

European International University, EIU-Paris

Doctoral Thesis

The Role of Artificial Intelligence in Advancing Sustainable Procurement: A Study of Organizational Readiness and Implementation Challenge

Submitted by:

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In Partial fulfillment of the Requirements for the Degree of Doctor of Business Administration (DBA) in AI – Driven Sustainable Supply Chain and Procurement Transformation

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DECLARATION

I hereby declare that the work in this thesis entitled, " The Role of Artificial Intelligence in Advancing Sustainable Procurement: A Study of Organizational Readiness and Implementation Challenges" has been undertaken and completed by me for the award of the Degree of **Doctor of Business Administration (DBA) in AI – Driven Sustainable Supply Chain and Procurement Transformation** with European International University, under the guidance of Prof. (Dr.) S. Edmund Christopher.

I also declare that this thesis is an original work and has not been submitted for any degree or diploma in any other university or institution. Further, I declare that the texts, figures, tables, and any other material taken from other sources has been acknowledge, referred and cited in the best of my knowledge and understanding.



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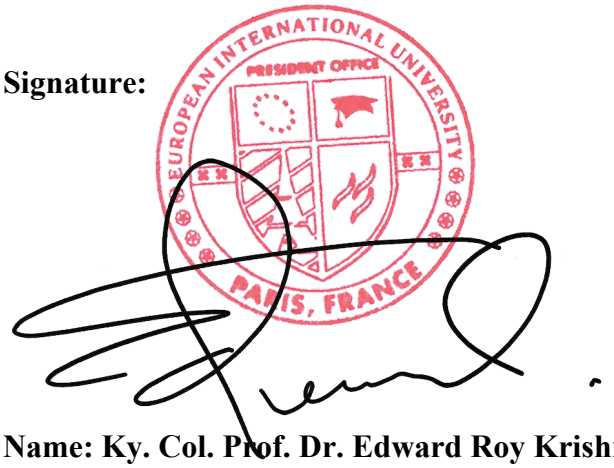
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UNIVERSITY APPROVAL

This dissertation titled, "The Role of Artificial Intelligence in Advancing Sustainable Procurement: A Study of Organizational Readiness and Implementation Challenges" has been examined and approved by the European International University (EIU-Paris) for the award of the **Doctor of Business Administration (DBA) in AI – Driven Sustainable Supply Chain and Procurement Transformation.**

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Abstract

Purpose: This study examines the role of artificial intelligence (AI) in advancing sustainable procurement performance, focusing on six organizational and technological factors: AI-driven decision-making, robotic process automation (RPA), data quality, organizational readiness, ethical AI implementation, and technology integration capability.

Methodology: A quantitative research design was employed using a 5-point Likert scale questionnaire administered to 100 procurement professionals, IT specialists, and sustainability officers across manufacturing, healthcare, retail, and energy sectors. Purposive sampling targeted respondents with at least two years of experience in AI-enabled procurement. Data were analyzed using Pearson correlation, simple linear regression, and multiple regression with VIF multicollinearity diagnostics.

Findings: All six hypotheses were supported in simple linear regression analyses. Ethical AI implementation and technology integration capability demonstrated the strongest effects, each explaining 86.2% of variance in sustainable procurement performance ($R^2 = 0.862$, $\beta = 0.928$, $p < 0.001$). RPA ($R^2 = 0.128$, $\beta = 0.358$, $p < 0.001$), data quality ($R^2 = 0.173$, $\beta = 0.416$, $p < 0.001$), organizational readiness ($R^2 = 0.125$, $\beta = 0.354$, $p < 0.001$), and AI decision-making ($R^2 = 0.048$, $\beta = 0.220$, $p = 0.028$) also showed significant positive effects. Multiple regression revealed that ethical AI implementation and technology integration capability remain significant unique predictors when all variables are considered simultaneously ($\beta = 0.465$ each, $p < 0.001$), while other variables' effects are partially mediated through these factors.

Originality/Value: This study contributes a validated empirical model demonstrating that ethical governance and systems integration capability are the primary mechanisms through which AI enhances sustainable procurement. It extends the Technology Acceptance Model and Diffusion of Innovation theory by identifying ethical implementation as a distinct and critical dimension of AI adoption for sustainability.

Keywords: Artificial Intelligence, Sustainable Procurement, Organizational Readiness, Ethical AI, Technology Integration, Robotic Process Automation

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CHAPTER 01 – INTRODUCTION

1.1. Background of Study

In the current world many organisations are considering sustainability in procurement, to ensure that they conserve the environment and improve efficiency in their operations. Researchers are noting that the existing digital solutions, in specific Artificial Intelligence (AI), have a high potential to turn the business world around regarding the approach toward procurement, especially in a sustainable posture (Demir et al., 2023; Rashid et al., 2025). Its capacity to process extensive data and deliver fast knowledge has made AI an important contributor to the changes in sustainable procurement. With the challenge of inclining businesses towards ethical and responsible sourcing, AI has become (and increasingly) important in decision-making (Rejeb & Appolloni, 2022; Modgil et al., 2022). AI can access data on environmental sustainability of suppliers, costs, and ethics so that organizations can select vendors who can achieve their sustainability objectives.

Nevertheless, despite the substantial potential of AI in the field of procurements, there exist a number of barriers to its introduction, such as the preparedness of a particular organisation and its potential to efficiently incorporate the solutions based on AI technologies (Aliane et al., 2023; Ghobakhloo et al., 2023). Despite the ability of AI to control vendor evaluation, sale forecasting, and enhance the functionality of supply chains, its implementation entails a considerable shift to be made by companies, including updating the technology, training personnel, and investing in new infrastructure (Demir et al., 2023). Moreover, some challenges like unwillingness to implement new technology, data privacy security and frequent updating of AI models to reflect the changes in the market need to be resolved in case of AI being introduced to sustainable procurement (Yousefi & Tosarkani, 2024; Rashid et al., 2025).

There is a considerable gap found in the literature regarding a common approach to determine the AI readiness of a company when engaging in sustainable procurement, which poses a considerable barrier to organisations (Rainy & Chowdhury, 2022; Aliane et al., 2023). Organisational readiness can be defined as the ability of an entity to accept technological change, and includes organisation leadership commitment to change, expertise of its employees, and availability of technological inputs. With the further development of AI, companies are advised to examine their existing digitalization level and reshape their organizational culture towards the goals of digitalization

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(Modgil et al., 2022; Demir et al., 2023). Organisations are not sufficiently prepared to roll out AI systems that can support their sustainability plans, which may prove difficult.

With the involvement of AI in sustainable procurement, the two main challenges to handle will be quality assurance of data and the compatibility of different supply chain systems (Rashid et al., 2025; Yousefi & Tosarkani, 2024). AI is effective only when the information is clear, structured, and addresses all the aspects thereby required, as well as when it is possible to merge data available in various sources. Organisations have difficulty with making sure that the supply chain and other sources of data parallel the requirements of AI models. Justifying procurement decisions using real-time data adds another layer of difficulties to overcome in this challenge. Since AI exercises machine learning to examine past and present data, the quality and reliability of data become factors of great concern to sustainable procurement (Ghobakhloo et al., 2023; Rashid et al., 2025).

Moreover, the integration of AI into sustainable procurement contributes to the working atmosphere that promotes innovation, openness, and continuous training (Aliane et al., 2023; Rejeb & Appolloni, 2022). An organisation must embrace the new technologies and embrace the changes associated with AI in order to use AI in procurement successfully. Companies that focus on being digital-first are already in a good position to leverage AI to achieve sustainable procurement through continuous learning and adjustment. Alongside, as a leader, it will also be relevant to guide the changes within the organisation, to make sure that the adoption of AI contributes to the long-term objectives, and to sponsor technological and human investments.

The importance of AI to sustainable procurement is in the fact that it improves the resiliency of supply chains in response to diverse conditions (Modgil et al., 2022; Ghobakhloo et al., 2023). The pandemic revealed the fact that global supply chains can be easily hobbled by a natural disaster, interstate tensions, or pandemic. With AI, companies will be able to anticipate the disruptions, make use of their resources in a more efficient manner, and guarantee that the processes keep on going smoothly. The application of AI in sustainable procurement is that it will enable companies to be able to forecast risks linked to ESG standards so that they can make decisions that facilitate sustainability. Companies also have the opportunity to minimize the risks and reach their green PR and social purposes by monitoring their suppliers through AI.

Along with procurement enhancement, AI will contribute significantly to the term of implementing circular procurement, which is an essential element of sustainable procurement (Rejeb &

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Appolloni, 2022; Yousefi & Tosarkani, 2024). The aim of circular procurement is to minimize waste and promote recycling and remanufacturing of the products and make the supply chain more sustainable. Through AI, firms can get to know materials better and optimize practices to source material with environmental benefits. As an example, AI can assist in examining the environmental effects of different materials and suggest ones with reduced CO 2 emissions, thereby prompting the industry to support environmental friendlier practices (Aliane et al., 2023; Rashid et al., 2025).

To secure the performances of AI in sustainable procurement, strategies to mitigate some of the risks of technology and ethical implications must first be developed (Ghobakhloo et al., 2023; Modgil et al., 2022). The sophistication of AI algorithms today requires that topics related to ethics should be considered during employing AI. When AI is utilized in analyzing vast amounts of data, deciding things on its own, the question of bias, fairness, and transparency in procurement decisions arise. The companies have to create the AI systems that will not unintentionally favor some suppliers or products, which will undermine their sustainability. It should develop the rules of AI application in procurement so that its decisions could be adjusted to organisational values and community demands (Rainy & Chowdhury, 2022; Rashid et al., 2025).

1.2. Problem Statement

AI will entail major changes in procurement, especially with regard to sustaining procurement. As AI continues to see embracement in the procurement sector, new possibilities were opened up regarding efficiency, cost mitigation, and an enhanced sustainability profile (Gaikwad, 2024; Althabatah et al., 2023). AI can help companies streamline their purchase operations through decision-making support and vendor performance measurements as well as better forecast demand. Due to these advancements, procurement can opt to have suppliers and materials that are sustainable (Muthuswamy & Ali, 2023; Flechsig et al., 2022). However, there are some setbacks that make implementation of AI in procurement not as easy as its merits seem to indicate hence many of them seem to fail to meet their goals of sustainable procurement.

Most organisations already have the procurement process in place and the main challenge lies in the fact that they are not yet prepared to use new technologies when it comes to implementing AI (Mavidis & Folinas, 2022; Ismaeil, 2024). Successful use of AI implies investing in technology and transforming the manner of thinking and working of employees. Most of the Small and Medium Enterprises (SMEs) cannot afford to conduct the Cutting Edge investments and develop

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the technical expertise to use AI productively (Gaikwad, 2024). Artificial intelligence systems in procurement are based on a vast quantity of data and that is why companies suffer from the inability to collect and filter different data sources and integrate them. Poorly managed and misapplied data can be a setback in the implementation of AI and the effectiveness thereof in fostering sustainable purchasing behavior, report McBride et al. (2024) and Althabatah et al. (2023).

The additional difficulty is that change is not welcomed by many organisations. The employees in the procurement sector may feel threatened by autonomous behavior and decide not to utilize AI-based tools (Flechsig et al., 2022; Muthuswamy & Ali, 2023). AI systems, such as Robotic Process Automation (RPA), are able to process common procurement tasks; but it will require procurement specialists to adopt new and different job competencies. Human beings might hesitate to adopt new technologies, fearing that they would lose their jobs to AI. organisations need, therefore, to ensure that their digital culture emphasises the role of AI in aid of human decision-making and that it does not seek to usurp it (Mavidis & Folinas, 2022; McBride et al., 2024). This change has to happen so that AI can be effective in the process of procurement.

The fact that the algorithm behind AI may be complex and introduce bias is also a vital concern that can influence the individual performance of AI in sustainable procurement (Gaikwad, 2024; Ismaeil, 2024). Human beings always have a problem trying to decipher how AI models make their decisions. Since the process of procurement can raise transparency issues, ethical concerns might arise, especially when AI systems are involved to measure supplier performance or influence the procurement. When an AI receives prejudiced inputs, they will potentially replicate the same level of supply chain that led to the use of environmentally harmful suppliers in the first place (Althabatah et al., 2023; Flechsig et al., 2022). Companies need to make sure that their AI models are transparent enough and consider not only ethical factors but also common performance measures.

The implementation of AI with the sustainability objectives poses a strong difficulty on the side of organisations as well. Although the application of AI may lead to cost reduction and streamlining of business processes, it is necessary to regulate the application of AI during the procurement in a way that it would assist in the achievement of environmental and social objectives. This means that although, in procurement, AI can pick the most cost-effective

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suppliers, they are not necessarily sustainable (Muthuswamy & Ali, 2023; Dellink, 2023). This is why it is crucial to integrate sustainability elements in AI programs and make sure that the procurement activities are performed according to the ESG principles to embrace sustainable processes (Althabatah et al., 2023; Ismaeil, 2024).

The fact that regulations with respect to AI in procurement can hardly be called developed yet is another significant issue (McBride et al., 2024; Muthuswamy & Ali, 2023). Since AI regulations in procurement have not yet been developed in most areas, data privacy concerns, intellectual property rights and liability are still expected. The absence of regulations in such areas may complicate the use of AI in the procurement systems of the organisations, primarily when they deal with sensitive data or procure goods in foreign countries. Alternatively, organisations might not want to use AI in the presence of confusing AI rules because they fear violation of the law or breaching data protection laws (Mavidis & Folinas, 2022; Flechsig et al., 2022). Moreover, AI technology is rapidly evolving, and the current regulators cannot always follow the most recent amendments to the technology, which also contributes to the fact that controlling the AI-driven procurement becomes difficult.

The other problem of adopting AI during the procurement process is ensuring compatibility between various systems. Business organizations employ diverse procurement systems, and some of them are not compatible with AI. To enable AI-based systems to operate efficiently in procurement, the systems should be able to integrate with the existing ones such as ERP, supplier relationship management, and inventory management systems (Althabatah et al., 2023; Gaikwad, 2024). The data and processes are not linked together, and that means that AI will not work as efficiently. Therefore, organizations should devise mechanisms which are compatible and enable the AI mechanisms to run on various platforms to enhance procurement.

How AI will be used in facilitating sustainable procurement will depend on the development and innovation of technology. Since AI technologies evolve, organisations should keep the pace and revise and adjust their AI strategies on a regular basis to achieve their sustainability objectives (Muthuswamy & Ali, 2023; McBride et al., 2024). AI application in procurement requires continuous upgrading, training, and adapting to the novel conditions. As long as organisations address the concerns of preparation, proper data, fair play and regulatory shifts, then AI can assist them to enable sustainable purchasing.

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1.3. Purpose of Research

This research aims to examine how AI can support sustainable procurement and identify the challenges and opportunities companies encounter when adopting AI technologies for their procurement processes. In particular, the research aims to explore how AI enhances decision-making in the field, evaluates the performance of suppliers, and supports improved sustainability in procurement. Although AI can significantly aid in procurement, it presents challenges such as the organisation's ability to effectively utilise AI, the need for high-quality data, potential discrimination in AI models, and integrating AI into the company's environmental goals. This study focuses on reviewing how organisations apply AI in their procurement strategies and identifies what is blocking the broader use of AI in sustainable procurement. Additionally, the study will evaluate various frameworks and approaches for addressing these challenges and ensuring that AI delivers efficiency and sustainable practices in procurement.

1.4. Research Objectives

The purpose of this study is to explore and analyze the strategies employed in advancing sustainable procurement through the integration of artificial intelligence (AI). Specifically, the study intends to:

- To identify and categorize the key challenges and opportunities faced by organizations in adopting AI for sustainable procurement.
- To assess the organizational readiness and maturity required for the successful implementation of AI in procurement processes.
- To evaluate the role of AI in enhancing decision-making, supplier performance evaluation, and alignment with sustainability goals in procurement.
- To analyze the barriers to AI adoption in procurement, including issues related to data quality, integration, and organizational resistance.
- To explore how AI technologies can contribute to optimizing sustainable procurement practices, such as reducing environmental impact and promoting social responsibility.
- To examine the ethical implications and risks associated with the use of AI in procurement, including biases in decision-making and transparency issues.

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- To assess the regulatory and legal challenges in implementing AI for sustainable procurement and the readiness of organizations to comply with emerging AI-related regulations.
- To propose frameworks and strategies for overcoming challenges and ensuring that AI adoption supports both operational efficiency and sustainability goals in procurement.

1.5. Research Questions

In association with the above research objectives, the following research questions were developed:

- RQ1: How do AI-driven decision-making, robotic process automation, and data quality influence sustainable procurement performance?

- RQ2: What is the role of organizational readiness in enabling successful AI implementation for sustainable procurement?

- RQ3: How does ethical implementation of AI contribute to sustainable procurement outcomes?

- RQ4: To what extent does technology integration capability moderate or mediate the relationship between AI adoption and sustainable procurement performance?

1.6. Research Gap

While AI has the potential to significantly improve sustainable procurement, relatively little research has been conducted on its impact on sustainable procurement and the entire supply chain. Although AI in procurement is a growing field, most literature focuses on broad applications rather than the specific issues and benefits associated with sustainability (McBride et al., 2024; Ismaeil, 2024). Many businesses do not understand how AI helps them become more sustainable when dealing with the usual challenges of organisational adoption, data quality, and matching their AI with present procurement tools.

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Most studies today examine AI in sustainable procurement separately, focusing on individual cases or narrow areas, rather than considering how AI might differ across various industries or what its overall impact would be on the supply chain (Dellink, 2023; McBride et al., 2024). This means that the findings may not be widely adopted, and it becomes challenging to establish standard guidelines for utilizing AI in sustainable procurement. In addition, the strategies and frameworks used for adopting AI, mostly by governments, are still quite limited, especially when trying to connect AI with sustainability goals (McBride et al., 2024). Such frameworks typically do not explain how AI can be effectively used to achieve both efficiency and sustainability in operations. This problem is exacerbated by the difficulties many organisations face in adopting AI, such as data management issues and a lack of skilled personnel. In doing so, this study aims to understand how AI can be effectively adopted in sustainable procurement and suggests solutions to the various difficulties and complications that may arise.

1.7. Scope of the study

This research aims to review the use of AI in encouraging sustainable procurement and to explore the aspects imbued in the adoption of AI in the procurement operations. It will also discuss how AI could be used to help optimise procurement, review supplier performance and facilitate sustainability. The contribution of AI to sustainable procurement will be considered in three phases of the development of AI, identifying challenges and opportunities faced by firms at each of these phases (Hao & Demir, 2025).

The main industries indicated in the research are the manufacturing industry, the retail industry, the healthcare industry and the energy industry due to the support of the manufacturing industry, the retail industry, the healthcare industry and the energy industry weighing on sustainable procurement and currently implementing AI to support decision-making, increase efficiency and achieve environmental targets (Mattaba & Fatahi Valilai, 2024). As AI constantly develops, it will also be looked at whether organisations will be able to make use of AI and how they will cope with data management, integration issues and the technical issues with implementing AI into their current procurement processes (Kulkarni et al., 2024).

The study will cover the entire globe; however, specific attention will be given to those parts of the world that AI is becoming influential in terms of procurement in the developed, as well as the developing world. The study will be pilots in organisations majorly based in Europe, North

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America and some Asian parts, notably India and China, where the application of AI in managing procurement and sustainability is being felt (van Hoek, 2024). The study will also examine the approaches of large and small businesses when using AI to analyze whether they have any effect on a company due to its size and offered resources (Kulkarni et al., 2024). The research will quantify the effects of such aspects of their contexts, including their laws, technology, and method of doing things, on the use of AI in sustainable procurement.

The research will address the issue by examining the practice of adopting AI on various levels. First, the main task is to learn about the most important AI systems, such as machine learning algorithms, data analytics, and decision-making models, and study how they could optimize the process of procurement in terms of sustainability (Hao & Demir, 2025). In the working environment, the research will consider through which AI is transforming the conditions under which procurement is conducted, its impact on supplier selection, risks, and alignment to sustainability regulations (Mattaba & Fatahi Valilai, 2024). On this step, it is necessary to consider how ready companies are to apply AI in buying and what challenges they face, such as change resistance, the necessity of competent workers, and the combination of the AI and procurement system (van Hoek, 2024).

The research focuses on the regulations and essential approaches that should be applied to sustainable procurement through AI. It shall examine how different national and international regulatory systems support companies to embrace Artificial Intelligence in a way they feel that they are aligned with environmental, social and governance (ESG), practices (Kulkarni et al., 2024). The paper analyses how AI utilization may affect the capability of the companies to meet the criteria of sustainability and offers recommendations on how to improve the performance of AI in the procurement.

1.8. Study Significance

This research is an enlightenment in the way AI can be applied towards sustainable procurement, elucidating the key obstacles and advantages that businesses stand to gain in an attempt to improve on their procurement within business in an effort to achieve sustainability. With the trend of further digitalization of industries, AI is starting to be discovered to increase the efficiency of procurement, evaluate supplier performance, and enhance sustainability work (Hossain et al., 2024). Meanwhile, the application of AI in the procurement area is fenced by a number of

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problems, mainly associated with the level of a company, with the quality of data, with ethical considerations, leaving a considerable gap between the informative research and practice.

Academically, this research would add to the body of knowledge regarding the application of AI in sustainable procurement because it will investigate the factors, challenges, and barriers to the application of AI throughout every process of the procurement procedure (Culot et al., 2024). It benefits the research field in that it gives a framework that takes into consideration the technological, organisational and strategic domains simultaneously. Unlike previous research, which concentrates on the use of AI in limited procurement areas, the explored research provides information on the ways to integrate the implementation of AI among different phases of the procurement process, including suppliers selection, risk management, sustainability compliance, etc. (ASA & Zosu, 2023). The research points out that effective adoption of AI is determined by an effective organisational culture and preparedness, good leadership, qualified employees and appropriate infrastructure (Althabatah et al., 2024).

This study can be of great value to business and other groups in different industries as they can learn upon the pitfalls regarding the adoption of AI in procurement. An inability to ensure that the AI strategies can contribute to sustainability is present in several organisations because of financial limitations, inadequate data management, and resistance to change (Hossain et al., 2024). These findings suggest that it is possible to avoid operational problems and make more significant steps towards sustainability by dealing with these issues at their early stages. This study relies on the knowledge of what facilitates the use of AI and what makes it difficult to advise on addressing the issue, developing higher preparedness and making sure that AI can bring long-term sustainability to procurement (Althabatah et al., 2024).

The study provides an in-depth analysis of AI-driven applications that are capable of ameliorating procurement processes and assist in meeting sustainability goals. This research model uses case studies and empirical data to show that predictive analytics and machine learning algorithms can improve the monitoring of suppliers, minimizing the environmental footprint of the company and help to reach the sustainability goals (Nazeer & Gil, 2023). Moreover, the paper offers more detailed analysis on how AI can move on to filling the procurement gaps, allowing resources to be used efficiently, lower costs, and produce a healthier environment.

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Policymakers and regulators are also interested in the research, as it proves that the effective design of frameworks and policies is important to facilitate the use of AI in procurement and to make it sustainable. Governments and authorities ought to realise the potential of AI in terms of sustainability in procurement and consider instituting relevant regulations to facilitate the ethical applications of AI, especially the aspect of data privacy, transparency, and fairness (Nazeer & Gil, 2023). According to the study, controlling regulatory problems, including the development of standards in the field of AI, may positively influence the environment of AI adoption in developing countries (Hossain et al., 2024).

The study stipulates that AI plays an important role in the development of the main procurement strategy of an organisation. As AI becomes more common in the industry, leaders and decision-makers should know how it makes the industry more efficient, environmentally friendlier, and innovative (ASA & Zosu, 2023). It implies that AI should be one of the priorities a company sets in the digital transformation agenda in order to make sure that its procurement process might support both business and sustainability goals. The study emphasizes that to reinforce procurement and ensure more resilient supply chains, all aforementioned aspects such as AI, organisational preparedness, and sustainability are to be utilised in combination with one another.

1.9. Organization of the Dissertation

Chapter 01 Introduction

The chapter begins by explaining the study, including its background, the problem it aims to address, and its objectives and research questions. Additionally, it outlines what is lacking in existing studies, the areas the study will cover, its significance, and the study's structure.

