE Framework to Green Innovation and AI Adoption

The TOE framework has been widely applied in studies of green innovation and sustainability. It provides a comprehensive theoretical model that integrates factors influencing green innovation into three core dimensions: technological, organizational, and environmental contexts. This multidimensional structure enables the systematic evaluation of diverse determinants affecting innovation processes. In particular, the TOE framework is effective in addressing the complex interplay of technological, organizational, and environmental factors, especially in high-pollution industries seeking optimal pathways toward green innovation (Lou et al. 2025, 4916–4918). Furthermore, its flexibility allows researchers to adapt the framework based on context-specific variables identified during the research process (Wang 2025, 2111). Empirical applications, such as fuzzy-set qualitative comparative analysis, demonstrate how TOE can identify distinct configurations of factors influencing the relationship between digital transformation and green innovation (Yin 2023, 100048–100050).

Within the TOE framework, the technological dimension encompasses factors such as the availability of eco-friendly technologies, R&D investment, green technology management capabilities, and the extent of digital transformation and application. The organizational dimension includes elements such as leadership awareness of green investments, organizational structure, availability of slack resources, executive attention to environmental issues, and overall organizational support. The environmental dimension captures external influences, including market competition, environmental regulations, government subsidies, enabling environments, and regulatory pressures (Lou et al. 2025, 4919; Liu & Wang 2025, 2113; Yin 2023, 100050). Collectively, these dimensions illustrate the effectiveness of the TOE framework in capturing the multidimensional nature of technology adoption within sustainability contexts.

Despite the broad application of theoretical perspectives in AI and sustainability research, existing approaches often provide only partial explanations of technology adoption. For example, the Dynamic Capabilities theory emphasizes an organization's ability to reconfigure internal and external resources in response to changing environments. In contrast, the Resource-Based View focuses on the role of valuable, rare, and difficult-to-imitate resources in achieving competitive advantage. (Feng et al. 2024, 1; Qalati et al. 2025, 2; Mansour et al. 2025, 3; Pu 2025, 1; Larbi-Siaw et al. 2022, 1; Abdelfattah et al. 2024, 155).

In the domain of innovation and technology adoption, several theories are frequently applied. These include Diffusion of Innovation, the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), Task–Technology Fit (TTF), and Technology Affordance Theory (Freihat et al. 2025, 1–4; Hamza & Karadas 2025, 1; Popa et al. 2025, 1; Raza et al. 2026, 3; Lin 2025, 473; Sabat & Bhattacharyya 2025, 9; Hutchby 2001, 442).

These frameworks primarily focus on specific dimensions of adoption. For example, they address user behavior, task–technology alignment, and social influence. However, they do not provide a fully integrated or holistic perspective on technology adoption processes. In contrast, the TOE framework provides a more integrative approach by simultaneously considering technological, organizational, and environmental determinants of innovation. It has been successfully applied across various domains, including social networks, e-procurement platforms, enterprise resource planning systems, e-business adoption, and green innovation (Xu & Lu 2022, 1; Rondovic et al. 2017, 252; Aguiar & Reis 2008, 122; Pan & Jang 2008, 92; Zhu et al. 2006, 1559; Zhang et al. 2020, 2–3). This broad applicability highlights its robustness and relevance for examining complex adoption phenomena.

Given the multifaceted nature of AI adoption for green innovation, a multidimensional analytical framework is essential. The TOE framework is particularly suitable for this study because it enables systematic categorization. More specifically, the drivers and barriers across technological, organizational, and environmental dimensions (Shaik et al. 2025, 2734). This structured approach enhances analytical clarity, reduces disconnected perspectives in the literature, and supports the identification of patterns across studies. Consequently, the TOE framework facilitates a strong theoretical foundation for examining the factors influencing AI adoption for green innovation at the organizational level.

2.3 Conceptual Framework

Based on the TOE framework, this study develops a conceptual framework for analysing the factors influencing AI adoption for green innovation. The framework categorizes these factors into three dimensions: technological, organizational, and environmental. This is represented using Figure 1

Figure 1. Conceptual Framework Based on TOE Framework

The figure 1 illustrates how technological, organizational, and environmental factors provide a structured lens for organizing the literature and understanding how different categories of factors are associated with the adoption of AI for green innovation. The framework is conceptual and non-causal, serving as a guiding structure for the analysis. These collectively influence what factors shape the adoption of AI for green innovation in organizations.

3 Research Methodology

The following section outlines the research approach and the justification surrounding the method of research used for this thesis. Additionally, the researcher emphasizes the key aspects of this strategy and provides arguments for its suitability for resolving the current study issue. The researcher subsequently goes on to explain the methods used to collect, analyze, and synthesize the results. Lastly, the researcher exhibits how trustworthy the thesis is.

3.1 Research Approach

This study adopts a structured approach to examine the factors influencing the adoption of AI for green innovation. The existing literature in this field lacks integration. It spans domains such as AI, sustainability, innovation management, and information systems (Hirtranusi et al. 2026, 491; Naveed et al. 2023, 1147). This conceptual inconsistency limits the development of a coherent and integrated understanding.

A systematic approach is therefore required. This study employs a SLR to address this challenge. The SLR enables the structured identification and synthesis of relevant studies. It supports the integration of dispersed knowledge across multiple research streams (Krüger et al. 2020, 629; Pati & Lorusso 2017, 15). Through this approach, the study aims to consolidate existing evidence. It also seeks to develop a clear and coherent understanding of the factors influencing AI adoption for green innovation.

A literature review article presents a holistic overview of literature aligned with a theory/theme/method and synthesizes previous studies to strengthen the foundation of knowledge. (Paul & Criado 2020,1). SLRs aim to collect and synthesize all relevant published evidence on a specific topic. They assess the credibility of the studies to ensure reliability. This process enables the development of transparent and verifiable scientific conclusions that address a defined research problem (Lame 2019, 1633). The SLR could be used in diversified forms. For example, SLR might be used based on domain, theory, or method (Palmatier et al. 2018, 3). SLR could also be represented in a more refined category, such as theme-based reviews, framework-based reviews, hybrid reviews, bibliometric reviews, conceptual reviews, and meta-analysis reviews (Paul & Criado 2020, 2-3).

This study adopts an SLR as its primary research design. Some of the reasons are: first, an SLR is a structured and replicable method for identifying, evaluating, and synthesizing existing research

(Tranfield et al. 2003, 209). It follows clearly defined procedures, which enhance transparency and reduce subjectivity. As a result, it improves the reliability of research findings (Booth et al. 2012).

Second, the choice of SLR is guided by the nature of the research problem. Research on AI-enabled green innovation is dispersed across multiple academic disciplines. This dispersion creates conceptual fragmentation and limits the identification of consistent patterns (Hirtranusi et al. 2026, 492). The SLR addresses this issue by organizing the literature in a systematic manner. It enables the development of a more coherent analytical perspective.

Third, the primary motive of this study is to identify the factors influencing the adoption of AI for green innovation. These factors are often examined in isolation across prior studies (Naveed 2023, 1126). The SLR allows these findings to be systematically aggregated and compared. This facilitates the identification of recurring themes and underlying relationships.

Fourth, the research process follows a transparent and structured procedure. It includes database selection, keyword formulation, and the application of inclusion and exclusion criteria. Relevant studies are screened and evaluated systematically (Tranfield et al. 2003).

Finally, the study employs thematic synthesis as an analytical technique. This approach supports the interpretation of findings beyond descriptive analysis. It allows patterns and relationships to emerge inductively from the data. This is particularly useful in examining adoption factors across diverse contexts (Hirtranusi et al 2026, 493; Rouhani et al. 2024, 9).

Overall, the SLR provides both descriptive and analytical value. It enables a systematic mapping of the literature. It also supports deeper insights into the factors influencing AI adoption for green innovation. This makes it a rigorous and appropriate methodological foundation for the study.

3.2 Search Strategy

The search strategy was carefully designed to identify relevant studies on the adoption of AI for green innovation systematically and transparently. A well-structured search process is essential in SLRs because it determines the scope, quality, and reliability of the final dataset. In this study, the search strategy was developed through a series of iterative steps to ensure both breadth and precision. (Harari et al. 2020, 1; Hirtranusi et al. 2026, 492).

The process involved three key components. First, an appropriate database was selected to ensure access to high-quality and peer-reviewed literature. Second, search keywords were developed and refined to capture the multidimensional nature of the research topic. Third, the temporal scope of the review was defined to ensure adequate coverage of the evolution of the field (Rouhani et al. 2026, 8; Marzi et al. 86-87).

The search strategy was continuously refined during the initial stages of the review. Preliminary searches were conducted to assess the relevance and adequacy of the results. Based on these initial findings, adjustments were made to the search terms and combinations to improve the balance between inclusiveness and specificity. This iterative approach helped ensure that the final dataset was both comprehensive and relevant to the research questions (Aromataris & Riitano 2014, 49; Marzi et al. 2024, 87)

3.2.1 Database Selection

This study relies exclusively on the Scopus database for literature retrieval. Scopus is frequently selected due to its extensive coverage and reliability as one of the largest abstract and citation databases of peer-reviewed research literature (Qaiser et al. 2017, 1378). Scopus indexes a large number of peer-reviewed journals across business, management, social sciences, and related fields (Hasan et al. 2017, 1378; Klarin 2024, 9). This makes it particularly suitable for interdisciplinary topics such as AI adoption and green innovation, where relevant studies are distributed across multiple domains.

Another significant advantage of Scopus is its advanced search functionality. It allows precise filtering based on subject area, extensive coverage, document type, publication stage, and language (Hirtranusi et al. 2026, 492-493). Moreover, relying primarily on Scopus for an SLR may result in a large volume of references (Paul & Criado 2020, 3). This is very useful for comparing literature from similar perspectives. These features are critical for conducting an SLR, as they enable researchers to apply consistent and transparent selection criteria.

The use of a single database also enhances methodological consistency. Combining multiple databases often introduces challenges related to duplicate records, inconsistent indexing, and variations in metadata (Tranfield et al. 2003, 208-209). By relying on Scopus alone, this study ensures a more controlled and replicable search process. Prior research in management and innovation studies has also shown that Scopus provides sufficient coverage for systematic reviews, particularly when strict inclusion criteria are applied (Hirtranusi et al. 2026, 492). Overall, the selection of Scopus assists in addressing the research questions of this study by ensuring access to high-quality literature while maintaining transparency and replicability.

3.2.2 Search Keywords and Search String

The development of search keywords is a critical step in SLRs, as it directly influences the relevance and completeness of the retrieved studies (Kruger et al. 2020, 645). In this study, the keywords were developed through an iterative process to reflect the multidimensional nature of the research topic (Aromataris & Riitano 2014, 49).

The research focus integrates four core dimensions. These include factors influencing adoption, AI technologies, green innovation concepts, and adoption-related processes. To capture these dimensions effectively, a combination of primary terms and their synonyms is used. This approach ensures that variations in terminology across different studies are adequately covered (Florek-Paszkowska & Ujwary-Gil 2025, 121; Freihat et al. 2025, 3).

For example, the concept of influencing factors was represented using terms such as factors, determinants, drivers, barriers, challenges, enablers, and facilitators (Youssef 2025, 1). Similarly, AI was represented using related terms such as AI, machine learning, data analytics, and intelligent systems (Mansour et al. 2025, 6). Green innovation was expanded to include eco-innovation, environmental innovation, and sustainable innovation (Freihat et al. 2025, 3). Adoption-related concepts were captured using terms such as adoption, implementation, acceptance, and diffusion (Haq et al. 2025, 5; Florek-Paszkowska & Ujwary-Gil 2025, 118).

The final search string used in the Scopus database is presented below:

(("factor*" OR "determinant*" OR "driver*" OR "barrier*" OR "challenge*" OR "enabler*" OR "facilitator*") AND ("artificial intelligence" OR "AI" OR "machine learning" OR "intelligent systems") AND ("green innovation" OR "eco-innovation" OR "environmental innovation" OR "sustainable innovation") AND ("adoption" OR "implementation" OR "acceptance" OR "diffusion"))

The use of wildcard operators, such as “factor*”, allowed the inclusion of multiple word variations, including singular and plural forms. Boolean operators were used to structure the relationships between different keyword groups. The “AND” operator ensured that all core dimensions were present in the retrieved studies, while the “OR” operator allowed for variation within each dimension.

This structured approach to keyword development helped achieve a balance between comprehensiveness and relevance. It ensured that the search captured a wide range of studies while minimizing the inclusion of unrelated articles. (Aromataris & Riitano 2014, 49)

3.2.3 Time Frame and Search Date

The literature search was conducted on 19 March 2026.

No strict lower time boundary was imposed at the initial stage of the search (Hiebl 2023, 239). This decision was made to capture the full evolution of research at the intersection of AI and green innovation. Given that both fields have developed over time, an unrestricted time frame allowed for a more comprehensive understanding of how the topic has emerged and evolved.

However, the results indicate that the majority of relevant studies were published in recent years. This reflects the rapid growth of interest in AI-driven sustainability and innovation, particularly in response to increasing environmental concerns and technological advancements (Florek-Paszkowska & Ujwary-Gil 2025, 118; Liu et al. 2025, 2). By adopting a flexible time frame while applying strict relevance criteria during the screening process, this study ensures both comprehensive coverage and contextual relevance of the selected literature.

3.3 Screening and Data Selection Process

3.3.1 Inclusion and Exclusion Criteria

To ensure both the relevance and methodological consistency of the selected studies, explicit inclusion and exclusion criteria were established before the screening process. Defining such criteria is a critical step in SLR. It reduces subjectivity and enhances transparency in study selection (Hirtranusi et al 2026, 492). In this study, the criteria were carefully designed to align with the research questions and to ensure that only high-quality and contextually relevant articles were included.

This study relied exclusively on the Scopus database due to its broad coverage and methodological consistency. Prior studies show that Scopus indexes a wider range of journals in business, management, innovation, and sustainability research compared to Web of Science (WoS). Particularly in emerging interdisciplinary fields (Mongeon & Paul-Hus 2016, 213-225; Paul & Criado 2020, 3). In contrast, WoS includes a more selective and comparatively smaller set of journals, with approximately 99% of WoS-indexed journals already covered by Scopus but not vice versa (Singh et al. 2021, 5113). As a result, using WoS alone may provide less comprehensive insights into AI adoption for green innovation unless combined with Scopus. Moreover, bibliometric results can vary significantly depending on the database selected (Mongeon & Paul-Hus 2016, 213-215, 226). However, combining multiple databases often creates substantial overlap in indexed journals, leading to duplicate records and inconsistencies in metadata, citation formats, and indexing structures (Kara et al. 2025, 1-2). Therefore, the use of Scopus alone was considered methodologically appropriate and sufficient for addressing the research questions of this study (Pranckutė 2021, 47-48; Singh et al. 2021, 5113).

The inclusion criteria focused on identifying studies that directly contribute to understanding the factors influencing AI adoption for green innovation (Hirtranusi et al 2026, 491). Only peer-reviewed journal articles were considered, as these are generally subjected to rigorous review processes and are widely recognized as reliable sources of academic knowledge. Limiting the dataset to English-language publications ensured consistency in interpretation and avoided potential inaccuracies associated with translation (Marzi et al. 2022, 88; Naveed et al. 2023, 1130).

Furthermore, only studies that explicitly addressed AI, green innovation, and adoption-related concepts were included (Qalati & Siddiqui 2026, 3). This ensured conceptual alignment with the research focus. To maintain disciplinary relevance, the search was restricted to subject areas such as Business, Management and Accounting, Economics, Econometrics and Finance, and Social Sciences. These fields are most closely associated with organizational adoption and innovation studies (Naveed et al. 2023, 1130).

In addition, only articles at the final publication stage were considered. This ensured that the analysis was based on complete and finalized research contributions, rather than preliminary findings. Conversely, exclusion criteria were applied to remove studies that did not meet the quality or relevance requirements. Conference papers, book chapters, and other non-peer-reviewed sources were excluded due to their varying levels of rigor. Non-English publications were also excluded to maintain consistency in analysis. Articles that did not directly address AI adoption or green innovation were removed to avoid conceptual dilution. Finally, studies lacking empirical or theoretical relevance to the research questions were excluded after detailed screening. For clarity, the inclusion and exclusion criteria applied in this study are summarized in Table 1.

Table 1. Inclusion and Exclusion Criteria

Criteria Type	Description
Inclusion Criteria	Peer-reviewed journal articles
	English language publications
	Studies addressing AI, green innovation, and adoption
	Relevant subject areas (Business, Management, Economics, Social Sciences)
	Final publication stage
Exclusion Criteria	Conference papers, book chapters, non-peer-reviewed sources
	Non-English publications
	Studies not focused on AI adoption or green innovation
	Studies lacking conceptual or empirical relevance

Table 1 represents the Inclusion and Exclusion Criteria applied in this SLR. By applying these criteria systematically, the study ensures that the final dataset consists of high-quality and relevant articles. This enhances the credibility and reliability of the subsequent analysis.

3.3.2 Systematic Screening

The screening and data selection process was conducted in multiple stages to systematically refine the initial dataset. A multi-stage approach is essential in SLRs, as it allows for the progressive elimination of irrelevant studies while maintaining transparency at each step (Hirtranusi et al. 2026, 493). Each stage of the process was carefully documented to ensure replicability and methodological accuracy.

The first stage is the planning stage. It includes the overall research design, database selection, search strategy, timeframe, and analytical methods guiding the review process. In the second stage, the initial search conducted in the Scopus database yielded a total of 169 documents. This dataset represented a broad collection of studies related to the search keywords and provided the foundation for subsequent filtering.

The third stage is Screening and Selection. It shows how the dataset was refined through four sequential filters. First, subject area filtering limited the records to relevant fields, reducing the dataset from 169 to 94 studies. Second, document type, language, and publication-stage criteria were applied, retaining only English-language journal articles at the final publication stage. It reduces the dataset to 49 studies. These 49 articles were retained for bibliometric analysis, as bibliometric techniques operate on the broader pre-screened dataset before final relevance filtering. Third, duplicate records were removed, leaving 47 literatures. Finally, relevance screening of titles, abstracts, and full texts excluded studies with insufficient conceptual or empirical relevance, resulting in 44 final studies.

The fourth stage represents the number of articles finally selected for the final study. After completing all screening stages, the final dataset consisted of 44 high-quality and highly relevant articles. This final sample forms the basis of the SLR.

The fifth stage, Data Extraction, involves the structured collection and organization of bibliographic, contextual, methodological, and analytical information from the selected studies. Finally, the sixth stage is Data Analysis and Synthesis. It employs thematic analysis, TOE-based categorization, and bibliometric techniques to identify recurring patterns, conceptual relationships, and key factors influencing AI adoption for green innovation. The final two stages extend beyond the scope of the literature selection process. They are included to illustrate how the selected studies were systematically processed, analyzed, and synthesized following the completion of article screening and selection.

The purpose of these sequential stages is to assess the direct relevance of each study to the research questions. Following the approach suggested by Fisch & Block (2018), studies were evaluated based on their contribution to understanding AI adoption and green innovation. Articles that only tangentially addressed the topic or lacked clear relevance were excluded. This resulted in the removal of three additional articles.

