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THE LINK BETWEEN SUSTAINABLE DEVELOPMENT AND AI INTEGRATION IN INTERNATIONAL COMPANY

Master's thesis

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

INTRODUCTION

Relevance of the topic: Artificial Intelligence is a key component of efficiency and resource optimization, and it fits in well with the fundamentals of sustainable development, which place an emphasis on responsible resource use. Artificial Intelligence reduces its impact on the environment by optimizing supply chains and consuming less energy through applications like predictive analytics. This puts multinational corporations at the forefront of ethical business practices and also contributes to environmental sustainability. AI additionally supports innovation in sustainability, giving businesses the chance to develop green products and tackle global issues. The way in which it promotes inclusivity and social impact is demonstrated by the creation of solutions addressing social issues in multinational corporations. AI integration is useful for a variety of tasks, including streamlining logistics, guaranteeing ethical sourcing in long-term, sustainable global supply chains, and promoting corporate social responsibility through moral behaviour and openness. It helps with long-term business viability as well as regulatory compliance and risk mitigation regarding social and environmental issues. AI's ability to facilitate global collaboration empowers businesses to share data and insights, thereby meeting the increasing expectations of investors and consumers for sustainability. This helps companies to significantly contribute to wider sustainable development goals.

Level of problem investigation: In examining the link between Sustainable Development and AI integration in international companies, a comprehensive investigation into associated challenges is crucial. Gupta, Sahi, and Cheng (2020) emphasize the need for a thorough analysis in their work, "Sustainable Business and Industry 4.0: Enhancing Competitive Advantage with Sustainable Practices." This underscores the importance of exploring the complexities which tend to arise whenever the integration of AI technologies within the framework of sustainable development is taking place.

A critical focus within this investigation lies on the ethical considerations surrounding AI integration. Mittelstadt et al. (2016) contribute to this discourse in "The ethics of algorithms: Mapping the debate," shedding light on ethical concerns and emphasizing their significance in the development and deployment of AI technologies. Further dimensions of investigation include the environmental impact of AI, as highlighted in Brooks' (2017) work, "Artificial Intelligence: The Revolution Hasn't Happened Yet," which points to the potential positive environmental contributions of AI. The exploration extends to understanding social implications and inclusivity, as demonstrated in Turilli and Floridi's (2009) research on "The ethics of information transparency," providing insights into ethical considerations related to transparency—an essential aspect of social inclusivity. Lastly, the investigation into the long-term viability and innovation aspects draws from the "Strategic

Management of Sustainable Innovation" (Horbach, Rammer, & Rennings, 2012), offering a strategic framework for understanding how AI can contribute to sustainable business practices. Together, these works form a foundation for researchers aiming to unravel the multifaceted challenges, opportunities, and ethical considerations entwined with the integration of AI and sustainable development in international companies.

Scientific problem is to identify the key indicators of AI integration which have an impact on sustainable development in an international company.

The object of the thesis is the link between Sustainable Development and AI integration in international company.

Aim of the thesis is to examine the link between Sustainable Development and AI integration in international company.

Objectives of the thesis:

1. In theoretical level find the link between sustainable development & AI integration in companies.
2. To evaluate the empirical level of research of AI integration on sustainable development in international company.
3. After analysing theoretical and empirical level of investigation, to design a research model of impact of AI on the sustainable development of international company.

This study utilized the quantitative research methods to explore the study objectives. The dataset for the study was collected using questionnaires in the form of an online survey. The theoretical significance of this study was mainly that key concepts of artificial intelligence and sustainable development were revealed theoretically. The practical significance of thesis mainly lied in the empirical unveiling of the relationship between artificial intelligence and sustainable development.

Structure and scope of work. This study comprises of the introduction part which briefly details the overview of the entire study, followed by a chapter on the theoretical aspects of the link between sustainable development and AI integration in international company, a chapter on the empirical research level of AI integration on sustainable development in an international company, and another on the empirical research level of AI integration on sustainable development in an international company.

Scientific significance. The study addressed the problem of identifying AI integration indicators that impact sustainable development scientifically. Upon identifying the problem,

background research was conducted, hypotheses were formulated, data collected, and analyzed before the conclusions were drawn.

Practical significance

Practically, the study has offered data-driven insights from this quantitative research that will assist international companies understand how AI integration impacts sustainability. The findings also encourage international companies to adopt AI in ways that facilitate ethics, inclusivity and transparency. These findings can also inform policymakers in creating informed policies on sustainable AI strategies in international business contexts.

This Master's thesis consists of an introduction, 3 parts and conclusions. The main aspects of the study are described in 50 pages, including 8 figures, and 13 tables. The study utilised a total of 87 sources of literature.

1. THEORETICAL ASPECTS OF THE LINK BETWEEN SUSTAINABLE DEVELOPMENT AND AI INTEGRATION IN INTERNATIONAL COMPANY

In this chapter, the intersection of sustainable development and artificial intelligence (AI) integration within international companies represents a dynamic and transformative domain. With data-driven decision-making and automation, AI technologies help businesses maximize resource utilization, cut waste, and lessen their impact on the environment. AI also makes creative solutions in supply chain optimization, energy management, and sustainable product design possible. This ensures economic growth, efficiency and competitiveness in the global market as well as meeting world sustainability goals.

1.1. The concept of sustainable development

Development: Development is the process of positive growth, improvement, or advancement in different aspects of life, society, or economies over time. Seers (1972) asserted that "development means the conditions for realisation of the human personality. Its evaluation must therefore take into account three linked criteria: where there has been a reduction in (1) poverty, (2) unemployment, (3) inequality".

