# INDUSTRY 4.0 AND ENVIRONMENTAL SUSTAINABILITY OF MANUFACTURING FIRMS IN NAIROBI, KENYA

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**24/00216**

**A RESEARCH DISSERTATION SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF MASTER OF BUSINESS ADMINISTRATION (CORPORATE MANAGEMENT) IN THE SCHOOL OF BUSINESS, KCA UNIVERSITY**

**NOVEMBER 2025**

## DECLARATION

I declare that this dissertation is my original work and has not been previously published or submitted elsewhere for award of a degree. I also declare that this contains no material written or published by other people except where due reference is made and author duly acknowledged.

31/10/2025

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**DENNIS MBAE NJARAMBA** Date

**24/00216**

I do hereby confirm that I have examined the master's dissertation of

**Dennis Mbae Njaramba's**

And have certified that all revisions that the dissertation panel and examiners recommended have been adequately addressed.

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## ABSTRACT

The adoption of Industry 4.0 technologies has become increasingly important in promoting environmental sustainability within the manufacturing sector. However, in Nairobi, Kenya, many manufacturing firms continue to face challenges in integrating these advanced technologies to minimize their environmental footprint. This study sought to establish the effect of Industry 4.0 on the environmental sustainability of manufacturing firms in Nairobi, Kenya. Specifically, the study aimed to examine the influence of smart manufacturing, determine the effect of cyber-physical systems, assess the influence of Internet of Things, and evaluate the effect of big data analytics on environmental sustainability. The study was anchored on four key theories: the Natural Resource-Based View theory, the Ecological Modernization Theory, the Technology-Organization-Environment framework and the Dynamic Capabilities Theory. The study adopted a descriptive correlational research design and targeted the 418 manufacturing firms operating within Nairobi County. A stratified random sampling technique was used to select 204 respondents from various manufacturing subsectors, and primary data was collected using structured questionnaires administered to operations and environmental sustainability managers. Quantitative data was analyzed using both descriptive and inferential statistics, including multiple regression analysis to test the hypothesized relationships. SPSS version 27 was used. The regression results revealed that Industry 4.0 technologies significantly enhanced environmental sustainability among manufacturing firms in Nairobi, with an $R^2$ of 0.776, $F(4,176) = 152.580$, and $p < 0.001$. The standardized coefficients indicated that cyber-physical systems ($\beta = 0.363$, $p < 0.001$) and smart manufacturing ($\beta = 0.316$, $p < 0.001$) had the strongest effects, followed by Internet of Things ($\beta = 0.199$, $p < 0.001$) and big data analytics ($\beta = 0.133$, $p = 0.002$). The study concluded that the adoption of Industry 4.0 technologies significantly enhances environmental sustainability by improving energy efficiency, reducing waste, minimizing emissions, and promoting resource optimization in manufacturing firms. The study recommends that policymakers and regulators formulate supportive policies and incentives to encourage the adoption of Industry 4.0 technologies across the manufacturing sector. This may include tax rebates, innovation grants, and infrastructure development to enhance technological readiness.

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## DEDICATION

This work is dedicated to my beloved family for their unwavering love, support, and encouragement throughout this academic journey. Their faith in me has been the driving force behind the successful completion of this study.

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## ABBREVIATIONS AND ACRONYMS

| | |
|---|---|
| **4IR** | Fourth Industrial Revolution |
| **BDA** | Big Data Analytics |
| **CLRM** | Classical Linear Regression Model |
| **CPS** | Cyber Physical Systems |
| **EMT** | Ecological Modernization Theory |
| **GDP** | Gross Domestic Product |
| **IoT** | Internet of Things |
| **KAM** | Kenya Association of Manufacturers |
| **KNBS** | Kenya National Bureau of Statistics |
| **NACOSTI** | National Commission for Science, Technology and Innovation |
| **SDG** | Sustainable Development Goals |
| **SME** | Small and Medium Enterprises |
| **SPSS** | Statistical Package for Social Sciences |
| **TOE** | Technology-Organization-Environment |

## DEFINITION OF TERMS

| | |
|---|---|
| **Big data analytics** | Big data analytics in Industry 4.0 involves the collection, processing, and analysis of large volumes of structured and unstructured data to uncover patterns, improve operational efficiency, support sustainability initiatives, and facilitate predictive and prescriptive decision-making (Sundarakani et al., 2024). |
| **Cyber-physical systems** | Cyber-physical systems are integrations of computation, networking, and physical processes where embedded computers and networks monitor and control physical processes through feedback loops. CPS facilitates intelligent production and self-adaptive manufacturing environments (Woschank et al., 2020). |
| **Environmental sustainability** | Environmental sustainability in the manufacturing sector involves practices that reduce ecological impact, such as minimizing carbon emissions, reducing waste, conserving energy, and optimizing resource use, while ensuring long-term ecological balance and compliance with |

| | |
|---|---|
| | environmental standards (Umar et al., 2021). |
| **Industry 4.0** | Industry 4.0 refers to the integration of digital technologies such as cyber-physical systems, the Internet of Things (IoT), cloud computing, and big data into manufacturing processes to create smart, interconnected systems that improve operational efficiency and sustainability. It emphasizes automation, data exchange, and real-time decision-making within production networks (Prause & Atari, 2020) |
| **Internet of things** | The Internet of Things in manufacturing refers to a network of physical devices—such as sensors, machines, and tools—embedded with software and connectivity to collect, exchange, and act on data, thereby enhancing process visibility and enabling sustainable decision-making (Nagy et al., 2020). |
| **Smart manufacturing** | Smart manufacturing is a technology-driven approach that uses interconnected systems, real-time data analytics, and automation to enhance production |

processes. It enables adaptability, predictive maintenance, and efficient resource usage to support sustainable manufacturing goals (Sundarakani et al., 2024).

# CHAPTER ONE

# INTRODUCTION

## 1.1 Background of the Study

In the current era of globalization, environmental sustainability has become a strategic priority for manufacturing firms due to intensifying environmental concerns and rising international scrutiny (Kamble et al., 2023). Global trade integration and industrial expansion have heightened the environmental impact of manufacturing, prompting greater accountability from firms operating in interconnected value chains (Sundarakani et al., 2024). Multinational buyers and consumers are increasingly demanding adherence to sustainable production standards, compelling manufacturers particularly in developing economies to align with global environmental benchmarks (Bag et al., 2022).

Moreover, global frameworks such as the Paris Agreement and the Sustainable Development Goals (SDGs) have exerted pressure on manufacturing industries to transition toward low-carbon and resource-efficient operations (Umar et al., 2021). In this context, environmental sustainability enhances not only regulatory compliance but also access to international markets, sustainable financing, and long-term competitiveness. As firms operate across borders, their environmental footprints are closely monitored by international stakeholders, making sustainability a critical determinant of reputation, risk management, and supply chain participation (Zhou et al., 2022). Consequently, manufacturers in Nairobi and other emerging industrial hubs must embrace sustainable practices not merely as ethical imperatives but as essential conditions for survival and growth in the globalized economy.

Industry 4.0 technologies provide innovative tools that significantly enhance environmental sustainability in manufacturing processes. Through real-time data collection and analytics, technologies such as the Internet of Things (IoT) enable manufacturers to monitor energy consumption and emissions more effectively (Woschank et al., 2020). Cyber-physical systems support autonomous production environments where machines self-optimize to minimize material waste and energy use (Prause & Atari, 2020). Additionally, big data analytics allows firms to anticipate and mitigate environmental risks by identifying inefficiencies and forecasting equipment failures (Sundarakani et al., 2024). These technological advancements facilitate circular production models, reduce the carbon footprint, and align industrial practices with global sustainability goals, making Industry 4.0 a critical enabler of green transformation in manufacturing.

The Fourth Industrial Revolution (4IR) is transforming global manufacturing by integrating digital technologies such as the Internet of Things (IoT), cyber-physical systems, and artificial intelligence into industrial operations. These technologies facilitate smart manufacturing, increase resource efficiency, and promote sustainable production practices (Luu et al., 2023). Globally, manufacturing firms are under increasing pressure to reduce carbon emissions, minimize waste, and shift towards cleaner production systems in response to climate change and regulatory frameworks (Duarte et al., 2024). The convergence of advanced manufacturing and environmental sustainability is seen as a strategic imperative for firms to remain competitive in an increasingly eco-conscious global economy (Umar et al., 2021; Nagy et al., 2020; Woschank et al., 2020).

In Africa, however, the adoption of Industry 4.0 technologies has been relatively slow, largely due to infrastructural limitations, skill shortages, and capital constraints (Bongomin et al., 2020). Despite these challenges, Industry 4.0 offers significant promise for African manufacturers, enabling them to overcome operational inefficiencies and achieve sustainability goals through innovations such as predictive maintenance, smart energy systems, and real-time data monitoring (Bag et al., 2020). The East African Community (EAC) has acknowledged the importance of participating in this digital transformation, recognizing that falling behind in the 4IR race could widen the technology gap between Africa and the rest of the world (Bongomin et al., 2020; Fonseca et al., 2020).

In Kenya, the government has identified manufacturing as a key pillar of its development agenda, but the sector faces persistent challenges including high energy costs, low technological uptake, and environmental inefficiencies (Rusungu et al., 2020). Although national policies such as the Green Economy Strategy and Kenya Vision 2030 support sustainable industrialization, few manufacturing firms have embedded Industry 4.0 solutions into their environmental sustainability frameworks (Ogur, 2023). Most Kenyan firms continue to rely on conventional production methods, resulting in excessive waste generation and inefficient resource utilization (Nganga, 2021). The disconnect between digital transformation and sustainability implementation at the firm level remains a critical issue in Kenya's industrial landscape (Barno, 2022).

Specifically, in Nairobi—the country's manufacturing hub—firms have varied in their uptake of digital solutions, with large multinationals showing some progress while many local firms lag behind due to high capital costs and lack of awareness (Koech, 2023). While studies have explored lean manufacturing and competitiveness in Nairobi, there is limited empirical research on how Industry 4.0 tools such as cyber-physical systems, IoT, and smart analytics impact environmental sustainability practices (Rusungu et al., 2020). Furthermore, existing studies tend to focus on operational efficiency or innovation without addressing the ecological dimension of industrial transformation (Barno, 2022; Nganga, 2021).

This study therefore sought to address these gaps by investigating how Industry 4.0 technologies influence the environmental sustainability of manufacturing firms in Nairobi. While global studies have demonstrated the potential of Industry 4.0 in enhancing sustainable manufacturing (Bag et al., 2022), there remains limited empirical evidence from Sub-Saharan Africa, particularly in urban industrial hubs like Nairobi, where technological adoption is often constrained by infrastructural, regulatory, and financial barriers (Ochieng et al., 2023). Moreover, most existing research has been conducted in developed economies, with contextual differences limiting the generalizability of such findings to Kenya's manufacturing sector (Sundarakani et al., 2024).

### 1.1.1 Industry 4.0

Industry 4.0, also referred to as the Fourth Industrial Revolution, represents the integration of advanced digital technologies into manufacturing and industrial processes. It encompasses innovations such as the Internet of Things (IoT), cyber-physical systems, artificial intelligence (AI), cloud computing, and big data analytics, which work together to create smart, autonomous, and interconnected production environments (Luu et al., 2023). The core idea is to enable real-time data-driven decision-making, enhance system efficiency, and facilitate adaptability and customization in production processes (Umar et al., 2021). Unlike previous industrial revolutions, Industry 4.0 not only focuses on automation but also emphasizes the seamless exchange of data between machines, systems, and people to improve productivity and sustainability (Bongomin et al., 2020).

The adoption of Industry 4.0 is increasingly recognized as a strategic driver of competitiveness, productivity, and sustainability in the manufacturing sector. It offers transformative benefits such as reduced production costs, improved product quality, enhanced flexibility in meeting customer demands, and optimized use of resources (Modgil et al., 2022; Kamble et al., 2023). More importantly, Industry 4.0 plays a vital role in promoting environmental sustainability by enabling manufacturers to monitor energy consumption, reduce waste, and implement cleaner production technologies (Bag et al., 2022; Sundarakani et al., 2024). In developing economies, where resource constraints and environmental degradation remain critical challenges, the transition to Industry 4.0 offers a pathway to modernize industrial operations while minimizing ecological impacts (Zhou et al., 2022). Consequently, the importance of Industry 4.0 goes beyond operational efficiency, positioning it as a cornerstone for sustainable industrial development in the globalized economy.

In the current study, Industry 4.0 was measured using four core technological dimensions: smart manufacturing, cyber-physical systems, Internet of Things (IoT), and big data analytics. These components have been selected because they represent the most prominent and transformative technologies driving digital manufacturing across the globe (Koech, 2023; Nganga, 2021). Furthermore, by focusing on distinct but interrelated technologies, the approach facilitates a nuanced understanding of how each component contributes to environmental sustainability. This methodology was justified as it aligns with previous studies in emerging markets while being adaptable to Nairobi’s unique industrial landscape (Barno, 2022).

### 1.1.2 Environmental Sustainability

Environmental sustainability refers to the capacity of industrial systems to operate in a manner that preserves natural resources, minimizes negative ecological impacts, and promotes long-term ecological balance. In the manufacturing sector, this concept emphasizes reducing energy consumption, lowering greenhouse gas emissions, optimizing raw material usage, and implementing environmentally friendly production practices

(Umar et al., 2021). The goal is to achieve economic productivity while maintaining the health of the environment for present and future generations (Sundarakani et al., 2024). As global concerns about climate change intensify, environmental sustainability has become a key strategic priority for manufacturing firms seeking to align their operations with green growth principles (Duarte et al., 2024).

In the current global landscape, environmental sustainability has become a strategic imperative for manufacturing firms due to mounting regulatory pressures, investor expectations, and consumer demand for eco-friendly products (Bag et al., 2022). The manufacturing industry is among the leading contributors to environmental pollution, greenhouse gas emissions, and resource depletion, prompting stakeholders to push for more responsible industrial practices (Kamble et al., 2023). Adopting sustainable production not only ensures compliance with international environmental standards but also leads to cost reductions through improved energy efficiency and waste minimization (Richnák & Fidlerová, 2022). Furthermore, firms that embed sustainability into their operations often enjoy enhanced brand reputation, competitive advantage, and access to sustainable finance (Duarte et al., 2024), positioning them favorably in both local and global markets.

In the current study, environmental sustainability was assessed using three core dimensions: energy efficiency, waste management, and emission reduction. These dimensions are consistently identified in the literature as fundamental indicators of environmental performance in manufacturing (Rusungu et al., 2020; Kamble et al., 2023). This measurement approach is justified as it allows for standardized comparison across different manufacturing firms while capturing practical, observable sustainability initiatives relevant to Nairobi's industrial landscape (Koech, 2023). Moreover, focusing on these three dimensions ensures alignment with both local environmental realities and global sustainability frameworks.

### 1.1.3 Manufacturing Firms in Nairobi, Kenya

Nairobi, Kenya's capital and largest urban economy, is the country's principal industrial hub, hosting a wide range of manufacturing firms across sectors such as food and beverages, textiles, pharmaceuticals, chemicals, and construction materials (KAM Annual Report, 2022). According to the Kenya National Bureau of Statistics (KNBS), Nairobi accounts for the largest share of formal manufacturing activity in the country, both in terms of output and employment. The city provides strategic advantages such as proximity to major markets, relatively better infrastructure, and access to skilled labor, making it a preferred location for local and multinational manufacturers (KNBS Statistical Bulletin, 2023). The Kenya Association of Manufacturers (KAM) identifies over 400 registered manufacturers in Nairobi, highlighting the city's critical role in Kenya's industrialization and economic transformation agenda (Republic of Kenya Policy Brief, 2021).

The adoption of Industry 4.0 technologies among manufacturing firms in Nairobi remains modest and uneven. While awareness of smart manufacturing, cyber-physical systems, Internet of Things (IoT), and big data analytics has grown, practical implementation is still largely confined to a few well-resourced firms (Koech, 2023; Barno, 2022). Many small and medium-sized manufacturers continue to face barriers such as limited technical capacity, high investment costs, and inadequate digital infrastructure, which inhibit the integration of these advanced technologies into their operations (Nganga, 2021). Although some firms have made initial investments in automation and data collection, the broader application of interconnected systems and real-time analytics remains limited. This lag in technology uptake suggests a critical need for empirical investigation into how Industry 4.0 technologies are currently utilized and the extent to which they influence key outcomes such as environmental sustainability.

Environmental sustainability efforts among manufacturing firms in Nairobi also reflect a mixed reality. A growing number of firms—particularly multinationals—have adopted practices aimed at improving energy efficiency, reducing emissions, and managing waste in response to both regulatory demands and global sustainability trends (Rusungu et al., 2020; Ogur, 2023). However, local firms often struggle to institutionalize these practices due to limited technical know-how, lack of investment in green technologies, and inconsistent enforcement of environmental regulations (Nganga, 2021). While frameworks such as Kenya Vision 2030 and the Green Economy Strategy encourage sustainable industrial development, measurable environmental performance indicators are either lacking or poorly monitored in many firms. As such, there is a growing need to explore how Industry 4.0 tools can bridge these gaps by enabling firms to adopt efficient, data-driven environmental practices that align with sustainability goals.