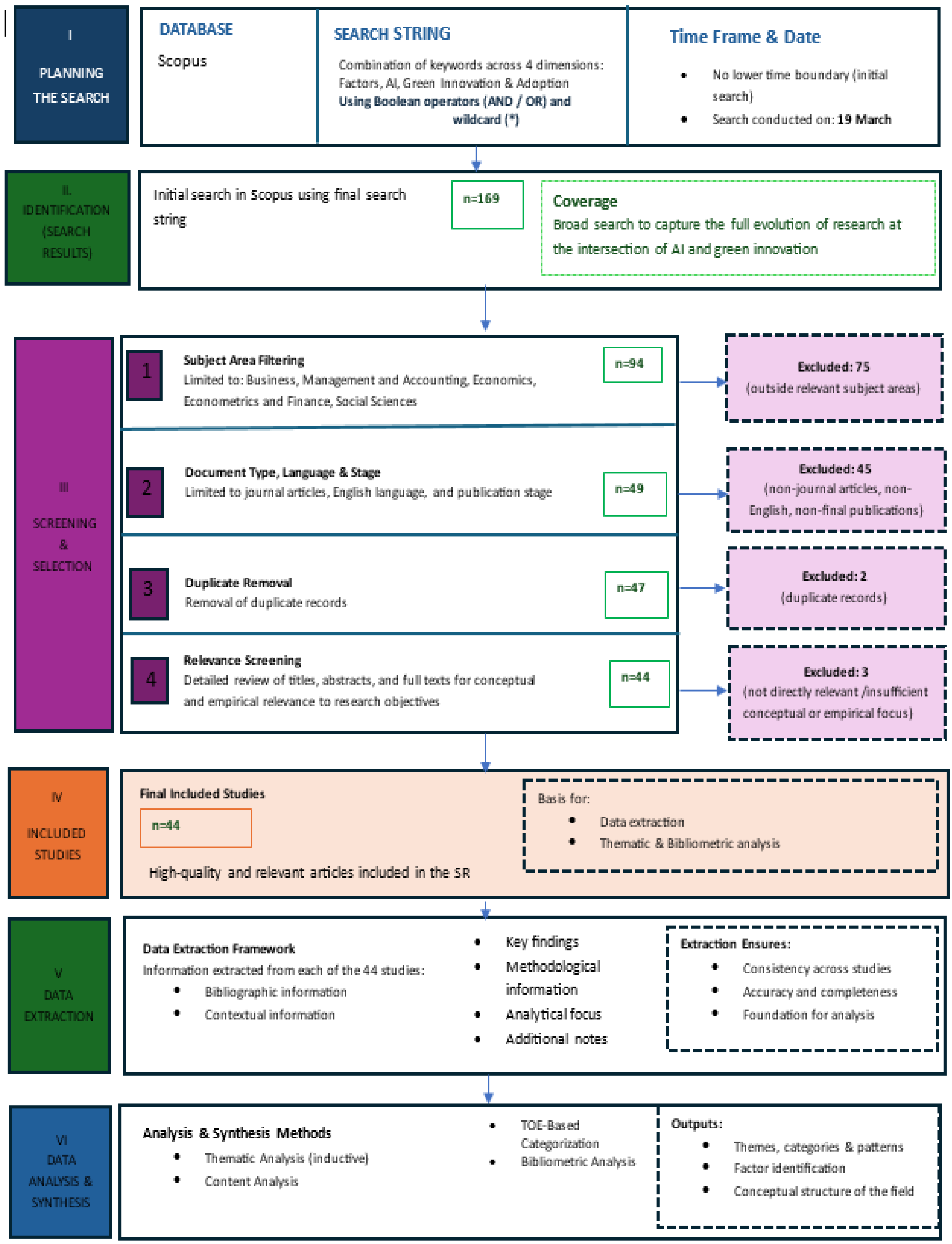

Figure 2. Systematic Literature Review Design, Screening, and Analytical Process

Figure 2 illustrates the SLR process adopted in this study. The figure outlines the sequential stages of the research design, including search strategy development, screening procedures, data extraction, and analytical synthesis. This reflects the methodological rigor and transparency underlying the review process.

3.4 Data Extraction and Metadata Analysis

3.4.1 Data Extraction

Data extraction was conducted in a systematic and structured manner to ensure consistency and accuracy across the selected studies. A data extraction framework was developed to capture key information relevant to the research questions. This step is critical in SLRs, as it provides the foundation for subsequent analysis and synthesis (Tranfield et al 2003, 209).

Each of the 44 selected articles was carefully reviewed, and relevant data were systematically recorded in a structured format. The extraction process focused on both descriptive and analytical information to support contextual understanding of the literature and the identification of broader research trends over time.

In addition, methodological and contextual information was extracted. This included the research context, study design, and analytical approach used in each article (Marzi et al. 2024, 95). Understanding these aspects is critical for interpreting the findings and assessing the robustness of the evidence. Most substantively, the extraction process focused on identifying the key findings of each study, particularly the factors influencing AI adoption for green innovation. For better understanding, the key data extraction elements are summarized in Table 2.

Table 2. Data Extraction Framework

Category	Extracted Information
Bibliographic Information	Author(s), Year, Journal
Contextual Information	Country/region, industry, research setting
Methodological Information	Research design, data collection method, analysis technique
Analytical Focus	AI application, type of green innovation
Key Findings	Identified drivers, barriers, and influencing factors
Additional Notes	Theoretical lens, limitations, future research directions

Table 2 presents the data extraction framework employed in this study. The framework supports the systematic collection and organization of bibliographic, contextual, methodological, and analytical information from the reviewed studies. This enables a consistent and structured foundation for thematic synthesis and interpretation.

3.4.2 Thematic Analysis

The primary analytical approach adopted in this study is thematic analysis. Thematic analysis is widely recognized as a robust and flexible method for identifying, analysing, and interpreting patterns across qualitative datasets, including SLRs. It enables the researcher to move beyond descriptive summarization and develop a structured and conceptually grounded understanding of complex phenomena (Rouhani et al. 2026, 9).

In the context of this study, thematic analysis is particularly appropriate because the objective is to identify and synthesize factors influencing the adoption of AI for green innovation across disperse research settings. These factors are often presented in varied forms and terminologies across studies. Therefore, a systematic and interpretive approach is required to consolidate them into coherent and meaningful categories.

The thematic analysis followed a multi-stage and iterative process, consistent with established practices in systematic review research (Fisch & Block 2018). The process was designed to identify recurring patterns, relationships, and broader conceptual themes emerging from the literature.

The first stage involved familiarization with the literature. All selected articles were read multiple times to develop a comprehensive understanding of their research questions, theoretical perspectives, methodologies, and key findings. This stage supported the identification of recurring concepts and initial analytical patterns within the data (Rouhani et al. 2026, 9–10). (Rouhani et al. 2026, 9-10).

The second stage involved initial coding. Coding was conducted at the sentence and paragraph level, focusing on segments of text that explicitly or implicitly described factors influencing AI adoption for green innovation. These included statements related to drivers, barriers, enabling conditions, and constraints. Each relevant segment was assigned a descriptive code representing its underlying meaning. For example, references to “lack of technical expertise” or “insufficient digital skills” were coded under capability-related constraints, while references to “cost reduction benefits” or “efficiency improvements” were coded under perceived technological benefits (Youssef 2025, 6; Gandía 2025, 5).

The third stage involved categorization. Similar codes were compared and grouped into broader conceptual categories based on recurring similarities and relationships across studies. This iterative comparison helped reduce redundancy while preserving the diversity and richness of the original findings (Hirtranusi et al. 2026, 491, 495).

The fourth stage involved the development of higher-order themes. These themes represent more abstract and integrative constructs that capture the underlying structure of the identified categories. Rather than simply aggregating similar factors, this stage focused on interpreting how different categories relate to each other within a broader conceptual framework (Hirtranusi et al. 2026, 492). The themes were inductively derived from the data rather than imposed a priori, consistent with the recommendations of Fisch & Block (2018). This inductive approach enhances the validity of the findings by ensuring that they are grounded in empirical evidence rather than theoretical assumptions.

Throughout the analysis, the coding and categorization process was iterative rather than linear. Codes and categories were continuously refined as new insights emerged from the data. This iterative refinement helped ensure that the final themes accurately reflected the patterns present across the literature (Aromataris & Riitano 2014, 49). In addition, careful attention was given to maintaining consistency in coding decisions, thereby reducing the risk of subjective bias (Carver et al. 2013, 205). Table 3 synthesizes the sequential stages used to identify, organize, and interpret recurring patterns related to the factors influencing AI adoption for green innovation across the reviewed literature.

Table 3. Thematic Analysis Process

Stage	Description
Familiarization	Repeated in-depth reading of all selected articles to understand context and key findings
Initial Coding	Identification and labelling of text segments related to drivers, barriers, and influencing factors
Categorization	Grouping similar codes into broader conceptual categories through iterative comparison
Theme Development	Development of higher-order themes that capture the underlying structure of the identified factors

Table 3 summarizes the thematic analysis process employed in this study. The process supports the systematic identification, organization, and interpretation of recurring patterns across the reviewed studies. This enables the development of coherent themes related to the factors influencing AI adoption for green innovation.

3.4.3 TOE-Based Categorization

To provide a coherent theoretical structure, the identified factors were organized using the TOE framework. The TOE framework is widely used in studies of technology adoption, as it captures the multi-level influences that shape organizational decisions (Prakash 2025, 76).

The use of the TOE framework in this study serves two main purposes. First, it provides a structured way to organize the identified factors into meaningful categories. Second, it enhances the theoretical grounding of the analysis by linking empirical findings to an established conceptual framework (Prakash 2025, 76, 79).

The identified factors were categorized into three main contexts. The technological context includes factors related to the characteristics of AI technologies, such as complexity, compatibility, and perceived benefits. The organizational context includes internal factors such as resources, capabilities, managerial support, and organizational culture. The environmental context includes external factors such as regulatory pressures, market conditions, and competitive dynamics (Baker 2011 432, Amini & Javid 2023, 1221; Prakash 2025, 76)

This categorization allows for a more systematic understanding of how different types of factors interact to influence AI adoption for green innovation. It also facilitates comparison across studies by providing a common analytical lens. For clarity, the TOE categorization is summarized in Table 4.

Table 4. TOE-Based Categorization Framework

Context	Description
Technological	Characteristics of AI technologies (e.g., complexity, compatibility, benefits)
Organizational	Internal capabilities and resources (e.g., skills, leadership, culture)
Environmental	External pressures and conditions (e.g., regulation, competition, market dynamics)

Table 4 presents the TOE-based categorization framework used to organize the factors influencing AI adoption for green innovation. The framework supports the systematic classification of the identified factors into technological, organizational, and environmental dimensions. This enables a structured and theoretically grounded interpretation of the reviewed literature.

3.4.4 Bibliometric Support (VOSviewer and Biblioshiny)

To complement the qualitative thematic analysis, this study employs bibliometric techniques as a secondary analytical layer. Bibliometric analysis provides a quantitative approach to examining the intellectual structure of a research field. It enables the identification of relationships among key concepts and reveals patterns within the literature (Paula & Criado 2020, 2). In this study, bibliometric analysis is used to support the interpretation of findings. It does not replace the primary thematic analysis. Instead, it provides additional evidence by mapping conceptual linkages and research trends.

Two established tools were used: VOSviewer and the Biblioshiny interface of the Bibliometrix package in R. These tools are widely used in SLRs within management and innovation research. They offer strong capabilities for visualization, clustering, and trend analysis (Klarin 2024, 4)

VOSviewer was used to generate network visualization maps. In these maps, nodes represent keywords, and links represent co-occurrence relationships. The size of each node reflects the frequency of occurrence (Klarin 2024, 4). The distance between nodes indicates the strength of association. Cluster colors distinguish groups of closely related concepts. These visualizations provide a clear representation of the conceptual structure of the field.

Biblioshiny was used for complementary analysis. It supports descriptive and longitudinal examination of the dataset (Klarin 2024, 1). Descriptive data included bibliographic details such as authors, publication year, trends, thematic evaluation, and journal (Tranfield et al 2003, 217). These insights help to contextualize the development of the research domain.

Centrally, bibliometric analysis functions as a supportive and triangulating method. The factors were recorded in detail to support subsequent coding, frequency assessment, and thematic analysis (Hirtranusi et al. 2026, 493). The patterns identified through keyword networks and descriptive metrics are used to validate the themes derived from qualitative coding (Marzi 2022, 94). This integration strengthens the credibility of the findings and enhances analytical rigor.

Overall, the use of bibliometric techniques provides a structured and visual perspective on the research landscape. It complements thematic insights and contributes to a more comprehensive synthesis of the factors influencing AI adoption for green innovation.

3.5 Evaluation of the Study

Ensuring methodological precision is a critical requirement in SLRs. The credibility of the findings depends on the transparency, consistency, and robustness of the research process (Florek-Paszkowska & Ujwary-Gil 2025, 121; Tranfield et al. 2003). In this study, several complementary measures were implemented to enhance both reliability and validity, in line with established guidelines for high-quality systematic reviews.

First, reliability is supported through the use of a clearly defined and systematic search strategy. All stages of the search process, including database selection, keyword development, search string construction, and filtering procedures, have been explicitly documented. This level of transparency ensures that the study can be replicated by other researchers using the same procedures. (Hirtranusi et al. 2026, 493)

Second, the application of explicit inclusion and exclusion criteria contributes to both reliability and validity by reducing selection bias. These criteria were defined prior to the screening process and applied consistently across all retrieved articles. By establishing clear boundaries regarding document type, language, subject area, and relevance to the research topic, the study ensures that only appropriate and high-quality sources are included (Hirtranusi et al. 2026, 493; Chetwynd 2022, 392). This enhances the internal consistency of the dataset and strengthens the overall credibility of the findings.

Third, the multi-stage screening and selection process further reinforces the quality and reliability of the dataset. The stepwise filtering of articles, from initial retrieval to final inclusion, allows for a systematic refinement of the sample (Rouhani et al. 2026, 6). Each stage serves a specific purpose, such as removing irrelevant subject areas, excluding non-peer-reviewed sources, and assessing conceptual relevance. This structured approach minimizes the risk of arbitrary selection and ensures that the final sample accurately reflects the research domain (Hiebl 2023, 231).

Fourth, the use of inductive thematic analysis enhances the internal validity of the study. The analysis is based on codes, categories, and themes derived directly from the data. This ensures that the findings are grounded in the empirical literature. It also reduces reliance on preconceived theoretical assumptions. (Liñán & Fayolle 2015, 910). This data-driven approach ensures that the identified factors genuinely reflect patterns observed across the reviewed studies, thereby improving the accuracy and trustworthiness of the findings.

Fifth, methodological triangulation was employed through the integration of thematic analysis, content analysis, and bibliometric techniques. The combination of qualitative interpretation and quantitative support enables cross-validation of findings from multiple analytical perspectives. For example, themes identified through coding were examined alongside keyword co-occurrence patterns and frequency distributions. This convergence of evidence strengthens the robustness of the conclusions and reduces the likelihood of subjective bias.

In addition, consistency in coding and interpretation was maintained through an iterative analytical process (Marzi 2022, 83). Codes and categories were continuously refined and compared across studies to ensure conceptual clarity and coherence (Hirtranusi et al. 2026, 495). This iterative refinement contributes to analytical reliability by minimizing inconsistencies in interpretation.

Overall, these methodological choices collectively enhance the reliability, validity, and transparency of the study. By ensuring replicability, reducing bias, grounding findings in the data, and triangulating across methods, the study meets the standards of rigor expected in high-quality SLRs and provides a solid foundation for subsequent analysis and interpretation.

3.6 Ethical Considerations

This study is based entirely on secondary data derived from publicly available, peer-reviewed academic literature. As such, it does not involve human participants, personal data, or primary data collection, and therefore does not require formal ethical approval in accordance with standard research ethics guidelines. However, ethical responsibility remains a critical consideration even in secondary research, particularly in ensuring the integrity and credibility of the review process.

To uphold academic integrity, all sources included in the study have been properly cited using appropriate referencing standards, and full credit has been given to the original authors. The study strictly avoids any form of plagiarism, including improper paraphrasing or omission of citations. In addition, the selection and analysis of articles were conducted in an objective and unbiased manner. The inclusion and exclusion criteria were defined in advance and applied consistently to minimize the risk of selective reporting and researcher bias. Furthermore, transparency and accuracy were maintained throughout the research process. All methodological steps, including search strategy, screening procedures, and analytical techniques, have been clearly documented to allow verification and replication. Care was also taken to interpret and synthesize findings without misrepresentation or overgeneralization, ensuring that the original meaning of each study is preserved. Overall, the study adheres to the principles of responsible research conduct, including honesty, transparency, and respect for prior research endeavour.

4 Findings

4.1 Descriptive Findings

This section presents an overview of the major trends and patterns identified within the final set of selected studies. It includes the analysis of scientific production and research trends, publication patterns, thematic structures, keyword interrelationships, and thematic mapping across the literature.

4.1.1 Overview of Scientific Production and Research Trends

This section provides a concise overview of the bibliometric characteristics and publication trends of the reviewed studies. Understanding the demographic structure and publication growth of the literature helps evaluate the maturity and development of the research field. A brief idea of the demographic feature is represented in Table 5.

Table 5. Demographic Information

Description	Results
Time Period	2020–2026
Total Documents	49
Total Sources	31
Annual Growth Rate	49.13%
Average Citations per Document	16.24
Authors	155
Average Co-authors per Document	3.27
International Co-authorship Rate	44.90%
Document Type	Journal Articles

Table 5 presents the key characteristics of the reviewed studies. The dataset consists of 49 journal articles published between 2020 and 2026 across 31 different sources, indicating that research on AI adoption for green innovation is emerging and moderately fragmented. The annual growth rate of 49.13% reflects increasing scholarly interest in the field. In addition, the average citation per document (16.24) suggests growing academic attention despite the recent emergence of the topic. The authorship structure further indicates a collaborative research environment, with an average of 3.27 co-authors per document and an international co-authorship rate of 44.9%. Overall, the findings indicate that AI adoption for green innovation is a rapidly developing research domain that is still evolving conceptually and theoretically.

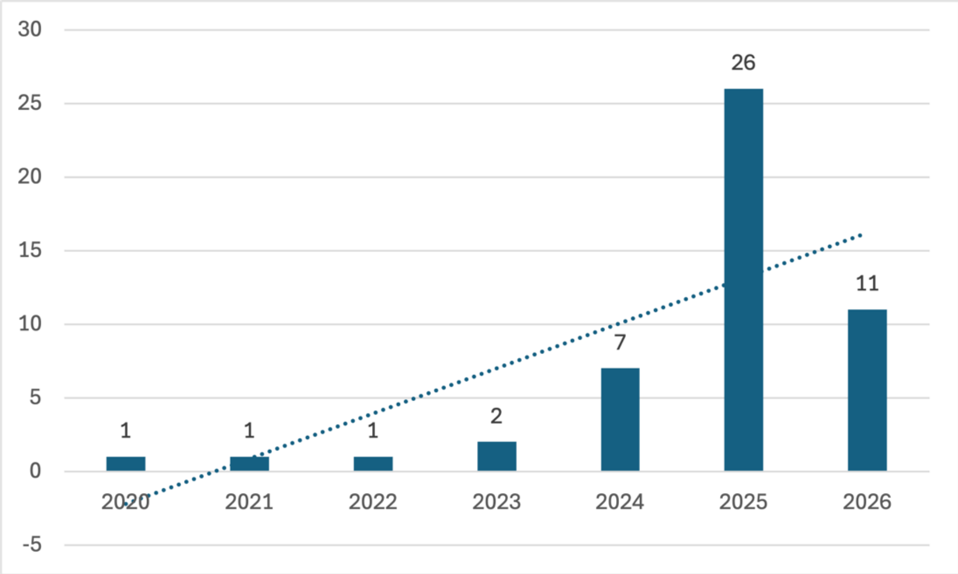

Figure 3. Annual Scientific Production

Figure 3 illustrates the annual scientific production on AI adoption for green innovation between 2020 and 2026. The findings show that research output remained limited during the early years but increased substantially after 2023. Publication activity peaked in 2025, indicating a rapidly growing scholarly interest in the intersection of AI, sustainability, and green innovation. Although publication frequency declined slightly in 2026, the overall trend remains strongly upward. These findings further indicate the emerging and expanding nature of the research field.

4.1.2 Publication Landscape and Source Distribution

This section examines the distribution of publications across academic sources and journals. Understanding the publication landscape helps evaluate the disciplinary orientation, maturity, and scholarly development of the research field. Such diversified prospects are represented in Table 6.