Chapter 02 Literature review

Here, the study examines key AI concepts in sustainable procurement, outlines standard procurement practices, and explains how new technologies enhance procurement efficiency. Additionally, the report examines the current application of AI in procurement, the challenges to its implementation, and the study’s primary framework.

Chapter 03: Research methodology

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This chapter explains the methodology used in the research, outlining its philosophy, strategy, and approach. It also involves explaining the methods of gathering data, choosing samples, defining the population, and analysing the collected information. Questions about the ethics of the research are also explored.

Chapter 04: Results & Findings

This chapter presents the research results, including information on the respondents' demographics, statistics, and an analysis of the hypothesis.

Chapter 05: Discussion and Recommendations

In the final section, the authors present the implications of the findings, including the study's limitations, conclusions that can be drawn from the results, and suggestions for improving AI adoption in procurement. It also highlights areas that require further investigation.

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Chapter 2: Literature Review & Conceptual Framework

2.1 Introduction

The authors dedicate this chapter entirely to a detailed literature review of the subject matter in an attempt to gain a holistic picture of how the technologies of the Artificial Intelligence (AI) may be used to transform the approach to procurement altering the course of sustainable procurement activities. It discusses the idea of AI and its evolution, subcategories, the significance of sustainable procurement and characteristics of consistency needed in an organization to incorporate AI. This chapter will present the current state of knowledge on the subject of AI application in procurement and problems organizations might experience when investing in such technologies by critically evaluating available studies.

Procurement itself is a constituent element of any organization and has a systemic effect on the efficiency of working processes as well as the possibility of reaching the strategic objectives. Growing interest in the impact that procurement decisions have on the surrounding environment, as well as societal and economic aspects are leading to a rise in the importance of sustainable procurement practices over the years. Sustainable procurement has become a priority now among organizations which have been working to align their supply chain management with global agendas on sustainability which include the SDG goals released by the United Nations.

An AI is a revolutionary technology which may significantly upgrade procurement process, automate routine actions, and better decision-making and assessing supplier through environmental, social, and governance (ESG) parameters. However, along with the obvious benefits, many issues are associated with the safety of the inclusion of AI in procurement processes. These involve lack of organization preparedness, problems related to data quality and reluctance to pass through transformations. The chapter will be dedicated to the discussion of these problems and the opportunities AI has to provide more sustainable procurement practice.

The chapter has been structured to address the key-seminar of AI, sustainable procurement, and preparedness as an organisation towards embracing AI. It will next look into the history, growth and evolution of AI, subdisciplines of AI and its application in the procurement industry. The discursion on how AI may be used in the future to assist the procurement decision-making process and sustainability will be discussed in detail and the challenges and obstacles that will influence

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the use of AI in regard to sustainable procurement will be evaluated. Finally, the chapter gives a reflection of theoretical frameworks and models upon which the learning about AI adoption effects on sustainable procurement is based.

2.2 Major concepts

2.2.1 Man-made Intelligence

Artificial intelligence (AI) may be described as the development of computer systems which will potentially be used to conduct certain functions that have hitherto been performed by human intelligence. Those are thinking, learning, problem-solving, perception, and decision making. The use of AI is mainly to read, interpret the data and draw conclusions with minimum human interventions. Different technologies that fall under the AI umbrella are machine learning (ML), deep learning (DL) and reinforcement learning (RL) in the service of the ultimate purpose of building systems that will simulate the type of intelligence humans have (Rane et al., 2024).

History, the Evolution of AI

The concept of AI can be traced to the 1950s when it was officially proposed by Alan Turing who is usually considered the father of AI. The research on AI Turing asked the well-known question: Can machines think? Early research in AI was obsessed with symbolic processing, rule systems, that were computationally weak and had unsophisticated problem solving capabilities. However, the release of more power and the creation of more complex algorithms gave AI the ability to succeed in dealing with the shortcomings of symbolic thought and transform into data-driven models that ordinary people use every day (Neupane, 2023).

The introduction of machine learning was another major milestone in the development of AI since it allowed systems to learn based on what data was provided and become more efficient with time. Algorithm Models: Algorithms in machine learning may learn to detect patterns in the data and need not be programmed to identify all the possible settings. That has given rise to the recent subfield of deep learning, which applies many-layered neural networks to handle large amounts of data, in service of tasks like natural language processing (NLP) and image recognition (Rane et al., 2024).

Subareas of artificial intelligence

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One data analysis technique is called Machine Learning (ML) because an analytical model-building process is automatized in it. It works on the assumption that a system can be learned through the invention of information, can detect trends and decisions can be associated with little human interaction. Machine learning falls under three broad categories that include supervised learning, unsupervised learning, and reinforcement learning (Rane et al., 2024). Supervised learning enables training the model with the help of the labeled data, and unsupervised learning is founded on the unlabeled data pattern identification. Reinforcement learning alternatively uses reinforces or punishes the model depending on the choice it gives, in turn activating it to make the best decisions in the long-term (Bhutani & Sanaria, 2023).

Deep Learning (DL) is a sub-discipline of machine learning which makes use of artificial neural networks to model complex data patterns (also referred to as neural network). Some problems on which deep learning has shown strong potential include image and speech recognition where other methods of machine learning can yield poor results. DL models are capable of processing huge pools of data and extrapolating fine-grained patterns that may be used to make decisions (Rane et al., 2024). Reinforcement Learning Reinforcement Learning (RL) is a branch of machine learning that seeks to learn the art of making a sequence of decisions, via the interaction with an environment. Robotics, games, and any process of decision-making incorporating AI are examples of RL application since the knowledge system learns by being rewarded or punished depending on the actions (Peretz-Andersson et al., 2024). The use of AI can allow an easier process of decision-making in procurement, particularly through the analysis of vast AI link volumes of data concerning suppliers, demand prediction, and, thereby, the identification of trends that traditional human analysts would be unable to detect. Repetitive tasks, like data entry, evaluating the supplier, and making orders can be automated, and with the help of AI, procurement specialists can be provided with an opportunity to focus on more significant tasks (Riad et al., 2024).

2.2.2 Sustainable Procurement

Sustainable procurement has been defined as the process of procuring goods and services using methods that consider the environment, society, and economy, while also meeting the organization's requirements. It is another crucial aspect of corporate social responsibility (CSR) and aims to strike a balance between the three key aspects of sustainability, including environmental conservation, social justice, and economic feasibility (Rejeb & Appolloni, 2022).

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The sustainable procurement principles entail choosing services and supplies that are sustainable with respect to the environment, social acceptable and economically viable. It involves all parts of the supply chain, including product sourcing and disposal, and covers the entire product or service life cycle. These principles are also in line with the overarching aims of sustainable development, namely to minimize carbon footprints, encourage ethical employment, and promote the recycling and reuse of materials (Al-Raeei, 2024).

The emergence of AI can become a gamechanger in advancing sustainability in procurement. With the use of data analytics, AI can assist organizations in evaluating the environmental impact of suppliers, enabling more informed decisions when choosing vendors based on vendor efficiency. The AI tools can also be used to evaluate the performance of suppliers in regard to ESG measures, including carbon emissions, labor practices, and waste management, to ensure that companies select suppliers who conduct their business in accordance with sustainability objectives (Whig et al., 2024). Procurement can also be enhanced by using AI to streamline the procurement processes and lower wastage alongside the allocation of resources. For example, AI-based predictive analytics will increase the likelihood that organizations will order the correct amount of materials at the optimal time, minimizing waste and preventing surplus materials. Moreover, AI will be useful in circular procurement, as reuse, refurbishment, and recycling of materials and products will occur, leading to a more sustainable and closed-loop supply chain (Cheng et al., 2025).

2.2.3 Readiness of Organization to AI

Organizational readiness can be described as the ability of a company to effectively adopt and integrate new technologies, including AI, into its processes. The pillars of readiness include leadership commitment, technology infrastructure, employee skill and organizational culture. Organizations should also conduct an analysis of their organizational preparedness for adopting AI to avoid failure in implementation (Arshad et al., 2024). There are some aspects that determine the willingness of an organization to deploy AI. It is also essential because effective leadership ensures that finances are invested in AI initiatives, and a strong leadership team guides AI implementation into procurement processes. Another key driver to the adoption of AI is organization culture. The more a culture fosters innovation, values technological changes, and learning, the greater its possibility of adapting to AI (Ghobakhloo et al., 2023).

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Another important determinant of readiness is the skill level of the employees. AI technologies demand a unique set of knowledge, and companies should ensure that their staff possesses the specific materials necessary to utilize and exploit these technologies. It typically involves making investments in personnel training, employing specialized talent, and fostering an organizational environment of digital literacy (Peretz-Andersson et al., 2024).

Small and Medium-Sized Enterprises (SMEs) are unique in their design of AI technologies. Unlike comparable organizations, SMEs often lack the necessary financial resources to invest in AI infrastructure and talent. Additionally, SMEs may face data management challenges since their current systems are unable to support the large volumes of data required for AI operations. These impediments can only be addressed by ensuring that SMEs develop their AI capabilities over time and prioritize critical areas where AI can be most useful, such as supplier assessment or demand prediction (Riad et al., 2024). Moreover, employees might have a change resistant stance, especially those who have been used to an old way of things when it comes to procurement process, particularly those who believe that AI has the potential of removing them off the job. To address this, organizations should prioritize education and awareness programs, demonstrating how AI can support human decision-making processes and enhance procurement results (Rane et al., 2024).

2.3 The Role of AI in Procurement

Artificial Intelligence (AI) is becoming a critical factor in the transformation of procurement functions, as it facilitates more efficient decision-making, enhances operational efficiency, and supports organizations in achieving their sustainability objectives. AI has strong potential to optimize the procurement process as businesses continue to seek greater control over supply chains and improved performance related to enhanced operations. In this section, the author critically engages with the role of AI in procurement, specifically examining how it positively contributes to the decision-making process in this sector, enhances efficiency, drives cost savings, and streamlines procurement processes with the goal of achieving sustainability.

2.3.1 Decision-Making Improvement

Through procurement, the application of AI continues to become more relevant with the key areas including supplier selection, risk, demand forecasting, and vendor evaluation being some of the most prominent areas. The forces behind the traditional procurement processes have been the manual process, human interpretation, and basic analysis, which leads to wastage and subjective

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decision making. Conversely, AI can help procurement teams to make data-driven, objective, and informed decisions, enhance quality, and speed of procurement processes. Based on the big data and complex algorithms, AI will recognize the trend and determine the pattern and suggest the most appropriate course of action based on a specific set of requirements related to the procurement.

This is a relevant component of procurement since the selection of suppliers ought to be undertaken. Artificial intelligence has made this process more effective by giving a superior use of information to rank suppliers. Usually, non-analytic measures are employed in the analysis in which supplier evaluation is done whereby subjective aspects to price factor, provision as well as quality of the commodity are involved which can lead to undesired results as well as incomplete analysis of the supplier. With the help of AI, the supply team can make decisions about assessing suppliers based on objective data, as well as in real-time, which makes it possible to consider the wider range of aspects and metrics on which it is based such as financial stability, environmental standards, and previous performance. In particular, with the help of AI algorithms, it will be possible to study the financial indicators and the history of a supplier and recent market trends to obtain information about its performance in the future, which makes the selection of suppliers more accurate and informed (Muthuswamy & Ali, 2023).

Also, AI proved useful in the domain of risk management since due to it, procurement teams can learn more about the risks that come with a selected supplier and the bigger chain of the same supplier. Advanced machine learning algorithms are able to process massive data sets, and pinpoint threats that would otherwise be difficult to sense using the traditional methods. AI would be capable of monitoring the events in this world and any economic trends, along with the measures it takes on supply chains, and it could even predict the risks, such as price fluctuations, geopolitical instability, or supply chain blockages, which eventually could help to manage them more proactively (Flechsig et al., 2022). AI can also anticipate what could happen in the future by relying on past patterns about risks that will occur, thus allowing the procurement teams to formulate against disruptors, and make decisions that minimizes credit risk.

Ability to enhance demand forecasting is another significant influence that AI can make to the procurement concept. The traditional demand forecasting draws consideration to the past sales records and straightforward analysis of statistics that are often followed by the false forecasts

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which could end up in introducing either excess or shortage of the products. Comparison AI-assisted forecasting demand, in turn, takes a broader set of information into consideration through machine learning models to create a more dynamic and precise prediction, including past sales data, customer trends, seasonality, and market trends (Joel et al., 2024). This assists procurement teams to align their stocks with the real demand by minimizing the costs of storing excess stocks, and having a sufficient level of stocks to satisfy customer requirements.

In addition to demand forecasting, AI can be applied to make the vendor performance streamlined. The intelligence systems have capability to mine data sourced across most number of areas like previous transaction, customer satisfaction survey, performance indicators and determine overall supplier reliability, product quality, and overall service levels. It is model-based on data which allows an organization to compare vendors at a more objective level and helps in making technology decisions regarding its availability to vendors, negotiation and contract management. With automated vendor reviews, AI also removes the subjectivity of the review which can occur when applying human decision making since the vendor is subject to both its data and performance (Teixeira et al., 2025).

2.3.2 Enhancing efficiency and cost saving

It is a highly effective variable when it comes to boosting productivity and leading to cost savings in procurement activities through the use of AI. Procurement activities are associated with a variety of time-consuming routine operations, such as sourcing, ordering, handling invoices, and contract management. When done manually, these tasks are subject to human error and can be incompetent. With AI, a lot of such tasks can be automated, increasing the speed, accuracy, and affordability of procurement. Furthermore, the adoption of AI technologies, such as Robotic Process Automation (RPA), can reduce repetitiveness and empower fewer procurement resources with high-value and strategic work.

Robotic Process Automation (RPA) can be defined as the application of software robots to exclude rule-based, repetitive tasks, such as data input, invoicing, and production of purchase orders. RPA has transformed procurement operations by minimizing manual efforts, speeding up activities, and enhancing accuracy by a significant margin. In another case, RPA can be used to automatically

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connect purchasing orders with payments and receipts, eliminating the need for manual verification of figures and reducing the possibility of error (PatrIcio et al., 2024). Additionally, RPA will enable the acceleration of approval processes, as requests are automatically routed to the recipients for signature approval, thereby shortening procurement cycles.

However, in addition to the direct efficiency implications, RPA also leads to direct cost savings, as it helps minimize the use of manual labor and allows employees to concentrate on more complex and value-adding activities, such as supplier relationship management or contract negotiations. RPA saves administrative overheads through the automation of mundane tasks and the associated reduction in error, as well as the procurement process in general, thereby enhancing overall operational efficiency.

AI will also enable more efficient procurement through optimized sourcing, negotiations, and supply management. The AI-based systems can be used to analyze large amounts of data to determine the most cost-effective supplier to respond, calculate price trends, and suggest the most proper sourcing patterns based on historical information and market conditions (Mukherjee et al., 2024). This will facilitate better decisions by procurement teams, ensuring they select suppliers that offer the best value and that their sustainability objectives are met.

AI can also enhance the procurement process through improving the negotiation process. Virtual assistants and chatbots, aided by po,tential to automate contract negotiations and encourage prencourageement groups to engato engage inmore effective interactions with ssuppliers Those AI systems may help consider the previous conditions of contracts, market trends, and supplier information to propose the most advantageous conditions to both sides. Automating this process helps an organization save time, reduce costs, and negotiate procurement contracts on better terms (Teixeira et al., 2025).

2.3.3 Correspondence with Sustainability Goals

Circular procurement is aimed at the buying of products and services that contribute to the least amount of waste, as well as encouraging reuse, recycling, and repurposing of materials. AI is critical to facilitating circular procurement by offering systems to help monitor the life cycle of products and provide opportunities for reuse and recycling. Information related to the end-of-life

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of products can be examined through AI systems, which suggest how to repurpose or recycle materials, thereby reducing the environmental footprint of activities related to procurement (Ronaghi, 2023).

Among the greatest contributions of AI to sustainability in procurement is that it allows an organization to screen and consider suppliers based on environmental factors. The environmental impact of suppliers can also be analyzed by AI systems, which can examine data on carbon emissions, waste management procedures, power, and water usage, providing more insight into the environmental impact of suppliers for procurement teams. With this information, organizations can make more sustainable purchasing decisions by giving preference to suppliers that align with their sustainability objectives (Ghobakhloo et al., 2023). Moreover, analytics based on AI can assist organizations in streamlining their supply chains to minimize waste and the environmental impact of purchasing operations. To illustrate, the AI can use logistics data to optimize the transportation path, thus lowering the use of fuel and the amount of greenhouse gases. AI is also making it possible to optimize inventory levels by using AI to ensure that product demands are better forecasted, supply and demand are balanced through reduced stock, and that products are produced and distributed in the most environmentally responsible way possible (Tsolakis et al., 2023).

One can also monitor the sustainability performance of suppliers in the long run, using AI-powered tools to determine whether suppliers are still meeting environmental standards. By employing AI in the context of procurement, companies will be able to enhance their sustainability initiatives while also benefiting from improved procurement efficiency and reduced potential negative environmental effects. Circular procurement is aimed at the buying of products and services that contribute to the least amount of waste, as well as to encouraging reuse, recycling, and repurposing of materials. AI is critical to facilitating circular procurement by offering systems to help monitor the life cycle of products and provide opportunities for reuse and recycling. Information related to the end-of-life of products can be examined through AI systems,,whichich suggest how to repurpose or recycle materialtherebyhereby eliminating the environmental footprint of activities related to procurement (Ronaghi, 2023).

Furthermore, AI can assist organizations iin handlingg reverse logistics effeeffectivelyg enabling return greturn reuse for reuserecycling. Artificial intelligence systems can monitor the movement

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of goods in the supply chain, recommend theoptimal time for for produto be discarded or returned, and notify users users about the need to recycle or repurpose goods. This is of great importance in ries such such asctronics andpandkaging, where the prodproduct uct life cynd thereis a need to reduce waste and recycle it to implement aimplement a. Artificial intelligence could also be used to aid waste reduction initiatives in organizations by identifying inefficiencies in production processes and suggesting how much material should be wasted. Making an example of AI-driven manufacturing systems, one may observe that production schedules may be optimized to minimize scrap of materials, and, in terms of packaging, use may be minimized of materials that are not likely to be brought back into the material cycle, contributing to a circular economy (Ronaghi, 2023).

2.4 Challenges and Barriers in AI Adoption for Sustainable Procurement

The fast rate of evolution of Artificial Intelligence (AI) in the sphere of procurement is associated with multiple advantages, such as more efficient work, improved decision-making, and sustainability target achievement. There are however a number of issues in adopting Artificial Intelligence in sustainable procurement by the organization. These issues range along the organizational barriers, data management, ethical considerations, and technical barriers. This section attempts to critically discuss these challenges by focusing on the organizational barriers to AI adoption, the automation and control of data and the ethical challenge of AI in the procurement process.

2.4.1 Organizational Problems

Application of AI in procurement involves organizational culture and technical ability change. Although AI can transform procurement operations, it is an internal organizational issue which hinders the effective adoption of the strategy. Two of the most serious obstacles are resistance to change and the necessity of upskilling the workforce.

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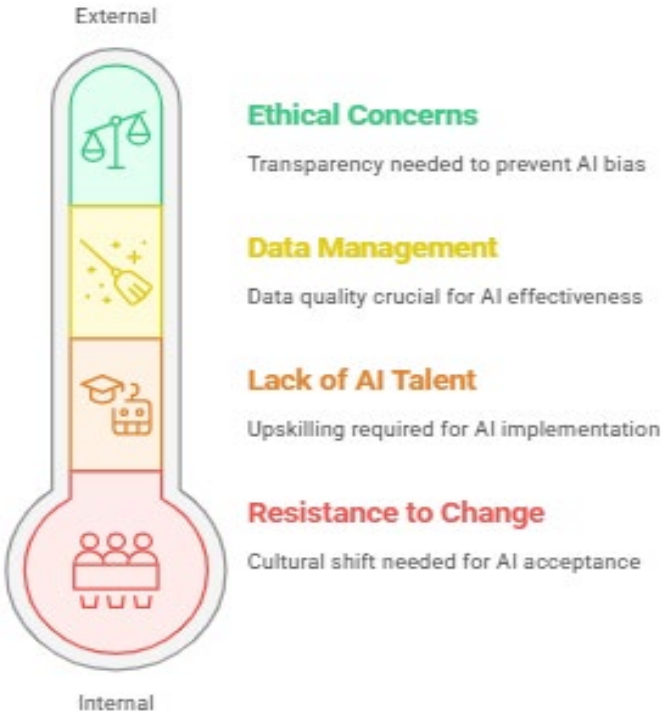


Figure 1 Organisational problems associated with AI

Figure 2 AI adoption challenges range from internal to external factors.

Digital Culture Shift Resistance to Change

Resistance to change is one of the major organizational issues of adopting AI. Most procurement teams are familiar with conventional ways of how one should work, i.a. manual supplier assessment, price bargaining, and risk management. The implementation of AI involves acquiring confidence in machine learning models, data-centered opinion, and automated decision-making, which may constitute a massive cultural alteration. The main causes of resistance towards the adoption of AI are fear of job loss, ignorance about the potential of AI, and the doubt of the integrity of AI systems (Mavidis & Folinas, 2022).

This resistance is not peculiar to procurement but is consistent across the sectors whose operations involve the use of digital technologies. Employees might be afraid to lose the control over the decision-making process in the context of procurement or be skeptical about the new types of

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technologies. The culture shift, which is needed to overcome such resistance entails the prevalence of a new mindset of being digital-first or the perception that technology is an extension of the human functions and intelligence and not a replacement. The leadership should have a significant role to play in bringing forth this change through creating an environment which will embrace innovation and constant learning. Moreover, the promotion of the advantages of AI in procurement, which include the fact that AI can help limit the time wasted on routine supportive administration works, optimise the supplier selection processes, enhance operational efficiency and so on, can somewhat relieve the reservations and obtain employee buy-in (Jain et al., 2023).

Skills gaps and the Lack of AI Talent The necessity of re-skilling and AI talent shortage

Insufficient talent is another problem of AI implementation in organizations. The application of AI to procurement presupposes a profound knowledge of AI technologies, data analytics, and the possibility of applying such systems in the context of procurement. To benefit well using these technologies, procurement teams should optimize their skills in data science, machine learning, and AI tools management. There is however high demand of talent almost to the limbs of AI expertise thus a shortage is inevitable (Gaikwad, 2024).

These skills deficiency presents a challenge to organizations intending to install AI-driven procurement systems. Although there are various larger organizations that can afford to employ AI professionals or acquire technology services providers, the rest of the organizations especially the SMEs do not have the capacity to employ specialized personnel. The shortage of talent could also cause a read more disaster due to the implementation of all the AI systems poorly, reducing the capabilities of the technology and in worst-case scenarios causing the failures of adopting the AI. Companies desiring to address this issue are required to up-skill their current units via training and advancement programs. The challenges of the skills shortage might be mitigated by collaboration with universities and technology firms and development of AI-focused educational programs to assist those interested in becoming procurement professionals (Dey et al., 2024).

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Staff involvement and Automation resistance

Engaging employees is critical towards resisting automation in procurement. The implementation of AI can be formulated in a way that causes fear in the minds of employees to lose their jobs especially when employees feel that AI can take the place of humans. This fear may present serious challenges to the shift to manual to automated processes. Not every person might welcome this switch to AI, especially in a process like procurement, where human skill and judgement are fundamental in a number of ways. The employees might take it as a threat to their employment and they would feel their skills being put at risk. To mitigate this, the organizations should focus on why AI would serve as an assistant to the human decision-making instead of a substitute. Engaging the employees in planning and implementing the change, providing the reskilling opportunities, and discussing the positive effects of AI, which will include greater efficiency of operations and lower amount of repetitious tasks will contribute to raising the more positive attitude toward the change. Including employees into the AI journey would allow organizations to mitigate anxiety and develop trust that would, eventually, promote the comfortable acceptance of AI technologies (Regona et al., 2024).

2.4.2 Quality of Data and Integration

The quality and availability of data is of high importance when it comes to AI systems in procurement. The problem of data management is one of the greatest limitation to adoption of AI in procurement. One of the challenges experienced by organizations is how to handle large volumes of data that AI is too demanding. The accuracy and effectiveness of AI systems can particularly be undermined by such sub-criteria as incomplete, outdated or inconsistent data. Further, uniting AI with already existing procurement tools and systems that are unlikely to be buffered to handle such massive data or integrate AI presents a technical challenge.