## 1.2 Statement of the Problem

Industry 4.0 technologies such as smart manufacturing, cyber-physical systems, IoT, and big data analytics offer transformative potential by enabling real-time monitoring, predictive maintenance, and intelligent resource management. These technologies can bridge the performance gap by enhancing environmental sustainability through innovation, automation, and data-driven decision-making (Koech, 2023; Barno, 2022). Environmentally sustainable manufacturing promotes efficient resource utilization, minimizes waste, and reduces carbon emissions all of which support long-term ecological balance and economic resilience (Sundarakani et al., 2024). Only a small percentage of firms have implemented energy efficiency measures or emission reduction programs, and many still rely on outdated, resource-intensive production models (Rusungu et al., 2020; Ogur, 2023).

Empirical studies on the intersection of Industry 4.0 and environmental sustainability in Kenya remain limited. Most research has focused either on digital transformation and competitiveness (Koech, 2023) or sustainable manufacturing strategies in isolation (Rusungu et al., 2020). For instance, Nganga (2021) explored the challenges of implementing Industry 4.0 among SMEs but did not link it to environmental outcomes, while Barno (2022) examined lean manufacturing without addressing the broader technological ecosystem. As a result, there is a critical knowledge gap in understanding how specific Industry 4.0 technologies influence environmental sustainability in Kenya's manufacturing sector. This study sought to fill that gap by empirically examining the relationship between Industry 4.0 and environmental sustainability among manufacturing firms in Nairobi, thereby contributing to evidence-based policymaking and sustainable industrial transformation.

### 1.3 Objectives of the Study

The general objective of this study was to establish the effect of Industry 4.0 technologies on the environmental sustainability of manufacturing firms in Nairobi, Kenya.

The specific objectives were:

i. To establish the effect of smart manufacturing on the environmental sustainability of manufacturing firms in Nairobi, Kenya

ii. To establish the effect of cyber-physical systems on the environmental sustainability of manufacturing firms in Nairobi, Kenya

iii. To examine the effect of internet of things on the environmental sustainability of manufacturing firms in Nairobi, Kenya

iv. To determine the effect of big data analytics on the environmental sustainability of manufacturing firms in Nairobi, Kenya

## 1.4 Research Hypotheses

The study addressed the following null research hypotheses:

1. **$H_{01}$:** Smart manufacturing has no significant effect on the environmental sustainability of manufacturing firms in Nairobi, Kenya
2. **$H_{02}$:** Cyber-physical systems have no significant effect on the environmental sustainability of manufacturing firms in Nairobi, Kenya
3. **$H_{03}$:** Internet of things has no significant effect on the environmental sustainability of manufacturing firms in Nairobi, Kenya
4. **$H_{04}$:** Big data analytics has no significant effect on the environmental sustainability of manufacturing firms in Nairobi, Kenya

## 1.5 Justification of the Study

This study was justified by the urgent need to promote sustainable industrialization in Kenya through the integration of advanced technologies that enhance environmental performance. Despite Nairobi being the country's manufacturing epicenter, existing evidence indicates that many firms have not adopted adequate measures to reduce their environmental impact, posing risks to ecological health and long-term industrial viability. Industry 4.0 technologies offer a transformative solution by enabling smarter, cleaner, and more efficient production processes; however, empirical research linking these technologies to environmental sustainability outcomes in Kenya is lacking. By examining this relationship, the study provides actionable insights for policymakers, manufacturers, and industry stakeholders on how to harness digital innovation to support green growth, align with national development goals, and enhance global competitiveness.

## 1.6 Significance of the Study

The study is of benefit to policy, practice and academia.

### 1.6.1 Policy

From a policy perspective, this study provides valuable evidence to inform the formulation and refinement of industrial and environmental policies in Kenya. As the government seeks to implement the Green Economy Strategy and Vision 2030's industrialization agenda, the study's findings will guide policymakers on how to effectively promote the adoption of Industry 4.0 technologies to achieve environmental sustainability in manufacturing. The research will also offer insights into policy gaps and barriers hindering technological transformation in the sector, supporting the design of incentives, infrastructure development, and regulatory frameworks that enable green industrial growth.

### 1.6.2 Practice

In terms of practice, the study will benefit manufacturing firms, especially those based in Nairobi, by highlighting practical pathways for integrating Industry 4.0 technologies to improve their environmental performance. Operations and sustainability managers will gain a deeper understanding of how tools such as smart manufacturing, cyber-physical systems, and big data analytics can reduce emissions, optimize energy use, and minimize waste. These insights can help firms not only comply with environmental regulations but also improve operational efficiency, reduce costs, and enhance competitiveness in both local and global markets.

### 1.6.3 Academia

For academia, the study contributes to the growing body of knowledge at the intersection of Industry 4.0 and environmental sustainability, particularly within the context of developing economies like Kenya. By addressing existing empirical gaps, the research offers a framework for future scholarly inquiry into digital transformation and green manufacturing practices. It also provides a foundation for comparative studies, curriculum development, and interdisciplinary research across technology, sustainability, and industrial management fields, supporting academic advancement and evidence-based teaching in higher education institutions.

### 1.7 Scope of the Study

This study focused on examining the influence of Industry 4.0 technologies on the environmental sustainability of manufacturing firms in Nairobi, Kenya. The study was limited to four key Industry 4.0 dimensions: smart manufacturing, cyber-physical systems, Internet of Things, and big data analytics as the independent variables, while environmental sustainability was measured through energy efficiency, waste management, and emission reduction. Geographically, the study was confined to Nairobi County, which serves as Kenya's primary manufacturing hub. Methodologically, the study adopted a quantitative research approach using structured questionnaires administered to operations and sustainability managers in selected manufacturing firms. The study was conducted between May and August 2025, and its findings reflected the status of Industry 4.0 adoption and environmental sustainability practices within the Nairobi manufacturing context during that period. The study was conducted between August and October 2025.

# CHAPTER TWO

# LITERATURE REVIEW

## 2.1 Introduction

This chapter presents a comprehensive review of existing theoretical and empirical literature relevant to the relationship between Industry 4.0 technologies and environmental sustainability. It is organized into four main sections: theoretical review, empirical review, conceptual framework, and research gaps. The review provides a scholarly foundation for the study by highlighting key concepts, measurement approaches, previous findings, and areas where further research is needed within the context of manufacturing firms in Nairobi, Kenya.

## 2.2 Theoretical Review

This section presents the theoretical foundations that underpin the relationship between Industry 4.0 technologies and environmental sustainability. The study was anchored on the Natural Resource-Based View (NRBV) theory, Ecological Modernization Theory, the Technology-Organization-Environment (TOE) framework, and the Dynamic Capabilities Theory.

### 2.2.1 Natural Resource-Based View Theory

The Natural Resource-Based View (NRBV) theory was introduced by Stuart L. Hart (1995) as an extension of the traditional Resource-Based View (RBV), emphasizing the strategic importance of environmental capabilities in achieving sustained competitive advantage. According to NRBV, firms can develop competitive advantages by building capabilities that support pollution prevention, product stewardship, and sustainable development. These capabilities enable firms to align their internal processes with environmental sustainability goals by minimizing ecological harm, optimizing resource use, and innovating in green product design (Hart, 1995). In the era of Industry 4.0, digital technologies such as smart manufacturing, cyber-physical systems, IoT, and big data analytics are increasingly seen as strategic enablers of environmentally conscious operations, supporting the NRBV's argument that sustainability-oriented resources and capabilities are key to long-term success (Dantas et al., 2022; Patyal & Sarma, 2024).

Despite its relevance, the NRBV has faced several criticisms. Some scholars argue that the theory overemphasizes the firm’s internal responsibility for sustainability while underestimating the influence of external institutional pressures such as regulation, industry standards, and consumer activism (Gupta et al., 2021). Others point out that operationalizing NRBV constructs—such as environmental capabilities and green innovation—remains challenging in empirical research, particularly in developing countries where sustainability data and investments are often limited (Wamba et al., 2020). Additionally, the NRBV is sometimes criticized for assuming that all firms have equal opportunity and access to environmental resources and innovation pathways, which may not hold in diverse industrial contexts with varying technological and infrastructural capacities (Duan et al., 2020).

In the context of this study, the NRBV theory was appropriate for explaining how the adoption of Industry 4.0 technologies can lead to enhanced environmental sustainability outcomes in Nairobi’s manufacturing sector. The theory predicts that firms that proactively integrate smart manufacturing, CPS, IoT, and big data analytics into their operations are better positioned to achieve energy efficiency, reduce emissions, and minimize waste, thereby transforming environmental responsibility into a source of competitive advantage (Patyal & Sarma, 2024). Given the variation in technological readiness among Nairobi-based manufacturers, the NRBV provides a valuable lens through which to analyze how digital capabilities aligned with ecological goals can drive sustainability in resource-constrained but innovation-driven environments (Dantas et al., 2022). Therefore, NRBV underpins the relationship between Industry 4.0 adoption and environmental sustainability.

### 2.2.2 Ecological Modernization Theory

The Ecological Modernization Theory (EMT) was developed in the early 1980s by scholars such as Joseph Huber and Martin Jänicke to explain how advanced industrial societies could reconcile economic development with environmental protection. EMT argues that modern environmental reform is most effective when driven by innovation, clean technologies, and institutional change rather than command-and-control regulations (Richnák & Fidlerová, 2022). The theory suggests that environmental protection can be integrated into the capitalist system by restructuring production and consumption through technological advances and collaborative governance models (Duarte et al., 2024). This framework assumes that industry and the environment need not be in conflict if ecological goals are aligned with economic rationality and technological modernization (Luu et al., 2023).

Despite its contributions, EMT has drawn several criticisms. Scholars argue that the theory is overly optimistic about the role of technology and does not sufficiently consider the political and social inequalities that may hinder sustainable transformation in developing economies (Awan et al., 2022). Another critique is its emphasis on top-down reforms and technological determinism, which may downplay the importance of behavioral change, community-driven innovation, and environmental justice (Prause & Atari, 2017). Furthermore, EMT tends to generalize success cases from developed nations and applies them uncritically to regions with vastly different institutional capacities and regulatory frameworks (Woschank et al., 2020).

In the context of this study, EMT was relevant for examining how Industry 4.0 technologies can be leveraged to achieve environmental sustainability in Nairobi's manufacturing sector. The theory predicts that integrating smart manufacturing systems, cyber-physical technologies, and big data analytics can enable firms to adopt cleaner production practices and improve resource efficiency (Duarte et al., 2024). Within Kenya's evolving policy landscape, EMT supports the notion that innovation-driven environmental practices—backed by supportive institutions and technology adoption—can yield both ecological and economic gains (Sundarakani et al., 2024). Therefore, EMT underpins how the adoption of Industry 4.0 technologies enables cleaner production and resource efficiency that improve environmental sustainability outcomes

### 2.2.3 Technology-Organization-Environment Framework

The Technology-Organization-Environment (TOE) framework, developed by Tornatzky and Fleischer (1990), is a well-established model that explains how technological innovations are adopted within firms based on three key dimensions: technology, organization, and environment. The technological context refers to both existing and emerging technologies relevant to the firm, including those that enable automation, real-time data processing, and interconnected systems (Bag et al., 2018). The organizational context relates to firm-specific characteristics such as size, managerial structures, human resource capabilities, and financial readiness that influence innovation decisions (Kayikci, 2017). The environmental context captures external forces such as industry dynamics, competitive pressure, customer expectations, and regulatory frameworks that shape the firm's decision to adopt and implement new technologies (Patyal et al., 2022). TOE offers a comprehensive lens through which digital transformation processes—like the adoption of Industry 4.0—can be evaluated in varied contexts, including developing economies.

Despite its strengths, the TOE framework has several limitations. It has been criticized for being descriptive rather than prescriptive, offering limited guidance on *how* firms can transition from intention to actual adoption (Santana et al., 2018). Moreover, it tends to overlook the interdependencies between its three dimensions, treating them as separate factors instead of interconnected systems (Kayikci, 2017). The framework also lacks a robust consideration of social and cultural factors, such as change resistance and employee engagement, which are especially crucial in Industry 4.0 transformations in emerging markets (Patyal et al., 2022). As a result, while TOE offers a useful starting point, it may need to be integrated with other theoretical perspectives or adapted to better reflect complex organizational realities in non-Western contexts.

In this study, the TOE framework was applicable in examining how Nairobi-based manufacturing firms adopt Industry 4.0 technologies to enhance environmental sustainability. The technological dimension of the framework helps assess the readiness and relevance of innovations such as IoT, cyber-physical systems, and big data analytics in the local manufacturing landscape (Bag et al., 2018). The organizational context informs how internal factors like top management support, digital skills, and financial resources shape a firm's ability to implement sustainable Industry 4.0 initiatives (Santana et al., 2018). Meanwhile, the environmental context allows for the analysis of how external drivers—such as environmental regulations, supply chain demands, and consumer pressure—influence digital and green adoption decisions (Kayikci, 2017). Therefore, the TOE framework underpins the pathway by which technological, organizational, and environmental contexts drive Industry 4.0 adoption, which in turn shapes environmental sustainability performance.

### 2.3.4 Dynamic Capabilities Theory

The Dynamic Capabilities Theory was advanced by Teece, Pisano, and Shuen (1997) to explain how firms build, integrate, and reconfigure internal and external competencies to respond to rapidly changing environments. The theory extends the traditional Resource-Based View by emphasizing the firm's capacity to adapt its resource base through learning, innovation, and renewal. According to Dantas et al. (2022), dynamic capabilities enable organizations to continually align technological and strategic processes with external market and environmental changes. Similarly, Bag et al. (2018) note that firms that cultivate agility in sensing opportunities and threats, seizing new technologies, and reconfiguring operations for sustainability are better positioned to maintain long-term competitiveness. Patyal et al. (2022) further observed that in dynamic and technology-intensive sectors, such as manufacturing, dynamic capabilities determine how effectively firms embed digital innovations into their operational systems to enhance performance and sustainability outcomes.

In the context of Industry 4.0, the Dynamic Capabilities Theory provides a robust foundation for understanding how Nairobi-based manufacturing firms leverage technological flexibility and adaptive learning to achieve environmental sustainability (Santana et al., 2018). Smart manufacturing and cyber-physical systems require firms to develop the capability to sense and respond to both operational and environmental shifts, while Internet of Things and big data analytics demand continuous integration of real-time data into decision-making processes (Duarte et al., 2024). Through dynamic capabilities, firms can enhance their absorptive capacity—interpreting technological trends, reconfiguring production systems, and aligning innovation with ecological objectives (Kayikci, 2017). This theoretical lens thus connects the strategic management of digital transformation to ecological performance in emerging manufacturing contexts such as Nairobi.

Therefore, the Dynamic Capabilities Theory underpins the relationship between big data analytics (independent variable) and environmental sustainability (dependent variable) by explaining how firms utilize data-driven adaptability, technological renewal, and learning-oriented innovation to create sustainable value and maintain competitiveness amid evolving environmental and industrial challenges.

## 2.3 Empirical Literature

This section reviews recent empirical studies on the relationship between Industry 4.0 technologies and environmental sustainability. The review focuses on how smart manufacturing, cyber-physical systems, Internet of Things (IoT), and big data analytics have been applied across different contexts to influence sustainable outcomes in the manufacturing sector.

### 2.3.1 Smart Manufacturing and Environmental Sustainability

Recent studies continue to affirm the environmental potential of smart manufacturing, particularly through the deployment of digital tools such as automated systems, real-time data analytics, and intelligent process integration. Jabbour et al. (2025) conducted a multi-country study among manufacturing firms in Latin America and sub-Saharan Africa and found that firms deploying smart manufacturing technologies reported significant reductions in carbon emissions and material waste. The study emphasized that the integration of smart systems facilitated cleaner production and enhanced compliance with sustainability metrics. However, the authors noted that such outcomes were strongly moderated by institutional support and firm-level digital readiness—factors that remain unevenly distributed across African urban industrial zones. This highlights the need for focused studies that isolate the environmental effects of smart manufacturing within Nairobi's unique regulatory and infrastructural context.

Patyal and Sarma (2024) explored how smart manufacturing contributes to environmental performance within India's mid-sized industrial clusters. Their findings revealed that firms using sensor-driven monitoring systems, automated scheduling, and cloud-integrated production units reported improved energy optimization and lower emissions. The study employed structural equation modeling and confirmed the mediating role of digital maturity. Nonetheless, it did not differentiate how distinct smart components—such as cyber-physical integration versus automated machinery—individually contribute to specific environmental metrics. This points to a conceptual gap in the disaggregation of smart manufacturing technologies when analyzing environmental sustainability outcomes.

In a highly digitized setting, Modgil et al. (2022) investigated the effects of smart factory adoption on sustainability performance in German manufacturing firms. The study confirmed that smart technologies enhanced environmental outcomes by reducing energy usage and material inefficiency. However, the firms examined benefited from robust technological infrastructure and favorable regulatory environments. The contextual advantages in Germany limit the transferability of findings to resource-constrained regions. This underscores the need for empirical testing in developing urban centers like Nairobi, where infrastructural limitations and cost constraints influence technology implementation outcomes.

Bag et al. (2020) analyzed smart production systems and their environmental outcomes in South Africa, revealing that smart integration led to lower emissions and improved material usage. While valuable, the study aggregated multiple digital practices without distinguishing the relative contribution of each to specific sustainability outcomes. It also placed minimal emphasis on small and medium-sized enterprises, which dominate the industrial landscape in Nairobi. The absence of a firm-size lens leaves a gap in understanding how smart manufacturing adoption scales across different organizational capacities in African cities.