Table 6. Sources Impact over Time

Sources	h_index	g_index	m_index	TC	NP	PY_start
Sustainability (Switzerland)	3	7	0.429	64	12	2020
Business Strategy and the Envt.	2	3	0.667	214	3	2024
Int'l Review of Econ. and Finance	2	2	0.667	67	2	2024
Sustainable Futures	2	2	1	12	2	2025
Agricultural and Food Economics	1	2	0.5	4	2	2025
Applied Economics	1	1	0.333	29	1	2024
British Journal of Management	1	1	0.5	15	1	2025
Discover Sustainability	1	1	0.5	4	1	2025
Economies	1	1	1	3	1	2026
Energy Economics	1	1	0.5	32	1	2025

Table 6 presents the source distribution and publication impact of the reviewed studies. The findings show that research on AI adoption for green innovation is distributed across multiple journals, with *Sustainability*, *Business Strategy and the Environment*, and *International Review of Economics and Finance* emerging as notable publication outlets. The relatively low publication frequency across most journals indicates that the literature is still developing and dispersed across different academic sources. The findings further suggest increasing scholarly interest in the intersection of AI, sustainability, and innovation, particularly within sustainability, management, and economics-related journals.

4.1.3 Conceptual and Thematic Structure

A keyword co-occurrence network analysis was conducted to examine the relationships among the major concepts within the literature.

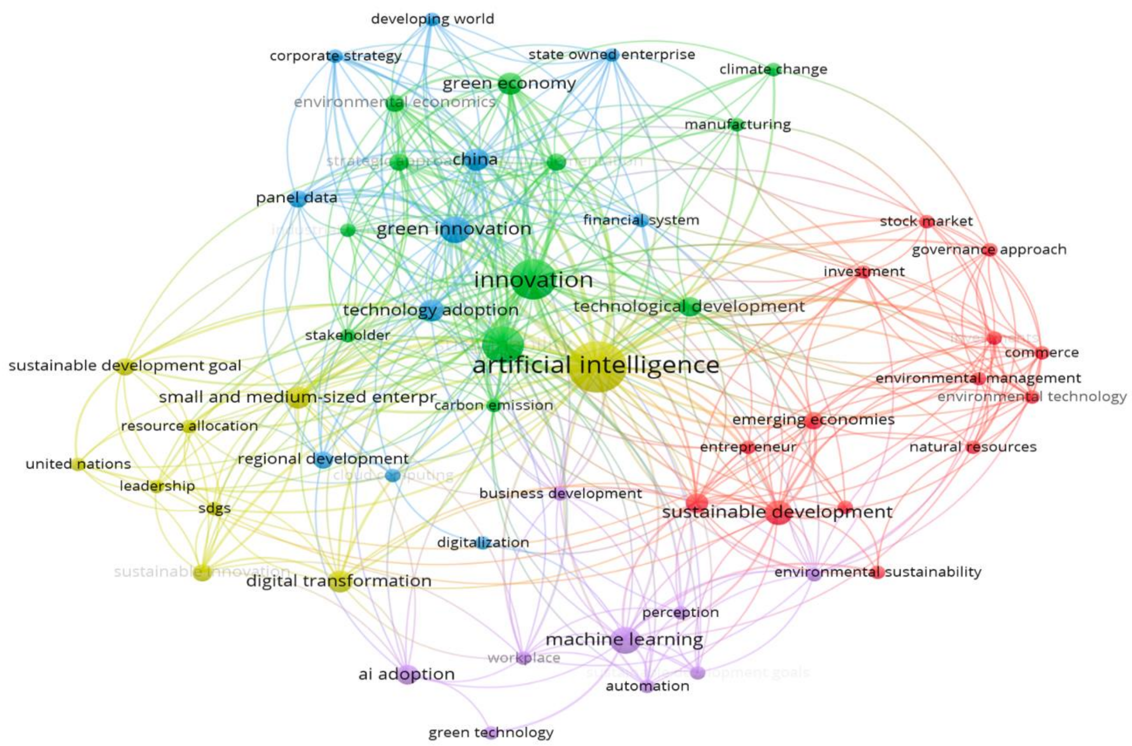

Figure 4. Co-occurrence of Keywords Network

Figure 4 presents the co-occurrence network of keywords, where nodes represent keywords and links indicate their relationships within the literature. The findings reveal that AI, innovation, and sustainability occupy central positions within the network, indicating that they form the core intellectual structure of the field. Several interconnected clusters are also visible, linking themes such as green innovation, machine learning, environmental management, digital transformation, and sustainable development. These connections suggest that the field is highly interdisciplinary and increasingly focused on integrating AI-driven technologies with sustainability-oriented organizational and strategic practices. To examine the maturity and interconnectedness of the research themes, a thematic map analysis was conducted.

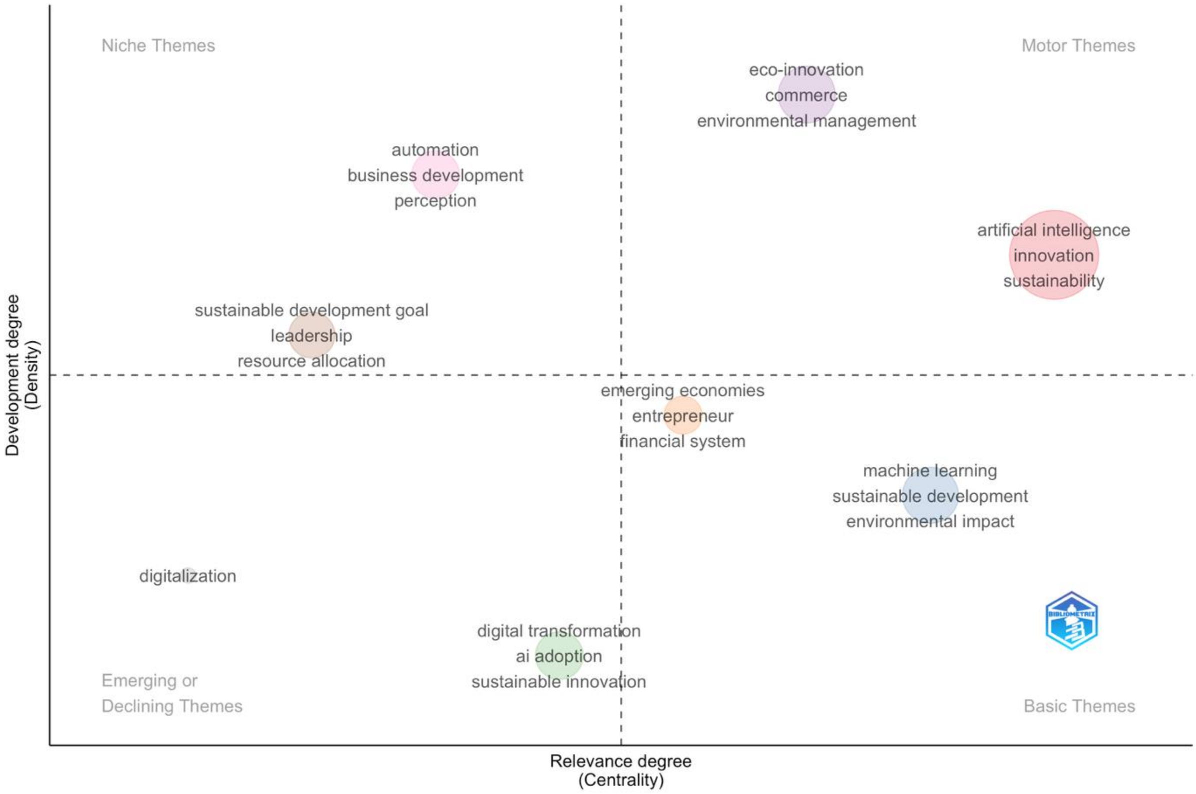

Figure 5. Thematic Map

Figure 5 presents the thematic structure of the research field based on theme centrality and development. Given the recent and disperse nature of the field, the thematic categorization should be interpreted cautiously, as many themes are still evolving conceptually (Qalati & Siddiqui 2026, 1). Themes related to AI, innovation, sustainability, eco-innovation, and environmental management appear as relatively central and developing themes within the literature (Youssef 2025, 1-4; Florek-Paszkowska & Ujwary-Gil 2025, 117-120; Larbi-Siaw et al. 2022; Qalati & Siddiqui 2026, 1-2). In contrast, machine learning, sustainable development, and environmental impact are positioned within the basic themes quadrant, indicating their foundational role in the field (Freihat et al. 2025, 5; Noronha & Vaz 2020, 5-8; Crocco 2025, 10207-10210). Themes such as digital transformation, AI adoption, and sustainable innovation appear within the emerging or transitional area (Freihat et al. 2025, 5-6). In contrast, themes related to automation, business development, and perception appear comparatively specialized and weakly interconnected within the broader research structure (Florek-Paszkowska & Ujwary-Gil 2025, 116-117). Overall, the findings demonstrate that research on AI adoption for green innovation remains interdisciplinary and conceptually dispersed, with the field still evolving toward greater theoretical integration and analytical maturity.

4.2 Contextual Findings Through TOE

This section systematically presents the factors identified across the reviewed studies within each dimension of the TOE framework. Its purpose is strictly evidential. It documents what the literature associates with AI adoption for green innovation, organized by technological, organizational, and environmental context. Interpretive arguments about how dimensions interact, what systems connect them, and why similar conditions produce different outcomes are reserved for section 4.4. Section 4.2.4 identifies the cross-dimensional connections visible in the evidence, without advancing explanatory claims beyond what the literature directly supports.

4.2.1 Technological Context

Digital infrastructure and AI-related capability emerge as the most consistently cited enabling conditions across the reviewed studies. Cloud computing, data analytics platforms, and advanced digital applications are associated with improvements in resource efficiency, process optimization, and sustainability-oriented decision-making (Pu 2025, 4, 16; Abdulmuhsin et al. 2024, 205). AI-driven tools additionally support knowledge sharing, operational coordination, and organizational sustainability efforts (Abdulmuhsin et al. 2025, 204; Ji &Tian 2026, 5). More scalable and accessible technologies demonstrate more consistent associations with green innovation outcomes. However, advanced AI systems often depend on stronger infrastructural capacity and organizational support to realize similar sustainability benefits. (Pu 2025, 16).

The literature also identifies a well-defined set of technological barriers. Implementation costs, integration complexity, scalability constraints, and technical incompatibility with existing systems are among the most frequently reported (Pu 2025, 16; Youssef 2025, 10). A distinct cluster of concerns relates to data governance. Concerns about data security, privacy, and the auditability of AI-generated outputs recur across studies on AI adoption in sustainability contexts (Naqbi et al. 2025, 1). Additionally, the explainability and transparency of AI systems represent a constraint wherever green innovation claims are subject to external scrutiny or regulatory verification.

A recurrent contrast in the literature is the differential performance of basic versus advanced AI technologies. Basic digital platforms demonstrate more consistent associations with green innovation efficiency. Advanced AI systems are frequently positioned as transformative in theory, but their practical effects are more uneven (Boonme et al. 2025, 2). Their outcomes depend on conditions outside the technological dimension itself. Consequently, the technological context should not be understood as a uniform enabler of green innovation. It is a domain whose enabling and constraining forces interact with organizational and environmental conditions. Figure 6 summarizes these elements.

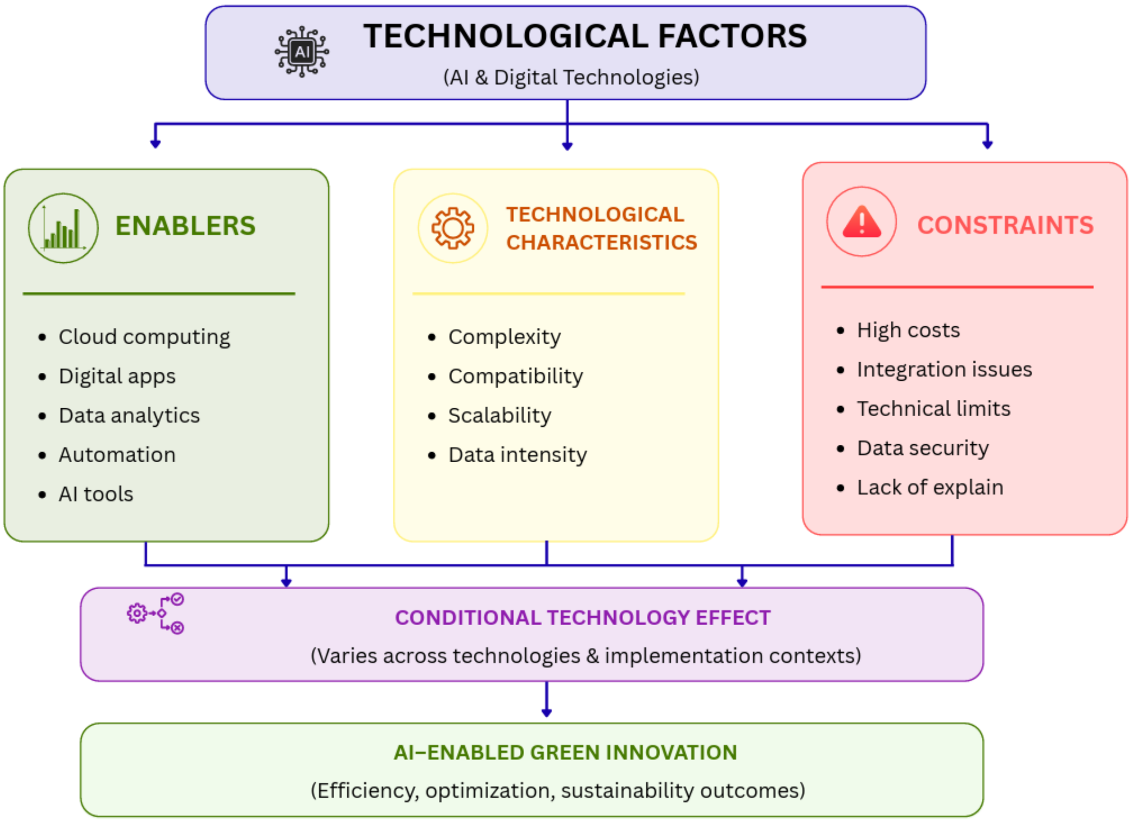

Figure 6. Summary Model of Technological Enablers and Constraints

Figure 6 presents a synthesized conceptual representation of the technological dimension influencing AI adoption for green innovation. The model illustrates that technological factors operate through a combination of enabling conditions and constraining forces, rather than acting as uniformly positive drivers. Technologies such as cloud computing, digital applications, and data analytics are consistently associated with enhanced efficiency and sustainability outcomes (Pu 2025, 5; Abdulmuhsin et al. 2024, 212). Moreover, their effectiveness is shaped by key technological characteristics, including complexity, compatibility, scalability, and data intensity. At the same time, the literature highlights significant constraints, such as high implementation costs, integration challenges, technical limitations, and concerns related to data security and explainability (Pu 2025, 15; Naqbi et al. 2025, 5).

Collectively, these findings indicate that the influence of AI and related technologies on green innovation is shaped by context. Their impact varies depending on the type of technology and the environment in which it is implemented. As such, technological factors should be interpreted as enabling yet constrained elements within the broader adoption process.

4.2.2 Organizational Context

The organizational context emerges as the primary internal environment within which AI adoption for green innovation is shaped, enabled, and constrained. The literature identifies four recurring organizational dimensions: capability development, leadership and strategic alignment, knowledge integration, and organizational readiness (Qalati & Siddiqui 2026, 1-2; Youssef 2025, 9; Ji & Tian 2026, 1-2; Haq et al. 2025, 5-6). These dimensions do not operate independently within the reviewed studies. They consistently appear in combination and are described as mutually conditioning.

Capability development is the most consistently reported organizational determinant. The literature distinguishes capability at multiple levels: employee-level AI capability, managerial-level AI knowledge, and organizational-level dynamic capabilities. Furthermore, it includes learning, sensing, seizing, and transformation. Studies on high-technology firms indicate that employee AI capability and knowledge-based dynamic capabilities are positively associated with digital green innovation (Ji & Tian 2026, 13). Broader organizational AI capabilities are similarly linked to stronger green innovation results (Qalati & Siddiqui 2025, 1). Absorptive, adaptive, and innovative capabilities further support sustainability-oriented organizational transformation by improving firms' ability to recognize sustainability opportunities and translate AI investments into operational improvements (Feng et al. 2024, 10). Contrasting evidence indicates that capability alone demonstrates a limited effect without supportive organizational structures and coordination systems (Pu 2025, 15; Mansour et al. 2025, 15).

Leadership and strategic alignment constitute a second prominent dimension. The reviewed studies associate sustainability-oriented leadership, managerial commitment, and digitally aligned leadership structures with stronger AI-enabled green innovation outcomes. Managerial commitment to sustainability strengthens the organizational environment for innovation (Housheya & Atikbay 2025, 14). Leadership is consistently described not as a stand-alone driver, but as a coordinating force that aligns technological initiatives with organizational priorities and sustainability goals (Youssef 2025, 9, 19; Shaik et al. 2024, 2733). Some evidence suggests that leadership effectiveness varies across organizational contexts, particularly where structural resource constraints limit leaders' ability to translate strategic intent into adoption outcomes (Pu 2025, 16).

Knowledge integration constitutes a third dimension. Technology-supported collaborative knowledge sharing enhances organizational sustainability by facilitating cross-functional exchange and collective problem-solving (Abdulmuhsin et al. 2024, 205). Studies on intellectual capital report that combining knowledge resources, R&D investment, and AI adoption is associated with stronger green product innovation performance (Abdelfattah et al. 2024, 154-155). Some contrasting evidence suggests that knowledge resources in isolation demonstrate limited sustainability impact when not supported by broader organizational alignment or adequate resource availability (Crocco et al. 2025, 10207).

Organizational readiness is the fourth dimension. Defined across the reviewed studies as the availability of resources, process maturity, and structural alignment with sustainability goals. It is reported as a boundary condition shaping both the likelihood and depth of AI adoption. Readiness supports effective AI integration within sustainability initiatives (Boonmee et al. 2025, 13; Mansour et al. 2025, 1; Shaik et al. 2024, 2734). Contrasting evidence confirms that resource limitations and process misalignment constrain adoption depth even when technological investment is adequate (Pu 2025, 16). Table 7 summarizes the organizational factors identified across the reviewed studies.

Table 7. Organizational Factors Influencing AI Adoption for Green Innovation

Organizational factor	**Key constructs**	**Supporting evidence**	**Contrasting evidence**	**Interpretive finding**
Capability development	AI capability; absorptive capacity; adaptive and learning capability	Employee AI capability and knowledge-based dynamic capabilities are positively associated with digital green innovation (Ji & Tian 2026; Feng et al. 2024; Qalati & Siddiqui 2025)	Capability demonstrates limited effect without structural coordination and leadership support (Pu 2025; Mansour et al. 2025)	Capability is the primary mechanism through which AI investment converts into sustainability outcomes. Its absence renders technological investment inert.
Leadership and strategic alignment	Sustainability-oriented leadership; managerial commitment; strategic integration	Leadership commitment and strategic alignment strengthen the organizational environment for AI-enabled green innovation (Housheya & Atikbay 2025; Boonmee et al. 2025; Youssef 2025)	Leadership effectiveness varies; structural and resource constraints can override strategic intent (Pu 2025)	Leadership activates and directs capability and knowledge resources toward sustainability goals. It functions as a coordinating force rather than an independent driver.
Knowledge integration	Communities of practice; intellectual capital; cross-functional R&D	Technology-supported knowledge sharing and R&D investment support AI-enabled green innovation outcomes (Abdulmuhsin et al. 2024; Abdelfattah et al. 2024; Crocco et al. 2025)	Knowledge resources in isolation show limited sustainability impact without organizational alignment and structural support (Crocco et al. 2025)	Cross-functional knowledge integration makes AI outputs organizationally usable for green innovation. Without it, analytical capability does not reach operational practice.
Organizational readiness	Resource availability; process maturity; structural alignment with sustainability goals	Organizational readiness is consistently associated with more effective AI integration within sustainability initiatives (Boonmee et al. 2025; Mansour et al. 2025; Shaik et al. 2024)	Resource constraints and process misalignment limit adoption depth even when technological investment is adequate (Pu 2025)	Readiness shapes the depth of green transformation, not merely its likelihood. Its absence produces shallow or symbolic adoption regardless of technological investment.