Matwantya (1991) posited that any development requirements of a starving population cannot be similar to a population that has adequate nutrition. According to Allen, T., & amp; Thomas, A. (2021), development is defined by development management as "An improvement qualitative, quantitative or both - in the use of available resources". He also argued that development does not mean to do with one view on how to improve the social, political and economic conditions. Instead, it is a generic term for a range of processes used for achieving socioeconomic/environmental change from one state to another. Therefore, it can be stated that development is the constantly constructive evolution of many aspects of life, society, and economies over time that creates the conditions necessary for the achievement of human potential, with the reduction of poverty, unemployment, and inequality serving as an essential criterion.

Sustainable development is as defined by the Brundtland commission in 1987, pp 43 as development that occurs in a manner that fulfils the requirements of the present without hindering the possibilities of the future generations fulfilling their requirements.

It encompasses two main ideas:

1. The idea of 'needs', especially that of the basic needs of the poor in the world, to which more attention should be paid.

2. The concept that the environment's capacity to support current and future needs is restricted by existing technological capabilities and the structure of society.

Sustainable development refers to a process of social and economic change (termed as 'development') which would ensure equal or even higher level of benefits from use of resources in

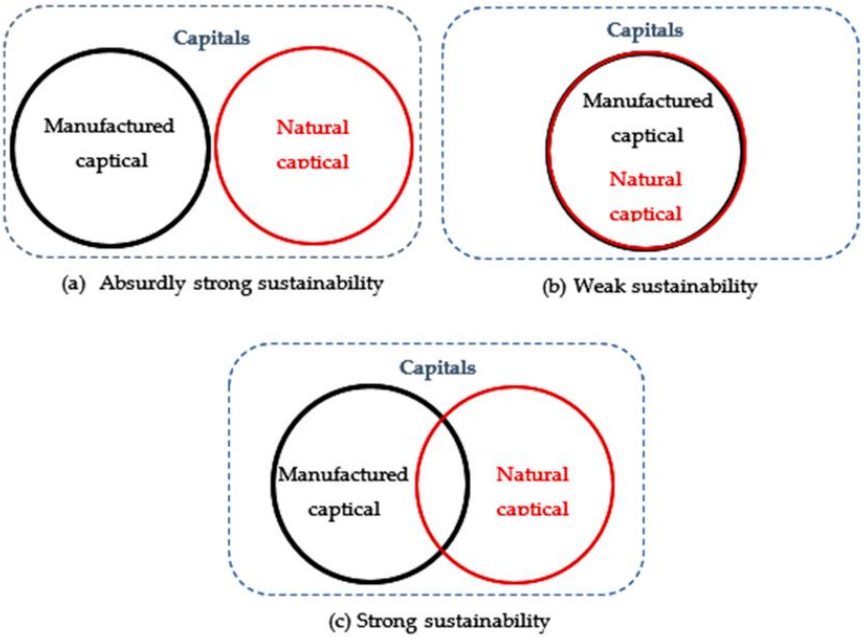
the present, in order not to undermine the potentiality of making similar or even greater benefits in the future. Sustainable development aims at reasonable (however this should be defined) and sustainable level of economic welfare that can be shared equally and sustained for generations of people in the future." (Goodland, R. and Ledec, G., 1987, p.36).

Sustainable development therefore is the use of resources naturally occurring ones in a method that will not in any way reduce their benefit to other generations in future. It also brings into equation the prudential use of non-renewable mineral resources so as not to run out of them in the future. In addition, exhaustible energy resources should be depleted slowly because it gives society enough time to phase out and adopt renewable energy sources. This given approach attempts to meet the current needs for resources while aiming to preserve the resources for the future to meet the needs of different generations (Goodland & Ledec, 1987, p. 37).

According to Markandya and Pearce (1988a), the core concept of sustainable development, particularly regarding renewable natural resources and the environment, is straightforward: the amount, quality and manner of using the inputs to the development process must persist over time. When the same concept is used for resources, sustainability is supposed to mean that specificity of a stock of resources – trees, soil, water etc, should not decrease. (pp9-10). Thus, Sustainable development is a strategy aimed at fulfilling current demands and at the same time being able to fulfill those of the coming generation. It requires a balanced integration of economic growth, social well-being, and environmental protection to achieve long-term, fair progress.

Types of Sustainable Development

According to Deng, B.2007 and Ekins, P et al. 2008 the globally acknowledge categories of capital include natural capital, manufactured capital, human capital, and social capital. It is therefore the accumulating and interplay of the four types of capital in human society over a specific period in order to achieve SD. Realizing the linkages between the four forms of capital determine the approach, analysis, and/or evaluation of sustainability (Wu, J. et al. 2014). As of right now, the mutual substitution of manufactured and natural capital is understood in three ways (Figure 1).



(Shi et al., 2019)

FIGURE 1: SCHEMATIC DIAGRAM OF DIFFERENT TYPES OF SUSTAINABILITY (NOTE: THE OVERLAPPING PARTS OF THE TWO CIRCLES REPRESENT CAPITAL THAT CAN BE REPLACED BY EACH OTHER).

Weak Sustainability: In weak sustainable development, it is assumed that natural capital can be replaced or substituted by manufactured capital. When the value of both types of capital does not decline, then development is deemed sustainable. Weak sustainability originates from the principles of neoclassical economic theory with regard to the argument that all human-made capital can balance the loss of natural capital (Deng, 2007). As stipulated by Williams et al. (2004), total capital is very crucial instead of focusing on the part capital. Wilson et al. (2017) affirms that this can justify environmental degradation in the event that economic output is experienced. Although implemented as policy in scientific contexts and extensively used for, for instance, green GDP, it misrepresents ecosystem capacity. Some critics have noted that it has an anthropocentric outlook and risks ignoring the irreversible harm to nature. However, it continues to be influential in policymaking owing to its compatibility with frameworks of economic growth development and implementation.