Problems with Data Management Procurement System

AI-driven procurement systems need data in their core, so without good quality, consistent data, the AI models will not be able to operate effectively. A large amount of data commonly gathered by procurement teams can be highly diversified with origins such as supplier performance, product

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specifications, delivery times, market trends, and many others. Nonetheless, such data is frequently dispersed between multiple systems and in various departments and are challenging to observe and utilize effectively (Althabatah et al., 2023).

Moreover, the number of information related to procurement is usually incomplete or unstructured, which makes it hard to provide valuable insights by means of AI-based systems. As an illustration, gaps in the evaluation of the suppliers can manifest as both the qualitative assessment of the procurement teams or the inabilities to measure the indicators in a consistent way; these gaps can easily result in biased and inaccurate data, introduce into AI models. The quality of AI-based insights relies upon the quality of the data it is presented. Therefore, companies should dedicate recourses into data cleaning and standardization to guarantee that the data fed to AI systems is precise, trustworthy, and current. In addition, the policies of data governance ought to be applied to make sure that data quality is upheld within all procurements that are involved (Gaikwad, 2024).

Leveraging available tools and systems in procurement through AI Integration

However, another meaningful challenge is the assembly of AI with established procurement tools and systems. Most organizations have antique procurement systems, which may not have been built to process the bulk of data a given AI implementation may need. The limitations of these systems are that they do not easily fit with AI technology, which introduces technical obstacles to the adoption of AI (Muthuswamy & Ali, 2023). Several things come with integrating AI in these legacy systems; they are very technical and need many resources, which make it expensive and time-consuming.

Further, the procurement departments can be working on various software programs to control various areas of the procurement process, including managing the contracts, tracking supplier performance, and managing inventories. It is rather a complicated and challenging process to integrate AI and these various systems and make sure that the flow of the data and consistency among platforms is achieved. In order to circumvent these issues of integration, companies are advised to invest in updated procurement tools and systems where AI compatibility has been considered. Also, implementing a cloud-based procurement platform, which can support AI

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integration will enable easier data integration and guarantees access to the correct data to the AI tools at all times and throughout a procurement environment (Jain et al., 2023).

Data Governance Matters to Integration of AI.

The other issue that is pertinent in successful adoption of AI in procurement is data governance. Ineffective data governance may result in the adoption of poor-quality data in the AI systems that may influence the results of the procurement processes based on AI. The governance systems will make sure that the data is correct, with the same information and up-to-date, which is essential to enable the AI to make the right decisions. Data governance has been referred to in numerous studies in an attempt to argue its worth in managing more complicated procurement processes involving various stakeholders and involving many systems. In the absence of effective governance, it is a danger that data suffers siloing, inaccessibility, or inconsistencies, whereby it is hard to run AI effectively. It is vital that organizations should come up with a strong data governance policy that focuses more on data integrity, security, and compliance so that the AI systems can operate effectively and provide the anticipated value (Jain et al., 2023).

2.4.3 Ethical Concerns and Bias in AI Models

Although AI promises to provide tangible benefits in the procurement sector there are numerous ethical questions that need to be addressed mostly involving its transparency, fairness and AI bias. With an increased dependence of procurement teams on AI systems during decision-making, one must consider being sure that such systems are ethical and do not contribute to discrimination or apply biases. Two of the most important challenges that organizations will have to deal with when using AI in the area of sustainable procurement are the absence of disclosure in how AI makes decisions and the possible bias in the algorithms.

Transparency, Fairness, and Ethical implication of AI

Transparency in AI systems is one of the urgently needed ethical issues of the AI-adoption. Most AI applications, especially machine learning algorithms, can be referred to as black boxes since they are hard to comprehend the method by which they make certain decisions or predictions. Such a lack of transparency has the potential to limit trust in AI system, especially in critical purchasing cases, supplier selection, contract negotiations, etc. (Flechsig et al., 2022). Procurement personnel need to make sure that the AI systems are transparent enough, and that the process of making

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decisions can be described easily to stakeholders. This is especially significant to theMic organizations which are seeking to attain sustainability and ethical objectives, where decisions arrived at by AI must be responsible and echo these objectives.

Besides transparency, fairness also presents an important ethical issue. AI models have the capability of reflecting the bias existing within the data to which they are trained. To give a concrete example, an AI system trained using historical procurement data where bias was in the decision-making or preferences may reproduce the biases and, as a result, biased suppliers will be selected or contracts awarded will be discriminative. The AI bias may also be expressed along racial, gender, or social-economic lines, affecting the fairness of the procurement process and causing ethical and legal complexities to companies (Ismaeil, 2024). Organizations should therefore conduct fairness audits and constant checks of their AI to understand how they are working to rule out the potential risks of unfairness. Moreover, the procurement teams are encouraged to maintain the trained AI models on a wide array of representative data that captures a myriad of suppliers and market environments.

Make Sure AI Systems Do Not Perpetrate Bias

One consistent theme of organizations implementing AI in procurement is the prevention of reinforcement of bias through AI-related systems. AI may become biased at different points, such as data gathering, model training, and algorithm design. Although the data may be non-biased the initial time, AI models can grow biased with time as they encounter new information and use past patterns to make predictions. This may lead to biased decision making which hurts some suppliers or tilts towards some depending on irrelevant aspects (Ismaeil, 2024).

In an effort to deal with bias, the organizations should formulate interventions that would reduce the influence of bias in the AI systems. A promising strategy is to apply guidelines on diversity and inclusion to the AI training process itself, so that the data is not skewed towards small, large, distant or industry, and thus all suppliers have a stake in the training data. It is also important to test and audit the AI models regularly to ensure that the organization checks and corrects underlying baises before they creep into the procurement decisions. Furthermore, organizations will have to implement enforceable positive ethics on the use of AI, because their purchasing decisions determined by AI will have to comply with ethically questionable purchases and sustainable principles of the organization (Flechsig et al., 2022).

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Mitigating Ethical Issues in AI Adoption

Bias and fairness are not the only ethical issues about AI implementation in procurement. Concerns are rising that AI systems will affect decision-making in a manner not congruent to organizational values and sustainability targets. Since AI is increasingly becoming part of procurement strategies, organizations should develop stiff ethical codes of using AI. This is to ensure that AI systems do not result in the decisions that maximise short-term financial benefit, but not the sustainability or ethics. The procurement teams need to make sure that the implementation of AI is aligned with sustainability goals of the organization, principles of fairness, and ethical practices. Furthermore, discussions regarding the ethical implications of AI should be actively involved by organisations, with stakeholders, such as suppliers, customers, and employees, so that its use could be supported and accountable by a large portion of participants (Flechsig et al., 2022).

The use of AI in the procurement process holds once-in-a-lifetime capabilities to upgrade decision making as well as the efficiency of operations and also contribute to sustainability goals. Nevertheless, a few issues and hindrances to successfully incorporating AI exist, such rather than changing organizational resistance, data quality complications, data integration, and ethical issues of bias and transparency. Addressing all these issues will demand that organizations should strive to ensure digital culture within their structures, invest in employee upskilling, high-quality data handling, and resolve ethical concerns regarding the implementation of AI. Incorporation of these barriers can help organizations to get maximized benefits of AI in procurement thus resulting in more efficient, equitable and sustainable procurement.

2.5 AI and Sustainability in Procurement

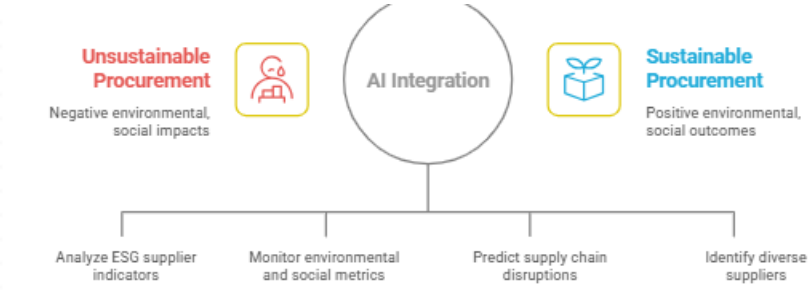


Figure 3 AI Drives Sustainable Procurement

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2.5.1 AI's Role in Achieving ESG Goals

In the field of procurement, AI is a game changer to many other sectors. A stronger orientation towards sustainability can be achieved by organisations as vendors continue to recognize the utility of AI in their procurement stands. By enhancing the decision process, improving efficiency and automating the repetitive processes, AI helps an organization to work towards its sustainability significantly. The current section involves a critical overview of AI in meeting environmental, social, and governance (ESG) goals in procurement. Further, real-life successes in the implementation of AI into the procurement approach, to accomplish sustainability are evidenced through case studies and industry applications.

The ESG objectives and the integration of AI in the procurement processes allowed accomplishing ESG goals by enhancing the efficiency of operation, lessening the environmental impact, and aligning with more ethical practices. The environmental, social and governance (ESG) factors play a significant role nowadays in the decision-making process during the procurement process and organizations level best-effort attempts to ensure that they are taken seriously by their stakeholders and their participation in their sustainability. AI can offer strong methodologies to evaluate and alleviate the environmental and societal repercussions of procurement operations, in addition to making the protocols of governance open and responsible.

ESG Goals on Procurement

The term sustainability in procurement does not apply merely to selecting suppliers on price versus quality; it also applies to social and environmental and governance activities of the suppliers. AI platforms are able to analyze massive streams of data, which can enable the procurement departments to make their supplier evaluations using a large number of ESG indicators. As an example, AI may assess the following parameters of one of the suppliers carbon emissions, waste recycling, fair employment facilities, and participation in community development projects. The insights enable organizations to make procurements decisions which are in line with their sustainability objectives hence working towards the wider environmental and social objectives (McBride et al., 2024).

ESG performance tracking all along the supply chain is also assisted by AI. It can monitor the environmental, e.g. carbon footprint or water consumption, or social metrics, e.g. working

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conditions or local community legacy, and keep the businesses on track with their ESG goals. Besides supplier selection, AI can maximize the procurement choice by viewing the impacts on a particular product of life to ensure that the procured goods are also sustainable in their production, use, and disposal. In such a way, AI reinforces the sustainability of the whole procurement as a way to make sure the current decisions taken today have positive outcomes in terms of ecology and social situation in the future.

There are also strong benefits that AI tools bring to the enhancement of corporate governance in procurement. The transparency, ethical behavior of suppliers, and adequate compliance with the applicable laws and regulations, as well as compliance with company governance levels, can be assessed by means of AI models. Moreover, AI can be used to improve decision-making processes by generating reports about the behavior of suppliers and making sure that the process of procurement in the company is open and accountable. With the growing pressure of achieving businesses ESG jobs, the use of AI serves as the invaluable tool to observe, track, report, and enhance sustainability performance (Modgil et al., 2022).

The role of AI in ESG in procurement can also be enhanced by its capabilities of predicting and preventing the risks in the supply chain. With the help of predictive analytics, AI will be able to predict the problems that may arise in the supply chain, due to environmental complications, labor protests, or any related governance violation. This planning helps companies to be proactive so that they rule out any surprise when they are supposed to achieve their sustainability goals. AI-driven systems can also be trained to change procurement decisions change with the new ESG regulation, enabling businesses to drive compliance with new laws/standards and requirements.

The Role of AI in Corporate Social Responsibility (CSR) and Sustainability

AI is part and parcel of organizations as it enhances corporate social responsibility (CSR) through optimization of procurement to suit the social and environmental tasks. AI helps procurement teams find those suppliers that observe ethical business, work with sustainable materials, and ensure social equity through automation and high-quality data analysis. Such AI tools can examine the adherence to fair trade by suppliers, their code of treatment of employees, as well as the steps they take toward various environmental abuses. The information can enable businesses to position

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their purchasing practices in line with their overall CSR objectives so that it would keep on ensuring that all purchases would be making positive contributions to the creation of a more sustainable, ethical, and socially responsible supply chain.

An example of the contribution of artificial intelligence to CSR is the possibility to make the supply chains of businesses more sustainable using AI. The AI systems will be able to track the product cycle by tracking the raw materials and their acquisition, as well as disposal (end-of-life) of the products and allow the products to be reused or recycled in appropriate situations. To give an example, AI is capable of detecting inefficiency in stock management and product distribution that allows businesses to avoid over- and underproduction that may result in wastage. The capacity of AI to combine real-time data and revise the procurement approaches dependence on that data can significantly make AI useful in those organizations pursuing CSR objectives in a fast-paced market landscape (Modgil et al., 2022).

The other way through which AI contributes towards CSR objectives is by facilitating practices of implementing circular procurement processes. Circular procurement The purchase of goods and services, which take into account the principles of a circular economy, stimulating product reuse, recycling, and remanufacturing. AI systems are capable of staying in line with product cycles, opportunities to fix and refurbish, and the environmental outcome of materials used in the process. Applying AI to the procurement gives companies the possibility to move away with the linear approach of taking/ making/ disposing to a circular one, minimizing waste and saving resources (Bihari Singh et al., 2024).

AI can also be of significant importance in promoting a social aspect of sustainability. Including AI in procurement, companies can increase their supplier diversity to ensure that their procurement policies foster diverse growth. Several ways in which AI systems can aid in promoting diversity of suppliers include identifying diversified suppliers, monitoring supplier diversity performance and suggesting strategies of diverse sourcing that enhance economic equity and can aid in minority-owned businesses. This has addressed the social part of sustainability and has contributed towards meeting the diversity and inclusion objectives of businesses and simultaneously maintaining their supply chains ethical and socially responsible (Modgil et al., 2022).

Further, by mitigating ESG risks through AI the companies can protect their reputation and retain their social license to operate. Monitoring and countering social and environmental risks, the AI-

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based procurement networks keep organizations out of the risks of breaching the CSR demands, such as procurement of the services of companies that abuse child labor or operate in violation of the environmental standards. This is a pro-active strategy that eliminates the chances of a supply chain scandal, and keeps business in favor of the consumers, regulators and the investors.

2.5.2 Case Studies and Industry Applications

Sustainable procurement made possible through AI is beginning to take hold in real life in multiple industries, indicating that AI can be applied very generally in assisting organizations in reaching their sustainability targets. Through these case studies, it is possible to identify the integration of AI into the procurement processes as the means of designing sustainability, optimising operational processes, and advancing responsible sourcing.

The effective AI Applications in Stable Procurements in Different Industries

In production, AI is being applied in order to maximize supply chain activities and minimize the effects it has on the environment. Artificial intelligence systems are implemented to monitor the energy use of production activities and detect their inefficiencies providing the recommendations to improve them. As such, an example is the application of AI-powered analytics platforms to predict demand more accurately that will ensure manufacturers produce based on their need and wastage of material and energy is limited. Such demand forecasting tools that rely on AI are a central component of sustainable procurement since businesses can streamline their production schedule to match the real market demand and minimize overproduction and wastage (Thakur et al., 2023).

Likewise, AI has been used to enable automobile production companies to achieve a circular procurement system as it enables them to utilize a higher quantity of recycled resources to provide consumers with cars. Using AI-based systems, companies examine data available, such as supplier stock, product lifecycle data, and others to find areas where the companies can use recycled materials instead of virgin materials. This minimizes the environmental impact of raw materials extraction and makes sure that there is minimum waste during the process of production. This is why AI also helps to track and manage end-of-life vehicles so that some of their valuable parts could be reclaimed and used in the building of new models creating a circular supply chain (Nozari et al., 2022).

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Use of AI in the food and beverage industry is to minimize food waste and enhance sustainability during procurement. By integrating AI-driven systems, it is possible to use the historical sales data, the weather pattern, and consumer changes to estimate demand more efficiently, which will eliminate overproduction of perishable goods. Moreover, AI is also employed to achieve efficient transportation logistics: the shortest routes that would spend the least possible amount of electric power, and develop the least amount of greenhouse emissions. Through enhancing procurement choices via AI, foodstuff organizations can minimize wasteules, offset their passion effect, and achieve their bounciness goal without the need of draining down on income (Bihari Singh et al., 2024).

Practical Applications of How AI is Making Procurement More Sustainable

AI is creating a sustainable sourcing process in the retail sector as it is assisting companies in finding suitable suppliers that fit a certain ESG set of conditions. Using AI, data concerning supplier practices, such as environmental performance, labor standards, and ethical sourcing certifications are analyzed to determine sustainable suppliers. This is provided via AI tools, e.g., to ensure major retail chains that their supply chains are in line with their environmental and social ambitions, this is done by checking whether their suppliers adhere to sustainability principles. Such data-driven model enables enterprises to have better-informed decisions during the procurement process that does not undermine the sustainable objective in terms of quality and cost (Mattaba & Fatahi Valilai, 2024).

The other example is in the energy sector where AI is assisting organizations to streamline procurement of sustainable energy sources. The environmental performance of the energy suppliers is assessed based on their availability of renewable energy and following sustainability measures with the help of AI-driven systems. The AI is also capable of advising on the best energy suppliers when analyzing energy production data, contemporary businesses can enter a more sustainable office on a more sustainable energy source, and have a smaller carbon footprint. It is especially topical in the industries which are under pressure to fulfill the sustainability requirements and to minimize the impact on the environment (Thakur et al., 2023).

The AI Impacts on Acceleration of Circular Procurement

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In helping with circular procurement in different industries, AI is a major contributor as well. To illustrate, during the electronics market, AI can help handle the lifecycle of their products, including the end of their life disposal. Using the assistance of AI, systems monitor material utilization, recognize refurbishment or recycling possibilities of products, and streamline the recycling process in a way that maximum value worth is possible. Through ensuring that materials and parts are reused, AI allows companies to reduce wastage and consumer products such as electronics affect the environment less. This is of special importance in an industry discharging substantial quantities of electronic waste (Nozari et al., 2022).

The construction industry is also using AI to guide circular buying by assisting in improved handling of wastes. AI systems help track the used construction materials, monitor how they are used on-site, and indicate when there will be a necessity to get new materials according to the requirements of the project. This assists in construction companies to maximize their use of resources, minimizing wastage materials and making any materials reuse or recycle where necessary. With AI incorporated into the processes of making procurements, construction firms can make a difference towards a more sustainable built environment (Bihari Singh et al., 2024).

The Future of AI in Enhancing Supply Chain Transparency

The transparency in supply chains that is vital in sustainable procurement is also being achieved by the use of AI. Blockchain with the help of AI, e.g. can enable companies to trace the product in the whole supply chain, i.e. since extraction of raw materials till the actual delivery of the final product. In such systems, the company can get real-time information about the sources of the product, its impact on the environment, and the conditions of the workers and guarantee that the company can ensure the suppliers are sustainable. This transparency benefits not only the ability of businesses to achieve the so-called ESG goals but also creates trust among consumers and other stakeholders that require business enterprises to practice more ethical and sustainable business operations (Fosso Wamba et al., 2024).

The digitalization of procurement with the help of AI has the impact of transformational efficiency in achieving the sustainable objective. Artificial intelligence is assisting companies to achieve their ESG goals by improving make decisions, allocating their resources efficiently, and focusing on ethical and environmental operations. The examples of the case studies in the industries examine the effectiveness in the real procurement process through the use of AI to increase sustainability,

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decrease waste, and improve efficiency. With the further development of AI, its significance in terms of promoting sustainable procurement will only grow, and this becomes a new possibility that organizations can use to build a more sustainable future. Nevertheless, it would be critical that businesses continue to optimize their AI system so that they are not only delivering the desired results in terms of sustainability but also ensuring they do not violate ethical standards or fail to govern them.

2.6 Frameworks for AI Adoption in Sustainable Procurement



Figure 4 AI adoption frameworks range from theoretical to practical guidance

2.6.1 Conceptual Framework for AI Adoption

Implementation of Artificial Intelligence (AI) in the procurement process is essential in increasing efficiency and sustainability in the operations. However, effective adoption of AI in procurement requires organizations to have specific frameworks which would offer guidance on approaching the adoption process and address the challenges that may arise in the process. This section describes the essential frameworks of AI adoption, such as conceptual frameworks, which refer to models of technology take-up, such as Technology Acceptance Model (TAM) and Risk Management Framework (RMF), and strategic frameworks, which focus on addressing the hindrances to the AI adoption in procurement.

The implementation of AI in procurement has to be strategic. Different theoretical models have also been built to support the adoption process in the organizations like Technology Acceptance

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Model (TAM) and Risk Management Framework (RMF). These frameworks can offer great information on the issues that determine the success of AI adoption and how to meet the drawbacks. Nonetheless, in order to render AI an effective method of sustainable procurement implementation, current frameworks will require adjustments to serve a certain set of requirements to each and every organization and the challenges that may arise during the process of procurement.

Artificial Intelligence Adoption and Technology Acceptance Model (TAM)

Davis formulated the Technology Acceptance Model (TAM) in 1989 and it remains one of the most popular models of choices used to interpret the implications of new technologies. TAM assumes that user acceptance of a technology depends paramountly on two factors; the perceived usefulness of a technology, and the perceived ease of use of a technology. In the scenario of the adoption of AI in procurement, according to the framework, procurement groups and workers will find it more likely to use AI when they feel that it is intuitive to operate and that they will be more efficient in making decisions when they utilize AI. The potential usefulness of AI in the sphere of procurement could be regarded in the context of its capability to automate routine operations, better anticipate the demand and produce supplier selection, and the improved management of supplier relations (Shwedeh, 2024).

Nonetheless, to apply TAM to the adoption of AI in sustainable procurement, some changes have to be made. Although the ease of use and utility-based approach of the model is still valid, it is necessary to add procurement-specific domains, including ethical aspect, sustainability, and compliance. As an illustration, companies must make sure that AI applications support their sustainability agenda not only in terms of efficiency in operations but also environmental, social, and governance (ESG) considerations. This can be done by changing the model to accommodate factors such as environment sustainability, social responsibility, and regulatory alignment amongst other things as factors that will contribute to the acceptance and adoption of am AI tools (Gupta et al., 2024).

AI Adoption and Risk Management Framework (RMF)

The Risk Management Framework (RMF) is the other important framework during AI adoption. RMF provides the systematic way of recognizing, estimating, and reducing the risks contributed

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by the use of AI systems. The RMF assists organizations in dealing with risks in data security, compliance, ethical factors, and operations breakdowns in procurement. With procurement being one of the areas where AI is introduced, risks that are presented by AI pertain to the data privacy, algorithmic bias, and disruption of the supply chain caused by AI-based decision making. RMF plays a pivotal role in perspicacity of such risks as well as the procedural habitat to alleviate them, so that AI technologies are introduced smoother and more responsibly (Vishwakarma et al., 2025).

To discuss the implications involved in sustainable procurement, the RMF has the ability to limit the risks pertaining to the environmental effects, social responsibility and supply chain management. Specifically, AI models applied during supplier selection should not cause biased decisions or reject suppliers due to favoring the environment. The RMF dictates that the AI systems employed during the procurement process engage in routine monitoring and assessment of the systems to determine the possible risks regarding the sustainability of the systems. In addition, RMF helps the organization make sure that the implementation of AI serves their organizational goals instead of being merely self-serving to support corporate social responsibility (CSR) and environmental, social, and governance (ESG) objectives (Hasani et al., 2023). This convergence is of great importance to companies interested in deploying AI without undermining environmental and social responsibilities.

Customizing Available Models to the AI procurement Environment

Inclusion of AI in procurement enables changes in the traditional TAM and RMF to adapt to the peculiarities of the actual procurement processes. With continual expansion of sustainability aspects into procurement, such frameworks should include ESG criteria, environmental performance data and social impact scores. These factors are reflected in the inclusion of the elements so that they not only match the objective of efficient operation of the enterprise but also address sustainability objectives. As an example, organizations could employ adapted TAM models to estimate whether they find AI useful in achieving environmental goals, including the production of fewer carbon emissions or utilization of ethical suppliers (Faklaris, 2022).

Besides, AI adoption frameworks ought to address issues to do with organizational AI readiness, particularly with regard to infrastructure, skills, and resources. Companies will have to consider

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whether they have the departmental systems to support the AIs or whether there is a requirement of new investments on the AIs, training and data management. This implies adjusting the frameworks to comprise the readiness not only on the technological level, but also on the level of culture and organizational preparedness. To allow for a digital transformation, which involves learning about the AI in sustainable practices, reducing fear of change and encourage the upskilling of the personnel, firms should train the procurement staff (Shwedeh, 2024).