Table 7 presents the four organizational dimensions, their key constructs, supporting evidence, contrasting findings, and interpretive observations. A consistent finding is that organizational factors are not uniformly enabling. Each dimension is associated with positive outcomes when present and negative outcomes when absent or underdeveloped. The four dimensions are also interrelated. Capability development, for example, appears more consequential when supported by leadership alignment and knowledge integration. This pattern of mutual conditioning provides the empirical foundation for the cross-dimensional analysis in section 4.2.4 and the synthesis in section 4.4.

4.2.3 Environmental Context

The reviewed studies identify four environmental dimensions shaping AI adoption for green innovation. These are: regulatory frameworks and policy incentives, competitive and market dynamics, institutional quality, and legitimacy and ethical governance (Haq et al. 2025, 2- 4; Zhao & Liu 2026, 2-3; Mansour et al. 2025, 20). The fourth dimension emerges with increasing prominence in recent studies and is treated here as a distinct factor given its independent influence on the credibility of sustainability outcomes.

Regulatory frameworks and policy incentives represent the most frequently cited environmental dimension. Environmental regulation and government intervention are consistently associated with increased organizational attention toward sustainability-oriented AI adoption (Abdulmuhsin et al. 2024, 205; Abdelfattah et al. 2024, 155; Haq et al. 2025, 3). Policy incentives are similarly reported to enhance alignment between technological investment and green innovation initiatives. However, the literature identifies a critical qualification. In contexts where regulatory frameworks are poorly designed or where institutional monitoring capacity is weak, firms may engage in compliance-oriented or symbolic responses. They meet measurable output requirements without generating genuine environmental improvement (Zhao & Liu 2025, 2; Li et al. 2025, 2). Regulation, therefore, shapes both the frequency and the substance of AI-enabled green innovation.

Competitive and market dynamics constitute a second environmental dimension. Market competition and turbulence encourage firms to adopt AI for efficiency and differentiation (Larbi-Siaw et al. 2022, 1, 12; Youssef 2025, 8). However, the same dynamics may simultaneously constrain adoption by amplifying investment uncertainty and reducing the attractiveness of long-horizon sustainability strategies (Larbi-Siaw et al. 2022, 3). Competitive pressure primarily affects adoption frequency and urgency rather than adoption quality.

Institutional quality and digital infrastructure represent the third environmental dimension and demonstrate the strongest contextual variation across the reviewed studies (Mansour et al. 2025, 2-3;

Youssef 2025, 9-10). Firms in developed or institutionally stronger environments benefit from better digital infrastructure, more accessible financing for AI investment, and more favourable regulatory ecosystems (Pu 2025, 16). In contrast, organizations in emerging or resource-constrained contexts face compounding barriers. Limited digital infrastructure reduces technological readiness. Weak institutional support limits access to knowledge and collaboration resources. Inadequate financing constrains organizational capability development (Naqbi et al. 2025, 5, 23). Institutional quality, therefore, shapes not merely the likelihood of adoption but the upper bound of what AI-enabled green innovation can achieve in a given context.

Legitimacy and ethical governance emerge as a fourth distinct environmental dimension in more recent studies. Concerns related to algorithmic transparency, data privacy, accountability frameworks, and the explainability of AI-driven sustainability decisions are consistently reported as factors shaping organizational willingness to adopt AI and stakeholder willingness to accept AI-enabled green innovation claims (Naqbi et al. 2025, 2; Mansour et al. 2025, 1). The absence of credible ethical governance generates legitimacy risk. This constrains adoption even when technological and organizational conditions are otherwise favourable. Table 8 summarizes the environmental factors.

Table 8. Environmental Influences and Contextual Variations

Environmental factor	Key constructs	Supporting evidence	Contrasting evidence	Interpretive finding
Regulatory frameworks and policy incentives	Environmental regulation; Government intervention; Policy design quality	Regulatory pressure and policy incentives are associated with increased sustainability-oriented AI adoption (Abdulmuhsin et al. 2024; Abdelfattah et al. 2024; Haq et al. 2025)	Poorly designed regulatory pressure may produce compliance-oriented or symbolic responses rather than genuine environmental improvement (Zhao & Liu 2025; Li et al. 2025)	Regulatory conditions shape the content of adoption, not merely its occurrence. Poorly designed incentives produce adoption without substantive depth.
Competitive and market dynamics	Market turbulence; Competitive pressure; Performance expectations	Market competition encourages AI adoption for efficiency and differentiation (Larbi-Siaw et al. 2022; Youssef 2025)	Competitive uncertainty constrains adoption through high investment risk and unclear sustainability returns (Larbi-Siaw et al. 2022)	Competitive conditions create adoption pressure but do not ensure substantive green innovation. They amplify the importance of internal capability readiness.
Institutional quality and infrastructure	Digital infrastructure; Institutional support systems; Financial ecosystem quality	Strong institutional environments support AI-enabled green innovation through infrastructure, knowledge ecosystems, and stable governance frameworks (Pu 2025; Naqbi et al. 2025)	Poor institutional quality and infrastructural deficits compound adoption barriers across all three TOE dimensions simultaneously (Naqbi et al. 2025)	Institutional quality is the structural boundary condition that determines whether organizational and technological conditions can function effectively.
Legitimacy and ethical governance	Algorithmic transparency; Data privacy; Accountability frameworks; Stakeholder trust	Ethical governance is associated with greater willingness to adopt AI for sustainability and stronger stakeholder credibility of green innovation claims (Mansour et al. 2025; Qalati & Siddiqui 2025)	Absence of ethical governance generates legitimacy risk that constrains adoption even when technological and organizational conditions are favorable (Naqbi et al. 2025)	Ethical governance determines whether AI-enabled sustainability claims are credible. Without it, adoption outcomes risk being perceived as performative rather than substantive.

Table 8 presents the four environmental dimensions and their associated constructs, evidence, and interpretive observations. The most significant pattern is that the environmental context does not function as a uniformly enabling or constraining background. Its influence on AI-enabled green innovation is contingent and directional. In several dimensions, environmental conditions specifically shape the credibility and depth of sustainability outcomes rather than merely their occurrence. The distinction between conditions that affect adoption frequency and those that affect adoption quality is a central input to the synthesis in section 4.4.

4.2.4 Cross-Dimensional Interpretation

The preceding sub-sections have documented factors within each TOE dimension separately. The reviewed literature, however, consistently points toward three cross-dimensional connections that cannot be observed within any single dimension. This section identifies those connections as they appear in the evidence. It does not advance interpretive claims beyond what the literatures directly support. That work is carried out in section 4.4.

The first connection concerns the technological and organizational contexts. Across the reviewed studies, the effectiveness of AI-related technological investments is repeatedly reported as contingent on the presence of organizational capability, leadership support, and coordination structures. Advanced technologies demonstrate limited sustainability benefits in organizations with weak absorptive capacity or fragmented coordination systems (Pu 2025, 2; Mansour et al. 2025, 15). Organizations with stronger capability bases, by contrast, appear better positioned to extract green innovation value from the same technological investments (Ji & Tian 2026, 3; Ma et al. 2025, 1-3). This conditional relationship indicates that the organizational context modifies whether technological potential is realized.

The second connection concerns the organizational and environmental contexts. Organizational strategies and capability investments do not operate independently of external conditions. Regulatory environments and policy incentives shape the organizational attention and resources directed toward AI-enabled sustainability initiatives (Li et al. 2025, 1; Abdelfattah et al. 2024, 154; Youssef 2025, 1). At the same time, institutional constraints restrict organizations' ability to translate technological opportunities into sustainable outcomes regardless of strategic intent (Naqbi et al. 2025, 1). The relationship is bidirectional. External conditions shape organizational capacity, while organizational structures determine how external conditions are interpreted and acted upon.

The third connection concerns the technological and environmental contexts. This relationship is largely mediated through organizational processes. Environmental pressures may stimulate investment in AI technologies. However, the effectiveness of that investment depends on how organizations respond to those pressures. Regulatory demands may drive AI adoption, but without organizational governance systems in place, the result may be shallow or symbolic green innovation outcomes (Zhao & Liu 2025, 4; Youssef 2025, 8; Li et al. 2025, 2). These three cross-dimensional connections establish the empirical foundation for the integrative synthesis developed in section 4.4.

4.3 Analytical Findings of Patterns

Building on the cross-dimensional interpretation, the synthesis reveals several recurring patterns across the reviewed studies. These patterns should not be interpreted as empirically verified causal systems, since the reviewed literature is largely cross-sectional, context-specific, and methodologically diverse. Instead, the findings indicate that certain organizational and environmental processes recur with sufficient consistency to warrant interpretive attention. In particular, the literature points toward three interconnected themes: capability-related patterns, coordination and integration patterns, and governance and contextual patterns (Abdelfattah et al. 2024, 165). Rather than functioning independently, these themes appear to interact in shaping how organizations translate AI adoption into sustainability-oriented innovation outcomes. Together, they deepen understanding of how the technological, organizational, and environmental conditions identified through the TOE framework become associated with different forms of green innovation outcomes.

4.3.1 Capability-Related Patterns

A consistent pattern across the literature suggests that capability development may play a role in shaping how organizations engage with AI for green innovation. Studies on employee AI capability, organizational learning, knowledge acquisition, and dynamic capability-related constructs consistently highlight the importance of internal organizational capabilities (Ji & Tian 2026, 1). Firms with stronger internal capabilities are more frequently associated with sustainability-oriented innovation outcomes. For example, evidence from high-tech firms indicates that employee AI capability and knowledge-based dynamic capabilities positively influence digital green innovation. This suggests that the ability to generate, acquire, and integrate knowledge plays a critical role in linking AI adoption with environmental innovation efforts (Ji & Tian 2026, 16).

Similarly, research on organizational sustainable AI capabilities highlights the importance of learning, sensing, seizing, and stakeholder integration capabilities. These capabilities are associated with sustainability-oriented innovation outcomes. This suggests that AI adoption becomes more effective when supported by a broader organizational capability base (Qalati & Siddiqui 2025, 1). This pattern is reinforced by studies emphasizing adaptive, absorptive, and innovative capabilities. The literature indicates that such capabilities may strengthen the relationship between AI adoption and green innovation efficiency, particularly in contexts where organizations must interpret complex technological opportunities while responding to sustainability demands (Feng et al. 2024, 11).

Related evidence also points toward the importance of intellectual capital. This appears to be associated with stronger green product innovation performance when combined with AI adoption and R&D investments (Abdelfattah et al. 2024, 154). Overall, these findings suggest that capability development may function as a significant interpretive pathway through which technological potential becomes associated with sustainability-oriented innovation. However, the literature also indicates that these capabilities appear more effective when supported by organizational coordination structures and favourable governance conditions (Mansour et al. 2025, 1-2). In this respect, capability-related factors should not be viewed only as background organizational resources. Instead, they appear to influence how effectively firms integrate AI into environmentally oriented innovation processes and sustainability-related decision-making.

At the same time, the literature also indicates that capability-related factors are unevenly distributed across contexts. Some studies suggest that technologically advanced solutions may have a limited effect where skill shortages, weak digital competence, or constrained organizational learning capacity remain unresolved (Youssef 2025, 10, 16; Mansour et al. 2025, 15; Zhao & Liu 2026, 2). This variation suggests that capability development should not be viewed only as a background condition. Instead, it appears to be a central factor influencing how organizations derive green innovation value from AI-related technologies (Saiyed et al. 2025, 880).

4.3.2 Coordination and Integration Patterns

A second recurring pattern suggests that coordination and integration may be closely associated with AI adoption outcomes in green innovation contexts. The literature indicates that organizations are more likely to align AI with sustainability goals when technological initiatives are integrated with broader organizational systems. Collaborative processes and cross-functional structures also support this alignment (Abdulmuhsin et al. 2025, 208; Qalati & Siddiqui 2026, 11). In this respect, the reviewed studies consistently point toward the importance of organizational alignment rather than isolated technological implementation.

One strand of evidence comes from studies emphasizing communities of practice and collaborative knowledge-sharing systems. These studies suggest that technology-supported collaboration can enhance organizational sustainability by facilitating knowledge exchange, problem-solving, and collective learning across functional boundaries (Abdulmuhsin et al. 2024, 210). Similarly, green HRM research indicates that AI appears more closely associated with green innovation when supported by aligned human resource practices, a supportive work climate, and an organizational environmental strategy (Housheya & Atikbay 2025, 13). These patterns suggest that the relationship between AI adoption and green innovation depends on more than the presence of technology alone. It is also influenced by how effectively the technology is embedded within coordinated organizational structures and processes.

The literature also points toward the relevance of strategic and process integration. Studies on business process maturity and technology alignment suggest that firms with stronger internal coordination structures may be better positioned to connect digital technologies with a sustainability focus (Boonmee et al. 2025, 13). Likewise, conceptual research on digital-sustainability ecosystems highlights the importance of integrating technologies such as AI, IoT, blockchain, and digital platforms with organizational processes. Stakeholder collaboration and repetitive learning structures also strengthen their contribution to sustainable innovation (Florek-Paszkowska & Ujwary-Gil 2025, 116).

This does not confirm coordination as a direct causal mechanism. However, it indicates a recurring association between organizational integration and the effectiveness of AI-enabled sustainability outcomes. The literature further suggests that coordination processes may function as bridging conditions through which AI-related capabilities are translated into sustainability-oriented innovation practices (Saiyed et al.2025, 878-880). In this respect, organizational alignment, collaborative integration, and process coordination appear particularly meaningful in enabling firms to connect technological adoption with environmental outcomes.

Contrasting evidence also deserves attention. Some studies suggest that digital or AI investments alone may not yield strong green innovation effects when integration remains weak or conceptually inconsistent (Pu 2025, 3). This suggests that coordination-related patterns are particularly critical for understanding why similar technologies appear to perform differently across organizations. Overall, the findings indicate that organizational integration is not a peripheral condition, but a recurring pattern associated with more effective AI adoption trajectories across sustainability-oriented contexts.

4.3.3 Governance and Contextual Patterns

A third recurring pattern in the literature suggests that governance and contextual conditions may play a significant role in shaping the association between AI adoption and green innovation. The reviewed studies consistently highlight the influence of regulation, legitimacy pressures, ethical concerns, and institutional quality on AI adoption outcomes (Zhao & Liu 2026, 3). These factors frequently appear alongside sustainability-oriented innovation activities. This suggests that AI-enabled green innovation is embedded within broader systems of accountability and external expectations.

Regulation is one of the most visible patterns in this regard. The literature indicates that environmental regulation and government intervention are often associated with increased innovation efforts and greater organizational attention to sustainability-oriented technologies (Haq et al. 2025, 3; Larbi-Siaw et al. 2022, 11). However, the findings also suggest that regulatory pressure may produce mixed effects. In some contexts, AI is associated with more substantive green innovation outcomes under strong environmental regulation. In other contexts, external pressure may encourage symbolic or lower-quality innovation responses. Such responses are often aimed at maintaining legitimacy rather than creating meaningful environmental value (Li et al. 2025, 2). This suggests that governance-related conditions are not uniformly enabling, but may shape both the depth and credibility of adoption.

Ethical and legitimacy-related concerns also emerge as significant interpretive patterns. Studies on generative AI and broader digital adoption consistently highlight concerns related to algorithmic bias, data privacy, transparency, explainability, and security. These issues influence organizational willingness and preparedness to adopt AI in sustainability-related contexts (Naqbi et al. 2025, 2). Such concerns suggest that AI adoption is not only a matter of technological feasibility or strategic ambition, but also one of trust, accountability, and perceived legitimacy. In this respect, the literature suggests that ethical governance is closely associated with the credibility of AI in sustainability initiatives. Strong ethical governance may help organizations view AI as a contributor to sustainability rather than a source of risk or reputational vulnerability (Mansour et al. 2025, 1; Qalati & Siddiqui 2026, 10).

Contextual variation further strengthens this interpretation. The findings indicate that firms in developed or institutionally stronger environments tend to face more supportive conditions for AI-related digitalization and green innovation. In contrast, organizations operating in emerging or resource-constrained environments often face infrastructural limitations, financial constraints, and weaker institutional support systems (Naqbi et al. 2025, 23; Pu 2025, 15). This implies that governance and legitimacy patterns are filtered through broader contextual settings. Furthermore, the external environment may shape not only the incentives for adoption but also the perceived risks, expectations, and constraints surrounding it.

Collectively, these findings suggest that governance and contextual conditions function as critical interpretive layers shaping AI adoption for green innovation. The literature points toward a recurring association between regulatory conditions, legitimacy concerns, ethical safeguards, and the quality of sustainability-oriented innovation outcomes (Mansour et al. 2025, 2; Zhao & Liu 2026, 4). More significantly, governance conditions appear to influence whether organizational capabilities and coordination structures produce substantive environmental improvements or more symbolic sustainability responses. This suggests that AI adoption for green innovation is embedded within broader socio-institutional environments rather than driven by technical rationality alone. The findings also reinforce the interpretation that adoption outcomes remain varied across different institutional and economic settings.

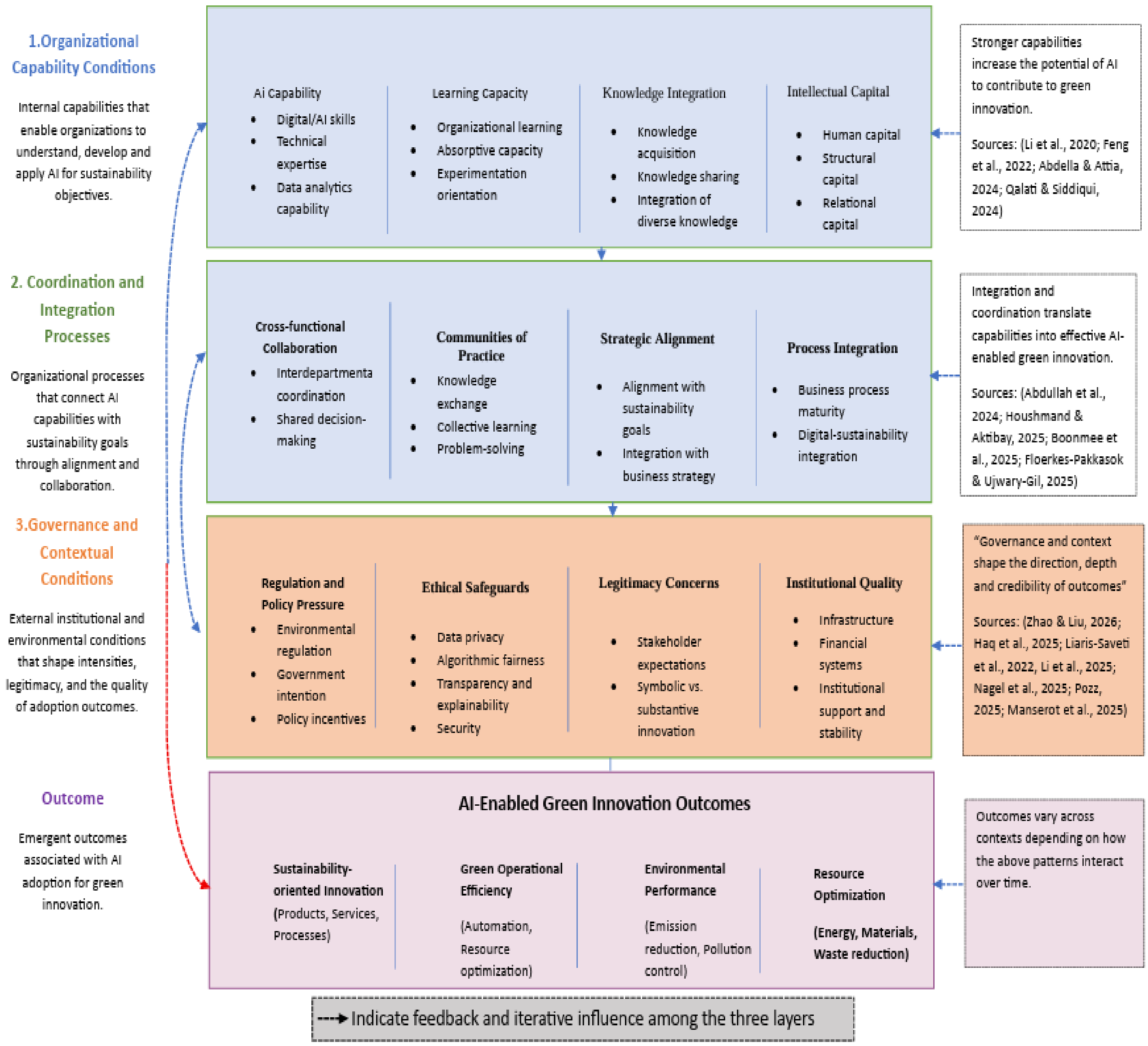

Figure 7. Interpretive Pattern Associated with AI Adoption for Green Innovation

Figure 7 presents an interpretive synthesis of the recurring patterns identified across the reviewed studies. The figure should not be interpreted as a causal or empirically validated model. Instead, it illustrates how the literature consistently associates AI adoption for green innovation with the interplay between organizational capabilities, coordination and integration processes, and governance-related contextual conditions (Ji & Tian 2026, 1, 4; Qalati & Siddiqui 2025, 1). The figure further suggests that AI-enabled green innovation outcomes are more likely when technological capabilities are supported by organizational integration and favorable governance conditions. In doing so, the figure complements the TOE-based discussion by highlighting the interconnected and context-dependent nature of AI adoption for sustainability-oriented innovation.