Strong Sustainability: Asserts that natural capital stock is precious and essential in meeting human needs. Manufactured capital fails to substitute this form of capital and must be maintained to ensure the non-violation of ecological boundaries. Strong sustainability theory is based in steady-state economic theory and postulates that natural capital forms the basis of all production and life-support processes (Molotch et al., 1998). In contrast with weak sustainability, it focuses on the preservation of ecosystems and the non-exceeding of the limits of the planet's carrying capacity (Liobikiene et al.,

2019). Sustainable development should maintain the structure of capital but not the overstepping certain environmental limits. It enhances ecological knowledge and economic rationality to implement the policies needed for maintaining ecosystem stability. While being more challenging to implement in real life, strong sustainability is gradually gaining popularity due to climate change and loss of biodiversity. Its normative motivation is based on assertiveness regarding responsibility for future generations and the biosphere.

Absurdly Strong Sustainability: It ceases not just the substitutability of natural with manufactured capital, but even the usage of ecosystems in totality. This is an extreme form of ecocentric idea which views development as something unworthy and needing to be stopped forcefully. Absurdly sustainable comes from radical ecology; this is the idea of not interfering with the setup nature provides (Wu, 2013). According to Daly (1995), it has its basis on equating humans and other species to each other recommending that development stop to reinforce balance. This perspective contradicts the anthropocentric approaches and considers any changes to an ecosystem as inequitable. However, it's useless in a world that requires socio-economic development to improve the lives of the citizens. While well-connected in academic discussions, this framework is scarcely institutionalized. It has been useful in overemphasizing the role of human beings as active agents on this planet while at the same time providing an unsustainable model for tackling current development problems in a holistic manner.

Goals of Sustainable Development

Sustainable development (SD) has been changing in a gradual and progressive manner due to the increasing challenges experienced by people in society. Jabareen (2004) affirmed that different periods have developed different development issues, so it has become imperative that sustainable development practice and goals are continually evolved. Beginning from the protection of natural resource to the call for eradication of poverty globally through the MDG and then to the inclusive structure of SDG, from resource-conserving to resource-revolting, SD shows the patterns of enlarging inclusiveness and integrating the economic, the social, and the environmental aspects.

Single-Factor Development Goals: Sustainable development as a concept and practice has its origins from the ideas of environmental carrying capacity and resource constraints. In the historical phase when agricultural societies prevailed, ancient scholars realized that the uncontrolled use of resources, including trees, fish, and wild animals, could become fatal to human beings due to resource depletion (Zhou, 2009). For instance, Hans Carl von Carlowitz wrote Sylvicultura Oeconomica in 1713 and this work is noteworthy because Carlowitz was the first to provide a systematic approach

to the proper management of the forest (Von Carlowitz, 2008). This early work prepared the ground for subsequent discourses on wise use of resources.

The official beginning of the modern age of sustainable development is attributed with the publication of the World Conservation Strategy (WCS) by the International Union for the Conservation of Nature and Natural Resources (IUCN) in 1980. This document presented the notion of sustainable development as a strategy for managing the exploitation of living resources. Subsequent years, several global initiatives, including the Brundtland commission's Our Common Future in 1987, the world conference on sustainable development also referred as the Earth summit in 1992 or the agenda 21 established environmental sustainability as a global developmental goal. Over the years, the International Monetary Fund (IMF) and the World Bank initiated the sustainability as a strategy that frames economic growth (The World Bank Group, 2008).

During this period, another technique was developed to measure environmental sustainability as well, like System of Integrated Environmental and Economic Accounting (SEEA) and Ecological Footprint (EF). The Millennium Ecosystem Assessment (2001–2005) also assessed other impacts of ecosystems on well-being (Lele, 1991). However, the main focus of this stage was the environmental management and protection of the environment coupled with the sustainability of natural resources.

Millennium Development Goals (MDGs): Sustainable development in the entering the twenty first century has taken another dimension with its changing from single environmental face to social and economic level. The Millennium Development Goals (MDGs) were formulated in 2000 by the United Nations as eight objectives meant for the eradication of extreme poverty minimum hunger, proper education for all, equality between male and female, optimum health, and sustainable environment. These goals were a focused attempt to impact the developing world and enhance the living standards of as many people as possible.

Combating poverty, improving access to education, gender equality, child health, adult stocks and global partnership as the goals of the MDGs were met in between the years 2000 and 2015. By UN accounts, extreme poor reduced by half; from 1.9 billion people living on just less than a dollar per day to 836 million people. The level enrolment in primary schools rose from 83 percent to 91 percent and the under-fives' mortality rate came down from 9 percent to 4.3 percent. Another interesting development that marked the growth of access to drinking water was that it rose from 76 percent to 91 percent in the entire world (The Millennium Development Goals Report, 2015).

However, the improvements brought about by the MDG still had some restrictions in the implementation process and results. Firstly, wars and other forms of violence remained a major concern for human development throughout this year. Secondly, the overall progress towards the accomplishment of personal objectives looked somewhat unbalanced. On the other hand, the goals regarding completion of primary schooling for children, agenda items mainly regarding women

education, maternal deaths and HIV/AIDS had not seen much progress. For instance, education goals, specifically gender parity, were only met by two thirds of developing countries and such health-related goals like, reductions in maternal and child mortality as well as ceasing the spread of epidemic diseases were also still unachieved (Henry et al., 2014; Gusmao Caiado et al., 2018).