Closer to the Kenyan context, Ogur (2023) examined Fourth Industrial Revolution technologies and their perceived role in sustainable industrial development. While the study recognized the growing awareness of smart manufacturing, it identified persistent adoption barriers such as high costs, limited skills, and policy ambiguity. Critically, the study did not empirically test the linkage between smart manufacturing and quantifiable environmental outcomes. This presents a methodological gap in validating the assumed benefits of smart manufacturing through measurable sustainability indicators in Nairobi's manufacturing sector.

Finally, Santana et al. (2018) used simulation modeling to evaluate lean-smart systems in Brazilian industrial operations. The study showed that energy efficiency and emission reduction were improved through digital scheduling and machine-level automation. However, environmental sustainability was treated as an ancillary benefit rather than a core outcome variable. This signals a theoretical limitation in existing studies that fail to position environmental sustainability as a central objective, a gap that the current study addresses by directly measuring energy efficiency, waste management, and emission control in relation to smart manufacturing practices.

In summary, while existing literature confirms the potential of smart manufacturing to support green industrial outcomes, there is limited empirical evidence from sub-Saharan African settings that evaluates this relationship in a disaggregated, context-specific manner.

Most studies are concentrated in highly digitized economies or rely on aggregated technological indices. This study contributes to filling this gap by examining the direct relationship between smart manufacturing components and environmental sustainability metrics within Nairobi's evolving manufacturing ecosystem.

### 2.3.2 Cyber-Physical Systems and Environmental Sustainability

Cyber-Physical Systems (CPS) represent a cornerstone of Industry 4.0 by enabling the integration of physical machinery with embedded digital intelligence for real-time data exchange and autonomous control. Recent studies affirm the potential of CPS in driving sustainable manufacturing, though their contextual effectiveness remains underexplored in developing economies. Patyal et al. (2023) evaluated the influence of CPS on environmental sustainability among Indian manufacturers using structural equation modeling. The findings confirmed that CPS improved sustainability through predictive maintenance, energy optimization, and defect prevention. However, the study was conducted among digitally mature firms operating within structured industrial zones, limiting its applicability to more diverse and resource-constrained manufacturing landscapes. This highlights a contextual gap in understanding how CPS impacts environmental outcomes in semi-formal and mid-scale industrial clusters such as those found in Nairobi.

Dantas et al. (2022) explored the relationship between CPS integration and circular economy practices in Latin America. Drawing on panel data across multiple sectors, the study revealed that CPS facilitated digital traceability, resource circularity, and regulatory compliance, thereby reducing environmental waste. However, while insightful, the study aggregated outcomes across national economies and focused more on macro-policy alignment than firm-level dynamics. This creates a methodological gap in assessing how

CPS adoption operates at the micro (firm) level, particularly in African manufacturing settings where technological assimilation varies widely across firms.

Gupta et al. (2021) conducted a study on CPS adoption in Southeast Asia and found that firms using CPS-enabled technologies such as smart sensors and embedded control systems demonstrated significant reductions in energy consumption and emissions. The systems allowed for cleaner production via real-time process adjustments and adaptive controls. Nonetheless, the majority of firms studied were multinationals within well-established industrial zones. The study does not capture the operational realities of Nairobi's mixed-scale industrial sector, where firms often operate with constrained resources and uneven infrastructure.

Rajesh et al. (2021) examined how CPS supports sustainable manufacturing in Indian firms deploying Industry 4.0 technologies. The study found that CPS reduced machine idle time and enabled more efficient inventory planning, which indirectly contributed to energy and material savings. However, environmental sustainability was not a central variable in the study—it was treated as a peripheral outcome. This reflects a conceptual gap in literature where CPS is evaluated primarily for operational efficiency rather than its direct influence on environmental indicators such as emissions, energy use, or waste management—an area this study seeks to explicitly address.

Similarly, Saucedo-Martínez et al. (2020) assessed the contribution of CPS to sustainability goals in Latin American manufacturing contexts. Using a mixed-methods approach, they found positive links between CPS use and environmental metrics such as resource efficiency, emissions control, and sustainable allocation. However, their analysis was conducted at an aggregate regional level and did not disaggregate results by city or industrial category. This limits the generalizability of their findings to localized urban industrial settings such as Nairobi, where manufacturing sectors vary in scale, digital readiness, and environmental policy compliance.

In summary, while global literature consistently recognizes CPS as a driver of sustainable manufacturing, most existing studies are concentrated in high-tech or policy-intensive contexts. There remains a limited empirical understanding of how CPS adoption influences environmental sustainability within urban African industrial zones. This study addresses this gap by examining the direct and disaggregated effect of CPS on energy efficiency, waste management, and emission control among Nairobi-based manufacturers operating under real-world constraints.

### 2.3.3 Internet of Things and Environmental Sustainability

The internet of things has emerged as a pivotal component of Industry 4.0, enabling interconnected devices to communicate and facilitate real-time monitoring of energy use, emissions, and equipment efficiency. In a recent cross-national study, Singh and Taneja (2025) analyzed the impact of IoT-enabled systems on environmental performance among 110 manufacturing firms across Kenya and Ethiopia. Their findings demonstrated that firms using sensor-driven IoT technologies reported improved energy monitoring, emissions tracking, and a 30% reduction in production waste due to intelligent feedback systems. While the study is regionally relevant, it concentrated on firms operating in well-established export processing zones with access to modern infrastructure and external incentives. This presents a geographic and operational gap in understanding how IoT influences environmental sustainability among firms operating outside such privileged industrial enclaves, particularly within Nairobi’s heterogeneous manufacturing ecosystem.

Rodriguez-Anton et al. (2024) conducted an empirical assessment of IoT-based environmental monitoring systems in Spanish and Portuguese SMEs. The study found that

IoT improved environmental compliance through real-time air quality and water usage monitoring, while also facilitating early detection of equipment inefficiencies. Although the findings are promising, the research context involved highly regulated European settings with mature digital infrastructure. The disparity between such environments and those in sub-Saharan Africa points to a contextual gap in understanding how IoT performs under weak enforcement, inconsistent internet access, and low investment in monitoring infrastructure—conditions common in Nairobi's manufacturing sector.

In India, Kumar and Gupta (2023) examined the relationship between IoT deployment and environmental performance in mid-sized manufacturing firms located in government-supported green clusters. The study confirmed that IoT adoption was strongly associated with reductions in emissions, energy consumption, and raw material waste, partly due to lifecycle tracking and real-time feedback loops. However, their sample was drawn exclusively from planned industrial zones designed with sustainability incentives, excluding informal or organically developed industrial sites. As such, the study leaves a gap in understanding how IoT contributes to sustainability in more fragmented industrial ecosystems—like Nairobi's—where digital investments are uneven and formal green policies may not be fully operationalized.

Alharthi et al. (2022) assessed the use of IoT to promote sustainability in Saudi Arabia's industrial sector, reporting enhanced operational transparency, better environmental reporting, and reduced regulatory violations. Predictive maintenance powered by IoT also led to fewer accidental emissions and equipment failures. However, the study emphasized regulatory compliance rather than internal operational efficiency and made limited effort to link IoT adoption to specific environmental metrics such as energy intensity or waste generation. This reflects a measurement gap in literature, where IoT's impact on environmental sustainability is often inferred from regulatory performance rather than directly assessed through sustainability indicators—an issue this study intends to address.

Duan et al. (2020) conducted a quantitative study of 132 Chinese manufacturing firms, showing that IoT deployment enhanced supply chain visibility, reduced emissions, and improved material efficiency through integration with environmental management systems. However, the firms studied were predominantly large, government-supported enterprises operating within a policy-rich context. This raises questions about how locally owned, mid-sized firms in resource-constrained settings like Nairobi might experience different outcomes due to financial, technical, and infrastructural limitations.

Collectively, these studies highlight the transformative potential of IoT in achieving environmental sustainability but also expose key limitations in existing research. Most studies are concentrated in advanced or structured industrial environments and focus either on compliance or aggregate digital adoption rather than firm-specific environmental outcomes. This study addresses these gaps by empirically examining how IoT adoption influences energy efficiency, waste reduction, and emissions control in Nairobi's diverse and evolving manufacturing sector—providing localized insights that are presently underrepresented in global literature.

### 2.3.4 Big Data Analytics and Environmental Sustainability

Big data analytics plays an increasingly vital role in supporting environmental sustainability by enabling firms to process large volumes of real-time data to optimize resource usage, monitor emissions, and implement predictive environmental controls. Jabbour et al. (2025) examined the integration of BDA into sustainability strategies among manufacturing firms in Brazil and South Africa. Their longitudinal analysis and expert interviews showed that BDA adoption facilitated significant gains in environmental efficiency through predictive energy planning, emissions tracking, and waste reduction. However, the study focused on firms participating in government-funded green innovation programs, often with access to incentives and policy support. This creates a gap in understanding how BDA impacts environmental outcomes in less-supported settings like Nairobi, where such incentives may be minimal or inconsistent across firms.

In the Indian context, Patyal and Sarma (2024) investigated the role of BDA in enabling circular economy practices among mid-sized manufacturing firms. Their findings demonstrated that data analytics improved raw material efficiency, pollution hotspot detection, and inventory control. While these results highlight BDA's value, the study's focus on circularity as an overarching framework limited its ability to isolate direct environmental performance indicators such as energy efficiency or emissions reduction. This signals a measurement gap in the literature, where BDA's effects on specific sustainability metrics remain underexamined—particularly in regions like Nairobi with diverse manufacturing profiles and variable digital maturity.

Zhang et al. (2023) explored how BDA influences environmental key performance indicators (KPIs) in high-tech Chinese electronics manufacturing firms. They found that advanced BDA tools, including real-time dashboards, anomaly detection, and process mining, significantly reduced production-related emissions and waste. However, the study was concentrated in a digitally advanced sector with high automation and technology investment. This sectoral bias limits the applicability of the findings to Nairobi's traditional manufacturing sub-sectors, which often lack integrated BDA infrastructure and must navigate implementation within constrained budgets.

Awan et al. (2022) focused on the role of BDA capabilities in improving sustainable supply chain management in Pakistani manufacturing firms. The study revealed that BDA enabled real-time alerts, simulation-based planning, and traceability, thus contributing to environmental risk mitigation across the supply chain. Yet, the emphasis on supply chain coordination rather than in-plant operational practices makes it difficult to assess how BDA affects factory-level environmental outcomes such as emissions and energy usage. This reveals a scope gap in current literature, which the present study addresses by directly measuring in-firm environmental performance metrics.

Wamba et al. (2020) examined how BDA supports green manufacturing initiatives in European multinational corporations. Their findings confirmed that BDA contributes to cleaner production through improved carbon tracking, process transparency, and lifecycle environmental assessments. While the study provides valuable insights, it was limited to developed economies with advanced technological ecosystems and supportive regulatory environments. This underscores a contextual gap, as BDA's application and performance in Nairobi's mid-sized, locally owned manufacturing firms may differ significantly due to infrastructural and financial limitations.

In summary, while extant literature supports the environmental potential of big data analytics, there is a marked deficiency in studies that focus on localized, firm-level impacts in African manufacturing settings. Most research either emphasizes multinational firms, digitally mature industries, or external-facing functions like supply chain sustainability. This study bridges these gaps by empirically investigating how BDA adoption affects in-plant environmental outcomes: namely energy efficiency, waste reduction, and emissions control within Nairobi's manufacturing firms, thereby offering novel insights into the role of digital transformation in green industrial development.

## 2.4 Summary of Literature Review

The reviewed literature reveals that Industry 4.0 technologies, specifically smart manufacturing, cyber-physical systems, Internet of Things, and big data analytics hold significant potential for advancing environmental sustainability in the manufacturing sector. Empirical evidence from diverse global contexts consistently shows that these technologies contribute to energy efficiency, emission reduction, waste minimization, and regulatory compliance. Smart manufacturing has been linked to automation-driven resource optimization, CPS enables real-time process control for environmental performance, IoT supports predictive monitoring and eco-efficiency, while big data analytics facilitates data-driven decision-making for green operations.

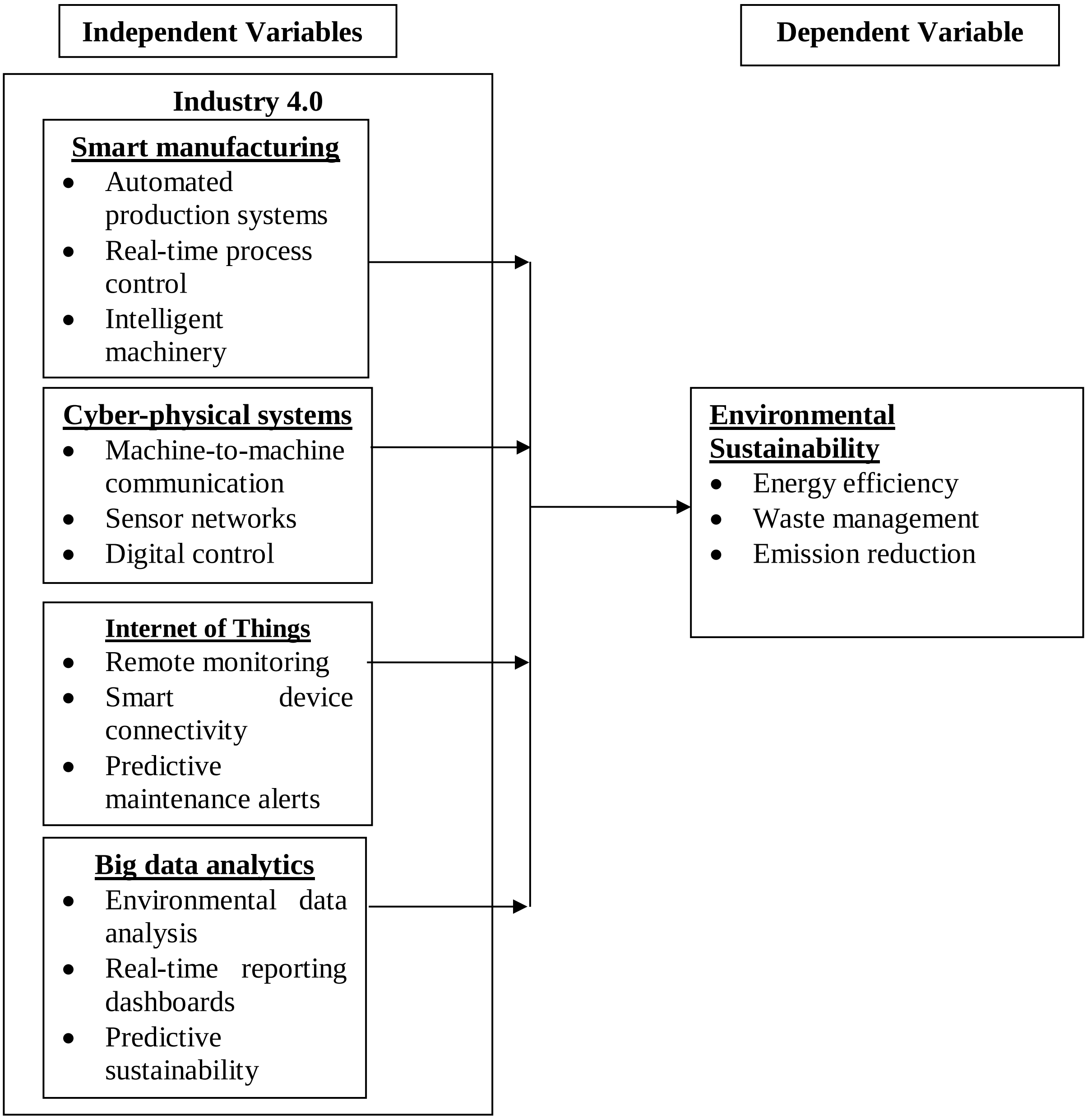
However, despite growing evidence globally, there remains a clear empirical gap in localized research from sub-Saharan Africa, particularly in Nairobi's manufacturing sector. Most existing studies focus on developed or emerging economies with advanced infrastructure and regulatory environments, often neglecting the implementation barriers, institutional limitations, and unique industrial dynamics in developing countries. Moreover, several studies examined sustainability in broad or aggregated terms, without disaggregating environmental indicators such as energy use, emissions, or waste. This study therefore addressed these gaps by empirically examining how smart manufacturing, CPS, IoT, and big data analytics influence environmental sustainability among manufacturing firms in Nairobi, Kenya.

## 2.5 Conceptual Framework

The conceptual framework for this study was designed to illustrate the hypothesized relationship between Industry 4.0 technologies and the environmental sustainability of manufacturing firms in Nairobi, Kenya. The model conceptualizes smart manufacturing, cyber-physical systems, Internet of Things, and big data analytics as the independent variables, which were expected to positively influence environmental sustainability, the dependent variable, measured through energy efficiency, waste management, and emission reduction. The framework provides a visual and theoretical guide for analyzing how digital transformation components interact with sustainability outcomes in the manufacturing context.