4.4 Synthesis

The preceding sections have produced three layers of findings. Section 4.1 documented the bibliometric structure of the field. It revealed rapid but fragmented growth, concentrated in sustainability, management, and innovation journals, with research still evolving conceptually and geographically. Section 4.2 presented factor-level findings within each TOE dimension. Section 4.3 identified three recurring interpretive patterns across the literature: capability-related patterns, coordination and integration patterns, and governance and contextual patterns. This synthesis does not re-examine those findings. Instead, it draws on all three sections to address a question they cannot be answered individually: how do the technological, organizational, and environmental conditions identified across the findings chapter combine to shape AI adoption for green innovation, and why does the same adoption produce substantially different sustainability outcomes across comparable contexts?

The synthesis advances three specific arguments that are not derivable from factor-level analysis alone. First, the three TOE dimensions function as mutually conditioning forces rather than independent or additive determinants. The contribution of any single dimension is contingent on the configuration of the others. Second, the organizational context operates not merely as one enabling condition among three, but as the active translating mechanism through which technological potential is either realized or lost. Third, the environmental context determines not only the likelihood of adoption, but the credibility and substantive depth of sustainability outcomes. This distinction, between adoption that generates genuine environmental improvement and adoption that produces the appearance of compliance, is underexplored in prior TOE applications. Figure 8 presents the integrative framework that emerges from these three arguments.

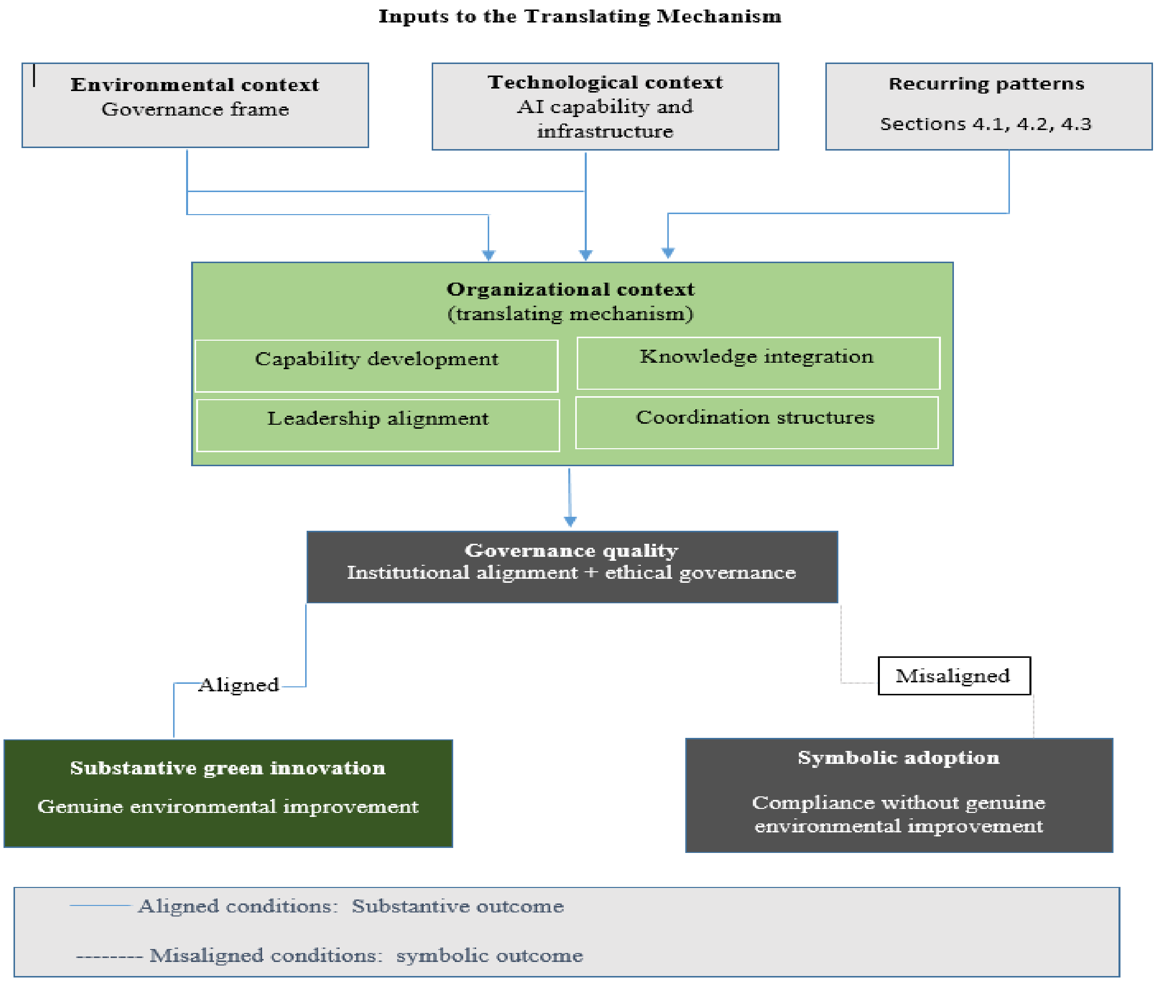

Figure 8. TOE-Based Integrative Framework for AI Adoption and Green Innovation Outcomes

Figure 8 presents the TOE-based integrative framework developed through the synthesis of this study. Three input conditions, namely the environmental context, the technological context, and the recurring patterns identified across sections 4.1, 4.2, and 4.3, feed into the organizational context, which functions as the central translating system converting technological potential into sustainability-oriented outcomes. The organizational layer comprises four interdependent components: capability development, leadership alignment, knowledge integration, and coordination structures. From the organizational layer, a single pathway leads to a governance quality node representing the combined influence of institutional alignment and ethical governance. This node determines which of the two outcome paths is activated. When conditions across the three TOE dimensions are aligned, the framework produces substantive green innovation characterized by genuine environmental improvement. When governance or capability conditions are weak or misaligned, AI adoption is more likely to remain symbolic. In such contexts, adoption often reflects compliance-oriented activity rather than meaningful environmental transformation. The framework is interpretive rather than causal and should be read as a conceptual synthesis of the conditional relationships identified across the reviewed literature.

4.4.1 Technology as a Necessary but Insufficient Condition

The first synthesis argument concerns the specific role of the technological dimension relative to the others. Section 4.2.1 documented a dual technological landscape: enablers including digital infrastructure, AI capability, and analytical platforms. However, significant constraints remain, particularly in relation to implementation costs, integration complexity, and data governance-related concerns. The bibliometric findings in section 4.1 are directly relevant here. The rapid growth of publications after 2023, combined with geographic concentration in East Asian economies and high-technology sectors, reflects a literature that has documented technological potential extensively while providing less evidence on implementation conditions. This bibliometric pattern reinforces the analytical caution warranted in interpreting positive technology-outcome associations.

The central finding is that technological readiness is a necessary but insufficient condition for AI-enabled green innovation. Organizations with stronger digital infrastructure and AI capability are better positioned to identify sustainability-related opportunities and connect AI investment with green operational improvements (Abdelfattah et al. 2024, 165; Ma et al. 2025, 16; Ji & Tian 2026, 16). However, this association is consistently qualified across the reviewed studies. Technological capability does not independently determine sustainability outcomes. Studies that document positive green innovation effects almost invariably attribute them to technological capability in combination with organizational readiness and strategic alignment (Qalati & Siddiqui 2025, 1; Feng et al. 2024, 10). Studies reporting weak or insignificant outcomes despite substantial technological investment often attribute these limitations to deficiencies in Internal capability, coordination, or governance capacity (Pu 2025, 3; Mansour et al. 2025, 15).

This asymmetry has a substantive implication. The literature does not treat technological capability as one enabling condition among many. It treats it as the input whose value is determined by its surroundings. Advanced AI systems without organizational embedding remain analytically powerful but strategically inert with respect to green innovation. This framing is represented in Figure 8 by the positioning of the technological context inside the organizational layer rather than alongside it.

The synthesis further identifies a credibility dimension of technological readiness that connects the technological and environmental contexts. The growing prominence of explainability, transparency, data privacy, and algorithmic accountability concerns across section 4.2.3 and the governance patterns in section 4.3.3 indicates that technological readiness in sustainability contexts extends beyond infrastructure and analytical capability. It additionally includes the organization's capacity to demonstrate that its AI systems are trustworthy and its sustainability claims are verifiable. This credibility requirement is absent from conventional TOE applications that focus on adoption likelihood alone.

4.4.2 The Organizational Context as the Translating Mechanism

The second and most influential synthesis argument concerns the specific function of the organizational dimension. The factor-level analysis in section 4.2.2 identified capability development, leadership alignment, knowledge integration, and organizational readiness as recurring organizational conditions. The synthesis repositions these not as a list of enabling factors, but as components of a single translating mechanism through which technological potential is converted into sustainability-oriented outcomes. This repositioning explains the empirically observed variation in outcomes across organizations with comparable technological investments.

The capability-related patterns identified in section 4.3.1 are the primary evidence for this argument. The literature does not merely associate organizational capability with stronger innovation outcomes. It associates the absence of capability with the systematic failure of technological investment to produce green innovation returns. Organizations with weak absorptive capacity, disperse learning structures, or constrained knowledge integration processes derive significantly less green innovation value from equivalent AI investments than organizations with stronger internal capabilities (Pu 2025, 3; Mansour et al. 2025, 15; Youssef 2025, 10, 16). This is not a finding about capability as a background resource. It is a finding about capability as the mechanism that determines whether technology's analytical outputs are organizationally legible and operationally actionable in sustainability contexts. Without this mechanism, technological capability circulates at the surface of the organization without conversion into environmental improvement.

Leadership operates within this synthesis not as an independent driver, but as a condition that activates and directs the translating mechanism. The literature associates leadership commitment and strategic alignment with stronger AI adoption outcomes (Housheya & Atikbay 2025, 13; Boonmee et al. 2025, 13; Youssef 2025, 9). More specifically, leadership aligns capability development priorities with sustainability goals and creates conditions that support knowledge integration across the organization. It also ensures that AI-related investments are evaluated against environmental performance criteria rather than purely operational objectives. In this respect, leadership amplifies the translating mechanism rather than substituting for it.

The coordination and integration patterns identified in section 4.3.2 provide the structural evidence for the translating mechanism argument. Organizations that embed AI initiatives within cross-functional collaboration structures, communities of practice, and aligned human resource practices are more likely to translate technological capability into green operational change (Abdulmuhsin et al. 2024, 210; Housheya & Atikbay 2025, 13; Florek-Paszkowska & Ujwary-Gil 2025, 116). These coordination structures are not additive to AI capability. They are the organizational architecture through which AI's potential is made accessible to sustainability-oriented decision-making. Their absence explains why technologically capable organizations sometimes fail to produce green innovation outcomes. The translating mechanism is present in component form but is not structurally assembled.

This characterization of the organizational dimension as the central translating mechanism advances the conventional TOE application, in which all three dimensions are treated as parallel enablers. The distinction matters theoretically because it repositions organizational processes as the explanatory locus of variation in adoption outcomes. It also matters practically because it implies that investments in AI capability without parallel investment in organizational capability development and coordination structures are unlikely to produce substantive green innovation returns.

4.4.3 The Environmental Context as the Governance Frame

The third synthesis argument concerns the specific function of the environmental dimension. Section 4.2.3 documented four environmental dimensions: regulatory frameworks, competitive dynamics, institutional quality, and legitimacy governance. The synthesis advances beyond factor documentation to argue that the environmental context performs a function qualitatively different from the other two TOE dimensions. It does not directly enable or constrain adoption. Rather, it sets the governance frame within which the other dimensions operate. Moreover, it determines whether adoption produces substantive or symbolic sustainability outcomes.

The governance and contextual patterns identified in section 4.3.3 provide the clearest evidence for this argument. The literature consistently reports that environmental regulation is associated with increased sustainability-oriented AI adoption (Abdulmuhsin et al. 2024, 205; Haq et al. 2025, 3; Larbi-Siaw et al. 2022, 11). However, this positive association is conditional on the quality, design, and enforcement capacity of regulatory frameworks. Under strong and well-designed regulatory conditions, AI adoption is associated with substantive green innovation outcomes. Under weak governance or compliance-oriented regulatory design, the same adoption pressure produces symbolic responses. Organizations meet measurable output requirements without generating genuine environmental improvement (Li et al. 2025, 2; Zhao & Liu 2025, 4). This distinction between substantive and symbolic outcomes is the most theoretically significant contribution of the environmental dimension to the synthesis. Prior TOE applications have primarily used the environmental context to explain variation in adoption rates. The present synthesis demonstrates that it also explains variation in adoption quality.

Legitimacy and ethical governance reinforce this argument and extend it to the credibility dimension of sustainability outcomes. The literature identifies a consistent association between the presence of ethical governance frameworks and organizational willingness to invest in AI-enabled sustainability (Naqbi et al. 2025, 2; Mansour et al. 2025, 1; Qalati & Siddiqui 2025, 10). More critically, ethical governance shapes whether AI-enabled green innovation claims are perceived as credible by external stakeholders, regulators, and investors. In contexts where ethical governance is weak, AI adoption in sustainability contexts generates legitimacy risk rather than legitimacy capital (Feng et al. 2026, 7). This constrains further adoption and undermines the organizational value of green innovation investments. This mechanism is absent from most existing TOE-based analyses and represents an extension of the framework's environmental dimension.

Institutional quality provides the structural boundary condition that determines the operating ceiling of the other two dimensions. Organizations in strong institutional environments can leverage both technological capability and organizational coordination structures to their full potential (Pu 2025, 15). Organizations in resource-constrained institutional contexts face compounding disadvantages. Weak infrastructure limits technological capability. Inadequate institutional support limits Internal capability development. Weak governance conditions increase the probability of symbolic rather than substantive adoption outcomes (Youssef 2025, 10; Naqbi et al. 2025, 23; Pu 2025, 15). This compound effect means that strategies effective in strong institutional environments may be systematically inapplicable in weaker ones. This finding has significant implications for the cross-context generalizability of conclusions drawn from the existing literature, which Section 4.1 identified as geographically concentrated.

4.4.4 Cross-Dimensional Interactions and Structural Tensions

The three synthesis arguments converge on a fourth claim. AI adoption for green innovation outcomes is shaped by the configuration of all three TOE dimensions together. Investment in any single dimension, without corresponding development in the others, produces predictably limited sustainability returns. This claim is not implicit in the factor-level findings of section 4.2. It requires the cross-dimensional reading that the synthesis enables.

The interaction between the technological and organizational dimensions produces what this synthesis identifies as the capability-technology complementarity. AI technologies support more sustainable outcomes when organizations possess coordinated structures that facilitate knowledge integration, collaborative learning, and strategic alignment (Abdulmuhsin et al. 2024, 210; Qalati & Siddiqui 2025, 1; Ji & Tian 2026, 13). This complementarity is asymmetric. Stronger organizational capability consistently improves the green innovation returns to a given level of technological investment. Stronger technological investment alone, however, does not compensate for weak organizational capability. Organizations with high AI capability but weak internal coordination systematically underperform relative to their technological investment (Abdelfattah 2024 154-158). Organizations with strong coordination structures derive disproportionate value from moderate technological capability. This asymmetry has not been explicitly identified in prior TOE-based studies on AI adoption and represents a specific contribution of the present synthesis.

The interaction between the organizational and environmental dimensions produces what this synthesis identifies as the institutional amplification effect. Leadership commitment, capability development, and coordination structures become more effective under supportive regulatory and institutional conditions (Haq et al. 2025, 3; Zhao & Liu 2026, 4). Conversely, weak institutional support and legitimacy concerns constrain organizations' ability to convert AI investments into credible sustainability outcomes. The reinforcing dynamic operates in both directions. Supportive institutional conditions strengthen the effectiveness of organizational investments and facilitate more substantive sustainability outcomes. In contrast, weak institutional conditions may encourage organizations to prioritize symbolic compliance-oriented adoption rather than meaningful sustainability transformation (Abdulmuhsin et al. 2024, 207-210). The organizational dimension cannot independently compensate for this distortion. The environmental governance frame is prior.

The synthesis also identifies three structural tensions that reflect genuine conflicts across the dimensions rather than simple contextual variation. First, competitive pressure creates tension between adoption urgency and adoption depth (Youssef 2025, 8). Urgency motivates rapid, broad-based AI investment, while substantive depth requires sustained organizational learning processes that are incompatible with rapid deployment timelines. Second, regulatory incentives create tension between adoption frequency and adoption substance (Zhao & Liu 2026, 2). Well-intentioned incentive structures may reward measurable compliance over genuine environmental improvement, particularly where institutional monitoring capacity is weak. Third, advanced AI technologies create tension between operational performance and legitimacy (Qalati & Siddiqui 2026, 1-2). Their opacity, data intensity, and algorithmic complexity may compromise stakeholder trust in sustainability-oriented contexts where credibility is essential (Popa et al. 2025, 6). These tensions indicate that optimizing AI adoption for green innovation within a single dimension may simultaneously generate constraints across the others.

4.4.5 Integrative Interpretation: Conditions for Substantive Green Innovation

The four arguments presented above collectively support an integrated interpretation of AI-enabled green innovation. The findings indicate that AI adoption is more likely to generate substantive sustainability outcomes when technological capability is supported by coordinated organizational structures. Furthermore, it is reinforced by institutional environments that encourage substantive environmental improvement rather than symbolic compliance. When any of these three conditions is underdeveloped or misaligned, the likelihood of substantive outcomes is reduced. This limitation does not arise from the independent weakness of a single condition. Rather, it reflects the lack of coherence across the three dimensions.

This conditional proposition extends the TOE framework in a specific direction. Prior applications have primarily used the framework to predict adoption probability as a function of dimension strength (Baker 2011, 232; Shaik et al. 2024, 2734). The present synthesis demonstrates that in sustainability-oriented adoption contexts, the relevant outcome is not adoption probability but adoption quality. Quality is determined by configurational coherence rather than dimensional strength assessed independently. An organization may possess strong AI capability, leadership alignment, and integrated knowledge structures. But still achieve only symbolic sustainability outcomes when regulatory conditions prioritize compliance over substantive environmental improvement (Zhao & Liu 2026, 1-2). Conversely, a well-governed institutional environment will not produce substantive green innovation in organizations where capability development and coordination structures are absent.