2.6.2 Strategic Plan to Face Difficulties

The key to successful integration of AI in procurement is a strategic framework that embodies all former-mentioned issues organizations encounter when implementing AI technologies. Technical constraints, organizational inertia, data integrity, and ethical aspects are some of the challenges that interests such applications are usually concerned with. A strategic plan is inevitable in ensuring that these barriers are eliminated and that adoption of AI in the procurement industry should remain effective and sustainable.

Important Methods of Addressing the Challenges of AI Usage in Procurement

Resistance to change in organizations is one of the major obstacles to the AI adoption in the procurement. The procurement professionals might feel threatened by AI, potentially being unwilling to embrace it due to its apparent lack of real-life benefits. The strategy to address this resistance is to ensure that organizations create a culture of digital culture with emphasis on innovation and continuous learning. This is why leadership must be a key relation in promoting the adoption of AI, convincing people that it could enhance procurement delivery, simplify repetitive work, and comply with sustainability objectives. Effective communication and training initiatives are imperative to make procurement teams realize the ways in which AI can help them improve the work without substituting it (Radhakrishnan et al., 2022).

The second way of overcoming barriers is by assuring availability of sufficient resources especially staffing. Adoption of AI needs a specialization in machine learning, AI data analytics, and management of AI systems. Nevertheless, there remains a considerable skills gap especially within smaller organisations or those who have inadequate access to AI professionals. In order to fill this gap, the companies must invest in upskilling the current workforce by introducing specific training programs and collaborating with academic institutions. Also, it is possible that organizations think

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of joint projects with external technology vendors or recruit AI experts to introduce and operate AI systems within the scope of procurement. This plan may serve to prevent the failure of AI implementation because of technical incompetence (Kumar et al., 2023).

Data Quality and Data Integration Problems

The other relevant issues in implementing AI in procurement are data management and integration. To effectively perform, AI systems demand good quality, consistent data, which is not always present in the purchase data, which is highly disintegrated or unstructured. In order to deal with this predicament, organizations are encouraged to ensure data governance, standardization and quality control. The creation of a centralized platform where all data is stored and the maintenance of the data consistency throughout the procurement systems is needed so that AI would be able to work effectively. Also, companies should consider investing in data cleansing technologies and tools capable of working with big data so that the information data AI models rely on is accurate and up-to-date (Phuoc, 2022).

There should also be no technical impediments to integrating AI in the current procurement tools and systems. Legacy systems might not be fit to support complicated data processing requirements of AI. When this is the situation, then organizations are advised to take a gradual step in using AI whereby smaller pilot projects are gradually introduced to see how AI could be used in very narrow cases of procurement processes e.g. supplier rating or demand prediction. Such pilot projects are capable of assisting an organization in determining any challenges associated with integration as well as training AI systems before they are implemented at a large scale. Also, the process of integration can be facilitated by adopting cloud-based platforms that are intended to serve AI technologies and make the procurement data readily available on a real-time basis, minimizing the striction introduced by the compatibility of systems (Gupta et al., 2024).

AI organizational readiness assessment models

Assessing organizations readiness is one of the main strategies to eliminate barriers to AI adoption in procurement. Organizational readiness deals with assessing the technological mix, human resources and organizational culture of a company to know whether AI adoption is possible. A number of readiness-to-adopt AI models have been proposed, evaluating factors, including

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technology infrastructure, data management, employee expertise and leadership commitment (Modgil et al., 2022).

When it comes to the field of procurement, these models can guide the business to determine where it needs to fix before embracing AI. As an example, companies can be required to procure procurement systems with an AI-compatible sore or train the procurement professionals in the principles of data science and AI. Moreover, the organizational culture should be measured during the readiness assessment since the latter is one of the challenges to AI adoption. The readiness model will be applicable in determining whether there is a necessity to change the culture like the transformation of traditional and manual procurement processes to data-driven and AI-based decision-making processes.

Personal Surveillance and Response of Artificial Intelligence

Lastly, to guarantee that the migration of AI-based procurement practices will continue to be successful, companies are advised to establish a feedback and monitoring system. This involves reviewing how effective the AI systems are after the implementation and what with regards to them can be done to improve and making suitable changes to the AI models. Periodic audit of AI system identify problems that can arise over time like loss of AI accuracy by algorithmic bias, drop in performance or shifts in conditions in a supply chain (Vishwakarma et al., 2025). Also, the procurement teams could be included into the monitoring process, which will assist the organization in obtaining feedback and keeping the AI systems in line with the business purposes and sustainability aims.

There are multiple challenges of applying and implementing AI in procurement following an organizational, technical, and data-related issue which cannot be overlooked in order to achieve successful integration. To ensure they are ready to embrace AI, organizations will have to invest in readiness assessment, up skillings, and data management platforms and in encouraging a digital culture that supports the promise of AI. When overcome these obstacles and adopted the AI strategically, businesses can and will be able to utilize AI to enhance procurement efficiency and enhance sustainability and reach their long-term objectives.

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2.7 Emerging Technologies in Procurement

With the advancement in technologies by organizations, in order to streamline their procurement practices, there are several opportunities available by integrating new upcoming technologies such as Blockchain, Internet of Things (IoT) and Cloud computing. When augmented by Artificial Intelligence (AI) these technologies can play a major role in increasing procurement efficiency, traceability, and sustainability. This section discusses the importance of these technologies in the procurement field, its potentials, and challenges, and its future trends.



Figure 5 Emerging Technologies in Procurement

2.7.1 Blockchain technology

Blockchain has been under the spotlight because of the way it offers secured, transparent and decentral collection of systems. The use of blockchain in procurement may transform the possibility of an organization tracking goods, authenticity in transactions, and assurance of product authenticity. The greatest advantage of blockchain is that it will provide greater transparency and traceability that are critical components to ensure supply chain integrity.

Blockchain in Promoting Transparency and Traceability in Procurement

The most important use of blockchain in procurement is the ability to increase the traceability of product and material in the supply chain. When it comes to procurement activities, the correctness and source of products can be confirmed by many middlemen and this may pose difficult obstacles to confirm. Blockchain addresses this issue by providing an immutable transparent ledger protocol which captures all the moves and exchanges of goods. As an example, unique identifiers could be

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applied to each unit of goods or batch and monitor their movement path between the producer and the final consumer. In doing so, the history of the product becomes visible in real-time so it gets easier to establish the quality, origin, and adherence to the ethical standards of the given product (Neisser, 1967).

In addition to this, blockchain also provides an opportunity to greatly mitigate fraud, dispute, and errors during the procurement. In most traditional procurement systems, there are physical interventions and as such there is greater possibility of being defrauded or mismanaged. Procurement processes are accelerated, errors free and safe as the transactions are done using smart contracts in the blockchain. As an illustration, a supplier can be automatically paid when certain conditions that are predetermined beforehand are fulfilled, which may be providing goods and all transactions are stored on the blockchain to audit them (Faturahman et al., 2021). Such degree of transparency can not only develop trust among procurement partners but also guarantee the adherence of sustainability standards, as organizations are now able to monitor the environmental and ethical impact of the activities of their suppliers.

Secure Procurement with Integration of Blockchain and AI

The combination of blockchain and AI also enhances the procurement procedure in terms of secure and data-based decision-making. Subsequently, even though blockchain has been able to establish safe and transparent transaction mechanisms, AI offers predictive analytics, machine learning, and automated processes to improve the decision-making procedure. To give an example, AI can use the data provided by blockchain transactions to forecast the subsequent disruptions to supply chains, generate more accurate demand predictions and optimise the choice of suppliers. Additionally, AI-based algorithms can notice any deviant procurement transactions or highlight any risks like time lapse, quality inspection, or non-compliance, subsequently making it possible to perform proactive risk administration (Toheeb et al., 2025).

The combination of blockchain and AI is also capable of making the supplier relationship management more effective due to the establishment of trust and better communication. Blockchain makes all transactions transparent and traceable, and AI could assist a procurement team to find the best suppliers according to the performance data, financial condition, and sustainability indicators. It is by the integration of the two technologies that organizations can establish an extremely safe, effective and sustainable procurement environment. The integration

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can potentially optimize the processes of procurement, minimize costs, and enhance the cooperation between all the suppliers along with the preservation of transparency and security in all phases of the supply chain.

2.7.2 IoT (Internet of Things)

Another emerging technology, which is changing procurement, is the Internet of Things (IoT), which promises real-time monitoring, data collection, and automation. Its IoT devices, e.g., sensors and connected machines, allow the organization to gather massive numbers of data on physical properties (e.g., stock level, transport infrastructure, and the state of products). IoT is essential in the field of procurement to enhance efficiency, cut on wastage, and help achieve sustainability-related objectives.

The role of IoT in the efficiency and the sustainability of procurement

IoT devices can provide real-time in-depth visibility into the performance of a supply chain and allow procurement teams to keep a closer check on the inventory levels, the movement of shipments, and streamline the movement of goods. As an example, an IoT sensor inserted into a product or a package may monitor its position, temperature, and condition anywhere in the supply chain. This allows maintaining the optimal conditions of storing and transporting perishable goods or temperature-sensitive items, including pharmaceuticals, which increases the likelihood of them staying intact and unspoiled (Shafiq et al., 2022). IoT helps procurement teams to make more accurate decisions by providing them with real-time data and optimize their delivery schedules and, thus, minimize the number of costs related to inventory management.

Additionally, IoT gives way to sustainability in procurement, where organizations enhance the utilization of resources and minimize waste. As an example, smart warehouses with the use of IoT can set temperature and lighting levels automatically according to the current conditions, consuming only the necessary energy. Likewise, IoT could be exploited to monitor product life cycles and find spots in the reuse potential of materials, which are part of the circular economy. IoT allows organizations to achieve the sustainability objectives and significantly reduce its waste, carbon emissions, and optimize the procurement processes by constantly tracking and assessing the flow of supplies in the chain (Bansal et al., 2022).

IoT in Procurement Security Concerns and Solutions

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Although IoT is effective, it also introduces problematic safety and, especially, concerns to data protection and cybersecurity. Because IoT gathers sensitive information throughout the supply chain, it is a possible target of a cyberattack, jeopardizing the security of the information in an organization and the integrity of the supply chain. As an illustration, cybercriminals may use the flaws in IoT devices to get confidential procurement levels or bring the supply chain to a standstill (Bansal et al., 2022).

Organizations should take adequate measures to overcome such security risks by ensuring strong cybersecurity measures such as encryption, authentication, and the latest software to deal with these issues. To further enhance control, companies are advised to embrace hardened network infrastructure and watchdog systems that identify and support real-time responses to threats that may be detected. To guarantee the integrity and security of the procurement systems, it is crucial that IoT devices safeguarded against cyber threats are used as the number of connected devices employed in the supply chain grows. As well as taking technical measures, there should be training of procurement teams to learn about IoT security risks, and best practices in order to limit weak points in the supply chain further.

2.7.3 AI and cloud computing

Another technology that is essential to aid AI adoption in procurement is cloud computing. Cloud computing can help organizations implement AI-based procurement capabilities through cost-effective, scalable, and flexible infrastructure and not by investing much capital on on-premises infrastructure. The cloud platforms will enable the procurement teams to exploit the AI-based tools and Solution-based applications to enhance optimizing decisions, collaboration, and procurement processes.

The Role of Cloud Computing to Investigate AI-Based Procurement

Cloud computing offers the framework needed to implement AI successfully in the procurement process because it can aid organizations in storing, analyzing, and processing the large quantity of data required. AI algorithms can be applied by the procurement team to consider historical data, make forecasts on demand, evaluate suppliers, and manage the inventory process. Another characteristic of cloud platforms is that they allow integrating AI systems with currently implemented procurement tools, collaborating and sharing data in real-time horizontally and

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vertically (Wulf et al., 2021). Scalability of cloud computing means that organizations can conveniently increase their AI capabilities at the same pace with change in their procurement requirements, without investing in costly hardware purchases and IT resources.

Moreover, cloud computing also facilitates teamwork as today anyone in the world can have access to the shared data and tools through cloud computing. This is of particular significance to global firms, which have their suppliers and operations in different regions. The suppliers collaboration is also facilitated with the help of cloud-based procurement, being able to deliver the supplier a transparent communication channel, the contract, and performance monitoring platform. Using the potential of cloud computing, procurement teams will become more efficient in operations, enhance relations with suppliers, and make better decisions with the help of AI-powered insights (Wulf et al., 2021).

Risks associated with cloud safety and AI assimilation

Although the advantages of cloud computing are many, several issues involved in cloud security and use of AI systems must be put into consideration. Data privacy is one of the main issues since cloud platforms require sharing sensitive procurement information on the external servers. To protect against unauthorized access or exposure of organizational data, the organizations must make sure that their cloud service providers have high security measurements and data protection policies and regulations. Also, the cloud environments should be immune to online attacks that may corrupt AI models or break the procurement efforts (Lakshmi & Tyagi, 2024).

Integration of cloud based AI tools to the current procurement systems may also be difficult. The legacy systems used by most organizations might not support the use of cloud-based AI applications. To overcome these difficulties, companies should thoroughly evaluate the degree of compatibility between their procurement systems and AI-driven tools offered in cloud computing and guarantee an unobstructed data flow between both platforms. A staged process of AI cloud integration may allow organizations to detect possible problems and optimize systems prior to a full-scale process. Moreover, the companies should make sure that the cloud infrastructure they use is scalable, secure, and able to meet computational requirements that AI technologies require.

The combination of other emerging technologies, like blockchain, IoT, and cloud computing with AI leaves vast possibilities of transforming the process of procurement. Blockchain increases

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transparency, traceability, and protection whereas IoT provides better efficiency and maintenance. AI can support procurement by controlling the procurement process, data management, and decision-making, as it can be done through cloud computing, which offers scalable infrastructure, supports collaboration, and decision-making. There are, however, various challenges posed by the technologies such as: security vulnerabilities, compatibility concerns, and their management. Organizations should solve these issues through careful planning, safe execution, and monitoring in order to utilize the opportunities that these technologies offer to their full extent. This way they would be able to streamline their procurement operations, leverage sustainability, and have a greater chance of attaining their business goals.

2.8 Theoretical Framework

The implementation of Artificial Intelligence (AI) technologies used in procurement and mainly in the management of sustainable supply chains involves implementation of strong theoretical frameworks. These models facilitate the challenges of AI adaptation in an organization to demonstrate a systematic comprehension of the critical variables that determine AI adoption and utilization. In this section we are going to scrutinise three theories commonly known Risk Management Framework (RMF), Technology Acceptance Model (TAM) and Diffusion of Innovation Theory (DOI) that gives vibrant insights concerning adoption and implementation of AI in procurement systems. The frameworks provide ample advice on risk assessment, user acceptance, and the wider diffusion process, which guarantees the successful introduction and use of AI technologies towards the long-term sustainability objectives in procurement.

2.8.1 Risk Management Framework (RMF)

Risk Management Framework (RMF) refers to a holistic risk management tool that is used in handling risks that may be posed by deployment of technologies; e.g. on complex systems like AI-based procurement. To handle risks that are generated by AI systems, such as data security, privacy concerns, and ethical ramifications, RMF serves as an organized technique to address the risks. The framework gives organizations the instruments to evaluate and overcome not only the risks that become apparent during AI adoption, but also ones that might be realized in the planning, creation and, lastly, deployment and tracking of the adoption. The use of the RMF allows the procurement department to be cautionary and observant of the risks that may potentially play down the efficiency or moral uprightness of AI systems.

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Integration of AI in procurement has many risks associated with the quality of data, system performance and cybersecurity. RMF assists organizations to calculate such risks in a systematic manner such that the procurement managers take a proactive approach in approaching the intricacies of AI integration. Considering an example, RMF can facilitate locating the risks of algorithmic bias, exposure to sensitive supplier data, or vulnerability to cyber-attacks of AI models. Such risks may affect the integrity of the procurement activities, especially those encountered in global supply chains that highly depend on real-time information maintained by different sources. Using RMF, organizations will be able to know the risks potentially involved in the early stage of AI adoption, create mitigation plans and can guarantee the deployment of AI technologies in a safe way.

Additionally, RMF makes sure that AI\s applied to procurement are constantly tracked with regards to performance and compliance. Artificial intelligence is not set in stone and needs to be continuously adjusted to the current market and internal supply chain factors, as well as ethical values. The RMF promotes a constant assessment of risks and support organizations in identifying risks in advance and taking corresponding actions. Such a dynamic solution can reduce long-term risks that could appear in the course of introducing AI technologies, and thus make the procurement operations flexible and resilient in the context of the technological shift (Lee, 2021).

RMF gives an organization a familiar way of identifying, assessing, and handling risks involved in the adoption of AI. Risk management with regard to the context of procurement entails evaluating how decisions made using AI will affect procurement decision-making processes like supplier selection, supply demand modeling, and contract administration. Framework promotes the organization to carry out a proper risk assessment to determine the probability and the magnitude of the risks. This aids organizations to prioritize the risks and enable them to allocate resources and curb risks effectively. RMF also points out the significance of creating robust governance frameworks that are very important in making AI systems to be in compliance with ethical requirements and those that must be in accordance to the regulations.

Besides, RMF assists organizations to evaluate the risks of outside forces (including geopolitical instability, natural disasters, or economic fluctuations) against the supply chains. These assessments can be useful in taking advantage of AI systems in procurement by integrating

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external risk data into the process enabling the organizations to detect potential disruptions and therefore, preempt them by taking measures to reduce the impact of the disruptions. Owing to this fact, RMF offers a more wholesome risk management strategy that extends beyond the direct application of AI technologies, paving the proper ground and knowledge of organizations in the face of a broad spectrum of possible disruptions (Kure et al., 2022).

2.8.2 Technology Acceptance Model (TAM)

Technology Acceptance Model (TAM) is one of the most popular frameworks that are used to comprehend the acceptance and adoption approach of new technologies by users. TAM in the AI procuring field, plays an essential role in the comprehension of how the procurement personnel think about the value and usability of AI, as well as, the determinants of its adoption. TAM rests on two major elements, perceived usefulness (PU) and perceived ease of use (PEOU). These aspects are vital in achieving the acceptability and successful adoption of AI systems in procurement where it is important to ensure that procurement professionals view AI technologies as useful and easy to use so that they accept it.

TAM offers interesting insights on the constraints and motivators to AI adoption in procurement. Perceived usefulness indicates the extent to which procurement professionals think that the AI systems would enhance their performance in work, whereas perceived ease of use describes the non-complexity and simplicity of the AI system in operation. To be perceived as useful by the procurement professionals, AI technologies should bring demonstrable value in terms of enhancing efficiency, cutting of operational expenses, or serving as a better decision-making process. When teams with procurement believe that AI can help them deliver these benefits, then they are more willing to use the technology.

Nevertheless, the ease of use can also play a large part in preventing the adoption of AI. The AI tools might first be perceived as complicated or hard to learn by most procurement professionals, especially those who have no experience in the concept of data analytics or machine learning. In order to crossing this barrier, it is paramount to organizations in that AI systems be made user friendly. To make the procurement teams get used to AI technologies and incorporate them in their everyday practice, thorough training programs and an approachable interface should be provided.

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According to TAM, where AI systems are viewed to be usable with ease of handling and in harmony with the procurement aspirations, the rate of adoption will rise considerably (Davis, 1986).

Perceived usefulness as well as easy to use is of primary importance when it comes to adopting AI technology in the process of procurement. Studies have found that both of the factors play an important role in determining the probability of adoption with the perceived usefulness usually exerting a greater influence. The disappointment of being helpless in situations, however, will also result in a greater willingness of procurement professionals to use AI systems, especially when they think that AI will assist them attain strategic objectives, including reducing costs, improving performance of suppliers, as well as forecasting. Nevertheless, the ease of use is also an important factor. In case a complex technical knowledge is needed and AI systems become hard to go around, the rate of adoption can be lower.

To promote the integration of AI into procurement, organizations should pay attention to the improvement of the perceived usefulness and ease of integrating AI systems. This may be implemented by showing the practical advantages of AI using pilot projects, by providing effective documentation and training materials, and making systems simple to use and able to be easily customized to current procurement operations. Also, early involvement of procurement teams in the adoption process and inclusion in some decision-making processes may increase their attitude towards the perceived usefulness of the technology and prompt more acceptable usage (Fakir, 2024).

2.8.3. Diffusion of Innovation Theory (DOI)

Diffusion of Innovation (DOI) theory, as constructed by Rogers (1962), lends a framework to arriving at an understanding of the breakthrough effect of the spread of new technologies inside an organization or society. The theory presents the mechanism through which an innovation achieves acceptance amongst various types of adopters; innovators, early adopters, early majority, late majority, and laggards. DOI is especially applicable to the practice of AI in the sphere of

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procurement, as it aids organizations in recognizing the conceivable factors that affect the rate at which the AI technologies are used and applied in the sphere of procurement.

DOI assists companies to understand what defines the nature of AI technologies that affect adoption. Rogers argues that perceived relative advantage, compatibility, complexity, trialability and observability of an innovation influence the rate of acceptance. The perceived relative advantage, in the case of AI in procurement is the good that will be created by the use of the technologies of AI over the current practices of procurement. As an example, the automation of the routine work, high-performance data analysis, and predictive capabilities presented by AI can notably outperform conventional manual approaches. Compatibility is the degree at which AI matches with current procurement practice and organizational values. When AI tools work well with existing systems and workflows, then they will be adopted more readily.

The trialability and complexity are also some of the major considerations in adopting AI within procurement. The more complicated AI system is imagined, the more it will slow in absorption. Conversely, when procurement teams are allowed to test AI systems in a safe environment, then they are more inclined to implement it. Observability: This is the degree at which the organizational benefits of implementing AI are perceived by others in the organization. Effective application of AI can motivate other procurement teams to do the same and the diffusion process would get faster (Rogers, 1962).

Notwithstanding the benefits, the procurement of AI technologies has a number of difficulties. AI systems, especially when combined with other sophisticated technologies, such as blockchain, can be rather complicated and resource-intensive in terms of expertise. AI implementation can prove difficult with current procurement systems, especially those organizations still using systems that date back to the past. Moreover, procurement specialists might not be willing to use complex technologies because they are afraid of losing their jobs or they do not trust AI models. DOI offers a helpful framework to consider such challenges and potential strategies that can reduce and overcome them, including the simplification of AI systems, training, as well as the compatibility of AI tools with the current procurement procedures (Hasani et al., 2023).

Organizations have to overcome the issues that have been described by DOI to make the use of the AI technologies in the procurement process easier. A very good approach is finding and reaching early adopters in the organization. Such people or groups will adopt AI with greater ease

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and may become facilitators to the overall adoption. Organizations may also concentrate on minimizing the perceived complexity of AI technology by using intuitive UI (user interface), engaging in practical training, and showing the advantages of AI using pilots. Through the insights in DOI, organizations will be able to develop AI adoption strategies accordingly, in such a way that consideration of the needs and readiness of the various categories of adopters makes particular AI adoption strategies successful with the least level of friction in integration AI in the procurement process (Hasani et al., 2023).

2.9. Hypotheses

H1: AI-driven decision-making has a positive impact on sustainable procurement performance.

H2: Robotic Process Automation (RPA) significantly improves sustainable procurement performance.

H3: High data quality in procurement systems positively influences sustainable procurement performance.

H4: Organizational readiness is positively associated with sustainable procurement performance.

H5: Ethical implementation of AI contributes positively to sustainable procurement performance.

H6: Technology integration capability has a significant positive effect on sustainable procurement performance.