**FIGURE 2.1:**

**Conceptual Framework**



## 2.6 Operationalization of Variables

**TABLE 2.1:**

**Operationalization of Variables**

| Variable type | Variable | Indicators | Measurement scales |
|---|---|---|---|
| Dependent | Environmental Sustainability | • Energy efficiency<br>• Waste management<br>• Emission reduction | Likert/ordinal |
| Independent | Smart manufacturing | • Automated production systems<br>• Real-time process control<br>• Intelligent machinery | Likert/ordinal |
| Independent | Cyber-physical systems | • Machine-to-machine communication<br>• Embedded sensor networks<br>• Digital control systems | Likert/ordinal |
| Independent | Internet of things | • Remote environmental monitoring<br>• Smart device connectivity<br>• Predictive maintenance alerts | Likert/ordinal |
| Independent | Big data analytics | • Environmental data analysis<br>• Real-time reporting dashboards<br>• Predictive sustainability modeling | Likert/ordinal |

# CHAPTER THREE

# RESEARCH METHODOLOGY

## 3.1 Introduction

This chapter outlines the research methodology adopted to examine the effect of Industry 4.0 technologies on the environmental sustainability of manufacturing firms in Nairobi, Kenya. It presents and justifies the research design, target population, sampling techniques, data collection methods, and data analysis procedures in alignment with the study's objectives.

## .3.2 Research Design

This study adopted a descriptive correlational research design to examine the relationship between Industry 4.0 technologies and environmental sustainability among manufacturing firms in Nairobi, Kenya. The descriptive component helped in systematically capturing the current state of adoption of smart manufacturing, cyber-physical systems, Internet of Things, and big data analytics, while the correlational aspect facilitated the assessment of the strength and direction of the relationship between these technologies and environmental sustainability indicators. This design was suitable because it allowed for the analysis of naturally occurring variables without manipulation and provides empirical evidence to support or refute the hypothesized associations. Furthermore, it aligned with the study's objective of establishing how specific components of Industry 4.0 influence sustainable manufacturing outcomes. According to Cooper and Schindler (2021), descriptive and correlational research designs are effective when seeking to describe variables and test relationships among them in real-world settings.

### 3.3 Target Population

The target population refers to the complete group of individuals or entities that share common characteristics relevant to a particular study (Kothari, 2020). For this study, the target population comprised manufacturing firms located in Nairobi County that have adopted at least one component of Industry 4.0 technologies, such as smart manufacturing systems, cyber-physical systems, IoT, or big data analytics. According to data from the Kenya Association of Manufacturers (2024), there are 418 such active firms across various industrial subsectors. These firms are categorized into four key sectors that are leading in digital transformation and environmental reporting: agro-processing, chemicals and pharmaceuticals, textile and apparel, and construction materials. The study focused on operations and environmental sustainability managers within these firms, as they are best positioned to provide relevant information on technological adoption and sustainability practices. Table 3.1 presents the sectoral distribution of the target population.

**TABLE 3.1:**

**Target Population**

| Sector | Population |
|---|---|
| Agro-Processing | 106 |
| Chemicals & Pharmaceuticals | 89 |
| Textile & Apparel | 94 |
| Construction Materials | 129 |
| **Total** | **418** |

Source: KAM (2024)

### 3.4 Sample Size and Sampling Procedure

Sampling is the process of selecting a portion of individuals or units from a larger population to represent the whole group (Cooper & Schindler, 2021). The method used to identify and select these individuals or units is referred to as the sampling technique. A sample size, in this context, refers to a selected subset drawn from the overall population, which serves as the basis for making inferences about the entire group. Since the target population for this study was fewer than 10,000, the Yamane formula, as outlined by Kothari (2020), was used to determine the appropriate sample size. The formula was expressed as:

$$n = \frac{N}{1 + Ne^2}$$

Where n is the desired sample size (if the population is less than 10,000)

N = 418.

e=is the precision or sample error i.e.,0.05

$$n = \frac{418}{1 + 418(0.05)^2} = 204$$

The study therefore sampled 204 firms from the target population of 418 firms.

To ensure proportional representation across different manufacturing sectors, the study adopted a combination of stratified random sampling and simple random sampling. First, stratified sampling was used to categorize the firms into four sectors: agro-processing, chemicals and pharmaceuticals, textile and apparel, and construction materials based on their primary operations. Within each stratum, simple random sampling was applied to select the required number of firms from each group. This approach ensured that each sector was adequately represented, enhancing the reliability and generalizability of the findings. The distribution of the sample across the sectors was as shown in Table 3.2.

**TABLE 3.2:**

**Sample Size**

| Sector | Population | Sample Size |
|---|---|---|
| Agro-Processing | 106 | 52 |
| Chemicals & Pharmaceuticals | 89 | 43 |
| Textile & Apparel | 94 | 46 |
| Construction Materials | 129 | 63 |
| **Total** | **418** | **204** |

### 3.5 Data Collection Instruments

This study utilized a structured questionnaire as the primary data collection instrument. The questionnaire was appropriate for this type of study because it enables the collection of standardized, quantifiable data from a relatively large sample, allowing for effective comparison and statistical analysis. Structured questionnaires are also cost-effective and time-efficient, particularly when targeting respondents spread across various firms and sectors. Given the study's focus on evaluating the effect of Industry 4.0 technologies on environmental sustainability, the questionnaire was carefully designed to capture responses across five core variables: smart manufacturing, cyber-physical systems, IoT, big data analytics, and environmental sustainability.

The questionnaire was divided into three parts: Part A gathered demographic and background information; Part B captured the adoption level of each Industry 4.0 component using Likert-scale statements; and Part C assessed environmental sustainability practices within the firms. A five-point Likert scale (ranging from 1 = Strongly Disagree to 5 = Strongly Agree) is used in Parts B and C to enable respondents to indicate the degree of their agreement with various statements. The use of a Likert scale was justified as it facilitated the measurement of perceptions and attitudes, which are central to assessing the level of technological adoption and sustainability implementation. The questionnaire was administered to operations and environmental sustainability managers, who were best placed to provide informed and relevant responses on the study variables.

### 3.6 Data Collection Procedures

Data collection involves the systematic gathering of empirical evidence to provide meaningful insights into a specific phenomenon and to respond to the study's research questions (Khan, 2018). Before initiating data collection, the researcher obtained all necessary approvals, including ethical clearance from the university and research authorization from the National Commission for Science, Technology and Innovation (NACOSTI). Permission was sought from the Kenya Association of Manufacturers (KAM) and participating firms to facilitate access to respondents.

The data was collected using a structured questionnaire targeting operations and environmental sustainability managers in each of the sampled manufacturing firms. These individuals were selected based on their direct involvement in both technological adoption and environmental sustainability practices, making them the most suitable respondents for the study. The questionnaire was administered electronically via Google Forms, which provided a flexible and user-friendly platform for data collection, especially in a geographically dispersed urban setting like Nairobi. To enhance the response rate, follow-up emails and phone call reminders were sent to non-respondents after the initial invitation, ensuring that the final dataset was both comprehensive and representative of the targeted firms.

### 3.7 Pilot Test

Ensuring the accuracy and appropriateness of the research instrument is essential for obtaining reliable results. To this end, a pilot study was conducted to assess the feasibility of the main study and to evaluate the reliability and validity of the questionnaire. The pilot test involved 10% of the total sample size, which translated to 21 respondents, as recommended by Kothari (2020), who considers 10% of the sample sufficient for a pilot study.

The questionnaire was distributed to these 21 respondents, drawn from manufacturing firms within Nairobi County that meet the study’s criteria. Feedback was gathered on the clarity, structure, and relevance of the questions. Participants were also encouraged to suggest improvements to enhance the instrument's consistency and ensure that it effectively addresses the study's objectives. Importantly, individuals who participated in the pilot test were excluded from the final data collection to eliminate any potential bias.

### 3.7.1 Validity of Data Collection Instrument

Validity refers to the extent to which a research instrument accurately captures the concept it is intended to measure (Cooper & Schindler, 2021). In this study, construct validity was ensured by aligning the operational definitions of smart manufacturing, cyber-physical systems, IoT, big data analytics, and environmental sustainability with their theoretical underpinnings. This helped confirm that the questionnaire items reflected the core concepts of the study. The researcher adapted questionnaire items from established empirical studies and modified them as necessary to suit the current research context.

Additionally, content validity was established through expert review. Academic supervisors with expertise in manufacturing technologies and environmental sustainability assessed the questionnaire to confirm that the items sufficiently covered all relevant aspects of each variable. Their feedback ensured that the instrument was conceptually sound, well-structured, and aligned with the study's theoretical framework.

### 3.7.2 Reliability of Data Collection Instrument

Reliability refers to the consistency of a research instrument in producing stable and repeatable results under similar conditions (Cooper & Schindler, 2021). A reliable instrument yields consistent responses across different contexts and over time. In this study, Cronbach's Alpha was used to assess the internal consistency of the Likert-scale items in the questionnaire. This statistical test evaluated how closely related the items were within each variable grouping.

According to Khan (2018), a Cronbach's Alpha coefficient between 0.7 and 0.8 is generally considered acceptable, while a coefficient above 0.8 indicates high reliability. The results of the pilot test were analyzed using SPSS to compute Cronbach's Alpha for each of the five study variables. Where necessary, questionnaire items were revised to improve internal consistency before administering the final version of the instrument in the main study.

### 3.8 Data Analysis and Presentation

Data analysis involves systematically organizing, examining, and interpreting collected data to derive meaningful insights that address the research questions and objectives (Cooper & Schindler, 2021). In this study, quantitative data obtained from the structured questionnaires was analyzed using Statistical Package for the Social Sciences (SPSS) version 27. The analysis followed a multi-step approach involving descriptive and inferential statistics.

Descriptive statistics—including frequencies, means, and standard deviations—were used to summarize the characteristics of the respondents and the level of adoption of Industry 4.0 technologies across the sampled firms. This provided a general overview of the data distribution for each variable.

To test the hypothesized relationships between the independent variables and the dependent variable, multiple linear regression analysis was conducted. The regression model evaluated the strength and significance of each predictor variable's effect on environmental sustainability. The findings were presented using tables, charts, and graphs to facilitate clarity, comparison, and interpretation of results. The significance level for hypothesis testing was set at 5% ($\alpha = 0.05$).

### 3.8.1 Model Summary

The regression model below was used:

$$\mathbf{Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \varepsilon}$$

Where: Y = Environmental sustainability

$\alpha$ = regression intercept.

$\beta_1$, $\beta_2$, $\beta_3$, $\beta_4$= Model coefficients

$X_1$ = Smart manufacturing

$X_2$= Cyber-physical systems

$X_3$= Internet of things

$X_4$= Big data analytics

$\varepsilon$ =error term

## 3.9 Pretesting of Multiple Regression Assumptions

Before conducting multiple linear regression analysis, it is essential to test for the classical linear regression assumptions to ensure the validity and reliability of the statistical results. Therefore, this study undertook a series of diagnostic checks to confirm that the data met the fundamental assumptions of regression analysis.

### 3.9.1 Normality Test

To assess whether the residuals from the regression model are normally distributed around the mean, normality tests such as the Shapiro-Wilk test and the Kolmogorov-Smirnov test were employed. These statistical tests helped determine if the distribution of the residuals deviates significantly from a normal distribution, which is a key requirement for reliable inference in linear regression.

### 3.9.2 Multicollinearity Test

The study tested multicollinearity using Variance Inflation Factors (VIF) to examine the strength of relationships among the independent variables. A VIF exceeding 10 was interpreted as an indication of multicollinearity, which can inflate standard errors and destabilize the regression coefficients (Cooper & Schindler, 2021). Identifying and managing multicollinearity is critical to ensuring that the estimated effects of the predictors on the dependent variable are reliable.

### 3.9.3 Heteroscedasticity

Heteroskedasticity must be identified and addressed to ensure that the assumptions of the Classical Linear Regression Model (CLRM) are upheld. The CLRM assumes that the error term has a constant variance, a condition referred to as homoscedasticity. However, if the variance of the error term is inconsistent across observations, it results in heteroskedasticity. While heteroskedasticity does not bias the coefficient estimates, it distorts the standard errors, potentially leading to unreliable hypothesis testing. In this research, heteroskedasticity was evaluated via the Breusch-Pagan / Cook-Weisberg test, as recommended by Khan (2018). The null hypothesis for this test assumed that the error variance was homoscedastic. Addressing heteroskedasticity ensured the reliability and validity of the regression results.

## 3.10 Ethical Considerations

Ethical integrity is a critical component of any research process, particularly when human respondents are involved. This study upheld high ethical standards to ensure the dignity, privacy, and rights of all participants are respected throughout the research process. Prior to data collection, the researcher obtained ethical clearance from the University and a research permit from the National Commission for Science, Technology and Innovation

(NACOSTI). Additionally, permission was sought from the Kenya Association of Manufacturers and individual manufacturing firms where the research was conducted.

All participants were provided with an informed consent statement explaining the purpose of the study, the voluntary nature of participation, and their right to withdraw at any point without any penalty. No personally identifiable information was collected, and all responses were treated with strict confidentiality and used solely for academic purposes. The data was stored securely and only accessible to the research team. Furthermore, the findings of the study were reported honestly, without fabrication, falsification, or misrepresentation, in adherence to academic and professional standards of research ethics.

# CHAPTER FOUR

# RESULTS AND DISCUSSION

## 4.1 Introduction

This chapter presents the results of data analysis and the corresponding discussion of findings based on the study objectives. It begins by outlining the response rate and demographic characteristics of the respondents, followed by detailed descriptive, correlation, and regression analyses for each variable. The findings are interpreted in relation to existing theories and empirical literature to provide meaningful insights into the relationships among smart manufacturing, cyber-physical systems, internet of things, big data analytics, and environmental sustainability. The discussion also highlights how these results contribute to understanding the role of Industry 4.0 technologies in promoting environmental sustainability within the manufacturing sector.

## 4.2 Response Rate

Table 4.1 presents the response rate of the study, indicating that out of the 204 questionnaires distributed, 181 were successfully completed and returned, while 23 were not returned. This translates to a response rate of 88.7 percent and a non-response rate of 11.3 percent. The table therefore shows that the majority of the targeted respondents participated in the study, reflecting a strong level of engagement and cooperation from the participants. Such a high response rate enhances the credibility of the data collected and ensures adequate representation of the study population, thereby reducing the potential for non-response bias and improving the accuracy of the findings.

The response rate of 88.7 percent exceeds the minimum acceptable threshold of 70 percent recommended by Khan (2018) for survey research. This high level of participation demonstrates the respondents' willingness to share insights on the study variables: smart manufacturing, cyber-physical systems, internet of things, big data analytics, and environmental sustainability. The excellent response rate can be attributed to timely follow-ups, clarity of the questionnaire, and the relevance of the topic to the respondents' professional context. Consequently, the data obtained from Table 4.1 provide a reliable foundation for subsequent statistical analysis and discussion of the study results.

**TABLE 4.1:**

**Response Rate**

| Response Rate | Frequency | Percent |
|---|---|---|
| Returned | 181 | 88.7 |
| Unreturned | 23 | 11.3 |
| **Total** | **204** | **100** |

### 4.3 Demographic Characteristics

This section presents the demographic characteristics of the respondents who participated in the study. The demographic information was collected to provide context and a better understanding of the background of the participants, which is essential in interpreting the study findings accurately. The analysis covers key attributes such as gender, age, level of education, department, and years of experience. Understanding these characteristics helps to establish the representativeness and diversity of the sample, ensuring that the responses reflect a balanced view of the target population involved in smart manufacturing and environmental sustainability initiatives.

#### 4.3.1 Gender of the Respondents

Table 4.2 presents the gender distribution of the respondents, showing that 97 participants, representing 53.7 percent, were male, while 84 participants, accounting for 46.4 percent, were female. This indicates that both genders were well represented in the study, with a slight predominance of male respondents. The near balance in gender participation demonstrates inclusivity and diversity among the study participants, which enhances the credibility of the findings by ensuring that perspectives from both male and female respondents were adequately captured.

The findings further suggest that the manufacturing sector, where the study was conducted, is gradually achieving gender parity in professional roles. Although male respondents slightly outnumbered their female counterparts, the difference is minimal, reflecting ongoing efforts toward gender inclusiveness in industrial and technological environments. This balanced representation provides a comprehensive understanding of the influence of Industry 4.0 technologies and environmental sustainability practices from a gender-diverse workforce perspective.

**TABLE 4.2:**

**Gender Distribution**

| Gender | Frequency | Percentage |
|---|---|---|
| Male | 97 | 53.7 |
| Female | 84 | 46.4 |
| **Total** | **181** | **100** |

### 4.3.2 Age of the Respondents

Table 4.3 presents the age composition of the respondents, showing that the majority, 79 respondents (43.7 percent), were aged between 41 and 50 years. This was followed by 69 respondents (38.1 percent) aged between 31 and 40 years, while 27 respondents (14.9 percent) were above 50 years, and only 6 respondents (3.3 percent) were below 30 years. The table therefore indicates that most of the respondents were middle-aged, representing individuals likely to have substantial professional experience and practical understanding of manufacturing operations and Industry 4.0 technologies.

The results imply that the study predominantly drew insights from mature professionals with extensive exposure to industrial processes and environmental sustainability practices. The dominance of respondents aged between 31 and 50 years suggests that the data collected is based on informed opinions from individuals actively involved in managerial or technical roles. The low representation of respondents below 30 years reflects the limited involvement of younger professionals in senior manufacturing roles, possibly due to the specialized skills and experience required in implementing smart manufacturing technologies.