The bibliometric findings of section 4.1 reinforce this interpretation at the field level. The field's rapid growth after 2023, its geographic concentration, and its dispersion across journals and theoretical perspectives. It demonstrates that the literature has progressed more rapidly in identifying individual enabling factors than in understanding the conditions under which those factors combine to produce substantive sustainability outcomes. The synthesis, therefore, identifies configurational coherence as a central concern for future research on AI adoption for green innovation. In contrast, the strength of individual dimensions alone appears insufficient to explain sustainability outcomes.

Research designs capable of examining configurational interactions across all three dimensions are accordingly better suited to the theoretical structure that the present synthesis identifies. These include fuzzy-set qualitative comparative analysis, necessary condition analysis, and longitudinal multi-case research. The synthesis further implies that context sensitivity is not merely a limitation of existing studies, but a structural feature of AI-enabled green innovation. The same technological investment and organizational capability may produce substantively different sustainability outcomes depending on the governance frame within which they are enacted. Understanding this context dependence is the central theoretical challenge for the field.

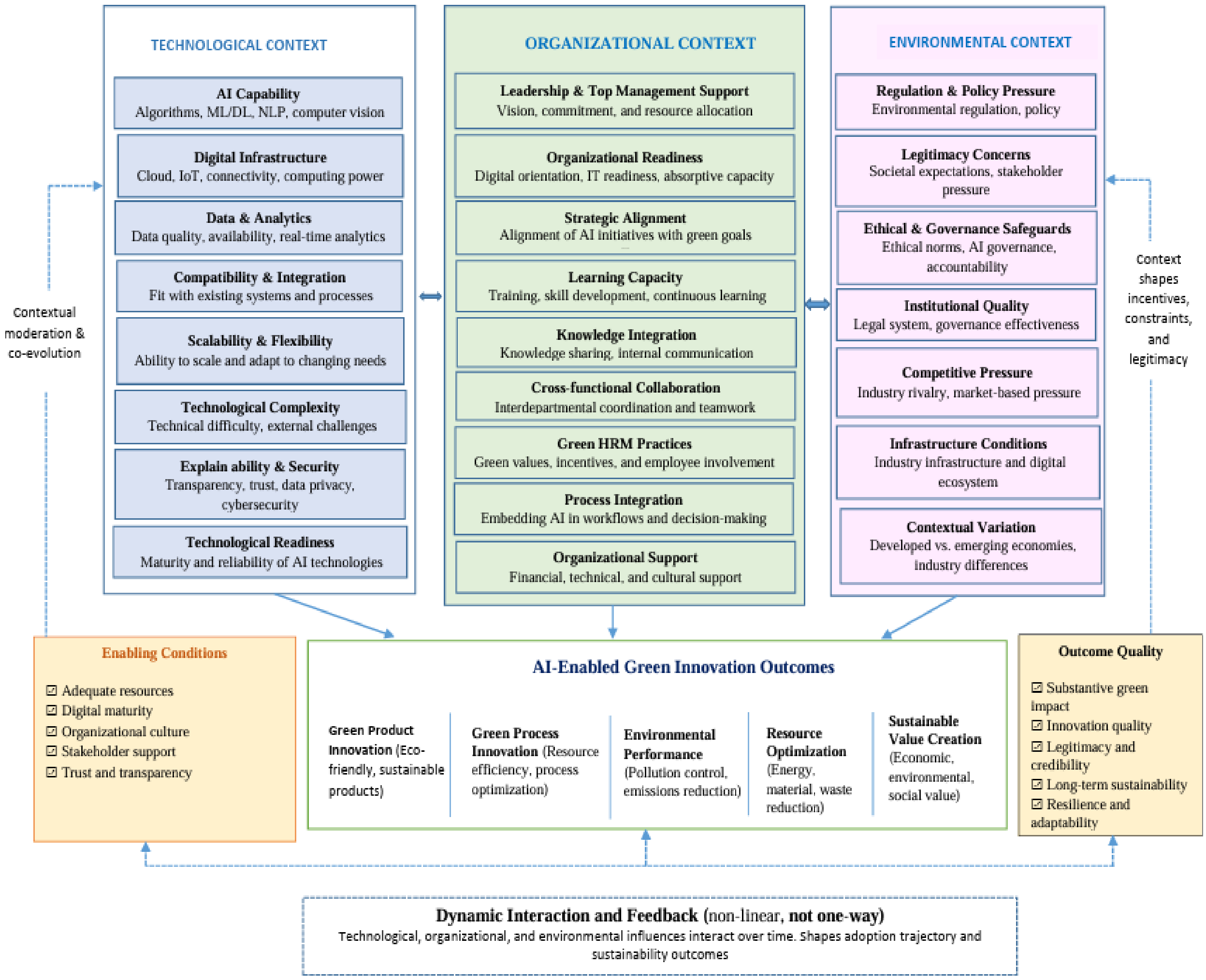

Figure 9. TOE-Based Conceptual Framework for AI adoption and Green Innovation

Figure 9 presents the TOE-based conceptual framework developed through the integrative synthesis of the reviewed literature. The framework illustrates how technological, organizational, and environmental conditions collectively influence AI-enabled green innovation outcomes. It further highlights how enabling conditions, governance influences, and contextual factors shape the effectiveness, legitimacy, and sustainability of AI adoption across different organizational and institutional settings.

The figure should not be interpreted as a causal or empirically validated model. Rather, it provides a conceptual synthesis of the recurring relationships and patterns identified across the reviewed studies. The framework suggests that sustainability-oriented innovation outcomes are more likely when technological capability is supported by organizational integration and favorable institutional conditions. In doing so, the framework complements the TOE-based interpretation by illustrating the multidimensional and context-dependent nature of AI adoption for green innovation.

5 Conclusions

5.1 Theoretical Contributions

This study makes five interrelated theoretical contributions to the literature on AI adoption, green innovation, and technology management. First, the study provides a systematic and integrative synthesis of factors influencing AI adoption for green innovation using the TOE framework as its primary organizing lens. Prior studies have examined individual determinants of AI adoption or green innovation within narrow empirical settings (Boonmee et al. 2025, 8; Lin 2025, 473; Teplova et al. 2023, 1). However, limited research has systematically consolidated technological, organizational, and environmental conditions within a unified analytical structure focused on sustainability-oriented organizational outcomes. By doing so, the study demonstrates that the TOE framework, originally developed for broader technology adoption analysis (Tornatzky & Fleischer 1990; Baker 2011, 232), retains substantial interpretive value within the emerging and theoretically disperse domain of AI-enabled green innovation. The study therefore extends the scope of TOE by illustrating its usefulness as a cross-disciplinary framework capable of capturing the multi-level complexity of sustainability-oriented technology adoption.

Second, the study advances the TOE framework by demonstrating that its three dimensions function as interdependent and mutually conditioning forces rather than as analytically separable or additive determinants. Specifically, the organizational dimension operates not as a coequal third factor but as the active translating mechanism through which technological potential is converted into sustainability-oriented outcomes. A recurring pattern across the reviewed studies is that technological capability alone rarely produces sustainability-oriented innovation outcomes. Instead, its effectiveness depends on organizational readiness, coordination mechanisms, and supportive environmental conditions (Pu 2025, 16; Ji & Tian 2026, 13; Qalati & Siddiqui 2025, 1). This finding refines how TOE is conventionally applied (Baker 2011, 232; Florek-Paszkowska & Ujwary-Gil 2025, 130). The synthesis suggests that AI adoption for green innovation is shaped through the interaction and alignment of technological readiness, organizational integration, and environmental support conditions. This interpretation contributes to a more dynamic and context-sensitive understanding of TOE within digitally intensive sustainability settings.

Third, the study foregrounds organizational capability-related conditions within the organizational dimension of TOE. These conditions include learning capacity, knowledge integration, adaptive capability, and AI-related absorptive processes. The reviewed literature consistently associates these process-oriented conditions with stronger sustainability-oriented innovation outcomes (Ji & Tian 2026, 16; Feng et al. 2024, 10; Abdelfattah et al. 2024, 165). Existing TOE-based research has primarily focused on structural and resource-related organizational factors. In contrast, more limited attention has been given to the organizational processes through which AI adoption is translated into green innovation outcomes. The present synthesis contributes by repositioning organizational coordination, collaborative integration, and knowledge-related processes as interpretive mechanisms linking technological adoption with sustainability-oriented transformation. In doing so, the study advances the TOE literature beyond factor identification toward a more integrative understanding of organizational operationalization.

Fourth, the study strengthens the environmental dimension of the TOE framework by demonstrating the importance of governance conditions, institutional quality, and legitimacy concerns in shaping AI adoption. These conditions influence not only the likelihood of adoption but also the credibility and substantive depth of sustainability outcomes. The reviewed literature indicates that regulatory pressure and policy incentives do not produce uniform effects. In some organizational contexts, they are associated with substantive green innovation outcomes. In other contexts, they appear linked to symbolic or compliance-oriented responses (Li et al. 2025, 2; Zhao & Liu 2025, 4; Naqbi et al. 2025, 2; Mansour et al. 2025, 1). This underexplored divergence in existing TOE applications highlights that institutional quality and ethical governance constitute meaningful boundary conditions for AI-enabled sustainability outcomes. It further suggests that the environmental dimension of TOE should be interpreted with greater sensitivity to legitimacy dynamics than prior research has typically afforded.

Fifth, the study contributes an integrative TOE-based synthesis that conceptually organizes the recurring technological, organizational, and environmental patterns identified across the reviewed literature into a unified interpretive structure. Existing studies have largely remained conceptually inconsistent across isolated factor-level discussions (Boonmee et al. 2025, 8; Teplova et al. 2023, 1). In contrast, the present synthesis illustrates how these dimensions interact and collectively shape AI-enabled sustainability outcomes rather than functioning as independent influences. The synthesis identifies two key interaction effects underlying this structure. The first is the capability–technology complementarity, where organizational coordination strengthens the effectiveness of technological investment. The second is the institutional reinforcing effect, where governance conditions shape whether organizational investments lead to substantive sustainability outcomes or merely symbolic adoption. The synthesis also identifies several underexplored areas, including governance-related tensions, organizational integration processes, contextual variation across institutional settings, and the limited development of longitudinal and multi-level investigations. By identifying these gaps, the study provides a structured conceptual foundation and a tractable empirical agenda for future TOE-based research on AI-enabled green innovation.

Overall, these contributions position the study as a theoretically integrative synthesis within a literature that remains disperse across disconnected empirical contexts. Rather than introducing competing theoretical explanations, the study demonstrates how the TOE framework can be applied and interpreted more dynamically to explain the multidimensional and context-dependent nature of AI adoption for green innovation. In doing so, the study advances a more coherent understanding of how technological readiness, organizational integration, and environmental conditions collectively shape sustainability-oriented innovation outcomes.

5.2 Managerial Implications

The findings of this study carry several significant implications for organizational leaders, sustainability managers, and policymakers involved in AI-enabled green innovation. These implications are derived from recurring patterns identified across the reviewed literature. They should therefore be interpreted as context-sensitive rather than universally prescriptive, particularly given the substantial variation observed across organizational and institutional settings.

A consistent pattern across the reviewed studies is that AI adoption rarely produces meaningful sustainability outcomes when organizations lack the internal capacity to interpret, integrate, and apply AI-related knowledge effectively (Ji & Tian 2026, 16; Feng et al. 2024, 10; Qalati & Siddiqui 2025, 1). This finding suggests that managers should invest in organizational capability development before, or alongside, AI deployment rather than after implementation. Employee skill development, cross-functional learning structures, and knowledge-sharing systems appear particularly prominent in strengthening organizational capacity. It translates technological investment into sustainability-oriented innovation outcomes. Organizations that treat AI adoption as a purely technological procurement decision without addressing capability gaps are therefore more likely to experience limited or inconsistent sustainability returns.

The findings also indicate that strategic alignment functions as a critical condition for AI-enabled sustainability transformation. AI adoption appears more strongly associated with green innovation outcomes when it is embedded within broader sustainability strategies. This relationship is further strengthened when leadership actively prioritizes environmental objectives (Housheya & Atikbay 2025, 13; Boonmee et al. 2025, 13; Youssef 2025, 9). In contrast, organizations that manage AI initiatives as isolated digital projects disconnected from sustainability goals, governance systems, or environmental performance metrics appear less likely to realize substantive green innovation benefits (Mansour et al. 2025, 1). Senior managers should therefore ensure that AI adoption is integrated into long-term sustainability planning rather than delegated solely to technology or operations functions.

The reviewed literature further emphasizes the importance of organizational coordination and integration in supporting AI-enabled green innovation. Cross-functional collaboration, communities of practice, knowledge-sharing systems, and aligned human resource practices consistently appear as central conditions linking AI adoption with sustainability-oriented operational change (Abdulmuhsin et al. 2024, 210; Housheya & Atikbay 2025, 13; Florek-Paszkowska & Ujwary-Gil 2025, 116). These findings suggest that organizations should develop coordination mechanisms that support the integration of environmental knowledge, operational expertise, and digital capabilities across different organizational functions. Effective coordination can strengthen communication, knowledge sharing, and sustainability-oriented decision-making within the organization. In practice, this may involve establishing sustainability and AI working groups to facilitate cross-functional collaboration. Organizations may also integrate green innovation objectives into performance management systems and align recruitment, training, and incentive structures with sustainability-oriented AI initiatives.

The findings also suggest that organizations should exercise caution when interpreting regulatory compliance as evidence of substantive green innovation. Regulatory pressure and policy incentives do not appear to produce uniform sustainability outcomes across contexts. In some organizational settings, external pressure appears associated with symbolic or compliance-oriented responses rather than meaningful environmental transformation (Zhao & Liu 2025, 4; Li et al. 2025, 2). Managers and boards should therefore distinguish between AI adoption activities that generate measurable environmental improvements and those that primarily serve reputational or regulatory purposes. Internal governance systems may help organizations evaluate whether AI-related investments generate substantive sustainability value. These systems can include transparent reporting practices, environmental performance auditing, and accountability mechanisms that support more credible and measurable sustainability outcomes.

Another critical implication relates to ethical governance and stakeholder trust. The reviewed studies consistently identify concerns regarding data privacy, algorithmic bias, explainability, and accountability as critical factors influencing organizational and stakeholder willingness to adopt AI in sustainability-oriented contexts (Naqbi et al. 2025, 2; Mansour et al. 2025, 1). These findings suggest that ethical governance should not be treated solely as a compliance requirement. Instead, it should be viewed as a strategic condition supporting long-term AI adoption and sustainability performance. Organizations that invest in transparent AI systems, accountable decision-making structures, and clear data governance frameworks are likely to strengthen both internal legitimacy and external stakeholder trust. This is becoming increasingly prominent as expectations related to environmental and digital accountability continue to intensify across regulatory, investor, and consumer environments.

Moreover, the findings also carry meaningful implications for policymakers and regulatory institutions. The reviewed literature suggests that the design of policy and incentive structures significantly shapes whether organizations engage in substantive or superficial forms of green innovation (Zhao & Liu 2025, 4; Li et al. 2025, 2; Larbi-Siaw et al. 2022, 11). Incentive systems focused primarily on measurable compliance outputs may unintentionally encourage symbolic innovation behavior rather than meaningful environmental transformation. Policymakers should therefore design regulatory frameworks that support long-term organizational capability development and strengthen digital infrastructure. In addition, regulatory support should encourage substantive sustainability-oriented innovation practices rather than short-term compliance-focused adoption. This appears particularly significant in resource-constrained contexts where infrastructural deficits and weaker institutional support systems continue to limit AI adoption effectiveness (Naqbi et al. 2025, 23; Pu 2025, 15).

Overall, the findings indicate that effective AI adoption for green innovation should not be understood primarily as a technological challenge. Rather, it appears as an organizational and institutional transformation process shaped by the interaction of capability development, strategic alignment, organizational coordination, ethical governance, and supportive environmental conditions. Organizations and policymakers that address these dimensions collectively, rather than in isolation, are more likely to translate AI's technological potential into credible and long-term sustainability-oriented innovation outcomes.

5.3 Limitations of the Study

While this study provides a systematic and integrative synthesis of the factors influencing AI adoption for green innovation, several limitations should be acknowledged. These limitations are methodological, conceptual, and analytical in nature. They also directly inform the future research directions proposed in the following section.

First, this study relies exclusively on the Scopus database and includes only peer-reviewed English-language journal articles published at the final publication stage. Although Scopus provides broad and reliable coverage across business, management, and social science disciplines (Mongeon & Paul-Hus 2016, 213–215; Pranckutė 2021, 12), the use of a single database may create a risk of selection bias. Relevant studies indexed in databases such as Web of Science, EBSCO, Google Scholar, or specialized repositories may not have been included. In addition, the exclusion of conference proceedings, working papers, policy documents, and other forms of grey literature may limit the inclusion of emerging and practice-oriented insights, particularly in a rapidly evolving field such as AI-enabled green innovation. The restriction to English-language publications may also introduce cultural and geographic bias toward Western and Anglophone research contexts. As a result, perspectives from emerging economies and non-English-speaking institutional environments may be underrepresented. Future research may therefore benefit from using multi-database, multilingual, and broader publication-source strategies to improve representativeness and contextual diversity.

Second, this study adopts an SLR design that synthesizes reported associations and recurring patterns rather than generating primary empirical evidence. Although thematic analysis, content analysis, and bibliometric techniques support the identification of recurring themes across the literature, the findings remain interpretive and do not establish causal relationships between AI adoption conditions and green innovation outcomes. In addition, the reviewed studies differ considerably in methodological design, theoretical perspective, contextual setting, and construct measurement. These differences limit direct comparability across the literature. The thematic analysis process also involves interpretive judgment during coding, categorization, and theme development (Carver et al. 2013, 205). Although systematic procedures were applied throughout the review process, the identification and organization of themes remain influenced by the researcher's analytical perspective. This challenge is particularly meaningful in a conceptually fragmented field where constructs such as organizational readiness, digital capability, and absorptive capacity are often defined inconsistently across studies. Future research may strengthen analytical consistency through inter-coder reliability procedures, Delphi-based expert validation, and computational text analysis techniques. Longitudinal and mixed-method research designs may also provide stronger insight into the causal systems linking AI adoption and green innovation outcomes.

Third, this study organizes its findings using the TOE framework as the primary theoretical lens. Although the TOE framework provides a widely applied and robust structure for examining organizational technology adoption (Baker 2011, 232; Tornatzky & Fleischer 1990), it remains largely static and classificatory in nature (Florek-Paszkowska & Ujwary-Gil 2025, 130). As a result, the framework does not fully capture the temporal, process-oriented, and evolving dynamics of AI-enabled green innovation identified across the reviewed studies. While the present study introduces a capability-oriented and cross-dimensional interpretive perspective to partially address this limitation, it does not formally integrate complementary theoretical frameworks. Consequently, the analysis may underrepresent the organizational processes, institutional dynamics, and evolving capability trajectories influencing AI adoption over time. Future research should therefore examine longitudinal change, process-oriented development, and configurational interactions within TOE-based sustainability research.

Fourth, the study identifies and synthesizes factors influencing AI adoption for green innovation but does not fully examine how these factors interact, reinforce, substitute for, or contradict one another across different organizational and institutional contexts. Although the synthesis highlights the interdependence of technological, organizational, and environmental conditions, the precise nature of these relationships remains underexplored. For example, the extent to which strong organizational capability compensates for weak institutional support, or whether certain regulatory environments reduce the importance of internal readiness, cannot be determined from the synthesized evidence. In addition, the study is limited in its ability to capture temporal dynamics and evolutionary trajectories within the field. Most reviewed studies adopt cross-sectional research designs. As a result, the review synthesizes findings across different periods without fully capturing how AI adoption conditions, organizational capabilities, and sustainability practices evolve. Consequently, the synthesis provides a consolidated overview of recurring patterns rather than a dynamic explanation of how AI-enabled green innovation develops and institutionalizes within organizations. These limitations reinforce the need for configurational approaches, including fuzzy-set Qualitative Comparative Analysis (fsQCA) and Necessary Condition Analysis (NCA).