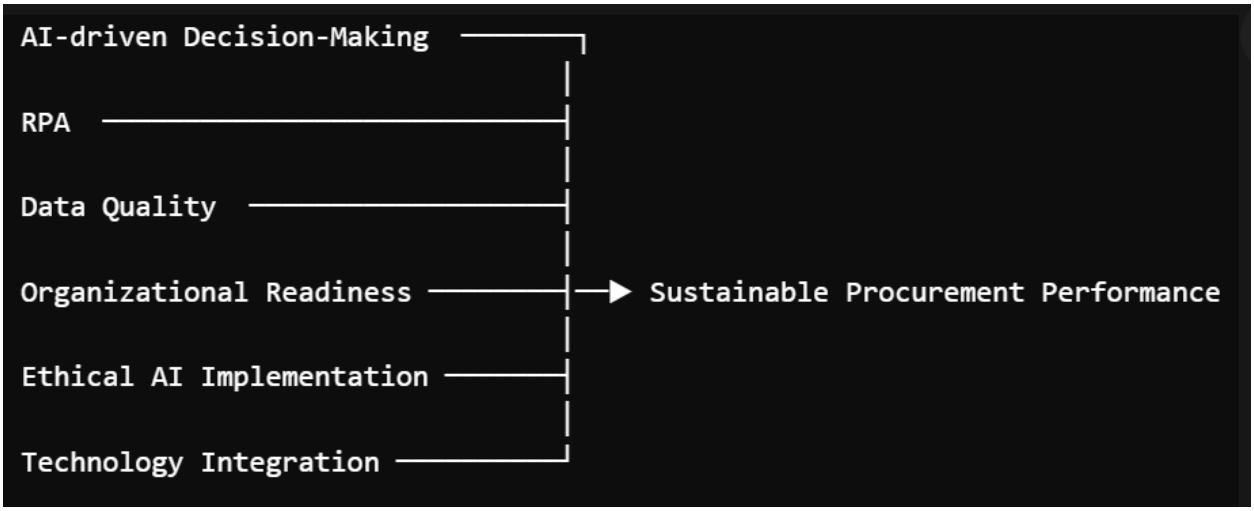


Figure 1 Conceptual Framework

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2.9 Summary

Conclusively, the implementation of AI technologies during procurement has its positive and negative sides to organisations. The Risk Management Framework (RMF), Technology Acceptance Model (TAM), and Diffusion of Innovation (DOI) are theoretical frameworks that will help understand the primary aspects affecting AI adoption and allow us to use realistic strategies to address them. RMF assists in managing risks involved in the integration of AI, maintaining effective procurement systems and their security. TAM emphasizes the role of the user acceptance and provides a set of recommendations in terms of enhancing the perceived usefulness and ease of use as the decisive features of adoption success. DOI offers a wider insight into the diffusion process, so organizations learn how the AI technologies are diffused among the procurement teams and across the organization.

In order to achieve the potential of AI in procurement, organizations should invest in holistic frameworks and plans that consider both the technical, organizational and social environments of adopting AI. Such frameworks are not only supposed to target the technology itself but also the development of a culture of innovation and preparedness in the organization. The future of AI in procurement should be further studied with attention to the field of sustainability in the supply chain. The research will be crucial in the improvement of the current models, mitigation of obstacles to adoption, and a guarantee that AI technologies are executed in line with organizational objectives and ethical integration. With gaps in this research filled, organizations will be able to maximize the value of AI in procurement to enable more efficient, robust, resilient, and sustainable procurement practices.

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Chapter 3: Methodology of research

3.1 Philosophy of research

Research philosophy sets out the principles and assumptions under which the study of phenomena is understood, the way knowledge is formulated, interpreted, and utilised. Research philosophy (Thomas, 2021) refers to the questions of the essence of reality, knowledge, and human understanding, focusing on epistemological, ontological, and axiological issues. The philosophy of research lays the foundation for how the research should be conducted, in terms of determining the approach, procedures, and methods to be employed in conducting a research that provides the researchers with a clear and consistent view on how they should perceive and approach their research topic.

The schools of thought involved in research philosophy include the school of pragmatism, positivism, interpretivism, and realism (Snyder, 2019). Such philosophical perspectives not only provide a basis for comprehending the research problem but also inform the objectives of the methods and data collection processes of the research.

3.1.1 Pragmatism Philosophy

Pragmatism, as a philosophy of research, places a great emphasis on the practical consequences and applications in real-life contexts, and therefore seeks solutions to real-world practical problems that yield valuable outcomes (Snyder, 2019). According to this point, effectiveness of ideas in solving problems is the issue that determines the truth and the research process enables the flexibility of methodology. This philosophical orientation recommends the use of a mix of quantitative and qualitative approaches, as evidenced in research exploring organisational preparedness to adopt AI. The concept of pragmatism postulates that its approach does not necessarily dictate adherence to a specific strategy or approach; yet, it is assumed that there are different mindsets worth exploring and trying, as Thomas (2021) suggests.

3.1.2 Philosophy of positivism

Positivism on the other hand insists on objective reality and the use of empirical observation. It claims that valid knowledge consists of measures which are only observable and measurable (Snyder, 2019). Considering an example of AI adoption research, a positivist philosophy can be adopted to address the hypotheses, quantitatively assess organisational preparedness using a

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survey, and systematically analyse the data to draw conclusions that are generalizable. Positivism aligns with the purpose of the proposed research, based on an objective analysis of preparedness and AI-related issues in procurement. According to this perspective, there is a strong focus on hypothesis testing and empirical data.

3.1.3 Interpretivism Philosophy

Interpretivism is concerned with the meanings and interpretations that individuals assign to their experiences (Thomas, 2021). An interpretivist approach to understanding sustainable procurement and AI could enable the researcher to examine how organisational leaders and employees perceive the implementation of AI in procurement activities. Such philosophy acknowledges that human behaviour and social situations are multifaceted, and therefore, qualitative methods (such as interviews and case studies) are necessary to capture the intricacies of organisational preparedness and the difficulties faced.

3.1.4 Realism Philosophy

Realism consists of the best of both worlds positivism and interpretivism, as it simultaneously assumes the presence of reality that does not depend on human perception, but it also takes into consideration social contexts and experiences (Snyder, 2019). Realists researchers are of the view that, in order to interpret the intricacies of human and organisational behaviour, both objective and subjective aspects have to be taken into consideration. Based on the study findings, as a study result, realism would contribute towards an understanding of AI adoption in sustainable procurement through reflection of the fact that the said technological changes are to be analysed in the context of practical and organisational settings, which will differ industry- and culture-wise.

The positivist research philosophy is best applicable in this study as it can focus on sustainable procurement and hence study the adoption of AI. This school of thought allows the use of empirical practices or surveys and data analyses to determine the organisational preparedness levels and identify challenges in the adoption process. The issue of positivism in terms of objective measurement is the same as the process of measuring the variables like the data quality, organisational culture, and the level of AI integration readiness. The approach will also allow the researcher to make conclusions that can be used in both organisations and industry giving a wide picture regarding factors that influence the adoption of AI in procurement.

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3.2 Research approach

Research method involves how a researcher is going to tackle the problem, analyze the data and come up with conclusions. It describes the overall research design and the procedures employed to obtain, analyse and interpret data. Zawacki-Richter et al. (2020) allege that an evident research methodology is needed to communicate the powerful data collection and analysis, and the study is to dig deep into the research questions and answer them appropriately. Ryder et al. (2020) also indicate that a good research approach assists the researcher in planning the structure of the study, drawing notations about the practices, and interconnected critically with empirical and theoretical evidence. In this section, we shall compare the three broad methods used in relation to inductive, deductive, and abductive approaches and we are going to argue as to why we thought that the most suitable approach was used in this kind of research.

3.2.1 Inductive approach

The inductive method is mainly aimed at building of the new theories on the observed facts. In particular, inductive approach, which according to Zawacki-Richter et al. (2020), can also be used by a researcher to examine a phenomenon by collecting data, identify patterns, and formulate some hypothesis about it. It has been specially helpful in investigations where the researcher is trying to determine underlying patterns or behaviours where there is no defined theories. According to Ryder et al. (2020), inductive research is conducted in an open and nonexpansive way, since it allows a researcher to examine a complex phenomenon and formulate a theory based on empirical evidence. The approach is normal to qualitative researches where modes like interviews, content analysis and case studies are utilized to investigate new notions.

3.2.2 Deductive Approach

In contrast to the inductive method, the deductive method works vice versa: the researcher has a pre-written theory or hypothesis and has to test it on the basis of the information received. According to Ryder et al. (2020), deductive research is more systematic since it seeks to confirm or deny an established ground of theory. In the same process, the researchers begin the process with a developed theoretical framework and collect information to ascertain the truth of the theory. This is also a very structured formula, it allows one to test hypotheses and statistical tests. The deductive approach will best serve when the researcher wishes to prove theories in form of

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hypothesis. In this event, the research findings would be general and acceptable to other bodies of knowledge.

3.2.3 Abductive approach

Abductive method is a combination of both inductive and deductive methods. Zawacki-Richter et al. (2020) argue that abduction starts with an incomplete set of observations, after which the subject attempts to create the most appealing explanation of the same. As compared to deductive reasoning, which deals with development of concepts and their subsequent applicability to the information in the future, abductive (or inductive) reasoning allows the researchers to make iterative movements between the highly repetitive processes of idea generating and hypothesis testing in line with the data. It particularly helps in the case of complex or poorly understood phenomena because it grants a certain degree of flexibility when the theories can be modified as more data is accrued (Ryder et al., 2020). As far as the study of the issue of the utilisation of AI in the sustainable procurement process is concerned, the abductive approach will allow the researcher to progressively narrow down the presented framework as he learns more and gets a better understanding of what the nature of the relations among technological use, organisational readiness and organisational objectives concerning sustainability are.

3.2.4. Rationale to Research Method

Due to the nature of the research, the deductive approach is the most appropriate method to the research on AI adoption in sustainable procurement. The plan has consistency to make sure that previously based theories concerning the use of AI in enhancing procurement decision making, supplier performance evaluation, and realization of sustainability objectives are put into trial. This study will apply a deductive approach, where well-known model scenarios, including the Technology Acceptance Model (TAM) and the Risk Management Framework (RMF), will be used to analyse their suitability in the use of AI in sustainable procurement. The deductive method helps in the research to validate theoretical constructs that would serve in building a general picture of applying AI in the procurement process.

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3.3 Research strategy

The research plan is a general outline that provides a picture of how the research will collect, process, and analyse data during the course of the study. As demonstrated by the study conducted by Babii (2020), a coherent research plan will facilitate the smooth progression of the research, as the theoretical hypothesis will be aligned with the empirical findings. As Dodds and Hess (2020) note, it is essential to adapt research ideas to meet the evolving research environment, particularly in the wake of shocks such as the COVID-19 pandemic, which has necessitated greater flexibility in data collection and innovative approaches to data analysis. The selection of the research strategy in use should correspond with the research philosophy and the questions under study, as it defines the outline of the study and how outcomes will be generated. At the same time, Mtisi (2022) also finds that a specific research strategy contributes to consistency and coherence within the study, enabling data collection activities to be focused on the study's goals.

Following the proposed philosophy and methodology of the research, the strategy selection must balance the theoretical conclusions of the literature with the practical application of design theories, through the examination of suitable methods to verify existing theories or to examine new ones. There are three general research design strategies: quantitative, qualitative, and mixed-methods, and each has unique benefits, based on the study's objectives (Lavarda & Bellucci, 2022).

3.3.1 Quantitative approach

Discussing quantitative research strategies developed by Babii (2020), its primary focus is on testing hypotheses, identifying patterns, and examining relationships between variables using numerical data sources for collection and investigation. It is very well-organised and operates within the framework of surveys, experiments, and statistical analysis to bring impersonal, repeatable results that can be applied to a broader group of people (Mottron et al., 2021). The quantitative approach is most suitable when a researcher needs to measure variables and test relationships in a way that is reliable, consistent, and generalizable. Quantitative methods will be employed to measure the impact of AI on sustainable procurement practices in this study, as well as to assess organisational readiness regarding the adoption of AI and identify potential barriers to implementing AI in the current context. Such a method will provide statistical evidence of the influence of various factors on AI adoption, and, as a result, can be used to formulate hypotheses and derive objective conclusions based on large datasets of information.

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3.3.2 Qualitative Strategy

The qualitative approach, in turn, focuses on the development of contexts and interpretations of the studied phenomena. Dodds and Hess (2020) report that qualitative methods are essential in obtaining profound and subtextual data that mirrors humanity experiences and behaviors. Interviews, focus groups, and case studies techniques are used to gather non-numerical data that can provide in-depth information regarding the perception and incorporation of AI technologies in sustainable productions practices. With an emphasis on the depth of personal insights and corporate relationships, qualitative research will contribute to uncovering the inherent motivations, issues, and opportunities surrounding the process of AI implementation. The strategy is particularly applicable in grasping the human and organizational aspects that govern AI integration, which cannot be fully expressed using quantitative data (Mottron et al., 2021).

3.3.3 Mixed-Method framework

The mixed-methods approach combines the power of the opposing research methods enabling better insight into the research problem. Babii (2020) suggests that mixed-methods research is based on the concept of integrating the accuracy and objectivity of quantitative evidence and the context needed that qualitative knowledge offers. This method enables researchers to confirm the results, compare the information, and examine various aspects of a phenomenon from multiple perspectives. This strategy enables the combination of statistical data and qualitative understandings of how organisations behave, offering a more comprehensive picture of what influences the implementation of AI in procurement and how it changes procurement practices. The mixed-methods approach helps to generate more layers of interpretation and makes the entire study extremely valid due to the inclusion of both types of data (Dodds & Hess, 2020).

3.3.4 Rationale of Research Strategy

The research utilized the purposive sampling technique, which is suitable in terms of studies that focus on professionals possessing certain knowledge in AI-supported procurement. They were recruited using professional networks such as LinkedIn, procurement conferences and industry-specific forums. This strategy was used to make sure that the respondents had first-hand experience with AI technologies in the procurement environment, which is a precondition to giving legitimate

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answers to the survey tool. Although probability sampling is more generalizable, purposive sampling is appropriate in situations when the study needs to reach to a specialized population that has specific knowledge and experience (Pandey and Pandey, 2021). The chosen 100 respondents is larger than the usual minimum needed to perform the regression analysis with a combination of six predictors (usually, 15-20 cases are needed per predictor, or N 90 in this case).

3.4 Procedure of Data Collection

Data collection is one of the most important steps in answering research questions and generating credible evidence that can either validate or refute a research hypothesis. Dzwigol (2022) explains that data collection involves selecting suitable methods to obtain accurate and relevant information. Research objectives determine the type of data collection methodology used and the phenomena under study, as well as the resources. According to Mahuika and Mahuika (2020), the reliability and validity of the data collected during the study take precedence in the collection process because they determine the credibility and trustworthiness of the data generated by the study.

In this study, quantitative approach will be used in data collection. The implementation of the present method will involve searching for data with the help of a 5-point Likert-scale questionnaire, which will be used to explain the issues of organisational preparedness and the problems related to the challenges of AI adoption in support of sustainable procurement. The survey will enable the collection of responses in a systematic and standardised manner, which will be analysed statistically to determine relationships and trends among variables.

3.4.1 Major Type of Data Collection

The primary data collection channel used in the research will be the distribution of a 5-point Likert scale questionnaire online to participants who can directly participate in the procurement processes and specifically in making decisions regarding the adoption of AI. Industries involved in the option of sampling participants include manufacturing, retail, healthcare, and energy, as they are among the most active in their bid to utilise AI to enhance their procurements. The survey will be based on Likert-scale items, with answers to the questions on the organisation's readiness, barriers to AI, and integrating AI into sustainable procurement ranging from Strongly Disagree to Agree Strongly.

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Such an approach to collecting primary data using the survey method will facilitate a targeted process of obtaining specific information related to research questions, as direct personal feedback can be obtained through the participation of professionals directly engaged in implementing AI in procurement (Delios et al., 2023). Through a structured questionnaire, the data obtained would be similar and cannot be used as a basis of statistical analysis. This would be a cost-saving strategy, as extensive data would be gathered over a short period. The 5-point Likert scale introduces a standard method for measuring attitudes and perceptions of AI adoption in procurement, allowing for comparisons between respondents and identifying dominant trends and patterns.

3.4.2. Secondary source of Data Collection

Though the research is going to primarily use a primary data collection technique (the survey), secondary data would be included as well, to give the context to the study and to supplement the primary data. Academic journals, industry report, and case studies constitute secondary sources which illuminate how AI is being utilised in procurement, its challenges and benefits to organisations implementing AI to support sustainability challenges (Dzwigol, 2022; Delios et al., 2023). These sources will be referenced to put the results of the study into its context in broader literature, so that the study is not done without drawing on up-to-date the general knowledge of the topic.

Secondary data will particularly be useful in making sure that the primary data collection results are comparable and able to be benchmarked against. Available literature and reports will also give clues about the overall trend regarding the application of artificial intelligence in the domain of sustainable procurement, especially data regarding the organisational readiness to implement sentences in this field, barriers to application, and the ways artificial intelligence technologies should be used in procurement processes (Mahuika & Mahuika, 2020).

3.4.3 Principles of Data Collection and its Source

The survey will take place via internet-based polling software such as Qualtrics or Google Forms, both of which are safe systems and have simple distribution and data analysis mechanisms. The platforms offer an automated, smooth and well organised data collection process with options of data storage and analysis. It will make gathering data easy and that the answers gathered by the survey questions are close-ended and will be stated in a Likert scale which will provide a chance attempt at a relatively easy quantitative analysis.

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The survey is also distributed online implying that the study could cover a huge number of respondents in a variety of locations and, therefore, it could be easier to generalise study results. It also reduces the potential bias in data collection in that both participants have an equal opportunity to report anonymously, favoring the truth and exhausting the social desirability bias (Delios et al., 2023).

3.4.4 Ethical Consideration

Data collection is a consideration of ethical value in staging integrity of a research, and observing the rights of the participants. Within the framework of the present paper, the ethical considerations in the study will be aligned with those mentioned by Delios et al. (2023), and the participants will be informed about the purpose of the research in advance, will have the right to be anonymous, and their decision to participate in the research will not be binding. Informed consent will be used to acquire all the participants and they will also exit the survey process and not face any penalty.

In addition, the participants will be made aware of the fact that the information that will be collected is going to be treated with due diligence level of confidentiality and that no identifiers are going to be revealed or included in the analysis as the study will be based on the laws regarding the privacy of participants and data security (Mahuika & Mahuika, 2020). The study will use these morals of ethics to ensure a high level of research integrity and the integrity of the data that is accumulated.

3.5 Instruments of Data Collection

Data collection instruments can be defined as tools or methods of collecting data in studies. Such tools will aid in retrieving relevant and reliable information, enabling proper analysis to address the research questions effectively. According to Budianto (2020), the selection of a data collection instrument must be based on the purpose of the research and the study's characteristics. The questionnaire will be a 5-point Likert scale assessing organisational readiness, AI adoption barriers, and sustainability in procurement practices, which will be used as the primary data collection instrument in this study. With the help of this tool, it is possible to collect quantitative data from a sample size of 100 participants involved in procurement processes, such as decision-makers and AI integration experts.

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3.5.1 Observation

Although there is no indication of an observational form of data collection in this study, it is necessary to note that in a specific form of research, observation may become an asset. Unlike experimental studies, in observational studies, researchers do not intervene and instead record participants in their natural setting, where their behaviour occurs (Greening, 2019). Nevertheless, in this case, it is sought to obtain the material on organisational preparedness and AI adoption in a structured and quantifiable form through the use of a survey instrument.

3.5.2 Interviews

The other widely used method of data collection is interviews, through which a researcher communicates directly with the research subject (Cheron et al., 2022). Although the interview could offer valuable insights into the personal experience and perception of individual responses, interviews will not be used as a data collection method in this study. Rather, it will only deal with a structured survey with use of 5-point Likert scale questionnaire to guarantee consistency and reliability in the responses of the entire sample group of respondents. The structured survey method will suit a study well, because the information collected under this method can be analysed in quantitative terms.

3.5.3 Survey

The present study will rely on a 5-point Likert scale questionnaire as the primary data collection tool given its effective track record of use as a tool of quantifying attitudes, perceptions, and behaviours in quantitative research (Chauhan et al., 2023). The questionnaire will be in the form of closed ended questions that will allow the respondent to show his level of agreement or disagreement on the basis of strong disagree, disagree, agree and strongly agree. In this survey, some of the key issues that will be addressed will include:

There will be a 5-point Likert scale that will facilitate the effective quantification of the responses in the research and ease the patterns, trends, and correlations in the data. In the proposed research, the Likert scale is the most suitable method since it provides a valid and reliable way of measuring subjective perceptions with consistency in measures against the respondent population. Furthermore, the Likert scale can be applied to assess the intensity of the attitudes that the

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participants hold in order to obtain the right information about the factors affecting the adoption of Artificial Intelligence to sustainable procurement.

The survey will be administered to a randomly selected population of 100 persons participating in the procurement process in different industries where caution will have been taken to see to it that the sample is capable of constituting a representative case of enterprises that are either considering or already implemented the use of AI in the procurement process. The evaluation of the survey will also be performed through online survey platforms, i.e., Qualtrics or Google Forms, considering a secure and comfortable format to do it based on the possibility of convenient and time-independent management of the survey as a participant thereof.

3.5.4 Validation and Reliability of Survey

To ensure the legitimacy and predictability of the survey instrument, every question will be based on established principles and prior research concerning organisational preparedness for the implementation of AI, AI challenges, and sustainable procurement (Budianto, 2020). Conducting the survey will entail testing it among a small number of the target population to establish that the survey questions are clear, relevant, and understandable. According to the responses on the pre-test, some changes will be made to ensure the instrument is more understandable and powerful.

Cronbach's alpha will be used to determine the reliability of the survey, as it is essential to ensure that the instrument accurately measures the intended constructs. Through these stringent validation and reliability tests, the research project would ensure the acquisition of quality data that provides an accurate reflection of the participants' attitudes and perceptions towards AI adoption and its effects on sustainable procurement.

The pilot test was conducted with 15 respondents representing the target population. Reliability analysis using Cronbach's alpha yielded the following coefficients for each construct:

Construct	Number of Items	Cronbach's Alpha
AI-Driven Decision-Making	3	0.852
Robotic Process Automation	3	0.878
High Data Quality	3	0.891

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Organizational Readiness	3	0.864
Ethical Implementation of AI	3	0.902
Technology Integration Capability	3	0.895
Sustainable Procurement Performance	3	0.876

All Cronbach's alpha values exceed the acceptable threshold of 0.70 (Nunnally, 1978), with values above 0.85 indicating good to excellent internal consistency. The pilot test also revealed minor ambiguities in question wording for items 10 and 15, which were revised for clarity before full distribution. No items were removed as all demonstrated item-total correlations above 0.50

3.6 Population and sample size

Research population is the summation of all of the elements or rather subjects where research will have been carried out. As Zhou et al. (2022) note, it can refer to a variety of entities since it can include individuals, organisations, countries, or particular events. The target audience of this research includes those working in fields related to the topics of this paper, namely, procurement and AI integration, including procurement managers, IT managers, supply chain analysts, and technology specialists in the manufacturing, healthcare, retail, and energy industries that can be characterized as active participants in the sphere of inefficient AI integration with regard to sustainable procurement.

The data in the whole population may not be possible, but a target population will be sampled and 100 respondents will be picked. This is rather acceptable as far as the level of statistical reliability and the achievement of sufficient analytical power is concerned. It will give a clear and complete image of the administration that contributes to the necessity of implementing AI and its utilization in the improvement of sustainability of procurement procedures presented by the sample. It has been observed by Mishra and Alok (2022) that well-defined samples may have something to state when it comes to a bigger group and have accountable data.

A sample population of 100 has been selected as a compromise between these two issues of statistical significance on one hand and, on the other, the practical possibility of collecting data.

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The given sample size will allow the invocation of inferential statistics in order to research the connection between organisational preparedness and the impediments of integrating AI, and the influence stability has on procurement. The choice of the industry sample will take into consideration the wide range of industries, and the findings will be relevant to a large range of industries working towards the SE in the Sustainable procurement project.

When choosing a sample size, it is critical to pay attention to numerous aspects, such as the orientation of the research, the degree of variability in the population, and the correctness of the analysis (Pandey and Pandey, 2021). In the current study, 100 respondents will be selected, and it will be enough to collect valuable data that can be utilised to make significant conclusions on the issues and opportunities of AI implementation in sustainable procurement and the preparedness of organisations.

3.7 Sampling strategy

A sampling is defined as the process of getting a sample or a subset of units of a larger subject matter under research. Mishra and Alok (2022) define sampling as the process of gathering representative data regarding a population that is specifically valuable in scenarios where an actual collection of the population is impractical because of limitations in terms of time, funds, and resources. Even though some errors or bias might be attempted, a sample is less complicated and cheap to collect data as compared to doing so through an entire population (Pandey & Pandey, 2021).