**TABLE 4.3:**

**Respondents' Age Composition**

| **Age** | **Frequency** | **Percentage** |
|---|---|---|
| Below 30 years | 6 | 3.3 |
| 31-40 years | 69 | 38.1 |
| 41-50 years | 79 | 43.7 |
| Above 50 years | 27 | 14.9 |
| **Total** | **181** | **100** |

### 4.3.3 Highest Level of Education

Table 4.4 presents the respondents' highest level of education, revealing that the majority, 107 respondents (59.1 percent), held a bachelor's degree, followed by 50 respondents (27.6 percent) with a master's degree. Additionally, 23 respondents (12.7 percent) had a diploma qualification, while only one respondent (0.6 percent) possessed a PhD. The table therefore shows that most of the participants were highly educated, with over 86 percent having attained at least a university degree, indicating a well-informed and professionally competent group of respondents capable of providing credible insights into the study variables.

The results suggest that the manufacturing sector attracts individuals with substantial academic qualifications, which aligns with the technical and analytical demands of Industry 4.0 technologies. The predominance of degree and master's holders implies that the respondents were likely to understand complex operational systems such as smart manufacturing, cyber-physical systems, and big data analytics. The limited representation of diploma and PhD holders further indicates that while practical technical training remains relevant, higher academic qualifications play a crucial role in driving innovation and environmental sustainability initiatives within the manufacturing industry.

**TABLE 4.4:**

**Highest Level of Education**

| Education | Frequency | Percentage |
|---|---|---|
| Diploma | 23 | 12.7 |
| Degree | 107 | 59.1 |
| Masters | 50 | 27.6 |
| PhD | 1 | 0.6 |
| **Total** | **181** | **100%** |

### 4.3.4 Years of Experience in Current Position

Table 4.5 presents the respondents' years of experience in their current positions. The results show that the majority, 88 respondents (48.6 percent), had worked in their current positions for more than five years, followed by 66 respondents (36.5 percent) who had served between four and five years. Additionally, 24 respondents (13.3 percent) had between two and three years of experience, while only 3 respondents (1.6 percent) had less than one year of experience. The table therefore reveals that most participants had significant experience in their current roles, indicating a mature and knowledgeable workforce capable of providing well-informed responses relevant to the study.

The findings in Table 4.5 imply that the data collected was derived from individuals with substantial organizational exposure and practical understanding of operational processes and Industry 4.0 technologies. The dominance of respondents with over four years of experience suggests stability and expertise within the workforce, which enhances the reliability of the study results. This level of experience also reflects institutional continuity and the likelihood that respondents have actively participated in the adoption and implementation of smart manufacturing practices, cyber-physical systems, and environmental sustainability initiatives within their respective organizations.

**TABLE 4.5:**

**Years of Experience in Current Position**

| Number of years | Frequency | Percentage |
|---|---|---|
| 0-1 years | 3 | 1.6 |
| 2-3 years | 24 | 13.3 |
| 4-5 years | 66 | 36.5 |
| Above 5 years | 88 | 48.6 |
| **Total** | **181** | **100%** |

### 4.4 Pilot Test Results

A pilot study was conducted to assess the feasibility of the main study and to evaluate the reliability and validity of the questionnaire. The pilot test involved 10% of the total sample size, which translated to 21 respondents, as recommended by Kothari (2020). Table 4.6 shows the reliability results of the research instrument.

**TABLE 4.6:**

**Reliability Test Results**

| Variables | Items | Cronbach Alpha | Remark |
|---|---|---|---|
| Smart manufacturing | 6 | .745 | Reliable |
| Cyber-physical systems | 6 | .756 | Reliable |
| Internet of things | 6 | .811 | Reliable |
| Big data analytics | 6 | .733 | Reliable |
| Environmental sustainability | 6 | .924 | Reliable |

The pilot test results in Table 4.6 indicates that all measurement scales achieved acceptable to excellent internal consistency. Based on the study's criterion that coefficients between 0.70 and 0.80 are acceptable and values above 0.80 indicate high reliability, each construct met or exceeded the minimum threshold: smart manufacturing ($\alpha = .745$), cyber-physical systems ($\alpha = .756$), internet of things ($\alpha = .811$), big data analytics ($\alpha = .733$), and environmental sustainability ($\alpha = .924$). These results show that the six items per construct cohered well, with environmental sustainability demonstrating outstanding reliability, IoT showing strong reliability, and the remaining constructs falling within the acceptable range; although big data analytics posted the lowest alpha among the predictors, it still satisfies the study's reliability benchmark. Overall, the instrument is dependable for subsequent analysis and interpretation.

## 4.5 Descriptive Statistics

This section presents the descriptive statistics of the study variables, which include smart manufacturing, cyber-physical systems, internet of things, big data analytics, and environmental sustainability. Descriptive analysis was conducted to summarize and interpret the respondents' perceptions and experiences regarding the influence of Industry 4.0 technologies on environmental sustainability within the manufacturing sector. The results are presented in terms of means and standard deviations, which indicate the central tendency and variability of responses, respectively. These findings provide an overview of the general trends and patterns in the data before proceeding to inferential analysis.

### 4.5.1 Smart Manufacturing

Table 4.7 summarizes respondents' views on smart manufacturing across six statements measured on a five-point scale. The overall mean score is 3.54 with a standard deviation of

0.60, indicating a generally moderate to high level of smart manufacturing practices with fairly consistent responses. Notably, two statements stand out with strong agreement and low dispersion: integration of digital systems to monitor production efficiency (mean = 4.20, SD = 0.40) and regular investment in upgrading manufacturing technologies (mean = 4.10, SD = 0.30). These results suggest that most firms have already embedded digital monitoring and maintain a steady commitment to technology renewal.

**TABLE 4.7:**

**Descriptive Statistics for Smart Manufacturing**

| **Statements** | **N** | **Mean** | **Std. Dev** |
|---|---|---|---|
| Our firm uses automated machines to streamline production processes. | 181 | 3.10 | 1.13 |
| Real-time production data is used to make operational decisions. | 181 | 2.71 | 1.01 |
| We have integrated digital systems to monitor production efficiency. | 181 | 4.20 | 0.40 |
| Our manufacturing processes are highly adaptive to customer specifications. | 181 | 3.71 | 0.78 |
| Smart technologies have reduced resource wastage in our operations. | 181 | 3.41 | 0.91 |
| We regularly invest in upgrading manufacturing technologies for better performance. | 181 | 4.10 | 0.30 |
| **Overall mean Score** | **181** | **3.54** | **0.60** |

The table also shows that manufacturing processes are perceived as adaptive to customer specifications (mean = 3.71, SD = 0.78), pointing to a meaningful but not universal shift toward flexible production. The relatively moderate variability here implies that while many firms can tailor outputs, others may still rely on more rigid process flows. Reduction of resource wastage through smart technologies records a moderate mean (3.41, SD = 0.91), suggesting tangible efficiency gains, though with room for improvement and some differences across firms in realizing waste reduction benefits.

Areas of comparative weakness are visible in the use of real time production data for operational decisions (mean = 2.71, SD = 1.01) and the use of automated machines to streamline production processes (mean = 3.10, SD = 1.13). These two items exhibit the lowest means and the highest variability, signaling uneven adoption. The dispersion indicates that while some plants apply advanced automation and data driven decision making, others have limited capability or are still in early stages of deployment.

Overall, Table 4.6 indicates that companies are strongest in foundational digitalization and ongoing technology investment, are making progress in process flexibility and waste reduction, but lag in real time analytics and comprehensive automation. Closing these gaps would likely amplify the impact of existing digital monitoring, enabling faster decision cycles, more stable quality, and deeper efficiency gains across the production system.

### 4.5.2 Cyber Security Systems

Table 4.8 presents the descriptive statistics for cyber-physical systems (CPS) and highlights how respondents rated various aspects of CPS adoption in manufacturing processes. The overall mean score of 3.85 with a standard deviation of 0.43 signifies a generally high and consistent implementation of CPS technologies among the surveyed firms. As shown in the table, the highest-rated statements were that machines are connected to digital systems enabling remote control (mean = 4.10, SD = 0.30) and that cyber-physical technologies are used to monitor real-time environmental indicators (mean = 4.10, SD = 0.30). These high mean values, accompanied by low variability, indicate that most firms have integrated strong connectivity and real-time monitoring capabilities, reflecting significant technological advancement and uniform adoption across the sector.

The table also shows that the use of embedded systems to automatically detect equipment faults (mean = 4.01, SD = 0.44) and the contribution of CPS integration in reducing energy and material losses (mean = 4.01, SD = 0.44) were both highly rated. These findings demonstrate that CPS technologies have enhanced operational reliability, reduced downtime, and improved resource efficiency. The low standard deviations suggest consistent agreement among respondents that such technologies have been effectively deployed to enhance production performance. This alignment points to maturity in adopting predictive maintenance tools and automated fault detection systems that contribute to better equipment performance and sustainability outcomes.

Furthermore, the statement indicating that the interaction between physical equipment and digital platforms is seamless (mean = 3.90, SD = 0.70) received a slightly lower but still strong rating. The higher variability suggests that while integration between hardware and software platforms is well established in some firms, others still face interoperability or data synchronization challenges. These differences could arise from disparities in technological investment, infrastructure readiness, or staff expertise. Nonetheless, the mean score demonstrates that many manufacturing firms have made significant progress toward full CPS integration, enabling smoother coordination between digital and physical operations.

The lowest-rated statement in Table 4.8 was that production systems adjust automatically based on sensor feedback (mean = 3.02, SD = 1.09), reflecting uneven progress in achieving fully autonomous control systems. The high standard deviation indicates substantial variation in firms' ability to utilize real-time sensor data for automatic adjustments. This suggests that while many organizations have invested in CPS infrastructure, the transition to adaptive, self-regulating production systems remains incomplete. Enhancing this capability through advanced analytics, better algorithmic control, and workforce training could enable firms to move closer to realizing the full potential of Industry 4.0—where systems not only monitor but also optimize processes autonomously for improved efficiency and environmental performance.

**TABLE 4.8:**

**Descriptive Statistics for Cyber Security Systems**

| Statements | N | Mean | Std. Dev |
|---|---|---|---|
| Our machines are connected to digital systems that enable remote control. | 181 | 4.10 | 0.30 |
| Cyber-physical technologies are used to monitor real-time environmental indicators. | 181 | 4.10 | 0.30 |
| We use embedded systems to automatically detect equipment faults. | 181 | 4.01 | 0.44 |
| CPS integration has helped us reduce energy and material losses. | 181 | 4.01 | 0.44 |
| Our production systems adjust automatically based on sensor feedback. | 181 | 3.02 | 1.09 |
| The interaction between our physical equipment and digital platforms is seamless. | 181 | 3.90 | 0.70 |
| **Overall Mean Score** | **181** | **3.85** | **0.43** |

### 4.5.3 Internet of Things

Table 4.9 presents the descriptive statistics for the Internet of Things (IoT) and illustrates the extent to which IoT technologies have been integrated into manufacturing operations. The overall mean score of 4.01 with a standard deviation of 0.24 indicates a high level of agreement among respondents that IoT applications are widely adopted across the firms surveyed. As shown in the table, the statements with the highest means are that firms collect and analyze data from IoT devices for environmental decision-making (mean = 4.10, SD = 0.30) and that IoT integration has increased visibility across production operations (mean = 4.10, SD = 0.30). These findings demonstrate that IoT systems are playing a critical role in improving real-time monitoring, enhancing operational transparency, and supporting data-driven decision-making in manufacturing environments.

The results in Table 4.9 also reveal strong consensus on the use of IoT devices to monitor equipment performance in real time (mean = 4.00, SD = 0.00) and to track environmental emissions (mean = 4.00, SD = 0.00). The perfect consistency indicated by a standard deviation of 0.00 suggests that all respondents unanimously agreed that IoT technologies have become integral to production processes. This underscores the reliability and dependability of IoT systems in supporting continuous monitoring, improving process efficiency, and facilitating compliance with environmental regulations. Such uniform responses reflect the sector's widespread recognition of IoT as a foundational enabler of smart manufacturing.

The table further shows that sensors are being used to reduce energy and material waste (mean = 3.99, SD = 0.45) and that IoT alerts help prevent equipment breakdowns and minimize production downtime (mean = 3.90, SD = 0.54). These moderately high mean values suggest that IoT tools are effectively contributing to preventive maintenance and resource optimization, key aspects of operational sustainability. The slight variability across these responses indicates that while most firms have realized these benefits, a few may still face challenges in fully leveraging IoT-enabled energy management or predictive maintenance systems. Nonetheless, the general trend confirms that IoT is enhancing productivity while advancing sustainability goals through reduced waste and efficient resource utilization.

Overall, the results presented in Table 4.9 imply that IoT adoption in the manufacturing sector is both extensive and impactful. The high mean values across all items demonstrate that IoT technologies have moved beyond experimental phases to become mainstream components of industrial operations. By enabling real-time monitoring, data analytics, and cross-system connectivity, IoT is fostering smarter, more agile, and environmentally responsible manufacturing practices. However, continued investment in data infrastructure, interoperability, and staff training could further strengthen the integration and utilization of IoT systems for even greater operational and environmental gains.

**TABLE 4.9:**

**Descriptive Statistics for Internet of Things**

| **Statements** | **N** | **Mean** | **Std. Dev** |
|---|---|---|---|
| We use IoT devices to monitor equipment performance in real time. | 181 | 4.00 | 0.00 |
| IoT technology has improved our ability to track environmental emissions. | 181 | 4.00 | 0.00 |
| Sensors are used in our processes to reduce energy and material waste. | 181 | 3.99 | 0.45 |
| IoT alerts help prevent breakdowns and reduce production downtime. | 181 | 3.90 | 0.54 |
| We collect and analyze data from IoT devices for environmental decision-making. | 181 | 4.10 | 0.30 |
| IoT integration has increased visibility across our production operations. | 181 | 4.10 | 0.30 |
| **Overall Mean Score** | **181** | **4.01** | **0.24** |

### 4.5.4 Big Data Analytics

Table 4.10 presents the descriptive statistics for big data analytics, showing how respondents rated the extent to which data-driven technologies are utilized to enhance environmental sustainability in manufacturing firms. The overall mean score of 3.92 with a standard deviation of 0.15 suggests that respondents generally agreed that big data analytics plays a significant role in environmental management and operational decision-making. As shown in the table, the highest-rated statement was that environmental data is integrated into decision-making through analytics (mean = 4.10, SD = 0.30), followed closely by three statements with identical mean scores of 4.00 and a standard deviation of 0.00—specifically, analyzing production data to identify inefficiencies, using predictive analytics for sustainable resource planning, and improving compliance with environmental standards. These results indicate strong and unanimous consensus that data analytics tools have become central in advancing environmental performance, supporting sustainability initiatives, and ensuring adherence to regulatory frameworks.

The table also shows that real-time data dashboards guide decisions on resource optimization (mean = 3.90, SD = 0.30), reflecting the increasing use of digital visualization tools to support operational efficiency. The high mean score and low variability suggest that many manufacturing firms have adopted interactive data systems that translate complex datasets into actionable insights for resource management and waste reduction. This adoption enhances transparency and enables timely interventions to address inefficiencies, reinforcing the role of analytics in sustainable production practices.

In comparison, the use of big data analytics to assess environmental performance scored a mean of 3.50 with a relatively higher standard deviation of 0.67. This indicates moderate adoption and some variation across firms, suggesting that while many organizations have begun using big data for environmental assessment, others are still developing capacity in this area. The variability may stem from disparities in technological infrastructure, data quality, or expertise in environmental analytics. Nevertheless, the results reveal a growing trend toward embedding data analytics into performance evaluation frameworks to measure and manage environmental impact more effectively.

Overall, the findings in Table 4.10 highlight that big data analytics has become an essential component of sustainable industrial operations. The high level of agreement among respondents demonstrates that data-driven insights are increasingly shaping how firms monitor environmental outcomes, plan resource use, and align with sustainability standards. However, to maximize the potential of big data analytics, firms should enhance data integration, build analytic skills, and invest in advanced predictive and prescriptive tools. Such efforts would deepen the use of analytics for continuous improvement, enabling firms to achieve greater efficiency, compliance, and long-term environmental sustainability.

**TABLE 4.10:**

**Descriptive Statistics for Big Data Analytics**

| Statements | N | Mean | Std. Dev |
|---|---|---|---|
| Our firm uses big data analytics to assess environmental performance. | 181 | 3.50 | 0.67 |
| Real-time data dashboards guide decisions on resource optimization. | 181 | 3.90 | 0.30 |
| We analyze production data to identify areas of environmental inefficiency. | 181 | 4.00 | 0.00 |
| Predictive analytics help us plan for sustainable resource usage. | 181 | 4.00 | 0.00 |
| Big data tools have improved our compliance with environmental standards. | 181 | 4.00 | 0.00 |
| Environmental data is integrated into our decision-making processes through analytics. | 181 | 4.10 | 0.30 |
| **Overall Mean Score** | **181** | **3.92** | **0.15** |

### 4.5.5 Environmental Sustainability

Table 4.11 presents the descriptive statistics for environmental sustainability, summarizing respondents' perceptions of their firms' environmental practices and performance. The overall mean score of 3.90 with a standard deviation of 0.54 indicates a generally high level of agreement that manufacturing firms have adopted sustainable operational practices. As shown in the table, the highest-rated statements were that firms actively monitor and reduce greenhouse gas emissions (mean = 4.10, SD = 0.30) and that staff are trained on environmentally sustainable practices (mean = 4.10, SD = 0.30). These results suggest that most organizations have embraced sustainability both at the strategic and operational levels—through emission control measures and workforce sensitization—which are critical pillars for long-term environmental performance improvement.