However, the achievement of the MDGs also varied enormously across the regions. East Asia and South America were better than the sub-Saharan Africa whose progress continued to lag behind. Social inequalities between the people in the rural sectors and those who stayed in urban areas, and between the less privileged individuals and the affluent were still apparent. In addition, several donor countries also failed to honour their pledges toward aid contributions which reduced the notion of partnership inherent to the MDG framework.

However, the concepts of sustainable development were not adequately embraced in the MDGs formulation and implementation. Their aim was mainly focused on eradicating poverty in the developing world but they paid little emphasis on environmental issues and structural changes required for sustainable development. These gaps revealed the importance of broader, comprehensive, and practical vision for the future development framework for the generation of post-MDGs.

Sustainable Development Goals (SDGs): After recognizing the shortcomings of the MDGs, the UN came up with the Sustainable Development Goals or the SDGs in 2015. The SDGs are set out in 17 goals and 169 targets encompassing economic, social, and environmental aspects. The SDGs, which were arrived at through six pillars, namely dignity, people, planet, prosperity, justice, and partnership, seek to change the world by 2030 (Rudra et al., 2018).

However, the main difference between MDGs and SDGs is that SDGs are global in nature. In contrast to MDGs that were designed mainly to address the developing countries, SDGs are expected to be for all the global countries, developed, developing as well as transitional ones (Zhang et al., 2019). This idea indicates that sustainable development issues are not limited to a particular region or groups with lesser incomes. In terms of scope, SDGs are even better expanded. For example, MDGs had one global measurement of ensuring environmental sustainability, but the SDGs have more detailed targets, for example, action against climate change (13), the sustainable use and conservation of oceans (14), and terrestrial ecosystems (15) (Leal Filho et al., 2018). This makes it easier to identify, measure, and achieve goals and objectives due to their specificity.

The SDGs also increase the level of aspiration. While MDGs sought to “cut” poverty by half, the SDGs want to “eradicate” poverty both extreme and sustained distressed poverty. Likewise, in education the concept of SDGs is not strictly limited to the number of people going to school but the kind of education they are receiving and their ability to continue learning throughout their lives (Goal 4). Another important shift is the focus on shared responsibility and partnership approaches. While

MDGs were set up as a vertical process where the developed world was expected to assist the developing one, SDGs call for enhanced cooperation by all parties. Goal 17 focuses on means of implementation, including finance, technology, capacity-building, trade, and system-related elements.

On the other hand, SDGs reflect on the relevance of data in the assessment of progress being made. Goal 17 also brings the idea of a 'data revolution' to underdeveloped countries to achieve the aim of strengthening their capacity to collect data of high quality and high frequency. This shift to focus on data has not featured strongly in the MDG and is a positive development towards evidence-based policy making.

Last of all, the SDGs are based on a new philosophy of development. The SDGs, on the other hand, foster an outlook to development where people can live with dignity, equity, and in a sustainable environment. Thus, according to Stafford-Smith et al. (2017), the SDGs recognise that continued economic growth cannot harm the environment and long-term human welfare depends on sustainable growth and conservation.

Thus, the evolution of sustainable development goals reflects stages of the global thinking on human progress. Starting from a specific set of environmental issues, pass through poverty, health in developing countries and concerns, to general and all-encompassing, as well as progressive approach, SD addresses the complexity of global issues. Despite the fact that the SDGs are still in the process of being implemented, their scope and inclusiveness turn them into a valuable framework to direct the future development on a more equitable, sustainable, and resilient basis.

1.2. Artificial Intelligence definition and types

Artificial Intelligence (AI) is the imitation of the human intellect by computer systems. While biological intelligence could be attributed to humans and animals, AI can be defined as the capability of a computing device to accomplish tasks that are normally performed by human intelligence. The concept and study of AI is cantered on the creation of smart apparatus that is able to perform such tasks independently. The term AI was first used in 1955 by John McCarthy, who described it as the science and engineering of designing machines that work and react like humans. It laid the groundwork for the creation of machines that could think and act like humans for several decades.

As stated by Copeland (2022), AI is the replication of skills associated with human minds in computers or computerized robots that are capable of learning and making decisions. This definition focuses on AI as a simulation of the human mind's highest cognition functions that were previously thought to be unique to humans.

Elaine Rich defines AI as the process of studying how to solve problems just as human being does but in a way that computer can do it better at the current time. Her definition enlightens this

aspect because as the technology develops, the standard of intelligence rates in machines also changes.

Russel and Norvig (2020) defined artificial intelligence as the branch of computer sciences that is focused on the development of intelligent entities for human-like capabilities. They include reasoning, learning, problem-solving, perception as well as language understanding. It is widely used in academic and practical fields as a workable definition of AI.

According to Nilsson (1998), AI systems are built with objectives of analysing enormous amounts of info, identifying intricate patterns and functioning independently to make decisions. However, in addition to its conceptual meanings, it is also known for its applications. AI is revealed by Verganti et al. (2020) and Wamba et al. (2020) as one of the significant digital technologies that contributes to business innovation and change. Mustak et al. (2021) pointed that it allows organizations adapt to the customer's ever-shifting needs.

Types of AI

AI has emerged as a significant technical advancement that has affected society in different aspects and changed the course of industries. According to Tim Urban of "Wait But Why", AI is one of the most defining elements of technological progress, driving innovation in so many industries.

Artificial Narrow Intelligence (ANI) is the most commonly found type of intelligence today. It is stable and serves designated functions within a specific and limited capacity. It is good at doing one thing: playing chess or recognizing faces, and cannot do anything else. For instance, it enables technologies such as Google Search, email filtering systems as well as self-driving vehicles (Strelkova, 2017). ANI is also crucial in organizations from military, financial and manufacturing sectors and includes such mature systems like high-frequency algo-trading in equities (Strelkova, 2017).