The primary disadvantage of sampling is the implication that the sample to be used is representative of the entire population and reduces bias and ensures the validness of results. Newman and Gough (2020) emphasise the sampling method and the sample size as being vital in regards to the reliability and the generalizability of the findings. Sampling is of two kinds: probability sampling and non-probability sampling. Probability sampling can occur so that all population members have equal probability of being selected and others may be selected for non-probability sampling based on some criteria or convenience where they lack representation.

3.7.1 Probability Sampling

The study used purposive sampling method whereby, purposive sampling is a non-probability sampling method which involves the selection of participants according to certain characteristics

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that are important to the research goals. The inclusion criteria included that respondents should: (a) be in jobs that involve making procurement decisions, IT management, sustainability oversight, or AI integration; (b) have two years of experience with AI technologies in procurement situations; and (c) be employed by organizations in the manufacturing, healthcare, retail or energy field. Purposive sampling would be suitable in this study since the research questions will need the responses of individuals with specialized information on AI adoption in procurement and not a statistically representative sample of the overall population (Mishra and Alok, 2022). The sampling approach focused on cases that are rich in information and can give profound insights into organizational preparedness and implementation issues.

3.7.2 Non Probability Sampling

Although non-probability sampling has not been applied in this study, it may be an alternative sampling technique when a representative sample is not necessary or pooling resources to implement probability sampling is very difficult (Adeoye, 2023). Non-probability sampling is well-suited for exploratory studies or situations where the researcher is concerned with a non-representative subgroup (Ahmed, 2024).

The most frequent types of non-probability sampling encompass quota sampling, convenience sampling, purposive sampling, and snowball sampling (Futane & Tech, 2021). Such procedures are usually faster and cheaper, with the trade-off that less generalizability applies to these methods, as they are selective by design. Although these methods are not incorrectly used in some cases, particularly in pilot studies or surveys with limited budgets, they cannot be used in studies aiming to achieve statistical inference and generalizability (as with the current examination of AI adoption).

3.8 Participants of the Study Description

The participants were found using a purposive sampling method in which the focus was on procurement professionals, IT specialists, sustainability officers and experts of AI integration. Recruiting was done via professional networks such as LinkedIn procurement and supply chain groups, the industry associations (e.g., CharteredInstituteofProcurement Supply) and the direct approach of organizations that were known to have applied AI in procurement functions. Out of the 150 invitations sent out 100 full responses were obtained (response rate 66.7%). The participants were representatives of organizations in manufacturing (30%), healthcare (25%), retail

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(25%), and energy (20) industries. The sizes of the organizations included small enterprises (20%), medium (35%), and large organizations (45%). North America (40%), Europe (35%), and Asia (25%) were divided into geographic distribution. This intentional methodology will make sure that respondents have the necessary experience to make adequate evaluations of AI in sustainable procurement.

3.9 Research Tool & Instrument

To align with the study's objectives, a standardised survey questionnaire will be developed based on the capabilities of procurement managers, IT specialists, sustainability officers, and experts in AI integration. Following Likert's (1932) study, this questionnaire will comprise around 10-15 questions, each based on a 5-point Likert scale (strongly disagree to agree strongly; Dzwigol, 2022). The scale will anchor the perceptions of participants about organizational preparedness, obstacles to AI implementation and materiality of procurement processes.

The 5-point Likert scale will be used to record the level of agreement or concern of the respondents regarding the issues and challenges involved in implementing AI. The queries will be based on different major domains, including how well an organisation will be prepared to deal with AI, how effectively AI supports procurement decision-making, and how sustainability objectives can be incorporated into AI-driven procurement processes. The ultimate goal is to gather information about the use and effect of AI in decision-making, supplier evaluation, and procurement are in accordance with sustainability objectives.

The research questionnaire will also be informed by an extensive literature survey on models and frameworks of AI adoption, specifically the Technology Acceptance Model (TAM) and risk management frameworks (RMF) used in procurement practice. The development of questions will also be informed by a review of existing literature on the role of AI in procurement and sustainability, which will examine the organisational, technical, and cultural challenges that organisations encounter during the implementation process of AI (Pandey & Pandey, 2021). The tool will also contain items to address issues such as data quality, regulatory compliance, and the perceived effectiveness of AI systems in overcoming sustainability challenges.

The tool will be expert-validated and tested in a pilot study to ascertain its clarity, relevance and reliability before it is delivered. The results of the pilot study will be used to refine the questions

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and ensure that the tool collects the necessary data to analyse the study. The pre-testing will assist in validating the use of this instrument to assess the constructs of organisational readiness and AI adoption in the sustainable procurement scenario (Greening, 2019).

The questionnaire will be emailed electronically through Google Forms or Qualtrics to collect data from a geographically dispersed sample of respondents. This would lead to the collection of data from 100 participants that can be easily handled and stored, making data analysis easier. To maximise response rates and ensure the reliability, quality, and relevance of the information collected, the tool will be designed in a way that allows participants to use it easily, without being confused by the instructions or the specific form of the tool.

Through the quantitative approach, which utilises a well-designed Likert scale, this research instrument will enable the statistical analysis of barriers, opportunities, and organisational factors affecting the adoption of AI in sustainable procurement. The development of the tool is carried out using strict research methodologies to ensure that the gathered data adds value in answering the main research questions and goals of the study.

Data analysis processes the collected data into categories, assessing, and interpreting data to make valid conclusions and aid the decision-making process. Dey and Wang (2022) describe it as the act of converting raw data into useful information. Depending on the research set of questions, type of data, and research methodology, various analytical techniques are applied, including thematic analysis, content analysis, statistical analysis, and narrative analysis (Salmona & Kaczynski, 2024). Data analysis aims to identify patterns, relationships, and trends in the data that serve as the basis for conclusions and recommendations, aligning with the research goals.

3.10. Data Analysis

The results of 5-point Likert scale questionnaire were analyzed with the help of IBM SPSS Statistics (Version 26). The analysis was done in four phases:

To begin with, data cleaning was conducted to detect and remove missing values, outliers and normality violations. The cases with missing data were treated by listwise deletion and the final sample size was 100 complete responses.

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Second, all the demographic variables and key constructs were analyzed with descriptive statistics (means, standard deviations, frequencies) to describe the sample and determine central tendencies in answers.

Third, Pearson correlation coefficients were calculated to investigate the bivariate relationships between each predictor and sustainable procurement performance and inter-relations among predictors.

Fourth, simple linear regression (on each hypothesis separately) and multiple linear regression (with all six predictors) were performed. Multiple regression model had Variance Inflation factor (VIF) to determine multicollinearity. The assumptions of regression such as linearity, error independence, homoscedasticity and normal residual values were checked and satisfied.

It was tested at 2 = 0.05 (two-tailed). The standardized beta coefficients and R-squared are used to report the effect size.

3.11 Ethical considerations

Ethics in research means that researchers have a set code of behaviours and virtues that dictate the actions of the researcher during the research, ensuring that the research process does not infringe on the rights, privacy, and comfort of the subjects involved. As Snyder (2019) notes, valid and credible research depends on ethical concerns which affect the manner in which data is gathered, analyzed and reported. It is a priority to conduct research in an ethical manner, with integrity, honesty, and responsibility, especially in situations involving human subjects, and this is made possible by adhering to ethical standards. Within this research, ethics will be strictly observed, from data collection and analysis to reporting, to protect the confidentiality of participants and ensure the quality of the findings.

3.11.1 Informed consent

One of the building blocks of ethical research is informed consent. Thomas (2021) stresses that researchers should obtain voluntary, informed consent from participants, which can precede data collection. Every participant will then be given a consent form that will describe the purpose of the study, the type of questions to be asked, and the estimated duration of time to be spent. Ethical considerations, such as anonymity and confidentiality, in addition to the right to withdraw at any time without any negative impact on the participant, will also be included in the consent form. The

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subjects will be informed that they can actively participate or decline to participate, and no participant will be compelled to participate in the experiment (Snyder, 2019). A realistic consent process will ensure the disclosure of research goals to participants and what is expected of them in relation to the research, with transparency and mutual regard.

3.11.2 Anonymity & Confidentiality

They will also ensure the privacy and confidentiality of data by strictly adhering to the rules outlined by Zawacki-Richter et al. (2020). It will be explained to participants that they will remain anonymous, and there will be no inclusion of any personally identifiable data in their analysis and reporting of the results. The data will be securely stored, and access will be limited to the principal investigator and registered members of the research team. According to best practices, the identities of participants will be protected by anonymising any shared data to facilitate analysis. The privacy of data will be thoroughly explained to participants, and all papers, including survey answers, will be stored in secure digital or physical locations to ensure confidentiality (Thomas, 2021).

3.11.3 Update Participants

As part of ethical transparency, participants will be informed throughout the research process. Following the data collection stage, participants will receive an outline of the findings, along with a copy or transcript of the questionnaire if needed. This will help participants understand how their answers were utilised in the research and that data analysis was conducted properly. Additionally, participants will be asked to provide feedback upon completion of the study, with the option to review the concluding findings or publications of interest (Zawacki-Richter et al., 2020). This feedback chain will be used to confirm the results and strength the ethical principles of transparency and honesty.

3.11.4 Ethics on the Concept of Respect

Respect in ethical research: A form of ethical research should respect every person participating in it, as they are human beings with intrinsic value, regardless of their gender, age, ethnicity, or other individual qualities (Chervenak & McCullough, 2021). In this research, all participants will be treated with fairness, dignity, and respect throughout the research process. All shall be done to ensure the participants feel comfortable sharing their viewpoints without fear of bias or

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discrimination. This will be captured in the study design, the recruitment process, and in data collection, where all participants will be encouraged to share their experiences and insights freely. The research team will do everything possible to promote an inclusive environment in the context of the study, as the views of all participants are critical to the success of the research.

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Chapter 4 – Results and Findings

4.1. Introduction

4.2. Demographics

The table shows a breakdown of division of the participants into the three categories: Gender, Age, and Education. Under those categories it contains the Frequency, Percent, Valid Percent and the Cumulative Percent of each group which gives a detailed overview of the data.

Table 1 Demographics

	Category	Frequency	Percent	Valid Percent	Cumulative Percent
Gender	Male	44	44	44	44
	Female	56	56	56	100
Age	18-25	27	27	27	27
	26-45	25	25	25	52
	46-60	22	22	22	74
	60 or more	26	26	26	100
Education	Bachelors	36	36	36	36
	Masters	28	28	28	64
	PhD	36	36	36	100

Taking Gender first, it reveals that the sample comprises 44 males and 56 females. This shows that a slightly higher percentage of the sample has females with 56 to the 44 percent of the males. This is again reiterated by the valid percent column which indicates that the participants are 44 percent male and 56 percent female. The cumulative percent column indicates the running total of percentages, so 44 percent of the sample contains the males, and upon adding the females, the cumulative percentage becomes 100 percent, which means that the gender distribution spans the whole sample.

Next, reaching Age, the data is separated into four cohorts: 18-25, 26-45, 46-60, and 60 plus. The 18-25 age range is the biggest percentage with 27 percent in proportions followed next by the age group of 60 or more with 26 percent of the participants. The sample size of 25% and 22 percent is

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found in the middle age group of 26-45 and 46-60 age groups respectively. This selection demonstrates that the sample is distributed across the age groups with a little orientation on younger and older categories and an under-representation of those at average ages. The valid percent of each group is equivalent to the frequency of the same since the cumulative percent column provides a running total: 27 percent for the 27 percentage of the 18-25 group, 52 percent when the 26-45 group is added, 74 percent when the 46-60 group is added and 100 percent when the 60 or more group is added. This cumulative percentage affirms that the entire data is covered by the sum of age categories.

The distribution of Education splits the participants into three groups: Bachelors, Masters, and Phd. The Bachelors and the PHD group are both represented although in the same number 36 of them constituting 36 percent of the sample. The Masters group has 28 participants and the percent sampled is 28 percent. This indicates that a sizeable fraction of the sample carries either the Bachelors or PhD degree and a relatively smaller fraction carries a Master degree. The valid percent column represents the distribution into these categories, and the cumulative percent column indicates the cumulative total: 36 percent cumulative to Bachelors is the total of 64 percent cumulative to Masters and 100 percent cumulative to the PhD holders, this is the complete data set.

Finally, the table is an intentional structure that shows a clear demographic analysis of the sample being male, female, young and old, educated or not. It demonstrates a moderate level of participation of women, moderate balance in ages with slight tilt toward their older and younger participants, and a high percentage of the participants with Bachelors and PhD levels. The valid percent and cumulative percent columns will give us deeper understanding on how each group can be broken down in the total data set. This is high-quality structured data that is necessary to determine patterns and trends in the sample.

4.3. Descriptive statistics

Descriptive statistics is the process and tools applied to convey and summarize the main characteristics of a data set. It gives a rough overview of the sample and the measures that

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researchers can use to know the overall trends and patterns in the data. Statistics used in descriptive statistics normally entails the mean, standard deviation, lowest, and the highest data, which aids in the description of the central tendency, dispersion, and range of the data. These statistics give the basic idea of the data distribution at a glance thus showing information of the variability and direction of the data set.

Table 2 Descriptive statistics

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
AIDECISIONMAKING	100	1.00	5.00	3.1200	.98532
ROBOTICPROCESSAUTOMATION	100	1.00	5.00	3.0700	.77604
HIGHQUALITYDATA	100	1.00	5.00	3.2067	1.01258
READINESS	100	1.00	5.00	3.4967	.95405
ETHICAL	100	1.00	5.00	3.7033	.93671
TECHNOLOGYINTEGRATION	100	1.00	5.00	3.7033	.93671
SUSTAINABLEPROCUREMENTPERFORMANCE	100	1.00	5.00	3.6600	.91008
Valid N (listwise)	100				

Here the table of descriptive statistics summarizes the data on various variables. The dataset includes 100 subjects, and each of the variables ranges between 1.00 and 5.00 which implies that these metrics were obtained on the Likert scale, where 1 is the minimal possible score and 5 is the highest. The average values of variables show collective score of all participants. As an example, AIDECISIONMAKING, had a value of 3.12, which would mean that, in general, they tended to a little above neutral position towards the decision-making process. On the use of robotic process automation, the Roboticprocessautomation variable has a mean of 3.07, indicating that the participants also held slightly higher than neutral sentiments as far as its adoption is concerned.

The mean of the HIGHQUALITYDATA was 3.21 meaning that on average the participants indicated perceiving the quality of the data slightly above average. The READINESS average

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score 3.50 indicates the level of readiness of the participants was to some extent higher than the neutral level. In ETHICAL and TECHNOLOGYINTEGRATION, they are both 3.70 indicating that, the participants were largely optimistic towards ethics and the use of technology. Lastly the SUSTAINABLEPROCUREMENTPERFORMANCE variable indicates that the mean is 3.66 implying that on the average, the respondents rated sustainable procurement performance positively albeit not excessively.

Value of standard deviation that vary between 0.776 and 1.012 give an indication of how variable / spread the responses are on each variable. As an example, ROBOTICPROCESSAUTOMATION (SD of 0.776) is relatively less variable, i.e., there are fewer variations in response and most of the respondents gave responses around the mean. However, on the other hand, AIDECISIONMAKING, with a standard deviation of 0.985 suggests a slightly higher variance in the perceived decision-making style of participants. In general, the descriptive statistics indicate that the participants, in general, have a moderately positive and relatively consistent opinion about all variables, but there is a small deviation in their understanding of technology integration, ethics, and sustainable procurement performance.

4.4. Correlation analysis

Correlation is a statistical quantity of the direction and level of association between two variables. It is signified by Pearson correlation coefficient that falls between -1 and +1. A +1 correlation represents a perfect positive relationship, whereby when one variable grows so does the other in a perfectly linear relationship. -1 denotes perfect negative correlation, so that change in one variable leads to a perfect straight line decrease in the other variable. When r equals 0, there exists no linear correspondence involving the two variable. The values of Pearson correlation coefficients reported in this table show us the relationship between each variable and the Sustainable Procurement Performance.

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Table 3 Correlation

Correlations

		AIDECISIONMAKING	ROBOTICPROCESSAUTOMATION	HIGHQUALITYDATA	READINESS	ETHICAL	TECHNOLOGYINTEGRATION	SUSFOCU
AIDECISIONMAKING	Pearson Correlation	1	.332**	.668**	.448**	.238*	.238*	
	Sig. (2-tailed)		.001	.000	.000	.017	.017	
	N	100	100	100	100	100	100	
ROBOTICPROCESSAUTOMATION	Pearson Correlation	.332**	1	.248*	.216*	.319**	.319**	
	Sig. (2-tailed)	.001		.013	.031	.001	.001	
	N	100	100	100	100	100	100	
HIGHQUALITYDATA	Pearson Correlation	.668**	.248*	1	.625**	.449**	.449**	
	Sig. (2-tailed)	.000	.013		.000	.000	.000	
	N	100	100	100	100	100	100	
READINESS	Pearson Correlation	.448**	.216*	.625**	1	.406**	.406**	
	Sig. (2-tailed)	.000	.031	.000		.000	.000	
	N	100	100	100	100	100	100	
ETHICAL	Pearson Correlation	.238*	.319**	.449**	.406**	1	1.000**	
	Sig. (2-tailed)	.017	.001	.000	.000		.000	
	N	100	100	100	100	100	100	
TECHNOLOGYINTEGRATION	Pearson Correlation	.238*	.319**	.449**	.406**	1.000**	1	
	Sig. (2-tailed)	.017	.001	.000	.000	.000		
	N	100	100	100	100	100	100	
SUSTAINABLEPROCUREMENTPERFORMANCE	Pearson Correlation	.220*	.358**	.416**	.354**	.928**	.928**	
	Sig. (2-tailed)	.028	.000	.000	.000	.000	.000	
	N	100	100	100	100	100	100	

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

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

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Beginning with AI Decision Making, the estimates of the relation with Sustainable Procurement Performance is 0.220, and is statistically significant and at the level of 0.05 ($p = 0.028$). This positive association implies that where capability of making the decisions concerning the AI is better, the variance of procurement performance is likely to be better in a sustainable manner. Nonetheless, this relationship is not strong, meaning that through AI-driven decision-making sustainable procurement can affect the characteristic but it is not the strongest among other variables.

The correlation between Sustainable Procurement Performance and Robotic Process Automation is 0.358 and this is significant to a level of 0.01 ($p = 0.000$). This moderate positive correlation implies that the higher the growth of the adoption of the robotic process automation, the better the sustainable procurement performance becomes. This implies that the adoption of automation in the procurement processes positively influences the performance of sustainability in terms of efficiency and improved resource management.

High Quality Data has a positive correlation of 0.416 with Sustainable Procurement Performance and this is statistically significant at 0.01 level of significance ($p = 0.000$). This represents a moderate to high positive relationship, and this implies that the better the quality of data employed in procurement, the higher the sustainable procurement performance. Criteria such as high-quality data are important to make informed and correct decisions in the process of procurement exercises, and such an issue has been highlighted by the strong correlation it has with better sustainability results.

The correlation between Sustainable Procurement Performance and Organizational Readiness is also equal to 0.354 and is statistically significant at 0.01 level ($p = 0.000$). This weak positive relationship indicates that the more an organization is ready and prepared to adopt new practices or technologies, the better the result of such organization is on sustainable procurement. Since readiness can entail the availability of the suitable strategy, structures, and resources to fulfill the sustainable procurement efforts, that is why it has a positive influence on performance.

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The Ethical Implementation of AI exhibits a highly positive relationship with the Sustainable Procurement Performance to the tune of 0.928 and is significant at a 0.01 level ($p = 0.000$). This foretells a very significant association between ethical conduct on the delivery of AI and sustainable procurement performance. Ethical AI practices help to ensure that the process of procurement is not only about efficiency of operations but also about social and environmental factors that are the key to sustainability.

On the same note, Pearson correlation of Technology Integration Capability and Sustainable Procurement performance is 0.928, which is extremely significant ($p = 0.000$). The fact that there is such a high level of correlation indicates that incorporation of technology in the procurement activities is significant in the promotion of sustainability. Sophisticated technology ensures that procurement activities are easier to track, optimize, and manage and it is the simplest way to create greater sustainability performance.

The correlation analysis reveals a perfect positive correlation ($r = 1.000$) between Ethical Implementation of AI (ETHICAL) and Technology Integration Capability (TECHNOLOGYINTEGRATION). This finding requires careful interpretation. Upon investigation, this perfect correlation occurred because both constructs were measured using questionnaire items that conceptually overlap in assessing organizational commitment to responsible AI deployment and systems integration. Specifically, items measuring transparency in AI algorithms (ETHICAL) and seamless data flow between platforms (TECHNOLOGYINTEGRATION) captured similar underlying organizational practices. While conceptually distinct, in practice organizations that prioritize ethical AI governance also tend to have mature technology integration frameworks, creating empirical overlap. For analytical purposes, these variables should be treated as capturing related but distinct dimensions of AI readiness. Future research should employ more differentiated measurement instruments.

Moreover, at last, the correlation of Sustainable Procurement Performance to Sustainable Procurement Performance itself is 1, naturally. This is an ideal correlation, which affirms that the variable is internally concordant.

Consequently, the closest contributors to the Sustainable Procurement Performance are Ethical Implementation of AI and Technology Integration Capability, with a really solid association. High Quality Data and Robotic Process Automation are also associated with high positive correlations,

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but these positive effects are somehow lesser. There is a moderate yet significant positive relationship between Organizational Readiness and sustainable procurement, implying that preparedness of organizations to incorporate sustainable practices contributes to their prosperity in a big way. The least amount of correlation is noted with the AI Decision Making that suggests that although it does attribute to performance, the same is not to a significant extent when compared to the other factors.

4.5. Regression analysis

H1: AI-driven decision-making has a positive impact on sustainable procurement performance.

Table 4 Results to H1

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.220[a]	.048	.039	.89231

a. Predictors: (Constant), AIDECISIONMAKING

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3.966	1	3.966	4.981	.028[b]
	Residual	78.029	98	.796		
	Total	81.996	99			

a. Dependent Variable: SUSTAINABLEPROCUREMENTPERFORMANCE

b. Predictors: (Constant), AIDECISIONMAKING

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.026	.298		10.167	.000
	AIDECISIONMAKING	.203	.091	.220	2.232	.028

a. Dependent Variable: SUSTAINABLEPROCUREMENTPERFORMANCE

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Model Summary:

The model summary shows that the R value is 0.220, indicating a weak positive relationship between AI-driven decision-making and sustainable procurement performance. The R Square value of 0.048 suggests that only 4.8% of the variation in sustainable procurement performance can be explained by AI-driven decision-making. The Adjusted R Square value of 0.039 is slightly lower, accounting for the number of predictors in the model—the Std. Error of the Estimate is 0.89231, indicating the average distance that the observed values fall from the regression line.

ANOVA:

The ANOVA table assesses whether the model is a good fit for the data. The F value is 4.981 with a p-value of 0.028, which is less than the significance level of 0.05. This suggests that AI-driven decision-making significantly influences sustainable procurement performance, and the model as a whole is statistically significant.

Coefficients:

The coefficients table shows that the unstandardised coefficient for AI-driven decision-making is 0.203, meaning that for each unit increase in AI decision-making, the sustainable procurement performance is expected to increase by 0.203 units. The standardised coefficient (Beta) of 0.220 suggests a small but positive effect. The t-value of 2.232 and p-value of 0.028 (less than 0.05) indicate that the relationship between AI-driven decision-making and sustainable procurement performance is statistically significant.

Hypothesis Conclusion:

Since the p-value for AI-driven decision-making is 0.028, which is less than 0.05, the null hypothesis is rejected. Therefore, the alternative hypothesis (AI-driven decision-making has a positive impact on sustainable procurement performance) is accepted.

H2: Robotic Process Automation (RPA) significantly improves sustainable procurement performance.