The table further shows that production processes are designed with sustainability in mind (mean = 4.01, SD = 0.64), highlighting firms' deliberate efforts to embed environmental considerations into process design and technology adoption. This finding implies that sustainability is no longer treated as an afterthought but as an integral part of production planning and resource utilization. The moderate variability suggests that while most firms are strongly aligned with sustainable design principles, a few are still transitioning toward fully eco-efficient manufacturing systems. The commitment to sustainable production aligns with the broader shift within Industry 4.0 toward cleaner technologies and circular economy principles.

Another important aspect reflected in Table 4.10 is the emphasis on energy efficiency and waste reduction. The statement "We have significantly improved our energy efficiency in recent years" scored a mean of 3.90 (SD = 0.54), while "Our firm has implemented effective waste reduction measures" scored a mean of 3.61 (SD = 0.66). These results show moderate to strong agreement that firms are taking concrete steps to minimize energy consumption and material waste, although the slightly higher variability indicates that such improvements are not uniform across all organizations. Differences in resource capacity, technology adoption, and management commitment may explain the variation in sustainability outcomes among firms.

Finally, the statement "Environmental performance is a key metric in our operations" recorded a mean of 3.94 with a standard deviation of 0.43, confirming that sustainability indicators are being integrated into performance management frameworks. This institutionalization of environmental performance underscores a growing recognition that sustainable practices not only meet regulatory requirements but also enhance operational efficiency and corporate reputation. Overall, the results in Table 4.10 suggest that manufacturing firms are actively progressing toward environmental sustainability through emission control, process redesign, energy efficiency, and staff training. However, continuous investment in clean technologies, waste management innovations, and performance tracking systems will be necessary to consolidate these gains and achieve more uniform sustainability outcomes across the sector.

**TABLE 4.11:**

**Descriptive Statistics for Environmental Sustainability**

| **Statement** | **N** | **Mean** | **Std. Dev.** |
|---|---|---|---|
| We have significantly improved our energy efficiency in recent years. | 181 | 3.90 | 0.54 |
| Our firm has implemented effective waste reduction measures. | 181 | 3.61 | 0.66 |
| We actively monitor and reduce greenhouse gas emissions. | 181 | 4.10 | 0.30 |
| Our production processes are designed with sustainability in mind. | 181 | 4.01 | 0.64 |
| We train staff on environmentally sustainable practices. | 181 | 4.10 | 0.30 |
| Environmental performance is a key metric in our operations. | 181 | 3.94 | 0.43 |
| **Average** | **181** | **3.90** | **0.54** |

### 4.6 Diagnostic Tests

This section presents the diagnostic tests conducted to ensure that the assumptions underlying multiple regression analysis were met before model estimation. Diagnostic tests are crucial for validating the reliability and accuracy of the statistical results by confirming that the data satisfy essential econometric conditions such as normality, multicollinearity, heteroscedasticity, and autocorrelation. By performing these tests, the study ensures that the regression model produces unbiased, efficient, and consistent estimates. The results of the diagnostic tests are summarized and interpreted in the subsequent subsections to demonstrate the suitability of the dataset for inferential analysis.

#### 4.6.1 Tests of Normality

Table 4.12 presents the results of the Shapiro–Wilk test used to assess the normality of the study variables. The results show that all variables—smart manufacturing ($p = .151$), cyber-physical systems ($p = .226$), internet of things ($p = .261$), big data analytics ($p = .266$), and environmental sustainability ($p = .261$)—recorded significance values greater than the 0.05 threshold. According to the Shapiro–Wilk criterion, when the significance level (Sig.) is above 0.05, the null hypothesis that the data are normally distributed cannot be rejected. This indicates that the dataset for each variable follows an approximately normal distribution, which satisfies one of the key assumptions required for parametric analysis.

As illustrated in Table 4.12, the normality of the data implies that the responses were symmetrically distributed around their means with no substantial skewness or kurtosis that could distort the regression results. This validates the suitability of the dataset for inferential analysis, particularly for correlation and regression tests that assume normally distributed residuals. The findings therefore confirm that the data collected on smart manufacturing, cyber-physical systems, internet of things, big data analytics, and environmental sustainability are reliable and appropriate for further statistical modeling.

**TABLE 4.12:**

**Test of Normality**

| | Shapiro-Wilk | | |
|---|---|---|---|
| Study variables | Statistic | Df | Sig. |
| Smart manufacturing | .931 | 181 | .151 |
| Cyber security systems | .835 | 181 | .226 |
| Internet of Things | .835 | 181 | .261 |
| Big data analytics | .814 | 181 | .266 |
| Environmental sustainability | .796 | 181 | .261 |

### 4.6.2 Tests of Multicollinearity

Table 4.13 presents the results of the multicollinearity test conducted to determine whether the independent variables were highly correlated with each other. The results show that all the Variance Inflation Factor (VIF) values range between 1.072 and 1.994, while the corresponding tolerance values range between 0.502 and 0.933. These results fall well within the acceptable thresholds of VIF < 10 and tolerance > 0.1, as recommended by Field (2018). The mean VIF of 1.559 further indicates that the predictors—smart manufacturing, cyber-physical systems, internet of things, and big data analytics—are not highly correlated, implying that multicollinearity is not a concern in this dataset.

As illustrated in Table 4.13, the absence of multicollinearity suggests that each independent variable contributes uniquely to explaining variations in environmental sustainability without inflating standard errors or distorting coefficient estimates. This strengthens the validity of the regression results and ensures that the model will produce stable and reliable parameter estimates. The low VIF and high tolerance values confirm that the predictors are distinct and can be used together in the same regression model to examine their collective and individual effects on environmental sustainability in manufacturing firms.

**TABLE 4.13:**

**Test of Multicollinearity**

| Variable | VIF | Tolerance |
|---|---|---|
| Smart manufacturing | 1.072 | 0.933 |
| Cyber security systems | 1.308 | 0.765 |
| Internet of things | 1.863 | 0.537 |
| Big data analytics | 1.994 | 0.502 |
| Mean VIF | 1.559 | |

### 4.6.3 Tests of Heteroscedasticity

Table 4.14 presents the results of the Breusch-Pagan/Cook-Weisberg test for heteroscedasticity, which was conducted to assess whether the variance of the residuals in the regression model is constant across observations. The test yielded a chi-square ($\chi^2$) value of 0.7328 with a corresponding probability (p-value) of 0.5416. Since the p-value is greater than the 0.05 significance level, the null hypothesis of homoscedasticity cannot be rejected. This indicates that the residuals have constant variance, implying that heteroscedasticity is not present in the data.

As shown in Table 4.14, the absence of heteroscedasticity means that the regression model meets one of the key assumptions of the classical linear regression model, where the error terms are assumed to have equal variance. This ensures that the estimated coefficients are efficient and that statistical tests such as t-tests and F-tests will yield valid inferences. Therefore, the results confirm that the dataset used in this study is suitable for regression analysis without the need for corrective transformations or robust standard error adjustments.

**TABLE 4.14:**

**Test of Heteroscedasticity**

| **Breusch-Pagan / Cook-Weisberg test for heteroscedasticity** | | |
|---|---|---|
| chi2(1) | = | 0.7328 |
| Prob > chi2 | = | 0.5416 |

### 4.7 Correlation Analysis

Table 4.15 presents the Pearson correlation matrix for the study variables based on listwise N = 181, with all tests conducted at the two-tailed 0.01 significance level. The table shows that environmental sustainability is positively and significantly associated with all four Industry 4.0 constructs. These coefficients indicate that higher adoption of these technologies is linked to better environmental outcomes, with particularly strong associations observed for cyber-physical systems and smart manufacturing.

Focusing first on smart manufacturing, the correlation with environmental sustainability is very strong (r = .828), suggesting that firms reporting greater use of automation, digital monitoring, and adaptive production also report superior energy efficiency, waste reduction, and emission management. This magnitude—well above the conventional "large" threshold—implies a pronounced bivariate relationship consistent with the descriptive evidence that firms invest steadily in technology upgrades and process flexibility. While correlation does not imply causation, the strength here signals that smart manufacturing capabilities are tightly intertwined with greener operational performance.

Cyber-physical systems post the strongest bivariate link to environmental sustainability ($r = .833$), reinforcing the role of sensor-rich, tightly integrated physical-digital control loops in driving environmental gains. The table also shows that CPS correlates substantially with smart manufacturing ($r = .667$, $p < .01$) and the internet of things ($r = .688$, $p < .01$), indicating that CPS typically co-occurs with broader digitalization and connectivity. This clustering suggests that firms advancing CPS integration often possess the foundational automation and IoT infrastructures that enable real-time monitoring and control, thereby amplifying sustainability benefits.

The internet of things also shows a strong positive correlation with environmental sustainability ($r = .700$, $p < .01$) and substantial interrelationships with smart manufacturing ($r = .625$, $p < .01$) and CPS ($r = .688$, $p < .01$). These patterns are consistent with the role of IoT in streaming high-frequency data from equipment and processes, which can then be acted upon by automated systems and CPS controls. By increasing visibility and enabling timely interventions, IoT appears to serve as a connective tissue that links data capture to operational adjustments, supporting the observed sustainability improvements.

Big data analytics exhibits a moderate-to-strong positive association with environmental sustainability ($r = .549$, $p < .01$) and moderate correlations with the other technologies (smart manufacturing $r = .548$; CPS $r = .447$; IoT $r = .406$; all $p < .01$). This profile suggests that while analytics is widely present, its environmental payoff likely depends on complementary capabilities—namely the availability of high-quality IoT data streams and digitally controlled production systems that can translate insights into action. Overall, Table

4.11 signals a coherent digital ecosystem in which CPS, smart manufacturing, and IoT have particularly strong direct ties to environmental sustainability, with analytics strengthening decision quality across this ecosystem.

**TABLE 4.15:**

**Correlation Results**

| | | Environmental sustainability | Smart manufacturing | Cyber-physical systems | Internet of things | Big data analytics |
|---|---|---|---|---|---|---|
| Environmental sustainability | Pearson Correlation | 1 | | | | |
| | Sig. (2-tailed) | | | | | |
| Smart manufacturing | Pearson Correlation | .828** | 1 | | | |
| | Sig. (2-tailed) | .000 | | | | |
| Cyber-physical systems | Pearson Correlation | .833** | .667** | 1 | | |
| | Sig. (2-tailed) | .000 | .000 | | | |
| Internet of things | Pearson Correlation | .700** | .625** | .688** | 1 | |
| | Sig. (2-tailed) | .000 | .000 | .000 | | |
| Big data analytics | Pearson Correlation | .549** | .548** | .447** | .406** | 1 |
| | Sig. (2-tailed) | .000 | .000 | .000 | .000 | |

**. Correlation is significant at the 0.01 level (2-tailed).
b. Listwise N=181

### 4.8 Regression Analysis

This subsection presents multiple regression results linking Industry 4.0 technologies to environmental sustainability. Model fitness statistics (Table 4.16) indicate how well the predictors: smart manufacturing, cyber-physical systems, internet of things, and big data analytics explain variation in environmental sustainability. Table 4.17 reports the ANOVA results that test the overall significance of the model, while Table 4.18 provides the estimated coefficients, their standardized effects, and significance levels used to interpret the individual contribution of each predictor.

Table 4.16 (Model Fitness) shows a strong model fit with R = .881 and $R^2$ = .776, indicating that 77.6% of the variance in environmental sustainability is explained jointly by the four predictors. The adjusted $R^2$ = .771 confirms that explanatory power remains high after accounting for model complexity, implying limited overfitting. The standard error of the estimate (≈ 0.206) is relatively small on the study's measurement scale, suggesting that predicted values cluster closely around observed outcomes. Collectively, these indices point to a robust explanatory model for environmental sustainability.

**TABLE 4.16:**

**Model Fitness**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | .881[a] | .776 | .771 | .205628435496302 |

a. Predictors: (Constant), Big data analytics, Internet of things, Smart manufacturing, Cyber-physical systems

Table 4.17 (ANOVA) confirms the model's overall statistical significance. The regression sum of squares (25.806) far exceeds the residual sum of squares (7.442), yielding an F-statistic of 152.580 with p = .000. This result means the set of Industry 4.0 predictors, taken together, significantly improves prediction of environmental sustainability compared to a model with no predictors. In practical terms, the probability that these results arose by chance is exceedingly small, validating the inclusion of the four technological factors in the model.

**TABLE 4.17:**

**Analysis of Variance**

| Model | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| 1 | Regression | 25.806 | 4 | 6.452 | 152.580 | .000[b] |
| | Residual | 7.442 | 176 | .042 | | |
| | Total | 33.248 | 180 | | | |

a. Dependent Variable: Environmental sustainability

b. Predictors: (Constant), Big data analytics, Internet of things, Smart manufacturing, Cyber-physical systems

Table 4.18 (Coefficients) indicates that all four predictors are positive and statistically significant determinants of environmental sustainability: smart manufacturing ($B = 0.227$, $\beta = .316$, $t = 4.122$, $p < .001$), cyber-physical systems ($B = 0.363$, $\beta = .363$, $t = 4.673$, $p < .001$), internet of things ($B = 0.352$, $\beta = .199$, $t = 3.994$, $p < .001$), and big data analytics ($B = 0.372$, $\beta = .133$, $t = 3.089$, $p = .002$). Interpreting standardized betas for relative influence, cyber-physical systems ($\beta = .363$) exert the strongest unique effect, followed by smart manufacturing ($\beta = .316$), internet of things ($\beta = .199$), and big data analytics ($\beta = .133$). The negative constant ($B = -1.137$, $p = .018$) simply centers the regression surface and does not imply a negative relationship for any predictor; rather, it reflects the expected sustainability score when all predictors are at zero on the study scale. Overall, these results suggest that deeper integration of CPS and smart manufacturing yields the largest marginal gains in environmental sustainability, with IoT and analytics providing additional, significant improvements.

**TABLE 4.18:**

**Regression Coefficients**

| Model | | Unstandardized Coefficients | | Standardized Coefficients | | |
|---|---|---|---|---|---|---|
| | | B | Std. Error | Beta | t | Sig. |
| 1 | (Constant) | -1.137 | .474 | | -2.397 | .018 |
| | Smart manufacturing | .227 | .055 | .316 | 4.122 | .000 |

| | | | | | |
|---|---|---|---|---|---|
| Cyber-physical systems | .363 | .078 | .363 | 4.673 | .000 |
| Internet of things | .352 | .088 | .199 | 3.994 | .000 |
| Big data analytics | .372 | .120 | .133 | 3.089 | .002 |

a. Dependent Variable: Environmental sustainability

The following is the regression model that was estimated from the study results:

$$\mathbf{Y = -1.137 + 0.316X_1 + 0.363X_2 + 0.199X_3 + 0.133X_4}$$

Where:

Y = Environmental sustainability,

$X_1$ – Smart manufacturing,

$X_2$ – Cyber security systems,

$X_3$ – Internet of things,

$X_4$ – Big data analytics

### 4.9 Hypotheses Testing

This section presents the results of hypotheses testing, which were conducted to determine whether the relationships proposed in the study's conceptual framework are statistically significant. Each hypothesis was tested using regression coefficients, t-values, and corresponding p-values derived from the multiple regression analysis. The decision rule applied was that a hypothesis would be supported if its p-value was less than 0.05, indicating a statistically significant relationship between the predictor and the dependent variable. The results of the hypothesis tests provide empirical evidence on the influence of smart manufacturing, cyber-physical systems, internet of things, and big data analytics on environmental sustainability within the manufacturing sector.

### 4.9.1 Smart Manufacturing and Environmental Sustainability

The first hypothesis sought to determine whether smart manufacturing has a significant influence on environmental sustainability. Results from the regression analysis in Table 4.17 show that smart manufacturing had a positive and statistically significant effect on environmental sustainability ($\beta = 0.316$, $t = 4.122$, $p < 0.001$). Since the p-value is less than the 0.05 significance level, the null hypothesis was rejected, confirming that smart manufacturing significantly enhances environmental sustainability in manufacturing firms. This implies that increased adoption of smart manufacturing practices—such as automation, real-time monitoring, and adaptive production systems—contributes to improved energy efficiency, reduced resource wastage, and lower environmental impact. The finding aligns with the principles of Industry 4.0, which emphasize intelligent production processes as key enablers of sustainable industrial growth.

The findings of the study, which established that smart manufacturing has a positive and significant influence on environmental sustainability, align strongly with the Natural Resource-Based View theory. According to the NRBV, firms can gain a sustainable competitive advantage by developing capabilities that promote environmental stewardship through efficient use of resources and pollution prevention. The study's results affirm this theoretical perspective by showing that manufacturing firms adopting automated machines, digital monitoring systems, and adaptive production processes achieved higher energy efficiency and reduced material waste. This demonstrates that environmental management, when embedded in technological innovation, becomes a source of long-term competitiveness. The findings also resonate with Jabbour et al. (2025), who found that smart manufacturing technologies significantly reduced emissions and waste across Latin America and sub-Saharan Africa, although they emphasized the moderating role of institutional support. Similarly, the current study confirms that when supported by digital readiness and policy alignment, smart manufacturing fosters cleaner and more sustainable production.