According to Iliashenko et al. (2019), Artificial General Intelligence (AGI) is the subsequent level of AI evolution after the existing types. This means a type of AI that can surpass human intelligence in terms of capability or performance in a given set of tasks. It can, for instance, analyze, design, problem solve, conceptualize, understand, and even learn in a limited way. Although AGI is yet to become real, this concept can open new horizons for industries and perform numerous intellectual tasks that are performed by people.

Artificial Super Intelligence (ASI), is the super intelligent system that would surpass the human intelligence found in science, creativity, and wisdom as well as in social aspects (Strelkova, 2017). ASI can not only transform various industrial segments but may also contribute to addressing global issues such as climate change or health care.

Applications of AI in Different Industries

AI is active in almost all the sectors, enhancing its performance and efficiency in the industry. In healthcare technology, there are already AI solutions such as virtual assistants or diagnostic equipment. They are also able to consult with massive data and provide health advice and even giving directions to a variety of emergencies (Holmes et al., 2019).

In education, AI is very important since applies on facilitating personalized learning. Intelligent tutoring systems allow for formative feedback to the learners and as such can enhance the learning to teaching process (Holmes et al., 2019). In the same manner, the adoption of AI in law has paved way for the feature where a law firm may use the AI system to search for cases that has similar grounds for litigation.

In the financial institutions industry, AI is evident by use of chat bots that provide core banking services to customers. In transport, advancements in Artificial Intelligence include self-driven automobiles like those offered by Tesla and Google. E-commerce giants like Amazon use AI to monitor consumer behaviour and provide recommendations based on purchasing trends. Last, in heavy industries, the robotic system by utilizing artificial intelligence is used in risky and tedious conditions to reduce risk associated with operations while increasing productivity.

Therefore, it can be stated that the objective of artificial intelligence is to create computers with intelligence that is at least as high as that of humans. The benefits of AI applications are becoming more widely recognized in many different fields. In the near future, artificial intelligence will undoubtedly permeate every industry due to the development of capable models employing AI techniques. There are many advantages for the computing industry from different AI approaches.

1.3. The link between Sustainable Development & Artificial Intelligence in International company

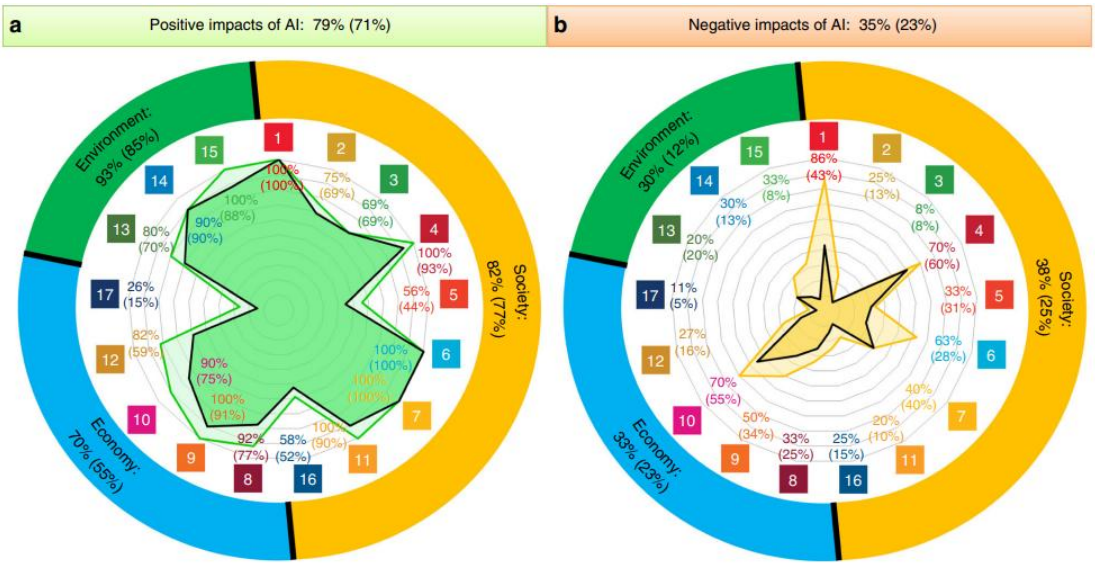
AI is now widely adopted in many industries across the world and is deemed as disruptive in almost every business and societal sectors. As stated in the National Artificial Intelligence Research and Development Strategic Plan (2016), AI has major economic and social implications. When the world entered into what Sachs (2015) has dubbed as the ‘Age of Sustainable Development,’ the best approach for global firms was the alignment of AI with the 17 United Nations Sustainable Development Goals (UN SDGs).

The field of Artificial Intelligence is already showing potential in mastering intellectual tasks related to data analysis, machine learning, and robotics. This change in intelligent automation was a two-edged sword in attaining sustainability. AI contributed to sustainability by improving the utilization of resources, minimizing waste, and enhancing process operations in fields like energy, manufacturing, and agricultural industries. Nevertheless, the advancement of AI solutions rapidly

progressed ahead of the growth of proper legal resolutions and structures that could address the ethical and societal concerns (Muñoz & Naqvi, 2018).

Harari (2017) further remarked that most of the regulatory structures are short-sighted in their strategic planning and thus could not predict the impacts of Artificial Intelligence in the long run. For Un, AI had a positive impact on 79% of the SDG goals by offering better access to technology, better data analysis, and efficient service delivery; on the other hand, it can have a negative impact and risks on 35% of the goal especially in job automation, privacy violation and environmental pollution (UN Economic and Social Council, 2019).