Fifth, bibliometric techniques, including keyword co-occurrence analysis, thematic mapping, and descriptive profiling through VOSviewer and Biblioshiny, were used primarily as supportive analytical tools rather than as the central method of analysis. As a result, several advanced bibliometric dimensions remain underexplored, including co-citation analysis, bibliographic coupling, co-authorship networks, intellectual structure mapping, and longitudinal thematic evolution. The study is also constrained by the scope and maturity of the existing literature. The reviewed studies vary considerably in conceptual clarity, theoretical grounding, and methodological rigor. Inconsistent definitions of key constructs, including AI, green innovation, and organizational adoption, create conceptual ambiguity that complicates comparison and synthesis across studies. In addition, the literature remains concentrated within specific geographic and organizational contexts, particularly China and other East Asian economies, as well as large publicly listed firms. This concentration may limit the broader generalizability of the findings across different institutional and organizational settings. Furthermore, AI-enabled green innovation remains a relatively recent and evolving research domain. Many of the reviewed studies, therefore, represent early-stage empirical contributions with limited theoretical development and narrow contextual focus. Consequently, the findings of this study should be interpreted within the context of a developing body of literature that is likely to continue evolving conceptually, methodologically, and empirically over time.

5.4 Future Research Directions

The synthesis of the reviewed literature reveals that while scholarly interest in AI adoption for green innovation is growing rapidly, the field remains theoretically dispersed, methodologically constrained, and contextually narrow. The following research agenda is organized around five interrelated domains: (i) theoretical and conceptual development, (ii) process-oriented and longitudinal investigation, (iii) methodological advancement, (iv) contextual and comparative research, and (v) emerging frontiers in governance, ethics, and digital ecosystems. Each domain is grounded in specific gaps identified across the reviewed studies and developed with sufficient depth to guide future empirical and theoretical inquiry. To provide an accessible overview before the detailed discussion, Table 9 synthesizes the proposed directions across all five domains.

Table 9. Consolidated Future Research Agenda for AI Adoption and Green Innovation

Domain	Key Gap	Illustrative Research Questions	Suggested Methods	Expected Contribution
Theoretical & Conceptual Development	TOE applied statically; capability and institutional dimensions underexplored	How do TOE dimensions interact configuratively? What processes translate AI capability into green innovation? How do institutional logics shape adoption depth?	Conceptual synthesis, fuzzy-set Qualitative Comparative Analysis (fsQCA), institutional analysis	More dynamic and integrative TOE-based theory
Process-Oriented & Longitudinal Research	Dominance of cross-sectional designs; adoption treated as a discrete event	How do adoption trajectories evolve? How do capability gaps close across adoption stages? What triggers organizational reconfiguration during adoption?	Longitudinal case studies, panel data, process tracing	Temporal and process-level understanding of adoption
Methodological Advancement	Over-reliance on single-method quantitative surveys; inconsistent constructs	How can TOE dimensions be measured consistently? How do configurational methods reveal interaction effects? How can mixed methods improve mechanism explanation?	Mixed methods, fsQCA, NCA, scale development, NLP	Methodological rigour and construct comparability
Contextual & Comparative Research	Context-specific studies; limited cross-national, cross-industry, and firm-size comparisons	How do adoption patterns differ across institutional environments? How does industry structure moderate TOE effectiveness? How do SMEs overcome resource constraints?	Cross-country studies, multi-industry comparisons, firm-type analyses	Context-sensitive and comparative understanding
Governance, Ethics & Emerging Frontiers	Ethical governance, greenwashing, ecosystem dynamics, and generative AI dimensions largely absent	How does ethical governance shape adoption credibility? How can greenwashing through AI be identified? How do ecosystems shape AI-enabled sustainability?	Qualitative research, policy analysis, network analysis, NLP	Broader institutional, societal, and technological scope

Table 9 presents the consolidated future research agenda derived from the integrative synthesis of the reviewed literature. The table identifies major theoretical, methodological, process-oriented, contextual, and governance-related gaps. Furthermore, it outlines illustrative research questions, suggested methodological approaches, and expected scholarly contributions. It thereby provides a structured foundation for advancing future research on AI adoption for green innovation across diverse organizational and institutional contexts.

5.4.1 Theoretical and Conceptual Development

One of the most significant theoretical needs identified through this synthesis is the development of more dynamic, process-oriented, and integrative frameworks. Such frameworks are necessary to explain how AI adoption becomes associated with green innovation outcomes across different organizational settings. Although the TOE framework provides a valuable organizing structure, its predominantly static and classificatory orientation (Florek-Paszkowska & Ujwary-Gil 2025, 130; Baker 2011, 232) limits its ability to explain the relational and process-driven dynamics repeatedly identified across the reviewed literature. Future research should therefore move beyond the identification of individual factors and place greater emphasis on explaining underlying mechanisms. In particular, research should examine how and under what conditions these factors interact to shape sustainability-oriented innovation outcomes associated with AI adoption.

A particularly influential direction concerns the conceptualization of organizational capabilities within the TOE framework. The reviewed studies consistently associate AI-related absorptive capacity, adaptive learning, knowledge integration, and cross-functional coordination with stronger green innovation outcomes (Ji & Tian 2026, 16; Feng et al. 2024, 10; Abdelfattah et al. 2024, 165). However, these process-oriented conditions remain theoretically underdeveloped within many existing TOE applications. Future research should therefore examine how organizations build, integrate, and reconfigure AI-related capabilities in response to evolving sustainability demands. Relevant questions include how organizations develop AI-specific absorptive capacity in sustainability-oriented contexts and how knowledge integration processes influence the effectiveness of AI adoption across different organizational settings.

Another prominent direction concerns the configurational interdependence of TOE dimensions. The findings reflect that AI adoption for green innovation is shaped through the alignment of technological readiness, organizational integration, and environmental support conditions rather than through the independent operation of each dimension. Future research should therefore examine how different configurations of TOE conditions produce distinct sustainability outcomes, building on recent configurational approaches and fuzzy-set qualitative comparative analysis in green innovation research (Lou et al. 2025, 4918; Yin 2023, 100048). Further inquiry is needed into which combinations of technological, organizational, and environmental conditions are most closely associated with substantive AI-enabled green innovation and how capability deficits in one dimension constrain the effectiveness of investments in another.

The synthesis also highlights the growing importance of legitimacy dynamics and institutional pressures within AI-enabled sustainability contexts. Regulatory conditions, governance quality, and ethical concerns appear to shape both the likelihood and depth of AI-enabled sustainability outcomes (Zhao & Liu 2025, 4; Mansour et al. 2025, 1). Future research should therefore examine how institutional pressures interact with organizational capabilities and technological readiness to produce substantive versus symbolic sustainability outcomes. Questions related to institutional quality, stakeholder legitimacy expectations, and regulatory effectiveness appear particularly significant across different economic and governance environments.

Future research may also benefit from extending TOE through carefully integrated complementary perspectives where theoretically appropriate. While the present study adopts TOE as its primary organizing framework, the reviewed literature suggests that certain dimensions of AI-enabled green innovation extend beyond factor-based adoption analysis alone. This is particularly evident in areas related to capability development, legitimacy dynamics, and ecosystem coordination, which may require additional theoretical perspectives for deeper explanation (Paul & Criado 2020, Art. 101717; Naveed et al. 2023, 1147).

5.4.2 Process-Oriented and Longitudinal Investigation

A major limitation of the existing literature is its overwhelming reliance on cross-sectional research designs. Such approaches provide useful snapshots of adoption conditions but remain limited in their ability to capture the temporal dynamics and evolutionary processes through which AI adoption becomes associated with green innovation outcomes. This limitation is particularly critical because the reviewed studies repeatedly emphasize learning processes, capability development, organizational adaptation, and integration over time (Ji & Tian 2026, 13; Feng et al. 2024, 11; Abdulmuhsin et al. 2024, 210).

Future research should therefore prioritize longitudinal designs capable of tracing how organizations move across different stages of AI adoption, including awareness, experimentation, implementation, integration, and institutionalization. Longitudinal case studies, panel data analyses, and process-tracing approaches may substantially improve understanding of how sustainability outcomes evolve as AI becomes increasingly embedded within organizational systems and routines. Additional inquiry is needed into how early adopters differ from late adopters in their capability development trajectories and how organizational sustainability outcomes change over extended adoption periods.

Process-oriented qualitative research would also provide meaningful insight into the organizational routines and social processes through which AI-enabled sustainability transformation unfolds. Existing studies rarely examine adoption as an iterative and socially embedded organizational process. Future research should therefore explore how organizations respond to capability gaps, adoption failures, implementation tensions, and organizational resistance over time. Such inquiry would deepen understanding of the systems through which organizations progressively align AI capabilities with sustainability outcomes.

Beyond individual organizations, future research should also examine how AI-enabled green innovation practices evolve at the industry and field levels. Understanding whether such practices become institutionalized, diffused across industries, or reshaped through technological change requires research extending across multiple organizations and time periods simultaneously. Such macro-level longitudinal inquiry would significantly enrich the predominantly firm-level perspective currently characterizing the field.

5.4.3 Methodological Advancement

The methodological composition of the reviewed literature reveals several constraints on cumulative knowledge development in this domain. The dominance of single-method quantitative survey studies conducted at one point in time limits the field's ability to capture organizational complexity, contextual variation, and process dynamics (Marzi et al. 2022, 88; Naveed et al. 2023, 1130). Future research should therefore advance methodologically across several complementary directions.

First, mixed-method research designs combining quantitative breadth with qualitative depth appear particularly valuable. Quantitative analyses may help identify the relative importance of adoption-related factors across large samples. In contrast, qualitative approaches such as interviews, ethnographic observation, and in-depth case studies can provide deeper insight into the interpretive processes through which organizations align AI with sustainability initiatives. Sequential mixed-method designs may be especially useful in explaining the systems underlying statistical patterns identified through quantitative analysis.

Second, greater attention is needed toward multi-level research designs capable of capturing interactions between individual, organizational, and institutional levels of analysis. The reviewed literature remains predominantly firm-level in orientation, thereby overlooking how employee capabilities, managerial decision-making, organizational coordination practices, and institutional conditions jointly shape adoption outcomes (Hirtranusi et al. 2026, 493). Future research employing hierarchical linear modelling, multi-level structural equation modelling, or nested case study designs may substantially improve understanding of these cross-level relationships.

Third, the field requires stronger investment in measurement development and construct standardization. Existing studies apply diverse and often inconsistent operationalisations of AI adoption, green innovation, organizational capability, and institutional support constructs, limiting cross-study comparability and cumulative knowledge development (Marzi et al. 2022, 94). Future studies should therefore develop validated multidimensional measurement scales for key organizational and environmental constructs. These may include AI-related absorptive capacity, sustainability-oriented AI capability, organizational integration quality, and institutional support quality. Computational text analysis and natural language processing approaches may also provide promising alternatives to self-reported survey data by enabling more objective measurement using sustainability reports, organizational documents, and patent databases.

Finally, configurational methods such as fuzzy-set qualitative comparative analysis and necessary condition analysis represent significant methodological opportunities for examining the non-linear and combinatorial relationships among TOE dimensions that conventional regression approaches often fail to capture adequately (Siddik et al. 2025, 1262; Saiyed et al. 2025, 892-893). These approaches appear particularly well-suited to the configurational interdependence identified throughout this synthesis. Future research may therefore examine which combinations of technological readiness, organizational capability, and institutional support are necessary or sufficient for substantive green innovation outcomes.

5.4.4 Contextual and Comparative Research

The synthesis reveals strong contextual variation in AI adoption outcomes across regional, industrial, and organizational settings. However, systematic comparative research remains comparatively underdeveloped. Many reviewed studies remain highly context-specific and therefore provide limited insight into which adoption patterns are context-dependent and which may be more broadly generalizable (Pu 2025, 15; Naqbi et al. 2025, 23; Mansour et al. 2025, 20).

One critical direction for future research concerns cross-national and cross-institutional comparison. The findings consistently indicate that organizations operating in developed institutional environments benefit from stronger digital infrastructure, more supportive regulatory systems, and greater access to AI-related resources. In contrast, organizations operating in emerging or resource-constrained contexts frequently encounter infrastructural deficits, financial limitations, and weaker institutional support systems (Naqbi et al. 2025, 23; Pu 2025, 15). Future cross-country research should therefore examine how AI adoption pathways differ across institutional environments. Furthermore, how national innovation systems, governance quality, and cultural dimensions shape organizational approaches toward AI-enabled sustainability.

Another critical direction concerns industry-level variation. The reviewed studies span manufacturing, high-technology industries, agriculture, banking, and services. However, systematic comparative analyses across industries remain limited. Future research should therefore examine how AI adoption strategies differ across technologically intensive and labour-intensive industries. It should also investigate how supply chain positions influence sustainability-oriented AI adoption and how industry-level conditions, including technological turbulence, competitive intensity, and sustainability exposure, shape adoption effectiveness.

The synthesis also highlights the need for more nuanced research examining firm-level heterogeneity, particularly differences between large firms and SMEs. Larger organizations often possess greater infrastructure, institutional support, and financial resources for advanced AI adoption. Smaller firms, however, may exhibit greater flexibility and responsiveness despite significant resource constraints (Boonmee et al. 2025, 13; Shaik 2024, 2731). Future research should therefore examine how SMEs overcome capability and financial barriers in AI-enabled sustainability contexts. It should also explore how collaborative partnerships, public institutional support, and platform-based AI adoption models enable resource-constrained organizations to engage with green innovation opportunities.

5.4.5 Emerging Research Frontiers: Governance, Ethics, and Digital Ecosystems

The synthesis identifies several emerging frontiers that remain critically underexplored within existing research. These frontiers reflect both the evolving nature of AI technologies and the expanding institutional and societal contexts within which AI-enabled green innovation is increasingly embedded.

Governance and ethical dimensions represent one of the most urgent future research priorities. Concerns related to data privacy, algorithmic bias, transparency, explainability, and accountability appear consistently across the reviewed literature (Naqbi et al. 2025, 2; Mansour et al. 2025, 1; Popa et al. 2025, 6). However, their implications for sustainability-oriented AI adoption remain theoretically and empirically underdeveloped. Future research should therefore examine how ethical governance frameworks shape organizational willingness to adopt AI for green innovation, influence stakeholder perceptions of AI-enabled sustainability claims, and affect the credibility of environmental outcomes. Additional inquiry is also needed into how organizations balance technological performance optimization with ethical governance requirements in sustainability-oriented contexts.

A closely related frontier concerns greenwashing through AI-enabled sustainability claims. The findings demonstrate that AI adoption may become associated with symbolic or compliance-oriented responses in contexts where external pressure is strong but institutional monitoring remains weak (Zhao & Liu 2025, 4; Li et al. 2025, 2). Future research should therefore develop conceptual frameworks and empirical approaches capable of distinguishing substantive environmental transformation from performative or legitimacy-oriented AI adoption practices. Questions related to disclosure standards, accountability systems, and verification systems appear particularly substantive in this regard.

Digital sustainability ecosystems represent another critical frontier. The reviewed literature suggests that organizations adopt AI within broader networks of technology providers, regulators, industry associations, knowledge institutions, and platform operators that collectively shape innovation conditions (Florek-Paszkowska & Ujwary-Gil 2025, 116). Yet most existing studies remain predominantly firm-level in orientation. Future research should therefore examine how ecosystem governance structures, inter-organizational collaboration, and digital platform arrangements facilitate or constrain AI-enabled sustainability innovation.

Finally, generative AI and next-generation AI technologies represent a rapidly emerging research domain. Existing studies focus primarily on established AI applications such as automation, machine learning, and data analytics. In contrast, comparatively limited attention has been given to generative AI, large language models, and AI-integrated Internet of Things systems (Arshed et al. 2026, 491; Naqbi et al. 2025, 1). Future research should therefore investigate how these emerging technologies create new possibilities and governance challenges for sustainability-oriented innovation across different organizational and institutional settings.

5.4.6 Synthesis of the Research Agenda

Collectively, the proposed research directions summarized in Table 9 suggest that future research initiatives must advance simultaneously across theoretical integration, methodological diversification, and contextual expansion. The field has successfully established that technological, organizational, and environmental conditions matter for AI adoption within sustainability contexts. The next critical step is to understand how these conditions interact, why similar configurations produce different outcomes across settings, and through what processes organizations translate AI capability into credible and long-term green innovation outcomes. Addressing these questions will require moving beyond predominantly cross-sectional, firm-level, and single-method approaches toward longitudinal, multi-level, configurational, and institutionally sensitive research designs.

The emerging frontiers of governance, ethics, digital ecosystems, generative AI, and greenwashing further indicate that the field is entering areas that existing theoretical frameworks and empirical approaches are not yet fully equipped to address. Developing the conceptual vocabulary, measurement tools, and methodological approaches necessary to investigate these frontiers. Therefore, represents a meaningful priority for future research at the intersection of AI, sustainability, and organizational management. By pursuing this research agenda, future studies may develop a more comprehensive and practical understanding of how AI can support sustainability transformation across different organizational and institutional contexts.

6 Summary

This thesis examined the factors influencing the adoption of AI for green innovation in organizations. Although scholarly interest in AI and sustainability has increased rapidly in recent years, the existing literature remains conceptually inconsistent, context-specific, and theoretically underdeveloped. Prior studies have often examined AI adoption and green innovation separately, without a unified analytical structure capable of explaining how technological, organizational, and environmental conditions interact within sustainability-oriented contexts. To address this gap, the study conducted a SLR guided by the TOE framework. The study aimed to identify, categorize, and synthesize the factors shaping AI adoption for green innovation at the organizational level.

The thesis was guided by one overarching research question concerning the factors shaping AI adoption for green innovation in organizations. Three sub-questions examined the specific factors influencing adoption, how these factors facilitate or hinder adoption under different contextual conditions, and what future research directions emerge from the synthesis of existing studies. To address these questions, a SLR was conducted using the Scopus database. Following a rigorous multi-stage screening process, 44 peer-reviewed journal articles published between 2020 and 2026 were retained for analysis. Thematic analysis served as the primary analytical method, supported by bibliometric techniques including keyword co-occurrence analysis, thematic mapping, and descriptive bibliometric profiling through VOSviewer and Biblioshiny.

The findings indicate that research on AI adoption for green innovation is a rapidly emerging but still fragmented field. The literature remains concentrated within sustainability, management, and innovation-related journals. In particular, strong emphasis is placed on digital transformation, environmental management, and AI-enabled sustainability practices. Thematic mapping and keyword analysis indicate that AI, sustainability, eco-innovation, and digital transformation represent central themes within the literature. At the same time, several related themes remain conceptually underdeveloped and continue to evolve.

The thematic findings, organized within the TOE framework, identified a broad range of technological, organizational, and environmental factors that shape AI adoption for green innovation. Within the technological context, digital infrastructure, AI capability, cloud computing, data analytics, and technological readiness consistently emerged as enabling conditions. At the same time, implementation costs, integration complexity, data security concerns, and explainability challenges positioned as critical barriers. Within the organizational context, capability development, leadership commitment, strategic alignment, knowledge integration, cross-functional coordination, and organizational readiness emerged as central determinants of adoption effectiveness. Within the environmental context, regulatory frameworks, government incentives, competitive pressure, institutional quality, and infrastructural conditions shaped both the likelihood and depth of AI-enabled green innovation across different organizational settings.