From the standpoint of the Ecological Modernization Theory, the study findings reinforce the argument that technological advancement can coexist with, and indeed accelerate, environmental improvement. The theory posits that environmental progress and economic growth are not mutually exclusive, as innovations in production processes can lead to resource efficiency and waste minimization. The observed positive relationship between smart manufacturing and environmental sustainability validates this premise. Firms employing automated scheduling, sensor-driven monitoring, and real-time data analytics were found to enhance energy optimization and emission control—findings consistent with Patyal and Sarma (2024), who reported similar outcomes in Indian manufacturing clusters. Moreover, the results advance the ecological modernization discourse by demonstrating that digital transformation within Kenyan manufacturing firms can support national environmental goals even in the face of infrastructural and policy limitations, a contextual dimension highlighted as critical by Ogur (2023).

The study's outcomes also fit well within the Technology-Organization-Environment framework, which emphasizes that successful technological innovation is influenced by the interplay of technological capabilities, organizational readiness, and environmental conditions. The strong association between smart manufacturing and environmental sustainability observed in this study suggests that firms with sufficient organizational commitment and supportive external environments can leverage advanced technologies for sustainable outcomes. This finding echoes Modgil et al. (2022), who reported that the effectiveness of smart manufacturing in Germany was reinforced by favorable regulatory and infrastructural contexts. However, unlike the German context, the present study extends the TOE framework to a developing economy perspective, showing that even under resource constraints, firms can achieve sustainability gains through strategic investments in digital technologies and employee capacity-building initiatives that enhance technological readiness.

The empirical alignment between this study and prior research, such as Bag et al. (2020) and Santana et al. (2018), underscores that smart manufacturing enhances material efficiency, energy conservation, and emission reduction. However, the current study advances the literature by disaggregating smart manufacturing components and empirically linking them to measurable environmental outcomes—a methodological improvement over earlier studies that aggregated digital practices without specifying their relative contributions. Furthermore, by situating environmental sustainability as a core outcome variable rather than an ancillary benefit, the study extends theoretical discourse and fills both conceptual and contextual gaps in African manufacturing research. Overall, the findings affirm that smart manufacturing is not only a technological evolution but also a strategic enabler of environmental responsibility, consistent with the NRBV, EMT, and TOE theoretical propositions.

### 4.9.2 Cyber Security Systems and Environmental Sustainability

The second hypothesis examined the relationship between cyber-physical systems and environmental sustainability. As shown in Table 4.17, cyber-physical systems had a positive and statistically significant effect on environmental sustainability ($\beta = 0.363$, $t = 4.673$, $p < 0.001$). Since the p-value is below the 0.05 threshold, the null hypothesis was rejected, indicating that increased integration of cyber-physical systems significantly improves environmental sustainability among manufacturing firms. This suggests that the use of interconnected physical and digital systems enhances real-time monitoring, predictive maintenance, and efficient resource utilization, thereby reducing energy losses and emissions. The results confirm that cyber-physical systems are a crucial driver of sustainable manufacturing, as they enable automation, precision control, and data-informed decision-making that collectively minimize environmental impact.

The study found that cyber-physical systems had a positive and statistically significant influence on environmental sustainability, confirming their central role in achieving sustainable industrial transformation. These findings align with the Natural Resource-Based View theory, which posits that organizations can achieve a competitive advantage by integrating technologies that enhance resource efficiency and minimize environmental harm. By connecting physical machinery with intelligent digital systems, cyber-physical systems enable firms to reduce waste, optimize energy use, and prevent production defects through predictive maintenance and autonomous controls. This resonates with Patyal et al. (2023), who found that cyber-physical systems improved sustainability among Indian manufacturers through energy optimization and defect reduction. However, unlike their study, which focused on digitally mature firms, the current findings demonstrate that even firms in developing economies such as Kenya can achieve significant environmental improvements when supported by appropriate technological integration and organizational commitment.

The results also reinforce the principles of Ecological Modernization Theory, which suggests that technological progress and environmental protection can coexist through systemic innovation. The significant relationship between cyber-physical systems and environmental sustainability observed in this study indicates that firms adopting digital control systems and embedded sensors are not only modernizing their operations but also reducing their ecological footprint. This finding corresponds with Dantas et al. (2022), who reported that cyber-physical systems facilitated digital traceability and resource circularity in Latin America. However, while their study concentrated on macro-level policy implications, the current research provides micro-level evidence showing how cyber-physical systems directly enhance firm-level sustainability performance. This reinforces the idea that modernization through technology, even in resource-constrained environments, can yield both environmental and operational gains.

The study's outcomes are further consistent with the Technology-Organization-Environment framework, which highlights the interdependence between technological capabilities, organizational readiness, and external conditions. The observed positive influence of cyber-physical systems on environmental sustainability demonstrates that firms with adequate technological preparedness and supportive external conditions are better positioned to benefit from digital integration. These results echo the findings of Gupta et al. (2021) and Rajesh et al. (2021), who found that cyber-physical systems enabled cleaner production through real-time process adjustments and reduced idle time. However, by making environmental sustainability the central focus rather than a secondary outcome, this study advances the empirical understanding of how technological innovation directly supports ecological goals in developing industrial settings such as Nairobi.

In addition, the findings contribute to bridging the contextual and methodological gaps identified in prior studies, such as Saucedo-Martínez et al. (2020), who analyzed cyber-physical systems at an aggregated regional level without accounting for firm-level variation. By focusing on individual firms within a developing economy context, this study offers granular insights into how cyber-physical systems operate under varying degrees of digital readiness, infrastructure limitations, and environmental compliance. The results confirm that effective integration of cyber-physical systems enables real-time decision-making, predictive maintenance, and precise resource allocation—all of which are critical in advancing sustainability. Overall, the findings substantiate that cyber-physical systems are not merely operational tools but strategic enablers of environmental performance, supporting the theoretical perspectives of the Natural Resource-Based View, Ecological Modernization Theory, and the Technology-Organization-Environment framework.

### 4.9.3 Internet of Things and Environmental Sustainability

The third hypothesis sought to establish whether the IoT has a significant influence on environmental sustainability. The regression results in Table 4.17 indicate that IoT had a positive and statistically significant effect on environmental sustainability ($\beta = 0.199$, $t = 3.994$, $p < 0.001$). Since the p-value is less than 0.05, the null hypothesis was rejected, confirming that IoT adoption significantly contributes to enhancing environmental sustainability in manufacturing firms. This finding implies that the use of IoT-enabled sensors and connected devices facilitates real-time tracking of energy consumption, emission levels, and production efficiency, allowing firms to make timely adjustments that optimize resource use and minimize waste. The results demonstrate that IoT plays a pivotal role in advancing sustainable operations by improving visibility, control, and responsiveness within industrial systems.

The study found that the Internet of Things had a positive and statistically significant influence on environmental sustainability, confirming its role as a central driver of sustainable industrial transformation. This finding aligns with the Natural Resource-Based View theory, which emphasizes the strategic importance of resource efficiency and environmental innovation in achieving a competitive advantage. Through IoT-enabled sensors and interconnected devices, firms can monitor energy consumption, track emissions, and optimize material use in real time. This enhances their ability to reduce waste and minimize environmental impact. The results correspond with Singh and Taneja (2025), who found that firms using IoT technologies in Kenya and Ethiopia achieved significant reductions in production waste and improved emissions tracking. However, while their research focused on firms in modern industrial zones, the current study demonstrates that even within Nairobi's more heterogeneous manufacturing landscape, IoT adoption significantly improves environmental outcomes, indicating that technological benefits are attainable even in less structured environments.

The findings are also consistent with Ecological Modernization Theory, which posits that technological innovation and environmental protection can evolve together through systemic modernization. The significant relationship between IoT and environmental sustainability observed in this study reinforces the notion that digital transformation is not merely an economic advancement but also an environmental necessity. By enabling real-time monitoring, IoT empowers firms to detect inefficiencies early, improve operational transparency, and maintain regulatory compliance—outcomes also reported by Rodriguez-Anton et al. (2024) in European contexts. However, the present study extends this understanding by confirming similar benefits in Nairobi's less digitally mature and weakly regulated industrial settings. This shows that, despite infrastructural constraints, IoT can still serve as a catalyst for environmentally conscious industrial modernization in developing economies.

The study's results further resonate with the Technology-Organization-Environment framework, which highlights that technology adoption is shaped by organizational readiness and environmental conditions. The strong relationship between IoT and sustainability outcomes in this study implies that firms with supportive organizational structures and flexible digital strategies are better able to leverage IoT for environmental benefits. This supports the findings of Kumar and Gupta (2023), who reported that IoT-enabled lifecycle tracking and feedback systems led to measurable reductions in emissions and resource waste. However, the current study extends these insights by examining firms outside formal green clusters, providing a realistic depiction of how IoT contributes to sustainability even where institutional support and digital infrastructure are uneven. The results confirm that the TOE model's components—technological capability, organizational preparedness, and external environment—must align to fully realize IoT's sustainability potential.

Additionally, the findings bridge methodological and contextual gaps identified in earlier research. Studies such as Alharthi et al. (2022) and Duan et al. (2020) focused on regulatory performance and large firms operating within strong policy environments, often overlooking the direct environmental metrics and operational realities of smaller, locally owned enterprises. By empirically testing IoT's impact on specific indicators such as emissions reduction, energy efficiency, and waste minimization, this study provides a more grounded assessment of IoT's sustainability contribution in developing contexts. The results affirm that IoT technologies enhance visibility, accountability, and resource management, allowing firms to align operational practices with sustainability objectives. Overall, the findings demonstrate that IoT is not merely a communication technology but a transformative environmental management tool, supporting the theoretical propositions of the Natural Resource-Based View, Ecological Modernization Theory, and the Technology-Organization-Environment framework.

### 4.9.4 Big Data Analytics and Environmental Sustainability

The fourth hypothesis evaluated whether big data analytics significantly influences environmental sustainability. As reported in Table 4.17, big data analytics had a positive and statistically significant effect on environmental sustainability ($\beta = 0.133$, $t = 3.089$, $p = 0.002$). With the p value below 0.05, the null hypothesis was rejected, indicating that greater use of analytical tools meaningfully enhances environmental outcomes. This result suggests that integrating environmental data into dashboards, diagnostic reports, and predictive models supports timely decisions on resource use, strengthens compliance with environmental standards, and guides targeted interventions that reduce waste and emissions, thereby improving overall sustainability performance.

The study found that big data analytics had a positive and statistically significant influence on environmental sustainability, confirming its growing importance as a strategic enabler of sustainable industrial transformation. This finding aligns with the Natural Resource-Based View theory, which emphasizes that firms can achieve a competitive advantage by developing and deploying capabilities that enhance resource efficiency and minimize environmental impact. Through the application of big data analytics, firms can process vast amounts of operational and environmental data to monitor emissions, optimize energy use, and manage waste more effectively. These results correspond with the findings of Jabbour et al. (2025), who established that analytics-driven firms in Brazil and South Africa improved environmental efficiency through predictive energy planning and emissions tracking. However, while their research was based on firms benefiting from policy incentives, the current study extends these insights to Nairobi's more resource-constrained context, demonstrating that environmental gains from data analytics can still be realized even with limited institutional support.

The study also reinforces the principles of Ecological Modernization Theory, which argues that environmental improvements can be achieved through technological advancement and innovation rather than by restricting industrial activity. The positive relationship between big data analytics and environmental sustainability observed in this study suggests that the use of data-driven decision tools fosters transparency, accountability, and proactive environmental management. By allowing real-time tracking and predictive modeling, big data analytics empowers firms to prevent inefficiencies before they escalate into environmental harm. This outcome aligns with Patyal and Sarma (2024), who found that data analytics improved pollution detection and raw material efficiency in Indian firms. However, unlike their study, which approached analytics through a broad circular economy lens, the present research isolates direct environmental metrics—such as energy efficiency, emissions, and waste reduction—thereby filling a measurement gap in existing literature and providing a clearer picture of analytics' tangible environmental benefits.

The findings are further supported by the Technology-Organization-Environment framework, which explains that the successful adoption of technological innovations depends on the interaction between internal organizational capacity, available technology, and external environmental conditions. The study's results show that manufacturing firms with strong data management systems, technological readiness, and supportive managerial structures are better positioned to leverage analytics for sustainability. This conclusion resonates with Zhang et al. (2023) and Awan et al. (2022), who demonstrated that analytics-driven insights enhance process transparency and environmental risk management across manufacturing operations and supply chains. Nevertheless, by focusing on in-plant performance metrics within a developing economy, the current study provides new empirical evidence showing that even mid-sized and locally owned firms can use big data analytics to achieve measurable environmental improvements when supported by a conducive organizational and technological environment.

Furthermore, the study contributes to closing the contextual gap identified in earlier research, such as Wamba et al. (2020), which focused on large multinational corporations in technologically advanced economies. By examining mid-sized manufacturing firms in Nairobi, this study provides localized insights into how big data analytics can drive sustainability despite infrastructure and budgetary limitations. The findings indicate that analytics facilitates cleaner production by improving carbon tracking, enhancing resource optimization, and supporting compliance with environmental standards. Collectively, these results affirm that big data analytics is not merely a monitoring tool but a strategic resource that transforms information into actionable insights for sustainable manufacturing. In line with the Natural Resource-Based View, Ecological Modernization Theory, and the Technology-Organization-Environment framework, the study concludes that integrating analytics into industrial decision-making is essential for achieving long-term environmental and operational resilience.

# CHAPTER FIVE

# SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

## 5.1 Introduction

This chapter presents a summary of the study findings, conclusions drawn from the results, and recommendations based on the objectives of the study. It revisits the key insights obtained from the analysis of data in Chapter Four, highlighting how the variables of smart manufacturing, cyber-physical systems, internet of things, and big data analytics influence environmental sustainability. The conclusions are derived directly from empirical results, providing clear implications for theory, policy, and practice. Finally, the chapter offers practical recommendations aimed at enhancing the adoption of Industry 4.0 technologies to promote sustainable manufacturing practices, followed by suggestions for future research.

## 5.2 Summary

This section provides a summary of the key findings from the study in relation to its specific objectives. It synthesizes the major results derived from descriptive, correlation, and regression analyses to highlight the influence of smart manufacturing, cyber-physical systems, internet of things, and big data analytics on environmental sustainability. The summary captures how each variable contributed to the overall model and explains the nature and strength of their relationships. By consolidating these findings, the section offers a concise overview of how Industry 4.0 technologies collectively enhance environmental performance within the manufacturing sector.

### 5.2.1 Smart Manufacturing and Environmental Sustainability

The study established that smart manufacturing had a positive and statistically significant influence on environmental sustainability, as indicated by the regression results ($\beta = 0.316$, $t = 4.122$, $p < 0.001$). This implies that the adoption of smart manufacturing practices, such as automation, digital monitoring, and adaptive production systems, enhances the efficiency of manufacturing processes while minimizing environmental degradation. The descriptive results also supported this finding, with respondents agreeing that their firms had integrated digital systems to monitor production efficiency, regularly upgraded manufacturing technologies, and reduced resource wastage. These practices contribute to lower energy consumption, minimized waste, and improved compliance with environmental standards.

The results further suggest that smart manufacturing promotes operational flexibility and data-driven decision-making, enabling firms to align production processes with sustainability objectives. By utilizing advanced technologies to optimize production, firms can reduce carbon footprints and achieve greater resource utilization efficiency. The strong positive relationship between smart manufacturing and environmental sustainability aligns with the principles of Industry 4.0, which emphasize technological innovation as a pathway toward sustainable industrial development. Therefore, the study concludes that investment in smart manufacturing technologies is a critical driver of sustainable transformation in the manufacturing sector.

### 5.2.2 Cyber Security Systems and Environmental Sustainability

The study found that cyber-physical systems had a positive and statistically significant effect on environmental sustainability, as reflected in the regression results ($\beta = 0.363$, $t = 4.673$, $p < 0.001$). This indicates that increased integration of cyber-physical technologies enhances environmental performance in manufacturing firms. Descriptive statistics also showed that most firms had adopted systems enabling remote control of machines, real-time monitoring of environmental indicators, and automatic fault detection. These capabilities facilitate predictive maintenance, minimize production disruptions, and reduce energy and material losses, thereby improving overall environmental outcomes. The strong association between cyber-physical systems and sustainability underscores their role in optimizing industrial processes and promoting resource efficiency.

Furthermore, the findings demonstrate that cyber-physical systems enable seamless interaction between digital platforms and physical equipment, creating intelligent and adaptive production environments. Such integration allows firms to monitor, analyze, and respond to operational data instantly, leading to improved control over resource consumption and reduced environmental waste. The study concludes that cyber-physical systems are instrumental in fostering sustainable manufacturing by ensuring real-time feedback, process precision, and enhanced operational reliability. These results align with Industry 4.0 principles, which position cyber-physical integration as a foundation for achieving environmentally responsible and technologically advanced production systems.

### 5.2.3 Internet of Things and Environmental Sustainability

The study revealed that the Internet of Things (IoT) had a positive and statistically significant influence on environmental sustainability, as indicated by the regression results ($\beta = 0.199$, $t = 3.994$, $p < 0.001$). This finding suggests that IoT technologies play a crucial role in enhancing environmental performance within manufacturing firms. Descriptive results further showed that most organizations used IoT devices to monitor equipment performance, track environmental emissions, and reduce energy and material waste through sensor-based systems. These capabilities enable real-time monitoring and control of operations, allowing for timely interventions that minimize inefficiencies and environmental harm. The consistent high mean scores across IoT-related statements reflect widespread adoption and confidence in IoT's contribution to operational efficiency and sustainability.