The SDGs were grouped into three thematic areas, the social, the economic and the environmental. In these categories, AI could influence in two ways. For example, in the economy, it increased efficiency but extended vulnerabilities in employment. In society, it created opportunities for education and health care but brought problems of surveillance. Environmentally, AI-supported conservation efforts yet contributed to energy consumption through data centres.



(Vinuesa et al., 2020)

FIGURE 2: SUMMARY OF POSITIVE AND NEGATIVE IMPACT OF AI ON THE VARIOUS SDGs

AI and societal outcomes: AI showed great promise in improving the status of SDGs in several areas of human activity and interaction. As noted by Fuso Nerini et al. (2019), approximately 82% of the group targets of the Society could be addressed through AI-based applications. In three of the goals including no poverty (SDG 1), quality education (SDG 4), clean water sanitation (SDG 6), affordable and clean energy (SDG 7), and sustainable cities (SDG 11), AI contributed by providing basic service delivery in the provision of food, health, water, and energy to the populations. AI also enabled the creation of smart and Low carbon city through innovations such as electric AVs smart

home appliances and elastic electricity grid. These technologies served purposes towards sustainability standards of energy use and incorporating solar and wind through smart grids. Nevertheless, 38 percent of the targets raised potential negative consequences of AI – be it higher levels of inequality or watchful surveillance – and discussing these risks is crucial in steering AI towards a constructively integrated benefit.

(Vinuesa et al., 2020)

FIGURE 3: DETAILED ASSESMENT OF THE IMPACT OF AI ON THE SDGs WITHIN THE SOCIETY GROUP

At the societal level, AI technologies offer significant potential for enhancing the human development agenda. According to Fuso Nerini et al., (2019), 82 out of 100 targets in the Society group possibly require AI solutions. AI contributes to the attainment of SDG 1 (no poverty), SDG 4 (quality education), SDG 6 (clean water and sanitation), SDG 7 (clean energy), and SDG 11 (sustainable cities) in that it improves service delivery in key essential service sectors like health, water, energy, and education. For instance, AI-enabled platforms can help identify the geographic location of poverty (SDG 1), customize learning materials (SDG 4), and facilitate efficient use of resources in cities (SDG 11). The use of AI in smart cities involves the utilization of renewable energy for electricity, electrical self-driving cars and smart devices, thereby making progress to achieving the sustainable development goals of 7, 11, and 13.

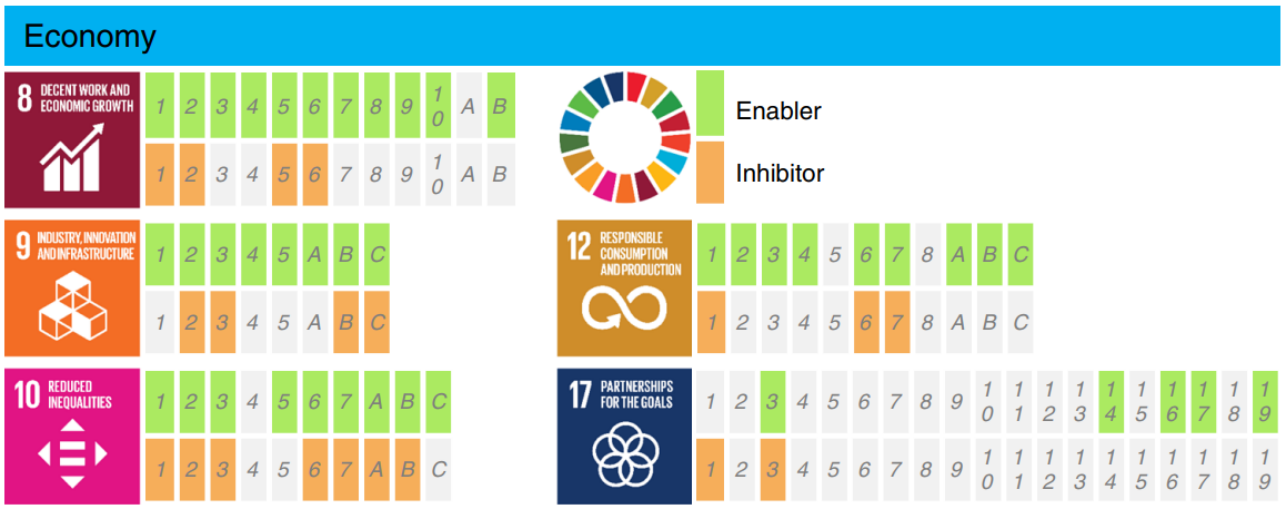
However, incorporate of AI is not always for the betterment of society. A critical evaluation acknowledged two-fold benefits of AI for society (Jones, 2018; Truby, 2018). The usage of computational resources has spiked due to the growth in demand of AI model training and large data storage and this has led to pollution of the environment. Cryptocurrencies electric consumption already equals that of some countries, which negatively impacts SDG 7 (Clean energy) and SDG 13

(Climate Change). According to the report, global ICT electricity consumption estimates for the year 2030 is said to range at 20%, from the current 1% (Ahmad et al., 2019).

Additionally, AI may exaggerate existing social disparities, particularly in developing states due to the availability of computing resources and digital literacy. Some advanced AI models may need massive amounts of resources which a low-income country cannot afford easily. It is also pertinent to acknowledge that AI systems could raise the skill demands for employment, thereby exacerbating inequalities and straining SDG 1.1 and SDG 4.3 (Nagano, 2018). The use of human knowledge in the creation of AI is offered as a partial solution to the two problems in a bid to lessen energy consumption.