A major contribution of the study lies in demonstrating that these TOE dimensions do not operate independently. The synthesis consistently showed that technological capability alone rarely produces meaningful sustainability outcomes. Instead, its effectiveness depends on organizational readiness, coordination systems, and supportive environmental conditions. This finding advances the TOE framework by highlighting the configurational and interdependent nature of AI adoption within sustainability contexts. The synthesis advances three specific arguments from these findings. First, technological readiness is a necessary but insufficient condition whose value depends on surrounding organizational and environmental conditions. Second, the organizational context functions as the active translating mechanism that converts technological potential into sustainability outcomes. Third, the environmental context operates as a governance frame that determines adoption quality, distinguishing substantive green innovation from symbolic compliance. Two named interaction effects underpin these arguments: the capability-technology complementarity and the institutional amplification effect. Three recurring interpretive patterns were further identified across the literature. First, capability-related patterns emphasized the role of learning capacity, knowledge integration, and absorptive processes in translating AI adoption into green innovation outcomes. Second, coordination and integration patterns highlighted the importance of organizational alignment and cross-functional collaboration. Third, governance and contextual patterns showed how regulation, legitimacy pressures, ethical governance, and institutional quality shape the credibility and substantive depth of sustainability-oriented innovation outcomes.

The study makes five key theoretical contributions. First, it provides a systematic and integrative TOE-based synthesis of factors influencing AI adoption for green innovation within organizations. Second, it advances the TOE framework by demonstrating that technological, organizational, and environmental conditions function as interdependent and mutually conditioning dimensions rather than isolated determinants. Third, it foregrounds organizational capability-related processes, including learning capacity, absorptive capability, and knowledge integration, as significant systems linking AI adoption with sustainability-oriented transformation. Fourth, it strengthens the environmental dimension of TOE by demonstrating that governance conditions, legitimacy concerns, and institutional quality shape both the likelihood and credibility of AI-enabled green innovation outcomes. Fifth, the study contributes an integrative TOE-based synthesis model that organizes the recurring patterns identified across the literature into a unified conceptual structure and provides a foundation for future research.

The managerial implications suggest that effective AI adoption for green innovation should not be treated solely as a technological challenge. Instead, organizations should invest in capability development, organizational readiness, strategic alignment, and coordination systems before or alongside technological deployment. The findings also highlight the importance of ethical governance, transparent AI practices, and institutional support systems in building credible sustainability outcomes. For policymakers, the study emphasizes the need for incentive structures and regulatory frameworks that encourage substantive green innovation rather than symbolic compliance, particularly within emerging and resource-constrained contexts.

The study also acknowledges several limitations. The review relied exclusively on the Scopus database and focused only on English-language peer-reviewed journal articles. The interpretive nature of thematic synthesis limits causal inference and remains influenced by coding and categorization decisions. In addition, the TOE framework does not fully capture the temporal and process-oriented dynamics of AI-enabled sustainability transformation. Most reviewed studies also adopted cross-sectional designs, limiting understanding of how adoption trajectories evolve over time. Furthermore, the literature remains geographically concentrated, particularly within China and other East Asian economies, and heavily focused on larger organizational settings.

These limitations directly informed the proposed future research agenda. The study highlights the need for more process-oriented and longitudinal research to better understand how AI adoption evolves. It also emphasizes the importance of stronger configurational analysis through approaches such as fuzzy-set Qualitative Comparative Analysis (fsQCA) and Necessary Condition Analysis (NCA). In addition, the findings indicate the need for greater methodological diversification through mixed-method and multi-level research designs. Broader contextual comparison across industries and institutional environments is also necessary to strengthen the understanding of AI adoption for green innovation. The findings also identify several emerging research frontiers, including ethical governance, AI-enabled greenwashing, digital sustainability ecosystems, and the implications of generative AI for sustainability-oriented innovation.

In conclusion, this thesis demonstrates that AI adoption for green innovation is not simply a technological phenomenon. Rather, it is an organizationally embedded and institutionally conditioned process shaped through the interaction of technological readiness, organizational integration, and environmental support conditions. By providing a comprehensive TOE-based synthesis of this emerging field, the study contributes a more dynamic, integrative, and context-sensitive understanding of how organizations can harness AI to support sustainability-oriented innovation.

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Appendices

Appendix 1 The articles that were reviewed in the systematic literature review

Title of the Article	Author/s	Journal	Year
Empirical insights on organisational sustainability: exploring the influence of communities of practice and associated technologies	Amir A. Abdulmuhsin, Abeer F. Alkhwaldi, Abdulkareem H. Dbesan, Ali Tarhini	Sustainability Accounting, Management and Policy Journal	2026
Revealing stock liquidity determinants by means of explainable AI: The role of ESG before and during the COVID-19 pandemic	Tamara Teplova, Tatiana Sokolova, David Kissa	Resources Policy	2023
The Role of Green HRM in Promoting Green Innovation: Mediating Effects of Corporate Environmental Strategy and Green Work Climate, and the Moderating Role of Artificial Intelligence	Nadin Housheya and Tolga Atikbay	Sustainability	2025
The Role of Digitalization in Enhancing Green Innovation Efficiency: Examination of Multiple Sub-Dimensions, Transformation Speed, and Heterogeneity	Tingqian Pu	SAGE Open	2025
Why AI Adoption Fails to Create Digital Green Innovation: The Transformative Role of Knowledge-Based Dynamic Capabilities	Zhe Ji and Feng Tian	Sustainability	2026
Investigating the interplay between green finance, eco-innovation, natural resources, and environmental sustainability: evidence from panel quantile and machine learning approaches	Mahmood Ahmad, Zahoor Ahmed and Kexin Wang	Financial Innovation	2026
Eco-innovation, sustainable business performance and market turbulence moderation in emerging economies	Otu Larbi-Siaw, Hu Xuhua Brou Ettien Fulgence, Ebenezer Owusu, Samuel Akwasi Frimpong, Abigail Owusu-Agyeman	Technology in Society	2022
Is AI a ‘substance driver’ or a ‘fiction booster’? The impact of AI application on corporate green innovation bubbles	Kai Zhao, Xiaoxi Liu	Finance Research Letters	2026
The Digital-Sustainability Ecosystem: A conceptual framework for digital transformation and sustainable innovation	Anna Florek-Paszkowska, Anna Ujwary-Gil	Journal of Entrepreneurship, Management and Innovation	2025
The future of competitive advantage in Oman: Integrating green product innovation, AI, and intellectual capital in business strategies	Fadi Abdelfattah, Hussam Al Halbusi, Mohammed Salah, Khalid Dahleez, Riyad Darwazeh	International Journal of Innovation Studies	2024

Exploring Twitter Discourse around the Use of Artificial Intelligence to Advance Agricultural Sustainability	Catherine E. Sanders, Kennedy A. Mayfield-Smith and Alexa J. Lamm	Sustainability	2021
Organizational sustainable artificial intelligence capabilities scale development, validation, and implications	Sikandar Ali Qalati, Faiza Siddiqui	Journal of Innovation & Knowledge	2026
Breaking new ground in sustainability (SD): a novel integrated framework for eco/green-innovation (EI) and green supply chain management (GSCM) implementation in emerging economies – evidence from Jordan's industrial transformation	Lana Freihat, Zayed Huneiti, Wamadeva Balachandran	Cleaner Logistics and Supply Chain	2025
Intelligent Manufacturing and Green Innovation—Evidence from China's Listed Manufacturing Firms	Xiaoshu Xu, Jiangpei Pan and Xuechen Meng	Sustainability	2024
Artificial Intelligence, ESG Governance, and Green Innovation Efficiency in Emerging Economies	Marwan Mansour, Mo'taz Al Zobi, and Mohammed Alomair	Economies	2026
The power of entrepreneurial innovation capital in higher education: A diffusion of innovation approach to Generation Z entrepreneurship education	Muhammad Hasan	The International Journal of Management Education	2026
Generative AI Integration: Key Drivers and Factors Enhancing Productivity of Engineering Faculty and Students for Sustainable Education	Humaid Al Naqbi, Zied Bahroun, and Vian Ahmed	Sustainability	2025
Towards sustainable business in the automation era: Exploring its transformative impact from top management and employee perspective	Jose´ Andre´ G o´mez Gandía, Sorin Gavrila Gavrila, Antonio de Lucas Ancillo, María Teresa del Val Nú˜ nez	Technological Forecasting & Social Change	2025
Twin Transition: Digital Transformation Pathways for Sustainable Innovation	Adel Ben Youssef	Sustainability	2025
Smart Lighting Solutions for Affordable Housing Projects: Bridging the Gap Between Intelligent Systems and Sustainability	Kali charan Sabat, Som Sekhar Bhattacharyya	International Social Science Journal	2025
Harnessing Artificial Intelligence for Enhanced Environmental Sustainability in China's Banking Sector: A Mixed-Methods Approach	Abu Bakkar Siddik, Li Yong, Anna Min Du and Arshian Sharif4 , Samuel A. Vigne	British Journal of Management	2025
Green Innovation as Business Strategy in Small Manufacturing Businesses: Artificial Intelligence and Blockchain Effects	Edoardo Crocco, Laura Broccardo, Nourah O. Alshaghda li, Vikram Kumar Sharma	Business Strategy and the Environment	2025
The impact of artificial intelligence on green innovation efficiency: Moderating role of dynamic capability	Fangfang Feng, Junjun Li, Feng Zhang, Jinghuan Sun	International Review of Economics and Finance	2024

Towards sustainable digital transformation: AI adoption barriers and enablers among SMEs in Northern Thailand	Chawis Boonmee, Jettapat Mangkalakeeree, Yongkuk Jeong	Sustainable Futures	2025
Can artificial intelligence technology improve companies' capacity for green innovation? Evidence from listed companies in China	Yingji Liu, Fangbing Shen, Ju Guo, Guoheng Hu, Yuegang Song	Energy Economics	2025
Modeling AI Adoption in SMEs for Sustainable Innovation: APLS-SEM Approach Integrating TAM, UTAUT2, and Contextual Drivers	Raluca-Giorgiana (Chivu) Popa, Ionut ,-Claudiu Popa, David-Florin Ciocodeică and Horia Mihălcescu	Sustainability	2025
Adopting green AI for SME sustainability: mediating role of green investment and moderation by green servant leadership	Faizan ul Haq, Norazah Mohd Suki, Made Setini, Asim Masood, Taimur Ahmed Khan	Sustainable Futures	2025
Digital Leadership, AI Integration, and Cyberloafing: Pathways to Sustainable Innovation in SMEs Within Resource Constrained Economies	Pshdar Hamza and Georgiana Karadas	Sustainability	2025
AI-driven green governance: Assessing the impact of artificial intelligence on corporate sustainability performance	Bimei Feng, Xi Chen, Hengyun Tang	Journal of Innovation & Knowledge	2026
Impact of intelligent transformation on the green innovation quality of Chinese enterprises: evidence from corporate green patent citation data	Feng Han & Xin Mao	Applied Economics	2024
How AI- Enabled Drivers Inspire Sustainability- Oriented Entrepreneurial Intentions: Unraveling the (In)congruent Effects of Perceived Desirability and Feasibility From the Entrepreneurial Event Model Perspective	Cong Doanh Duong	Sustainable Development	2025
Digitalizing agriculture in Pakistan: enhancing grain supply chains via ICT, environmental literacy, and eco-innovation	Ali Raza1, Hongliang Lu1, Xiaoli Ma and Tingyu Yang	Agricultural and Food Economics	2026
Sustainable Entrepreneurship in Emerging Economies: The Role of Financial Planning, Environmental Consciousness, and Artificial Intelligence in Ecuador—A Cross-Sectional Study	Martha Cecilia Aguirre Benalcázar, Marcia Fabiola Jaramillo Paredes and Oscar Mauricio Romero Hidalgo	Sustainability	2025
Sustainability singularity theory for AI green innovation climate governance and future generations	Bablu Kumar Dhar and Sabrina Maria Sarkar	Discover Sustainability	2025
Cloud Computing and Green Total Factor Productivity in Urban China: Evidence from a Spatial Difference-in-Differences Approach	Liangjun Yi, Wei Zhang and Yiling Ding	Sustainability	2025

Automation and Its Influence on Sustainable Development: Economic, Social, and Environmental Dimensions	Ahlam I. Almusharraf	Sustainability	2025
Environmental regulations and eco-innovation as catalysts for green agricultural practices: insights from Pakistan-China agricultural cooperation	Ali Raza1, Lu Hongliang, Zhu Yue, Tingyu Yang and Nian Wei	Agricultural and Food Economics	2025
Exploring the role of open innovation and artificial intelligence in green innovation: A dynamic capabilities approach	Vitor Mel˜ ao Cassˆ anego, Herick Fernando Moralles, Daniel Luiz de Mattos Nascimento, Guilherme Luz Tortorella	Journal of Innovation & Knowledge	2025
Green Innovation Optimization for Climate Change ESG Business Readiness: Role of Generative AI in BRICS Countries	Noman Arshed, Yassine Bakkar, Marco De Sisto, Mubbasher Munir, Shajara Ul-Durar	European Financial Management	2026
Tapping into the green potential: The power of artificial intelligence adoption in corporate green innovation drive	Murtaza Hussain, Shaohua Yang, Umer Sahil Maqsood, R. M. Ammar Zahid	Business Strategy and Environment	2024
Artificial intelligence (AI)-driven strategic business model innovations in small- and medium-sized enterprises. Insights on technological and strategic enablers for carbon neutral businesses	Aqueeb Sohail Shaik Safiya, Mukhtar Alshibani, Girish Jain, Bhumika Gupta, Ankit Mehrotra	Business Strategy and Environment	2024
Artificial intelligence, data elements, digital economy, and corporate innovation performance	Yuan Ma, Wenchao Zhang, Chengxiang Ma, Yudong Ai, Jun Hu	International Review of Economics and Finance	2025
AI-Driven Pedagogical Empowerment in International Education: Transforming Teaching Practices for College Faculty Through Faculty Centered Innovation	Ding Lin	Journal of Education Studies in Education	2025
Harnessing artificial intelligence to strengthen green innovation capacity in pursuit of sustainable development goals: Evidence from Taiwan's manufacturing sector	Sahilali Saiyed, Mahedi Hasan, Redoyan Chowdhury, K. M. Tousif Bin Parves, Eko Hariyadi, Vimal Kumar	Equilibrium. Quarterly Journal of Economics and Economic Policy	2025

Appendix 2 Specimen of literature analysis procedure

Author/s	**Method, Theory/Model/ Basis**	**Crucial Factors and barriers (if any)**	**Major Findings**	**Future Research**
Abdulmuhsin et al. 2024	Quantitative; Knowledge Management Theory, Structural Equation Modelling (SEM)	Community of Practices, Community of Practices Technologies	The findings provide actionable insights for oil and gas (O&G) companies aiming to integrate sustainability through technology-driven CoPs	Additional variables, including leadership and KM processes, can be introduced in the future to investigate their effect on activating OS in the O&G sector
Teplova, Tatiana Sokolova and Kissa, 2023	Quantitative; Game theory, Neural networks	Environmental innovations, Use of green technologies.	Russian investors changed their preferences during the pandemic and started to view stocks of eco-friendly companies as defensive assets.	Research can be expanded by taking into account big data, including the tonality of text materials on ESG agenda
Housheya and Atikbay, 2025	Quantitative; Partial least squares structural equation modeling (PLS-SEM), Resource Based View (RBV)	Green HRM, Corporate Environmental Strategy, Green work Climate perceptions, Green Innovation. **Barrier**: Enhanced effect of AI	Implementing GHRM can have a positive impact on environmental performance and organizational sustainability.	Actively seeking knowledge about different cultures, employing techniques such as translation and back-translation, and engaging researchers from various backgrounds
Pu 2025	Quantitative; Data envelopment analysis (DEA), RBV, Agency theory, Dynamic capabilities theory (DCT)	Cloud Computing, Digital Technology, Speed of Digital Innovation **Barriers**: Artificial Intelligence, Blockchain, and Big data face implementation challenges	Firms that rapidly adopt digital technologies can better align their operations with environmental imperatives, reducing inefficiencies and achieving sustainability goals more effectively.	Examining the relationship between digitalization speed and other industry-specific factors could provide a deeper understanding of its role in driving sustainable innovation globally.
Ji and Tian 2026	Quantitative; Knowledge based view, DCT	Employee AI capability, Knowledge based dynamic capacity, Digital Green Innovation	The study highlights the importance for environmental managers of strengthening employee AIC and organizational KBDC to implement AI-driven	Could adopt a longitudinal approach to better uncover the causal systems and dynamic evolution of this relationship.

			sustainability strategies more effectively.	
Ahmed, Ahmed and Wang, 2026	Quantitative; The stochastic impacts of population, affluence, and technology (STRIPAT) model	Green Finance, Eco-Innovation **Barriers:** Resource Curse (Rents, Natural Resources)	Eco-innovation significantly moderates the association between natural resources and the ecological footprint, indicating that eco-innovation can be a viable tool for curing the resource curse.	Might introduce green bonds and renewable energy R&D as proxies for green finance in alternative models, comparing their effects on various environmental and growth indicators
Larbi-siaw et al. 2022	Quantitative; RBV and Contingency theory (CT), PLS-SEM model and Artificial Neural Network Analysis (ANN)	Eco-innovation (Product, Process, Organization), Economic, social, Environmental, **Barriers:** Market turbulence (Environmental, Technological)	A manufacturing firm's environmental performance can be considerably improved by implementing the triumvirate of product, process, and organizational eco-innovation	May evaluate the selection criteria for eco- Innovation (EI) based on a sustainable mechanism
Zhao and Liu 2025	Quantitative; RBV, Signaling theory Institutional Theory and Competition Theory.	Organizational capability, Substantive innovation **Barriers:** Institutional pressures, competitive market forces and Stringent environmental regulation.	AI application significantly suppresses green innovation bubbles, demonstrating a substantial reduction effect at the sample mean	Explore the dynamic evolution of AI's impact over time, testing whether a "J-curve" effect exists as firms develop complementary capabilities

Appendix 3 Explanation of the use of AI

The researcher confirms that Artificial Intelligence tools were used in an ethical and transparent manner during the preparation of this study. These tools were applied in a limited and clearly defined way to support the research process.

AI tools	Intention of use	Scope and Ethical Considerations
ChatGPT (OpenAI)	Primarily used to enhance clarity of academic language, correct grammar, and refinement of sentence structure. In addition, also been used to support idea organization, improve logical flow, and ensure consistency across sections.	The researcher retained full responsibility for interpretation, findings, and conclusions. No original content, arguments, or analyses were produced by the tools. All suggestions were critically assessed. The final text reflects independent reasoning and the researcher's original contribution.
Grammarly	Used to check grammar, spelling, and punctuation. This improved the accuracy and clarity of the text.	Grammarly was used only to refine the language. All corrections were reviewed and approved by the researcher. The researcher made all decisions regarding revisions. All substantive edits, interpretations, and final writing were completed independently.
Scispace	Used to support efficient summarization and comprehension of academic literature	The researcher checked all summarized content with the sources. This ensured accuracy. Moreover, it also ensured academic integrity.
Canva	Used to present text in a visual format in different styles. It is only used for presentation purposes.	Canva is only used to assist in drawing frameworks. It is not used to generate any analytical or subjective contents.
Zotero	Used to manage references, organize citations, and format the bibliography. It was also used to categorize information through color-coded highlighting, such as identifying key concepts, drivers, barriers, and contextual factors related to AI adoption for green innovation.	Zotero was used only as a tool for reference management and organization. All highlighted and categorized materials were independently reviewed by the researcher. This ensured accurate interpretation and maintained academic integrity.

Sample queries to Scispace:

Generate concise summaries of selected papers. Additional queries were used to obtain brief explanations of abstracts, the method utilized, theories applied in the related articles.

Sample queries to ChatGpt:

1. Clarify the major theme comprehensively covered in this abstract. Make it concise, understandable and insightful.
2. Clarify the concept of robustness test used in this paragraph.
3. Clarify concepts like heteroscedasticity, heterogeneity used in this particular paragraph.
4. Suggest few renowned articles in the field of systematic literature review.

The use of these AI tools followed the ethical standards of academic research and the University of Turku’s quality assurance guidelines. All intellectual decisions were made by the researcher. Theoretical applications and final analyses were also carried out independently by the researcher.