The results further imply that IoT technologies enhance data collection, transparency, and decision-making within production systems. By providing continuous data streams and actionable insights, IoT facilitates predictive maintenance, reduces downtime, and improves compliance with environmental standards. The ability to integrate IoT-generated data into environmental decision-making processes strengthens firms' capacity to manage resources responsibly and implement sustainable production practices. The study concludes that IoT adoption is a vital enabler of sustainable manufacturing, as it enhances visibility across operations, supports data-driven decisions, and promotes eco-efficient industrial practices aligned with the goals of Industry 4.0.

### 5.2.4 Big Data Analytics and Environmental Sustainability

The study established that big data analytics had a positive and statistically significant effect on environmental sustainability, as shown by the regression results ($\beta = 0.133$, $t = 3.089$, $p = 0.002$). This indicates that the application of big data analytics contributes meaningfully to improving environmental performance among manufacturing firms. Descriptive statistics further revealed that respondents strongly agreed their firms used analytics to assess environmental performance, guide decisions on resource optimization, and ensure compliance with environmental standards. The high mean scores across most indicators reflect widespread utilization of analytics for monitoring production efficiency and reducing environmental inefficiencies. These findings demonstrate that firms leveraging big data tools can identify waste patterns, enhance operational efficiency, and implement sustainable resource management strategies more effectively.

Moreover, the results highlight that integrating environmental data into decision-making processes through advanced analytics enables firms to make informed and proactive sustainability decisions. Predictive analytics, in particular, allows organizations to anticipate future resource demands, optimize usage, and mitigate potential environmental risks. The study concludes that big data analytics serves as a strategic enabler of sustainable industrial practices by transforming large volumes of operational data into actionable insights. This capability not only supports regulatory compliance and efficiency but also reinforces the role of Industry 4.0 technologies in driving environmentally responsible and data-driven manufacturing systems.

## 5.3 Conclusions

This section presents the conclusions drawn from the study findings in relation to each specific objective. The conclusions summarize the key insights derived from the analysis and highlight how smart manufacturing, cyber-physical systems, internet of things, and big data analytics collectively and individually influence environmental sustainability. By linking empirical results to theoretical expectations, this section provides a concise interpretation of the study's implications for sustainable manufacturing practices within the context of Industry 4.0 adoption.

### 5.3.1 Smart Manufacturing and Environmental Sustainability

The study concludes that smart manufacturing significantly enhances environmental sustainability in manufacturing firms. The findings demonstrated that firms adopting advanced manufacturing technologies such as automation, digital monitoring, and adaptive production systems achieve improved energy efficiency, reduced waste, and lower emissions. This suggests that smart manufacturing not only optimizes operational processes but also aligns industrial activities with environmental conservation goals. Therefore, the integration of smart manufacturing practices is essential for firms seeking to achieve both productivity and sustainability under the Industry 4.0 framework.

### 5.3.2 Cyber Security Systems and Environmental Sustainability

The study concludes that cyber-physical systems play a vital role in promoting environmental sustainability within manufacturing firms. The results revealed that integrating physical equipment with digital control systems enhances operational precision, real-time monitoring, and predictive maintenance, leading to reduced resource wastage and lower energy consumption. These systems enable firms to detect inefficiencies promptly and optimize production processes, thereby minimizing their environmental footprint. Consequently, the adoption of cyber-physical systems is a key driver of sustainable industrial performance, supporting the transition toward smarter, cleaner, and more efficient manufacturing operations.

### 5.3.3 Internet of Things and Environmental Sustainability

The study concludes that IoT significantly contributes to environmental sustainability in manufacturing firms. The results showed that IoT-enabled sensors and connected devices enhance real-time monitoring of production processes, equipment performance, and environmental emissions. By providing continuous data flow and instant feedback, IoT allows firms to make timely and data-driven decisions that optimize resource utilization and reduce waste. Therefore, the integration of IoT technologies strengthens environmental management practices, enabling firms to operate more efficiently and sustainably in line with Industry 4.0 principles.

### 5.3.4 Big Data Analytics and Environmental Sustainability

The study concludes that big data analytics has a significant positive influence on environmental sustainability in manufacturing firms. The findings revealed that the use of data-driven tools enables firms to assess environmental performance, identify inefficiencies, and make informed decisions aimed at resource optimization and waste reduction. Predictive analytics further supports proactive planning for sustainable resource use and enhances compliance with environmental regulations. Thus, the integration of big data analytics into manufacturing operations fosters continuous improvement, efficiency, and accountability, making it a critical component in achieving sustainable industrial development.

## 5.4 Recommendations of the Study

Based on the study findings, it is recommended that policymakers and industry regulators promote the adoption of smart manufacturing technologies across the manufacturing sector through targeted incentives and supportive frameworks. Government agencies such as the Ministry of Industrialization and the Kenya Association of Manufacturers (KAM) should develop policies that encourage automation, digital monitoring, and adaptive production systems. This can be achieved through tax incentives for technology investments, low-interest innovation grants, and capacity-building programs to enhance firms' technological readiness. By institutionalizing smart manufacturing, firms will be better positioned to improve operational efficiency, reduce waste, and meet national sustainability targets aligned with Kenya's Vision 2030 and global sustainable development goals.

Additionally, firms should prioritize the integration of cyber-physical systems to improve real-time monitoring and control of production processes. Policymakers can support this through the establishment of technology transfer centers and public–private partnerships aimed at knowledge sharing and innovation diffusion. Industrial players should invest in intelligent systems that connect physical machinery with digital platforms to enhance automation, precision, and resource efficiency. At the same time, industry associations should formulate operational standards for CPS adoption to ensure interoperability, data security, and consistency across firms. This will promote resilient, responsive, and environmentally conscious manufacturing operations.

Further, both policymakers and practitioners should focus on scaling up the Internet of Things infrastructure to strengthen environmental monitoring and reporting mechanisms. Government institutions such as the Communications Authority of Kenya and ICT ministries should facilitate affordable and reliable digital connectivity to support IoT deployment in manufacturing zones. Firms, on their part, should integrate IoT sensors to track energy consumption, emissions, and material usage in real time. Training programs should also be developed to equip engineers and managers with the technical skills required to interpret IoT data for sustainability-focused decision-making. This collaborative approach will ensure that IoT becomes a cornerstone for sustainable industrial management.

Finally, the study recommends that both policymakers and manufacturing firms institutionalize big data analytics as part of their sustainability strategies. The government should promote data infrastructure development and enact policies that facilitate data sharing and analysis while protecting confidentiality. Manufacturing firms should invest in analytical tools and skilled data professionals capable of transforming large datasets into actionable environmental insights. The adoption of predictive analytics will enable firms to anticipate environmental risks, improve regulatory compliance, and optimize resource utilization. Collectively, these initiatives will enhance evidence-based policy formulation and strengthen the manufacturing sector's contribution to Kenya's green economy transition.

## 5.5 Research Areas for Further Studies

Future research should explore the long-term sustainability outcomes of Industry 4.0 adoption across diverse sectors beyond manufacturing, such as agriculture, healthcare, and construction. While this study focused on manufacturing firms, the transformative potential of digital technologies extends to other industries that face distinct environmental and operational challenges. Longitudinal studies could be conducted to assess how continuous investment in smart technologies influences sustainability performance over time. Such research would provide deeper insights into the durability and scalability of Industry 4.0 solutions in achieving environmental and economic balance.

Further studies could also investigate the human and organizational dimensions of Industry 4.0 adoption, including leadership, organizational culture, and employee readiness for technological transformation. Understanding the behavioral and managerial factors that enable or hinder successful implementation of digital technologies is crucial for ensuring sustainability outcomes. Mixed-method research approaches incorporating both quantitative and qualitative data would be particularly valuable in capturing the experiences and perceptions of employees, managers, and policymakers regarding technology-driven sustainability practices.

Another potential area of research involves examining the role of government policy, institutional support, and regulatory frameworks in shaping the diffusion and effectiveness of Industry 4.0 technologies. Comparative studies across countries or regions could shed light on how varying policy environments, infrastructure quality, and governance systems influence the relationship between technology adoption and sustainability. Such studies would help identify best practices and policy interventions that foster sustainable industrial innovation in developing economies like Kenya.

Finally, researchers could explore emerging technologies and hybrid models within the broader Industry 5.0 paradigm, which emphasizes human–machine collaboration, resilience, and circular economy principles. Future studies could analyze how combining artificial intelligence, blockchain, robotics, and renewable energy systems can further enhance sustainability performance. This would expand the knowledge base beyond the current Industry 4.0 focus and provide valuable insights into the next generation of industrial transformation aimed at achieving sustainable, inclusive, and human-centered growth.

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# APPENDICES

## Appendix I: Introduction Letter

May 2025

Dennis Njaramba

Masters Student

KCA University

**RE: REQUEST FOR RESEARCH DATA**

I am undertaking a degree in Master of Business Administration at KCA University, and I am expected to submit a research paper on **“effect of Industry 4.0 on the environmental sustainability of manufacturing firms in Nairobi, Kenya”** as part of my course work**.**
To accomplish this, your company has been chosen to collect the data needed for this research. Your name will not be included in the research, and this info will be used solely for academic purposes. The research conclusions will be made availed on demand.

Kind regards.

**Dennis Njaramba**

**Masters Student – Researcher**

**KCA University**

**Appendix II: Research Questionnaire**

This questionnaire has been developed to collect information on the effect of Industry 4.0 on the environmental sustainability of manufacturing firms in Nairobi, Kenya. Kindly take the time to carefully read the questions and provide the best insight you can. The information acquired will be used solely for scholarly purposes.

**Instructions**

Pick only a response (box) for every question.

**PART A: BACKGROUND INFORMATION**

1. Kindly indicate your gender

   a) Male ( )

   b) Female ( )

2. Please indicate your age

   (a) Below 30 years ( )

   (b) Between 31-40 years ( )

   (c) Between 41-50 years ( )

   (d) Above 50 years ( )

3. How long have you been in your current position?

   a) Less than 1 year ( )

   b) Between 2-3 years ( )

   c) Between 4-5 years ( )

   (d) More than 5 years ( ).

4. Please indicate the highest level of education

(a) Diploma ( )

(b) Undergraduate Degree ( )

(c) Master's Degree ( )

(d) PhD ( )

**PART B: INDUSTRY 4.0**

This part has four sections: smart manufacturing, cyber-physical systems, Internet of Things, and big data analytics.

**Smart Manufacturing**

To what magnitude do you concur with the following assertions? Rate in a scale of 1 to 5 (1 Strongly disagree, 2 Disagree, 3 Neutral, 4 Agree, 5 Strongly Agree)

| **Statement** | **1** | **2** | **3** | **4** | **5** |
|---|---|---|---|---|---|
| Our firm uses automated machines to streamline production processes. | | | | | |
| Real-time production data is used to make operational decisions. | | | | | |
| We have integrated digital systems to monitor production efficiency. | | | | | |
| Our manufacturing processes are highly adaptive to customer specifications. | | | | | |
| Smart technologies have reduced resource wastage in our operations. | | | | | |
| We regularly invest in upgrading manufacturing technologies for better performance. | | | | | |

**Cyber Security Systems**

To what magnitude do you concur with the following assertions? Rate in a scale of 1 to 5 (1 Strongly disagree, 2 Disagree, 3 Neutral, 4 Agree, 5 Strongly Agree)

| **Statement** | **1** | **2** | **3** | **4** | **5** |
|---|---|---|---|---|---|
| Our machines are connected to digital systems that enable remote control. | | | | | |
| Cyber-physical technologies are used to monitor real-time environmental indicators. | | | | | |
| We use embedded systems to automatically detect equipment faults. | | | | | |
| CPS integration has helped us reduce energy and material losses. | | | | | |

| | | | | | |
|---|---|---|---|---|---|
| Our production systems adjust automatically based on sensor feedback. | | | | | |
| The interaction between our physical equipment and digital platforms is seamless. | | | | | |

**Internet of Things**

To what magnitude do you concur with the following assertions? Rate in a scale of 1 to 5

(1 Strongly disagree, 2 Disagree, 3 Neutral, 4 Agree, 5 Strongly Agree)

| **Statement** | **1** | **2** | **3** | **4** | **5** |
|---|---|---|---|---|---|
| We use IoT devices to monitor equipment performance in real time. | | | | | |
| IoT technology has improved our ability to track environmental emissions. | | | | | |
| Sensors are used in our processes to reduce energy and material waste. | | | | | |
| IoT alerts help prevent breakdowns and reduce production downtime. | | | | | |
| We collect and analyze data from IoT devices for environmental decision-making. | | | | | |
| IoT integration has increased visibility across our production operations. | | | | | |

**Big Data Analytics**

To what magnitude do you concur with the following assertions? Rate in a scale of 1 to 5

(1 Strongly disagree, 2 Disagree, 3 Neutral, 4 Agree, 5 Strongly Agree)

| **Statement** | **1** | **2** | **3** | **4** | **5** |
|---|---|---|---|---|---|
| Our firm uses big data analytics to assess environmental performance. | | | | | |

| | | | | | |
|---|---|---|---|---|---|
| Real-time data dashboards guide decisions on resource optimization. | | | | | |
| We analyze production data to identify areas of environmental inefficiency. | | | | | |
| Smart Manufacturing help us plan for sustainable resource usage. | | | | | |
| Big data tools have improved our compliance with environmental standards. | | | | | |
| Environmental data is integrated into our decision-making processes through analytics. | | | | | |

**PART C: ENVIRONMENTAL SUSTAINABILITY**

To what magnitude do you concur with the following assertions? Rate in a scale of 1 to 5 (1 Strongly disagree, 2 Disagree, 3 Neutral, 4 Agree, 5 Strongly Agree)

| **Component** | **1** | **2** | **3** | **4** | **5** |
|---|---|---|---|---|---|
| We have significantly improved our energy efficiency in recent years. | | | | | |
| Our firm has implemented effective waste reduction measures. | | | | | |
| We actively monitor and reduce greenhouse gas emissions. | | | | | |
| Our production processes are designed with sustainability in mind. | | | | | |
| We train staff on environmentally sustainable practices. | | | | | |
| Environmental performance is a key metric in our operations. | | | | | |

**THANK YOU**

## Appendix III: University Introduction Letter

Thika Road, Ruaraka
P.O. Box 56808-00200 Nairobi Kenya
Pilot Line: +254 20 8070408/9

Tel: +254 20 3537842
Fax: +254 20 8561077
Mobile: +254 734 888022, 710 888022
Email: kca@kca.ac.ke
Website: www.kca.ac.ke

**BOARD OF POSTGRADUATE STUDIES**

*KCAU/BPS/2025* *Date: Wednesday, September 03, 2025*

**NATIONAL COMMISSION FOR SCIENCE, TECHNOLOGY & INNOVATION (NACOSTI)**
**P.O BOX 30623-00100**
**NAIROBI**

Dear Sir/Madam,

**RE: DENNIS NJARAMBA- REG NO. 24/00216**

It is my distinct pleasure to introduce Dennis Njaramba, a student at our institution pursuing a Master of Business Administration – Corporate Management degree in the School of Business.

Dennis is conducting research on the topic ***"Industry 4.0 and environmental sustainability of manufacturing firms in Nairobi, Kenya."*** His study has been reviewed and approved by the University's Ethics Review Committee, Approval No. KCAUSERC/SOB0206. The Approval period is from 21st July 2025 – 21st July 2026.

Any assistance accorded to him is highly appreciated.

Yours faithfully,

**DR. JACKSON NDOLO**
**DIRECTOR, BOARD OF POST GRADUATE STUDIES**

## Appendix IV: KCA Ethical Approval

KCA UNIVERSITY

**Thika Road, Ruaraka**
P.O. Box 56808-00200 Nairobi Kenya
**Pilot Line:** +254 20 8070408/9

**Tel:** +254 20 3537842
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**Mobile:** +254 734 888022, 710 888022
**Email:** kca@kca.ac.ke
**Website:** www.kca.ac.ke

**KCA UNIVERSITY SCIENTIFIC & ETHICS REVIEW COMMITTEE**

REF: **KCAU/SERC/ SOB0206** **Date: 21ST JULY 2025**

TO: **DENNIS NJARAMBA (24/00216)**

Dear Sir/Madam,

**RE: INDUSTRY 4.0 AND ENVIRONMENTAL SUSTAINABILITY OF MANUFACTURING FIRMS IN NAIROBI, KENYA**

This is to inform you that KCA University Scientific Ethics Review Committee (KCAUSERC) has reviewed and approved your above research proposal. Your application approval number is ***KCAUSERC/*SOB0206.** The approval period is ***21st July 2025 – 21st July, 2026.***
This approval is subject to compliance with the following requirements;

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

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

Yours sincerely

Dr. Caroline Ntara
**Chairperson**
**KCA University Scientific & Ethics Review Committee**

## Appendix V: NACOSTI Permit

REPUBLIC OF KENYA

NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Ref No: **775176**

Date of Issue: **30/September/2025**

**RESEARCH LICENSE**

**This is to Certify that Mr.. Dennis Mbae Njaramba of KCA University, has been licensed to conduct research as per the provision of the Science, Technology and Innovation Act, 2013 (Rev.2014) in Nairobi on the topic: INDUSTRY 4.0 AND ENVIRONMENTAL SUSTAINABILITY OF MANUFACTURING FIRMS IN NAIROBI, KENYA for the period ending : 30/September/2026.**

License No: **NACOSTI/P/25/4180191**

**775176**

Applicant Identification Number

Ag. Director General
NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Verification QR Code

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**See overleaf for conditions**