AI & Economic outcomes: Several impacts of economies with regard to the implementation of AI have been reported and these fall under both the positive and negative consequences on the achievement of the SGDs. Of the targets in this group, AI applications have a fit for 70% and many of those are often related to the development goals such as, economic development (SDG 8), infrastructure and innovation (SDG 9) and inequality (SDG 10). As pointed out by Acemoglu and Restrepo (2018), AI can stimulate productivity growth and lead to economic growth. AI helps sectors to enhance resource utilisation and improve industrial productivity through data analysis automation, and enhancement.

However, some authors argue that AI also has the potential to deepen the gap in income between countries as well as within them. Cockburn et al. (2018) and Bissio (2018) have highlighted that AI technologies have the ability to widen the divide between the global north and the global south as the developed countries are poised to benefit more than the developing countries from the AI



(Vinuesa et al., 2020)

FIGURE 4: DETAILED ASSESSMENT OF THE IMPACT OF AI ON THE SDGs WITHIN THE ECONOMY GROUP

technologies. This means that the more advanced the AI tools and data resources the better technological market position is achieved, jeopardizing SDGs 8, 9, and 10 where these are developed in the more developed nations. At a national level, the continuation of AI advancements may benefit a selected few who have formal education and skills in handling digital tools. According to Brynjolfsson and McAfee, AI has ensured that individuals with higher education earn better wages while at the same time decreasing the wages of individuals with lesser education. The four shifts of income from workers wage to machines benefits the owners of the companies, increase concentration of wealth.

Dobbs et al. (2016) provide a great comparison between Detroit's "Big 3" auto makers in 1990 and Silicon Valley's "Big 3" technology giants in 2014. The tech firms generated similar revenues to the manufacturing firms yet they had about nine times a smaller number of employees and possessed far greater market capitalization. Such examples mirror the new era of capitalist economy supported by AI, which offers little employment yet high returns on capital. However, there is social impact as a result of applying wrong algorithms in a digital platform. Francescato (2018) points out that, due to the algorithm-driven mechanisms deployed by most Social Media platforms in filtering the content displayed to each user, social media can contribute to the reinforcement of polarising political divides and the reduction of social inclusion with implications on pathway 10 of SDG. The adverse effects of bias in the labour market in relation to the use of AI in posting job vacancies (Dalenberg, 2018) brings out the fact that bias exists in the training data for the machine learning algorithms and calls for ethical design and use of data for AI.

AI and environmental outcomes: The environmental group of SDGs including: SDG 13-Climate action, SDG 14- life below water and SDG 15-life on land has revealed high percentage figures regarding the possible optima ai technologies for the SDG targets with percentage of 93% found to be potentially benefiting from these technologies. Vinuesa et al. (2018) have pointed out that AI can be applied to modelling climate systems, estimate changes in the environment, and effectively use natural resources. AI also contributes to low-carbon energy transitions, energy efficiency, forecasting the output of renewable energy and enhancing the balance and efficiency of the electricity grid. All these applications well respond to the call of SDG 13.

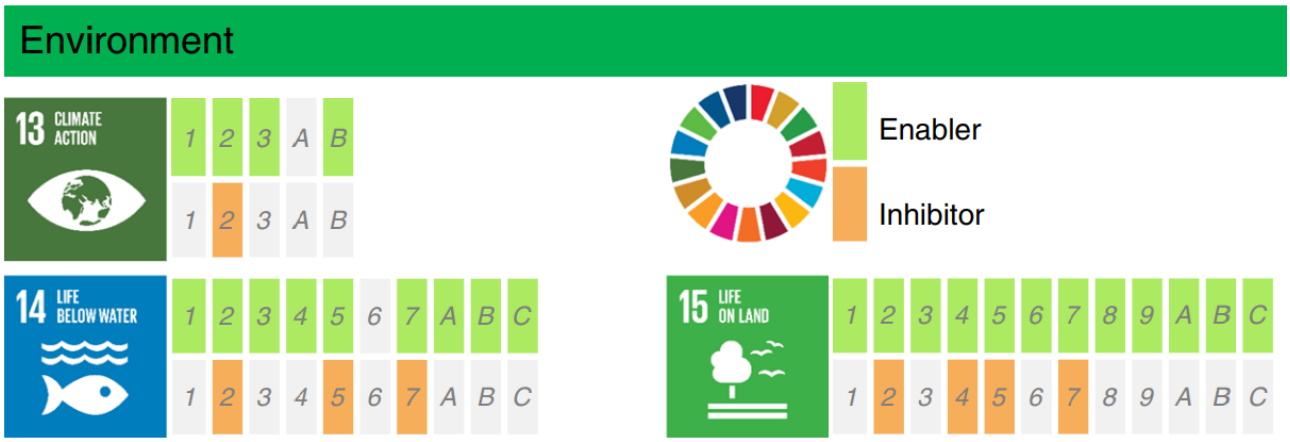


FIGURE 5: DETAILED ASSESSMENT OF THE IMPACT OF AI ON THE SDGs WITHIN THE ENVIRONMENT GROUP OF AI TECHNOLOGY

(Vinuesa et al., 2020)

AI also has a direct contribution to the maintenance of ecosystems. Keramitsoglou et al., 2006 have shown how AI methods assist in the identification of marine oil spills, in relation to SDG 14.1 dealing with marine pollution. Target 15.3, which is related to desertification and land degradation, can be supported by applying image classification and further analysing the trends through the help According to Mohamadi et al. (2016), there are massive prospects in applying neural network on vegetation mapping that can help in sustainable land-use management and plant regeneration.