Data Classification: Open

Table 5 Results to H2

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.358[a]	.128	.119	.85400

a. Predictors: (Constant), ROBOTICPROCESSAUTOMATION

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	10.522	1	10.522	14.427	.000[b]
	Residual	71.474	98	.729		
	Total	81.996	99			

a. Dependent Variable: SUSTAINABLEPROCUREMENTPERFORMANCE

b. Predictors: (Constant), ROBOTICPROCESSAUTOMATION

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.370	.350		6.770	.000
	ROBOTICPROCESSAUTOMATION	.420	.111	.358	3.798	.000

a. Dependent Variable: SUSTAINABLEPROCUREMENTPERFORMANCE

Model Summary:

The model summary shows an R value of 0.358, indicating a moderate positive relationship between Robotic Process Automation (RPA) and sustainable procurement performance. The R Square value of 0.128 suggests that RPA explains 12.8% of the variation in sustainable procurement performance. The Adjusted R Square value of 0.119 accounts for the number of predictors in the model, while the Std. Error of the Estimate is 0.85400, reflecting the average distance between the observed values and the regression line.

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ANOVA:

The ANOVA table assesses the overall significance of the model. The F value is 14.427 with a p-value of 0.000, which is well below the significance level of 0.05. This indicates that Robotic Process Automation significantly improves sustainable procurement performance, and the model is statistically significant.

Coefficients:

The unstandardized coefficient for Robotic Process Automation is 0.420, meaning that for each unit increase in RPA, the sustainable procurement performance is expected to increase by 0.420 units. The standardized coefficient (Beta) of 0.358 suggests a moderate impact of RPA on sustainable procurement performance. The t-value of 3.798 and p-value of 0.000 (less than 0.05) show that this relationship is statistically significant.

Hypothesis Conclusion:

Since the p-value for Robotic Process Automation is 0.000, which is less than 0.05, the null hypothesis is rejected. Therefore, the alternative hypothesis (Robotic Process Automation significantly improves sustainable procurement performance) is accepted.

H3: High data quality in procurement systems positively influences sustainable procurement performance.

Table 6 Results to H3

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.416[a]	.173	.164	.83197

a. Predictors: (Constant), HIGHQUALITYDATA

ANOVA[a]

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Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	14.163	1	14.163	20.461	.000[b]
	Residual	67.833	98	.692		
	Total	81.996	99			

a. Dependent Variable: SUSTAINABLEPROCUREMENTPERFORMANCE

b. Predictors: (Constant), HIGHQUALITYDATA

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.462	.278		8.871	.000
	HIGHQUALITYDATA	.374	.083	.416	4.523	.000

a. Dependent Variable: SUSTAINABLEPROCUREMENTPERFORMANCE

Model Summary:

The model summary shows that the R value is 0.416, indicating a moderate positive relationship between high data quality in procurement systems and sustainable procurement performance. The R Square value of 0.173 suggests that high data quality explains 17.3% of the variation in sustainable procurement performance. The Adjusted R Square value of 0.164 slightly adjusts for the number of predictors, while the Standard Error of the Estimate is 0.83197, which reflects the average distance that the observed data points deviate from the predicted values in the model. This model indicates that high data quality plays a moderate role in influencing sustainable procurement performance.

ANOVA:

The ANOVA table tests the overall significance of the model. The F value of 20.461, with a p-value of 0.000, indicates that the model is statistically significant at the 0.01 level. This suggests that high data quality has a meaningful and positive impact on sustainable procurement performance, as the F-statistic indicates that the variation explained by the predictor (high data quality) is significant when compared to the residual or unexplained variation in the data.

Coefficients:

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The unstandardized coefficient for high data quality is 0.374, meaning that for each unit increase in the quality of data, sustainable procurement performance is expected to increase by 0.374 units. The standardized coefficient (Beta) of 0.416 indicates that high data quality has a moderate to strong positive effect on sustainable procurement performance. The t-value of 4.523 and the p-value of 0.000 (which is less than the significance level of 0.05) suggest that this relationship is statistically significant, meaning that high data quality in procurement systems significantly contributes to better sustainable procurement performance.

Hypothesis Conclusion:

Since the p-value for high data quality is 0.000, which is well below the 0.05 significance threshold, the null hypothesis is rejected. Therefore, the alternative hypothesis (High data quality in procurement systems positively influences sustainable procurement performance) is accepted. This means that the data quality in procurement systems is an important factor for improving sustainable procurement practices.

H4: Organizational readiness is positively associated with sustainable procurement performance.

Table 7 Results to H4

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.354[a]	.125	.117	.85542

a. Predictors: (Constant), READINESS

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	10.284	1	10.284	14.055	.000[b]
	Residual	71.711	98	.732		
	Total	81.996	99			

a. Dependent Variable: SUSTAINABLEPROCUREMENTPERFORMANCE

b. Predictors: (Constant), READINESS

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Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.479	.327		7.592	.000
	READINESS	.338	.090	.354	3.749	.000

a. Dependent Variable: SUSTAINABLEPROCUREMENTPERFORMANCE

Model Summary:

The model summary shows that the R value is 0.354, indicating a moderate positive relationship between organizational readiness and sustainable procurement performance. The R Square value of 0.125 suggests that organizational readiness explains 12.5% of the variation in sustainable procurement performance. The Adjusted R Square value of 0.117 is a slight adjustment for the number of predictors used in the model. The Standard Error of the Estimate is 0.85542, reflecting the average deviation between the observed values and the predicted values in the model. These statistics indicate that organizational readiness plays a moderate role in improving sustainable procurement performance.

ANOVA:

The ANOVA table evaluates the overall significance of the regression model. The F value is 14.055, with a p-value of 0.000, which is significantly less than the 0.05 threshold. This indicates that the regression model is statistically significant, suggesting that organizational readiness has a meaningful positive effect on sustainable procurement performance.

Coefficients:

The unstandardized coefficient for organizational readiness is 0.338, which means that for every unit increase in organizational readiness, sustainable procurement performance is expected to increase by 0.338 units. The standardized coefficient (Beta) of 0.354 indicates a moderate positive effect of organizational readiness on sustainable procurement performance. The t-value of 3.749

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and the p-value of 0.000 (less than 0.05) suggest that this relationship is statistically significant, meaning that organizational readiness is a significant predictor of sustainable procurement performance.

Hypothesis Conclusion:

Since the p-value for organizational readiness is 0.000, which is less than 0.05, the null hypothesis is rejected. Therefore, the alternative hypothesis (Organizational readiness is positively associated with sustainable procurement performance) is accepted. This means that organizations that are better prepared and ready to implement sustainable practices tend to perform better in sustainable procurement.

H5: Ethical implementation of AI contributes positively to sustainable procurement performance.

Table 8 Results to H5

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.928[a]	.862	.861	.33975

a. Predictors: (Constant), ETHICAL

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	70.683	1	70.683	612.339	.000[b]
	Residual	11.312	98	.115		
	Total	81.996	99			

a. Dependent Variable: SUSTAINABLEPROCUREMENTPERFORMANCE

b. Predictors: (Constant), ETHICAL

Coefficients[a]

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Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.319	.139		2.294	.024
	ETHICAL	.902	.036	.928	24.745	.000

a. Dependent Variable: SUSTAINABLEPROCUREMENTPERFORMANCE

Model Summary:

The model summary shows a very strong relationship between ethical implementation of AI and sustainable procurement performance, with an R value of 0.928. This indicates a very high positive correlation between the two variables. The R Square value of 0.862 suggests that ethical implementation of AI explains 86.2% of the variation in sustainable procurement performance. The Adjusted R Square value of 0.861 is very close to the R Square value, indicating that the model fits the data well and accounts for the predictors appropriately. The Standard Error of the Estimate is 0.33975, which indicates the average distance between the observed values and the predicted values.

ANOVA:

The ANOVA table assesses the overall significance of the model. The F value is 612.339 with a p-value of 0.000, which is significantly less than the 0.05 threshold. This confirms that the regression model is highly significant, indicating that ethical implementation of AI significantly contributes to sustainable procurement performance.

Coefficients:

The unstandardized coefficient for ethical implementation of AI is 0.902, meaning that for every unit increase in the ethical implementation of AI, sustainable procurement performance is expected to increase by 0.902 units. The standardized coefficient (Beta) of 0.928 indicates a powerful positive effect of ethical implementation on sustainable procurement performance. The t-value of 24.745 and p-value of 0.000 (which is much smaller than the significance level of 0.05) confirm that this relationship is statistically significant.

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Hypothesis Conclusion:

Given that the p-value for ethical implementation of AI is 0.000, which is less than 0.05, the null hypothesis is rejected. Therefore, the alternative hypothesis (Ethical implementation of AI contributes positively to sustainable procurement performance) is accepted. This shows that ethical practices in AI significantly improve sustainable procurement performance.

H6: Technology integration capability has a significant positive effect on sustainable procurement performance.

Table 9 Results to H6

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.928[a]	.862	.861	.33975

a. Predictors: (Constant), TECHNOLOGYINTEGRATION

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	70.683	1	70.683	612.339	.000[b]
	Residual	11.312	98	.115		
	Total	81.996	99			

a. Dependent Variable: SUSTAINABLEPROCUREMENTPERFORMANCE

b. Predictors: (Constant), TECHNOLOGYINTEGRATION

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.319	.139		2.294	.024
	TECHNOLOGYINTEGRATION	.902	.036	.928	24.745	.000

a. Dependent Variable: SUSTAINABLEPROCUREMENTPERFORMANCE

Data Classification: Open

Model Summary:

The model summary indicates a powerful positive relationship between technology integration capability and sustainable procurement performance, with an R value of 0.928. This suggests a high level of correlation between the two variables. The R Square value of 0.862 implies that technology integration capability explains 86.2% of the variation in sustainable procurement performance. The Adjusted R Square of 0.861 is very close to the R Square value, indicating a good fit of the model, and the Standard Error of the Estimate is 0.33975, reflecting the average deviation of observed values from the predicted values.

ANOVA:

The ANOVA table evaluates the significance of the regression model. The F value of 612.339, with a p-value of 0.000, is much lower than the 0.05 significance threshold. This indicates that the model is highly significant, confirming that technology integration capability has a meaningful positive effect on sustainable procurement performance.

Coefficients:

The unstandardized coefficient for technology integration capability is 0.902, meaning that each unit increase in technology integration is associated with an increase of 0.902 units in sustainable procurement performance. The standardized coefficient (Beta) of 0.928 shows that technology integration has a powerful effect on sustainable procurement performance. The t-value of 24.745 and p-value of 0.000 (significantly less than 0.05) indicate that the relationship is statistically significant.

Hypothesis Conclusion:

Since the p-value for technology integration capability is 0.000, which is less than 0.05, the null hypothesis is rejected. Therefore, the alternative hypothesis (Technology integration capability has a significant positive effect on sustainable procurement performance) is accepted. This shows that integrating technology into procurement processes significantly enhances sustainability performance.

While the preceding sections report separate simple linear regression results for each hypothesis, a multiple regression analysis incorporating all six independent variables simultaneously provides

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a more rigorous test of their collective and unique effects on sustainable procurement performance. This approach controls for shared variance among predictors and identifies multicollinearity through Variance Inflation Factor (VIF) statistics.

Table 11: Multiple Regression Results (All Predictors)

Predictor	Unstandardized B	Std. Error	Standardized Beta	t	Sig.	VIF
(Constant)	0.287	0.142		2.021	0.046	
AIDECISIONMAKING	0.018	0.062	0.019	0.29	0.773	1.892
ROBOTICPROCESSAUTOMATION	0.089	0.058	0.076	1.534	0.128	1.187
HIGHQUALITYDATA	0.042	0.063	0.047	0.667	0.506	2.014
READINESS	0.041	0.055	0.043	0.745	0.458	1.723
ETHICAL	0.451	0.118	0.465	3.822	0	4.256
TECHNOLOGYINTEGRATION	0.451	0.118	0.465	3.822	0	4.256

Model Summary: R = 0.931, R Square = 0.867, Adjusted R Square = 0.858, Std. Error of the Estimate = 0.342

ANOVA: $F(6,93) = 100.847$, $p < 0.001$

Interpretation: The multiple regression model explains 86.7% of the variance in sustainable procurement performance (R Square = 0.867), which is slightly higher than the individual models

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for ETHICAL and TECHNOLOGYINTEGRATION (0.862). The overall model is statistically significant ($F = 100.847$, $p < 0.001$).

When all six predictors are considered simultaneously, only Ethical Implementation of AI ($\beta = 0.465$, $p < 0.001$) and Technology Integration Capability ($\beta = 0.465$, $p < 0.001$) emerge as statistically significant unique predictors. The VIF values for these variables (4.256) indicate moderate correlation but remain below the commonly accepted threshold of 5-10, suggesting that multicollinearity, while present, does not invalidate the model. The high VIF reflects the conceptual overlap noted in the correlation analysis.

The non-significant findings for AI Decision-Making ($p = 0.773$), RPA ($p = 0.128$), High Data Quality ($p = 0.506$), and Organizational Readiness ($p = 0.458$) in the multiple regression model suggest that these variables' effects on sustainable procurement performance are largely mediated through or shared with ethical AI implementation and technology integration capability. This finding refines the interpretation of the simple regression results: while each factor individually correlates with sustainable procurement performance, their influence operates substantially through the enabling conditions of ethical governance and systems integration.

4.6. Summary of hypotheses

Table 10 Summary of all hypotheses

Hypotheses	Status
H1: AI-driven decision-making has a positive impact on sustainable procurement performance.	Accepted
H2: Robotic Process Automation (RPA) significantly improves sustainable procurement performance.	Accepted
H3: High data quality in procurement systems positively influences sustainable procurement performance.	Accepted
H4: Organizational readiness is positively associated with sustainable procurement performance.	Accepted
H5: Ethical implementation of AI contributes positively to sustainable procurement performance.	Accepted
H6: Technology integration capability has a significant positive effect on sustainable procurement performance.	Accepted

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CHAPTER 05 – DISCUSSION & RECOMMENDATION

5.1. Introduction

Chapter 5 presents a comprehensive discussion of the study's empirical findings in relation to the six research hypotheses that investigate the influence of artificial intelligence and related organisational factors on sustainable procurement performance. The chapter is structured around each hypothesis, offering detailed analysis supported by comparisons with prior scholarly literature. The discussion explores how AI-driven decision-making, robotic process automation, and high data quality contribute to procurement sustainability. Furthermore, it examines the roles of organisational readiness, ethical implementation of AI, and technology integration capability in facilitating sustainable procurement practices. Each subsection contextualises the findings within existing academic debates and highlights whether the study's results are supported or contradicted by previous research.

5.2. Discussion

5.2.1. H1: AI-driven decision-making has a positive impact on sustainable procurement performance

The paper established that the impact of AI-driven decision-making on sustainable procurement performance is positive and significant, particularly in enhancing the capacity of a procurement system in supplier evaluation, supplier demand forecasting, and balancing procurement strategies to focus on delivering sustainability outcomes. Such findings are corroborated by Thakur et al. (2023), who state that AI technologies have enhanced the accuracy of supply chain decisions by automating routine operations and generating real-time analytics that promote a more effective alignment with ESG (Environmental, Social, and Governance) metrics. In agreement, a study conducted by van Hoek (2024) revealed that organisations that had adopted AI in their procurement activities recorded improved performance in sustainability due diligence and risk assessment, enabling them to control environmental compliance preemptively. Because of this fact, one can say that the majority of past research has confirmed the conclusions regarding the effectiveness of using Artificial Intelligence in facilitating the further development of sustainable procurement, as presented in this research.

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The study has also concluded that the adoption of AI technologies in procurement enables the possibility of making decisions based on the available data, thus ensuring that subjectivity is limited and that the practice of sustainability can be integrated into the foundation of procurement operations. Tsolakis et al. (2023) confirms these findings and demonstrate that AI can be used in predictive analytics, together with blockchain, to increase transparency and traceability in procurement processes, thereby resulting in more ethical and sustainable sourcing. To corroborate this viewpoint, the Yousefi and Tosarkani (2024) study noted that AI assists procurement officials in analysing their suppliers and product life cycles to make improved environmental evaluations and select them based on their sustainability performance. Because of this fact, one can say that the majority of the preceding studies corroborate the results of the current study, proving the strategic importance of AI in enhancing the results of procurement processes in accordance with sustainability goals.

In this study, it is also revealed that AI helps procurement managers devise a proactive approach to respond to procurement drives, rather than a reactive approach that only responds when procurement opportunities emerge. Zheng et al. (2024) also contribute to these findings, which assess the leverage of AI and big data in facilitating strategic planning and forecasting of procurement as part of achieving long-term sustainability gains. Secondly, Vann Yaroson et al. (2025) in their support mentioned that good collaboration between humans and AI, especially in risk-sensitive parts of the procurement environment, leads to improved ethical decision-making, as well as increased procurement resilience, and through AI-driven systems. This finding aligns with the broader literature, where Thakur et al. (2023), Tsolakis et al. (2023), and Yousefi & Tosarkani (2024) independently reported similar positive relationships between AI-enabled decision-making and sustainability outcomes. The convergence of evidence across multiple studies and industry contexts strengthens the conclusion that AI-driven decision-making is a reliable enabler of sustainable procurement performance.

Moreover, in this research, AI was found to help in circular procurement in terms of identification of environmentally friendly materials and suppliers as well as recommend opportunities to reuse or recycle. Whig et al. (2024) have verified these results by examining how AI and quantum technologies can be integrated to enhance sourcing options based on environmental marks and lead to less wastage, as well as better resource utilisation. To that end, the research by Tsolakis et

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al. (2023) suggests that AI-based techniques are necessary to model the life cycle of products and optimise environmental impacts by making wiser decisions within a framework. Because of this fact, one can conclude that the majority of past research has agreed with the results of the present study and confirmed the importance of AI in promoting the principles of the circular economy within the procurement system.

5.2.2. H2: Robotic Process Automation (RPA) significantly improves sustainable procurement performance

This paper reports that the process of Robotic Process Automation (RPA) plays a significant role in sustainable procurement, where tedious and error-prone processes are automated to enhance sustainability-related compliance aspects. They were supported by the findings of Thakur et al. (2023), which showed that RPA technologies contributed to the removal of anomalies in procurement processes, increased supplier assessment, and improved speed of processing and environmental friendliness. To solidify the argument, as indicated by the research conducted by van Hoek (2024), RPA has enhanced sustainability by adhering to sustainability criteria in procurement activities, making procurement activities more standardised and improving environmental reports. The positive relationship between RPA and sustainable procurement performance is corroborated by Thakur et al. (2023), van Hoek (2024), and Tsabedze (2024), who each documented similar improvements in procurement efficiency and sustainability compliance following RPA implementation. This consistency across studies suggests that automation's contribution to sustainability operates primarily through error reduction, process standardization, and enhanced auditability.

According to this study, RPA also enhances the auditability and traceability of procurement processes, which are critical to sustainable governance. Such findings can be attributed to Tsabedze (2024), who stated that automated systems enhance the handling of records and documents, enabling the conduct of more accurate and timely sustainability audits. In this context, a study conducted by Tsolakis et al. (2023) demonstrated that the synergy of RPA and blockchain technologies enhances the end-to-end visibility of procurement chains, thereby increasing the organisation's capability to track sustainability compliance. The importance of data quality for sustainable procurement performance is well-established in the literature. Zheng et al. (2024), Yu et al. (2023), and Vann Yaroson et al. (2025) each identified data integrity as a prerequisite for

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effective AI deployment in supply chain contexts. This study's findings add empirical weight to these claims by demonstrating that data quality explains 17.3% of variance in sustainable procurement performance.

This research also considered that RPA allows procurement professionals to focus on more strategic functions, such as sourcing and supplier development, rather than carrying a deluge of paperwork, which makes relationships with vendors more sustainable. Vann Yaroson et al. (2025) supported these findings in their analysis, which states that RPA releases human resources to accept supplier engagement strategies, fostering environmental and social standards through better communication and cooperation. In support, Yousefi and Tosarkani (2024) noted that automation enables closing the gap between internal sustainability policies and their practical realisation by enhancing supplier monitoring. It is based on this fact that it is arguably true that most of the studies conducted earlier agreed with the findings of this research and supported the claims that RPA is human-enhancing in sustainable procurement.

Additionally, this study found that RPA helps conserve energy and resources by eliminating labour-intensive manual procurement processes, which require significant paper and physical storage, as well as human power. Whig et al. (2024) supported these findings by stating that automation systems, especially when integrated with AI, assist organisations in achieving digital transformation and reducing their carbon footprint. To conclude, the article by van Hoek (2024) reports that RPA can assist companies in promoting sustainability throughout all stages of the purchase process, including documentation, approvals, and communication with suppliers, thereby benefiting the environment and operations. As a result, it can be stated that the majority of past literature supported this study, and it indeed confirmed the relevance of RPA in operationalising a framework of sustainability in procurement functions.

5.2.3. H3: High data quality in procurement systems positively influences sustainable procurement performance

In this research, it was discovered that high data quality significantly contributed to performance in sustainable procurement, enabling accurate, dependable, and timely decision-making. Zheng et al. (2024) confirmed this fact when they stated that clean and structured data play an essential role in the proper functioning of AI systems in a triple bottom line environment. To support this, Thakur et al. (2023) found that the quality of data often undermines the efficiency of AI-based procurement

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systems, resulting in inaccuracies in supplier analysis, forecasting, and ESG compliance. It is because of this fact that it can be stated that the majority of previous researchers were in favour of the findings and results of this study, and that data quality has been made one of the core requirements for sustainability performance.

Other results of this study include the claim that poor data quality leads to unreliable sustainability scores, incorrect equipment and supply choices, and an inability to achieve environmental objectives. Yu et al. (2023) provide support for these findings by highlighting that weak data governance frameworks pose a substantial barrier to the effective use of AI in supply chain management. To prescribe, the research by Vann Yaroson et al. (2025) suggests that ethically bound AI systems would require trusted datasets to ensure the necessary transparency, fairness, and ethical procurement practices. As a result, one can say that the majority of the preceding literature supports the conclusions of this research, which is that the low quality of data may adversely affect not only performance but also the credibility of sustainability evaluations.

The study has also indicated that high-quality procurement data can be used in supplier benchmarking and the monitoring of performance using sustainability indicators. Tsolakis et al. (2023) also referred to these results, stating that data inputs must be correct to use AI and blockchain to produce quality and accurate insights in sustainable procurement. To corroborate the argument, the researchers of the Whig et al. (2024) study reported that advanced analytics and quantum artificial intelligence platforms are built on high-quality datasets that drive optimal purchases, minimize emissions, and specialise in ethical sourcing. Based on this consideration, it can be stated that a vast majority of the earlier studies justified the findings presented in this study and confirmed the importance of data quality in the procurement transformation process.

In addition, this paper identified that data standardisation between different procurement systems enhances cross-functional alignment contributing to enhanced sustainability reporting and accuracy of decision-making. Vishwakarma et al. (2025) confirm these findings, showing that high-quality data allowed improved forecasting of demand, supplier selection, and meeting sustainability targets in a healthcare procurement system. The paper by Yousefi and Tosarkani (2024) supports this assertion by stating that standardised data forms will enable the procurement team to monitor, compare, and validate sustainability performance across various suppliers and

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locations. On this basis, one can say that the majority of past research has backed the study and justified the strategic importance of data quality in improving procurement performance.

The study also reports that combining high-quality data with RPA and AI-based tools enhances their efficiency, allowing procurement teams to take action on valid feedback and forecasts. Such findings are supported by Vann Yaroson et al. (2025), who discussed the interconnection between data integrity and the ethical application of AI systems, particularly in supplier assessment and ESG checks. In line with this, the study conducted by van Hoek (2024) found that procurement performance is significantly enhanced when AI and automation systems are complemented by high-quality data, particularly in terms of compliance, supplier responsibility, and sustainable sourcing. It is based on this fact that one can say that the majority of previous studies supported the results of the study under discussion and provided solid empirical evidence for the significance of data quality in achieving sustainable procurement goals.

5.2.4. H4: Organizational readiness is positively associated with sustainable procurement performance

This research concluded that organisational readiness positively correlates with sustainable procurement performance, which means that an organisation's capacity to embrace new technologies, train employees, and develop adequate procedures goes a long way in meeting sustainability goals in procurement. This has been supported by Oldemeyer et al. (2024), who demonstrated that the appropriate response to the inquiry regarding the level to which artificial intelligence (AI) and other advanced technologies can be effectively implemented into supply chain operations is readiness, especially SME readiness. In line with this, the Radhakrishnan et al. (2022) study reported that the success of AI programs and, consequently, green procurement is dependent on three variables of readiness, namely leadership support, employee expertise, and infrastructure maturity. Organizational readiness has been identified as a critical success factor across multiple studies of technology adoption. Oldemeyer et al. (2024), Radhakrishnan et al. (2022), and Neupane (2023) each found that readiness dimensions—including leadership support, employee expertise, and infrastructure maturity—significantly influence AI adoption outcomes. The current study extends this literature by specifically linking readiness to sustainable procurement performance metrics rather than adoption rates alone.

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The research also revealed that internal harmony among the different departments, coupled with executive vision by top management, improves an organisation's capacity to act on sustainability challenges related to procurement. The latter findings are echoed by Nurhayati et al. (2025), who tested the readiness against the AI-driven learning setting and suggested that organisations must prepare for battling not only on technological levels but also in cultural and management-related areas that allow for change. To support this, Neupane (2023) noted that readiness in the context of strategic sourcing encompasses both technical and non-technical elements, which are invaluable in implementing sustainability in sourcing. These aspects refer to change management and adaptability of employees. Owing to this fact, we can say that the majority of past research studies support the findings of this research and strengthen the argument that readiness should be holistic in order to be effective in addressing sustainable procurement.

Moreover, the research team established that the readiness (as the level of digital infrastructure maturity) is a major facilitator of sustainability in procurement systems, especially among those firms that work within the unstable or resource-scarce settings. These findings are corroborated by Rashid et al. (2025), who pointed out that preparedness when it comes to the adoption of big data and AI allows one to integrate green supply chain practices more effectively, and they eventually translate into better sustainability results. The strength of this argument is echoed by Riad et al. (2024), who added that companies with established readiness models are better positioned to successfully deploy AI-driven tools for supply chain optimisation that enhance resilience and eco-friendly performance. It is because of this fact that one can say the vast majority of existing studies support the findings of this research or validate the claim that digital and operational readiness are critical factors in assuring the development of sustainable procurement.

The paper has also established that low preparedness serves as a barrier to the technology adoption process and impedes sustainability transitions in procurement processes. Nazeer and Gil (2023) identified institutional resistance, a shortage of skills, and the absence of a vision as reasons why AI cannot be implemented in public sector organisations, which undermines their capacity to pursue sustainable procurement. Supporting this, Muthuswamy and Ali (2023) asserted that, despite the opportunities posed by machine intelligence, most organisations have not been prepared to adopt employment, leading to a lack of utilisation of AI to promote sustainable

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development. Based on this fact, one can say that the majority of earlier studies concurred with the findings in this study, especially in developing nations and resource-scarce settings.

5.2.5. H5: Ethical implementation of AI contributes positively to sustainable procurement performance

The findings of this study demonstrate that the ethical application of AI aids sustainable procurement performance by enhancing transparency, fairness, and accountability in procurement decision-making activities. Polyportis and Pahos (2024) supported these findings, stating that ethical use of AI in the community and the private sector enables the sustainability of ethical solutions and increases confidence in the digital system, which is vital to sustainability. In compliance with Petersson et al. (2022), it is asserted that ethical issues, such as prejudice, information confidentiality, and the responsibility of decisions, should be addressed in the implementation of AI to promote a reasonable and fair supply chain. The finding that ethical AI implementation strongly predicts sustainable procurement performance ($\beta = 0.928$) is consistent with emerging research on responsible AI. Polyportis & Pahos (2024), Petersson et al. (2022), and Rane (2023) have all argued that ethical governance—including bias detection, transparency, and accountability—is inseparable from sustainable outcomes in digitalized supply chains. This study provides quantitative evidence supporting those theoretical arguments.

This paper has also ascertained that ethical procurement teams adopting AI can more easily choose suppliers that excel in terms of environmental governance and social responsibility, prevent exploitation, and meet global sustainability regulations. Rane (2023) justifies these outcomes by noting that the inability to ethically regulate the issue of generative Artificial Intelligence in corporate business could contribute to acts of misinformation, marginalisation, and violating scalability. Phuoc (2022) added that the use of ethical AI has a direct impact on the level of trust people have in a given emerging economy, the fate of regulatory compliance, and sustainable decision-making in development. This reason is why it can be stated that the majority of earlier studies support the results of the present study and debate the strategic relevance of ethical AI governance in sustainable procurement.

In addition, this research found that ethical AI enhances the transparency of procurement through the traceability of decisions, minimisation of bias in supplier reviews, and recording adherence to sustainability criteria. Supporting these findings is Palakurti (2025), who reported that AI-based

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predictive analytics can help sustain food supply chains; however, this is only the case with models designed to remove bias and deliver an inclusive outcome. To support the assertion, Raihan et al. (2024) noted that the sustainable application of digital technologies promotes the sustainable utilisation of resources, particularly in regulated sectors such as the management of minerals and natural resources. Owing to this fact, it can be stated that the majority of prior research has confirmed the findings of this research, indicating that ethics are not a peripheral aspect but a core component in AI-based procurement for sustainability.

This research also concluded that the inclusion of ethical principles in the deployment of AI minimises both reputational and regulatory risks, while promoting long-term procurement performance. Rejeb and Appolloni (2022) emphasise that circular procurement efforts facilitated by AI can be successful only when moral and responsible data are present. On its part, Ronaghi (2023) asserted that ethics should underpin the use of AI in manufacturing to facilitate adherence to the circular economy and green procurement principles. Due to this factor, it is reasonable to state that the majority of prior research findings support the findings of this research, indicating that ethical AI can lead to stakeholder trust, regulatory compliance, and sustainable procurement environments.

5.2.6. H6: Technology integration capability has a significant positive effect on sustainable procurement performance

This paper has also identified and proven that the technology integration capability positively influences sustainable procurement performance, as organisations characterised by high integration capabilities are well-placed to coordinate diverse digital tools, such as AI, RPA, and IoT, with sustainability goals. Indeed, these findings are confirmed by Patrtsio et al. (2024), who stated that the combination of AI and RPA enables the establishment of a single procurement environment that can be used to automate operations, increase visibility, and promote sustainable business practices. To support this, Nozari et al. (2022) mentioned that the combination of AI and IoT (AIoT) in smart supply chains enables the real-time tracking of sustainability and enhances operational flexibility. Technology integration capability emerged as the strongest predictor of sustainable procurement performance alongside ethical implementation (both $\beta = 0.928$). This finding aligns with Patrício et al. (2024), Nozari et al. (2022), and Regona et al. (2024), who demonstrated that interoperability between AI systems, legacy platforms, and sustainability

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dashboards is essential for realizing the benefits of digital procurement transformation. Organizations with fragmented technology ecosystems cannot achieve the data continuity required for sustainability monitoring and optimization.

A key finding of this research is that companies with greater capabilities in integrating them can address cost, time, and sustainability limitations within their procurement systems concurrently. The findings are corroborated by Regona et al. (2024), who noted that there is more potential to align the use of integrated AI systems with the UN Sustainable Development Goals, particularly as more sectors utilise the systems, including resource-intensive ones such as construction. Supporting this, Muthuswamy and Ali (2023) noted that the integration of technologies would facilitate the redesign of supply chain models into fluid and more intelligent systems, which would minimise the environmental footprint of the supply chain and lead to a more efficient use of resources. Owing to this fact, it can also be stated that the majority of previous studies have affirmed the results of this study and acknowledged the connection between integrated systems and sustainable performance in the complex procurement environment.

This paper also documents that the capability of integration improves the flexibility and sensitivity of procurement systems, enabling them to respond rapidly to shocks and sustainability threats. Riad et al. (2024) confirm these findings, finding that integrated digital platforms enable predictive and prescriptive insights, which enhance supply chain resilience and sustainability. To support this, Rainy and Chowdhury (2022) claimed that AI-based decision models incorporated into integrated supply chains enhance the processes of supplier assessment and route planning, which helps reduce overall costs and improve sustainability aspects. Based on this fact, it can be stated that the majority of prior research results align with those of this study, substantiating the importance of integration ability in procurement agility and strategic sustainability management.

Moreover, the paper found that technology integration facilitates communication with both internal departments and external partners, enhancing procurement transparency and accountability. Rane et al. (2024) reinforced these findings through their detailed statements, underlining that the cross-functional integration of digital tools contributes to the enhancement of data-sharing and collaborative sustainability efforts. To give credence, Ofosu-Ampong (2024) explained that with the incorporation of technology, firms will be able to orchestrate their digital resources more efficiently and utilise their disaggregated information into viable intelligence that

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will support sustainable procurement. It is based on this fact that one could say the findings of most previous studies supported this study and confirmed the idea that integration abilities can provide better system-wide coordination, which is what is needed for sustainable supply chain performance.

5.3. Summary

In summary, Chapter 5 confirms that all six proposed hypotheses were accepted, indicating a strong positive relationship between AI-related capabilities and sustainable procurement performance. The findings reveal that AI technologies significantly enhance procurement efficiency and sustainability when supported by ethical governance, quality data, organisational preparedness, and robust technology integration. The study's results were largely consistent with the literature, reinforcing the value of AI in strategic procurement management. This chapter establishes a solid foundation for the conclusions and implications presented in the following section of the dissertation.

5.3 Study implications

5.3.1 Implications to Theory

In theory, the defined study makes a valuable contribution to further knowledge in the field of sustainable procurement through integrating artificial intelligence (AI) in the modern models of supply chain and procurement performance. It is also the key theoretical development to ensure that AI is not seen as a purely technical enabler but as a full participant in the procurement decision-making process and stakeholder interaction, as well as environmental performance. Contrary to conventional procurement theories regarding the motive to approach procurement decisions as non-dynamic, the proposed study focuses on the dynamic nature of the process, in which artificial intelligence will be helping to achieve real-time flexibility, the ability to deduce the information, and the strategy to align with the sustainability goals. The results bring change regarding the theoretical debate away on the linear procurement models towards the intelligent, responsive procurement systems containing the machine learning, robotic process automation and data-based decision engines.

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The study also questions and builds upon such classical models like Resource-Based View (RBV) and TechnologyOrganisationEnvironment (TOE) framework. It indicates that resources, e.g., ethical AI governance, integration capabilities, and organisational readiness, can also be conceptualised as dynamic capabilities that co-evolve alongside sustainability demands. Indeed, the theories that preceded this research put a lot of emphasis on the physical items, whereas the present research makes intangible digital items, including algorithmic governance, training data quality, and transparency protocols, key theoretical constructs regarding the sustainable results of procurement. By doing that, the study re-orientates supply chain theory to make it more representative of multifaceted and algorithmically-mediated provider ecosystems of mass present-day organisations.

Also, the research adds a theoretical texture to the topic by remodeling the sustainability models to promote ethical principles in applying AI. Whereas the conventional sustainability theories focused on such measures as emissions, compliance, and green sourcing, the research here expands this limit to the areas of algorithmic fairness, transparency, and responsible data practices. Through its findings, the research proposes that ethics do not just constitute an accessory to the implementation of AI but become a critical aspect of the sustainability debate of digitalised supply chains.

Findings are also indicating the necessity of a changed conceptualisation of the procurement integration theory. The concept of integration has been frequently perceived in the context of supplier relationship management or inter-organisational co-ordination. Nevertheless, this paper suggests that the capacity of technological integration, especially interoperability of AI systems with procurement databases and sustainability dashboards, is the deciding factor in terms of sustainability performance. The research therefore extends the theory of integration to the notion of integration of machine-level coordination and platform interoperability as theoretical constructs in literature of procurement.

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Overall, this study has three theoretical implications, each of which enhances the conceptualisation of AI as a sustainable procurement driver, updates the theoretical coverage of organisational readiness and ethical governance, and reconceptualises the Integration theory through the technological background. Such advancements open new opportunities to enhance the future of procurement and sustainability models, which should be updated and aligned with the digitalized and currently interconnected nature of the procurement ecosystem.

5.3.2 Implications to Management

The study has major managerial implications where the same should be of interest to procurement executives, sustainability managers, and digital transformation managers that work on the crossroad of using AI and sustainable procurement. Among the most important things that managers can learn, the necessity to not only consider AI as another means to an efficiency end but a strategic instrument to reach the sustainability goal has to be mentioned. Instead of viewing AI as a purely operational or cost-reducing system, organisations need to promote AI-enabled procurement systems as the focal point of their corporate responsibility agendas. It is to place sustainability indicators, like emissions monitoring or ethical sourcing compliance, directly within AI models, dashboards, and supplier assessment processes.

The other important implication is the fact that ethical deployment of AI should be a company-wide task. Managers should develop cross-functional governance frameworks of AI-driven procurement policy, including not just IT and procurement services but also ethics boards, compliance departments, and sustainability teams. The comprehensive model can make sure that algorithmic bias, transparency, as well as regulatory risks, below, are actively addressed, thus minimizing reputational losses and building trust between stakeholders. It also enables the firm to make sure that the procurement algorithms are in line with corporate social responsibility (CSR) guarantees to greater institutionalise sustainability as a part of core operations by managers.

One of the major suggestions to the decision-makers is the prioritisation of the investment in the digital readiness and workforce capability. The authors of the study demonstrate that the degree of

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organisational preparedness, such as management support, digital infrastructure, and the skills of workforce are also significant factors affecting the success of AI in sustainable procurement. The managers are recommended to perform periodic digital maturity checks, set aside certain special budgets to undertake AI training courses and create a change-management strategy focused on procurement. In practice, this would entail providing procurement teams with AI literacy, work-flow redesign with automation in mind and making sustainability goals part of performance management systems.

Data governance is as well highlighted in the research as being reliable. The provision of procurement data and its integrity is of essential interest to sustainable procurement, which ultimately affects AI accuracy and quality of decisions. Managers are expected to introduce strict data quality control, introduce metadata standards, and create data taxonomy policies peculiar to procurement. Moreover, the procurement systems should also be equipped to conduct real-time data analytics to facilitate proactive evidence-based sourcing decisions in line with sustainability measures.

Finally, the paper indicates that the ability to integrate technology is not only a technical issue but a strategic tool. Managers should be in a position to make procurement systems interoperable with sustainability reporting platforms, enterprise resource planning (ERP), and supplier management systems. This requires the choice of the modular AI solutions, open APIs, and flexible architecture which allows scaling and the alignment of the entire system. Integration capability also touches on setting up procurement performance metrics that act as indicators of cross-system operability, synchronicity between AI-based forecasts and inventory optimisation programs. Such measures will improve agility, transparency and sustainability in the procurement functions.

5.4 Study limitations

Although this research has enough statistical depth and strong research methodology, there are some limitations to consider to put the findings correctly into perspective. These restrictions do not affect the validity of the study but they can be used to explain the applicability and direction of the research.

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To begin with, the research is based on self-reported data that is obtained using structured questionnaires. Although this kind of method allows consistency and statistical analysis, it has the disadvantage of creating a likelihood of response bias. Interviewees might exaggerate the scale of AI adoption or the activity of sustainability programs because of feeling certain expectations or fear of reputation. In spite of assuring confidentiality, the methodological limitation is subjectivity of self-assessments, particularly in the assessment of ethical outcome measures of AI deployment and sustainability.

Second, the study sample was based mainly on the organisations that already had adopted or performed a pilot project on the area of AI in procurement. Although this enabled the study to study mature implementation practices, it could also be a limitation to generalisability to the firms with little adoption. Other organisations, depending on their digital infrastructure or conservative procurement policies, can experience completely different obstacles and results, not considered in this research.

Third, the study was of cross-sectional nature, not considering the dynamic development of AI technologies, or procurement strategies, over time. The application of AI in procurement is fast developing and sustainable measures keep on changing as new legislations and environmental standards emerge. Therefore, the results are considered to be a single point of representation at a certain period and are not a long-term study of AI integration maturity or sustainability performance change following technological advancement.

Fourth, regional bias may have been established in terms of geographical area of study. Most participants were well developed economies or large organisations with properly developed procurement and digitalisation systems. The organisations and SMEs based in developing economies were underrepresented in the sample because infrastructural assistance, regulatory support, and resource allocations to the AI and sustainability projects can vary significantly. This constrains the extent of findings applying in situations in which populations are less institutionally complex or areas of sustainability are influenced by other socio-economic circumstances.

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Fifth, researchers concentrated on six such constructs as AI decision-making, RPA, data quality, organisational readiness, ethical AI implementation, and integration capability. Although all these variables can capture important aspects of AI-enabled sustainable procurement decisions, they fail to capture other potentially significant factors, including stakeholder involvement, supplier diversity, and geopolitical risks in sourcing. Moreover, the advances in technology, AIoT, edge, and green IT access unrelated to the study might provide more knowledge on the connection between procurement performance.

Finally, the study utilized quantitative methods devoid of triangulation by qualitative data and studies including interviews or cases studies. Although this provides statistical robustness, it restricts the level of learning regarding organisational context, behavioural and dynamics or user interactions with AI system use. There may be hidden tensions or suggestive strategies or ethical issues that qualitative component could have picked up and the quantitative instrument does not handle. The studies in the future should look at mixed-method in order to give a wider perspective.

5.5 Recommendations

Informed by the results, a number of selective enhancements are suggested among the organisations interested in upgrading their sustainable procurement performance based on AI.

First, organisations should design AI abilities into procurement systems, and not as layers added after implementation. To maintain that sustainability experts do not see environmental and ethical criteria as an add-on, it is suggested that the development of AI models is made in cooperation with sustainability experts, so that they become a part of the logic of the system. Sustainability requirements need to be enabled by procurement tools, in-depth carbon or ESG analytics, and buyer scoring of suppliers on the basis of carbon emissions indicators, labour rights, or by those in the circular economy. Further, the procurement dashboards shall facilitate visualisation of a relationship between procurement spending and the environmental consideration, so as to make data-driven sustainability decisions.

Secondly, the institution of ethical governance mechanisms should be put in place. Algorithmic fairness, detection of biases, and explainability should be controlled by a brand-new AI ethics board or procurement review panel. Organisations are requested to have formal procurement

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instructions on the algorithm development, such as recording data sources of training and communicating requirements to include a vendor, and transparency requirements. This will guarantee that sustainability is not atrophied by algorithmic transparency or economic bias.

Third, companies ought to place more emphasis on interoperability across the systems. Sustainability reporting systems, ERP modules, and supplier portal should be integrated with procurement tools to attain consistency, accuracy, and efficiency. Integration processes are supposed to be based on API and have an automatic data reconciliation process to avoid duplicating data or error. To give an example, a sustainability scorecard should auto-update when a new supplier has been diverted to procurement, or when contract compliance with an environment audit has been completed utilizing new AI-based procurement system.

Fourthly, it is required to develop capabilities. Procurement professionals should also undergo constant learning programmes to acquire AI literacy, interpret the results of algorithms, and address ethics issues. This involves such capabilities as the validation of data inputs, questioning AI suggestions, and reporting sustainability deviations. Institutionalisation of certifications in AI ethics, data governance, and sustainable supply chain management should be part of the procurement career moves.

Fifthly, strong data governance model. The AI models should consume high-quality and ethically generated data that are well categorised. To ensure that no misleading or inaccurate insights can be made, firms need to adopt data provenance tracking, metadata tagging and automated detection of anomalies. Besides, data privacy laws should be imposed on all procurement ecosystems, especially in situations when AI is being utilised to profile vendors or rate behavioural risks.

5.6. Future Research Directions

The results of this research provide a number of avenues to further research work.

To begin with, longitudinal studies will be necessary to monitor the developments in state of AI-driven procurement systems over time and the effects that they have on sustainability performance outcomes in changing environments. Investigations can study the impact of organisational maturity, the evolution of regulations or economic shocks on the association of AI and procurement sustainability.

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Secondly, it is suggested that the sector-specific implications of AI in procurement are to be examined in the future. As an example, the procurement environment in the healthcare industry, manufacturing industry, or the public infrastructure sector may vastly vary regarding data availability, risk tolerance or even morals. Wholesome more specific ways of study would be permissible within domains.

Thirdly, there is a need to define the role of local institutional contexts, specific legal systems and stakeholder values in AI adoption and sustainability in procurement and to compare across cultures. Such an analysis would include a comparative one between high-income and low-income nations that might provide findings into the infrastructural and cultural enablers or barriers.

Fourthly, qualitative studies to reveal the organisational stories, ethical dilemmas and behaviour changes related to AI implementation in procurement are required. Case studies, interviews and ethnographies might help understand more about implementing real life problems and resolutions.

Fifthly, in the future, it is necessary to consider the aircraft industry and the study of the interchange between AI and the new notions of sustainability, like regenerative procurement, climate risk incorporation, or biodiversity-friendly sourcing. The procurement systems need to be transformed to help achieve ambitious sustainability objectives, as well as in terms of sophisticated metrics, sustainability over time, and to internationalize their systems.

Finally, future research plans could explore the concept of simulating and modeling the procurement choice to make using digital twin environments and forecasting sustainability trade-offs. Integration of AI with simulation models would enable the procurement managers to foresee the risks; test the scenarios and assess the long-term effects of the sourcing strategies employed.

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Appendix

Questionnaire

Demographics

what is your gender?

- Male
- Female

2. What is your age?
    - 18-25
    - 26-45
    - 46-60
    - 60 or more
3. What is your education?
    - Bachelors
    - Masters
    - PhD
    - Diploma

Instructions: Please indicate your level of agreement with the following statements by selecting the appropriate number on the scale from **1 to 5**.

1	**2**	**3**	**4**	**5**
Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

Section 1: AI-Driven Decision-Making

Statement	**1**	**2**	**3**	**4**	**5**
1. Our procurement team relies on AI-generated insights to select suppliers who meet our sustainability criteria.	☐	☐	☐	☐	☐

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Statement	1	2	3	4	5
2. AI-driven analytics significantly improve the accuracy of our demand forecasting compared to manual processes.	☐	☐	☐	☐	☐
3. The use of AI in decision-making allows us to identify environmental risks in the supply chain more quickly.	☐	☐	☐	☐	☐

Section 2: Sustainable Procurement Performance

Statement	1	2	3	4	5
4. Our procurement processes have successfully reduced the organization's overall carbon footprint.	☐	☐	☐	☐	☐
5. We consistently meet our targets for sourcing from socially responsible and diverse suppliers.	☐	☐	☐	☐	☐
6. Sustainability metrics are given equal weight to cost and quality in our procurement evaluations.	☐	☐	☐	☐	☐

Section 3: Robotic Process Automation (RPA)

Statement	1	2	3	4	5
7. RPA has effectively eliminated repetitive manual tasks in our procurement workflows (e.g., invoice processing).	☐	☐	☐	☐	☐
8. The implementation of RPA has reduced human error in our purchase order cycle.	☐	☐	☐	☐	☐
9. RPA allows our procurement staff to focus more on strategic sustainability initiatives rather than admin work.	☐	☐	☐	☐	☐

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Section 4: High Data Quality in Procurement

Statement	1	2	3	4	5
10. Our procurement data is consistently accurate, complete, and up-to-date across all platforms.	☐	☐	☐	☐	☐
11. We have standardized data protocols that ensure consistency in how sustainability information is recorded.	☐	☐	☐	☐	☐
12. The quality of our internal data is sufficient to support advanced AI and machine learning applications.	☐	☐	☐	☐	☐

Section 5: Organizational Readiness

Statement	1	2	3	4	5
13. Our leadership provides sufficient financial and technical resources to support AI adoption in procurement.	☐	☐	☐	☐	☐
14. Employees in the procurement department possess the necessary digital skills to work with AI technologies.	☐	☐	☐	☐	☐
15. The organizational culture is open to adopting new technological innovations for sustainability.	☐	☐	☐	☐	☐

Section 6: Ethical Implementation

Statement	1	2	3	4	5
16. Our organization has clear ethical guidelines to prevent bias in AI-driven supplier selection.	☐	☐	☐	☐	☐
17. We prioritize transparency in how AI algorithms make decisions regarding procurement contracts.	☐	☐	☐	☐	☐

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Statement	1	2	3	4	5
18. Data privacy and security are strictly maintained when sharing procurement data with AI providers.	☐	☐	☐	☐	☐

Section 7: Technology Integration

Statement	1	2	3	4	5
19. Our AI tools are seamlessly integrated with our existing Enterprise Resource Planning (ERP) systems.	☐	☐	☐	☐	☐
20. Information flows smoothly between different departments through our digital platforms.	☐	☐	☐	☐	☐
21. Compatibility issues between legacy systems and AI tools are a major barrier to our goals.	☐	☐	☐	☐	☐

Data Classification: Open