However, there are some issues and drawbacks to its application such as energy requirement that affects the environmental sustainability. As mentioned earlier, training of AI models requires much energy and, unless the energy source used is renewable, the training of the AI models goes against climate goals. A related issue relates to the use of ecological data; there is a risk of their improper usage. As stated by Kwok (2019), the application of AI can improve the monitoring of biodiversity yet the availability of such information may also result in further allocation of resources in unsustainable manners especially when in the hands of commercial gain-oriented parties.

THEORETICAL MODEL:

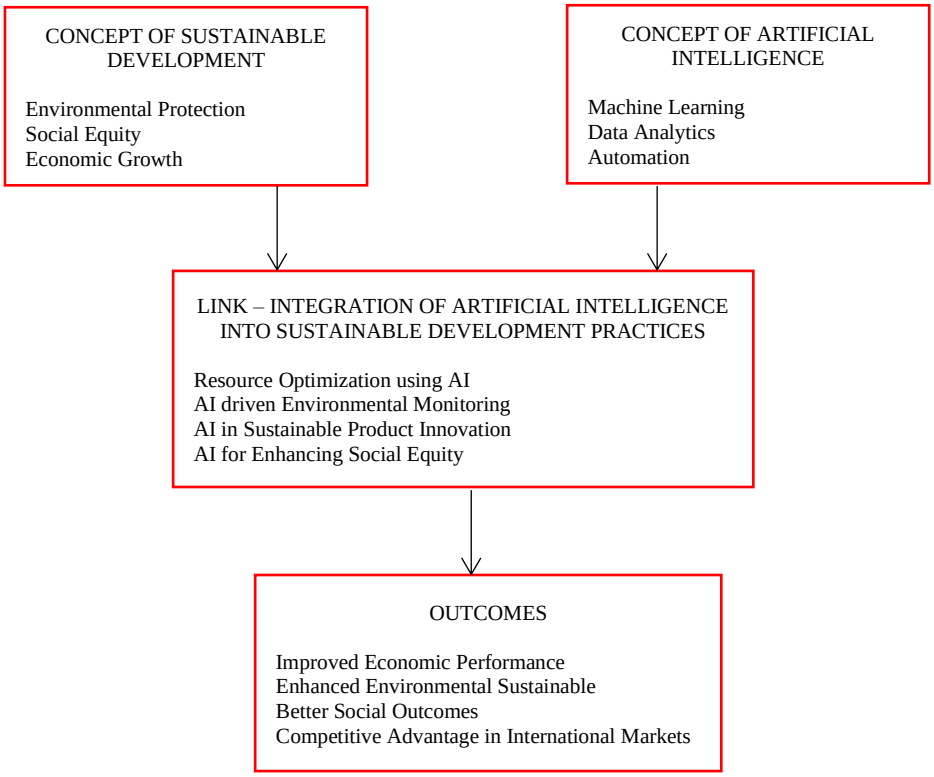


FIGURE 6: THEORETICAL MODEL BASED ON LITERATURE REVIEW

This theoretical review explores the complex dynamics of the link between artificial intelligence (AI) and sustainable development in the context of giant global multinational companies. It explores how through appropriate use; AI technologies can be leveraged to bring about positive adjustment to major social issues.

The research focuses on AI as an active participant in the advancement of the specified goal, including zero poverty, quality education, clean water and sanitation, affordable and clean energy, and sustainable cities and communities. The thesis also emphasizes that AI can play a role in improving the delivery of such critical services as food delivery, health, water, and energy to various people. It also emphasizes the need to promote the principles on the use and development of responsible AI applications, bearing in mind the cultural and economic dynamics in countries. Altogether, the reviews critically put on a demonstration of how AI can foster the achievement of sustainable development goals on the global level and state the necessity to avoid its negative impact and embrace its potential for making the world better.

2. EMPIRICAL RESEARCH LEVEL OF AI INTEGRATION ON SUSTAINABLE DEVELOPMENT IN AN INTERNATIONAL COMPANY

Through this chapter, different research undertaken by authors from various organizational backgrounds. Specifically, research pertaining to the relationship between AI integration and sustainable development will be evaluated.

2.1. Research on the links between Sustainable Development and AI integration in international companies

AI-Driven Innovations in Sustainable Supply Chain Management in International Companies. Panigrahi et al., (2023) expanded the unlimited sector of AI chatbot adoption by exclusively capturing the Small and Medium Enterprises (SMEs) sector. In their paper in the Sustainability journal, they used structural equation modeling to investigate the role of artificial intelligence technologies in improving supply chain transparency and innovation. Drawing participants from 246 subjects and employing Smart PLS-4.0 to analyze the results, the researchers identify diverse connections between the application of AI chatbots and sustainable supply chain performance. The study outcomes suggested that supply chain transparency and innovation potential are enhanced through the contextual use of AI chatbots in emerging markets. This research advances beyond a study by Pal (2023) which offers a narrower yet substantial view of technological integration in the context of SMEs, recognizing the context differences in AI implementation at the company scale.

Pawlicka and Bal (2022) research in the Management Journal offered a distinctive perspective by exploring AI's role in Omni-channel logistics within the clothing industry. In using the exploratory case study method, which includes document review, field observation, and informal interviews, the researchers were able to design an implementation model that would make the available supply chain finances sustainable. Based on studying their experience, they found out how to use AI to improve relations with suppliers, build competitive advantages, and use resources more effectively (Pawlicka & Bal, 2022). Therefore, the study's major contribution is to highlight the specific application of AI in industry to improve Sustainability and general innovations within the industry. The present viewpoint reinforces Pal (2023) other conclusions and gives more detailed, sector-oriented data.

In another study, Dash et al., (2019) critically investigated AI's application in supply chain automation, emphasizing the technology's potential to revolutionize business operations. Their article in the Journal of Strategic Innovation and Sustainability discovered that AI can deliver near-perfect demand forecasts, manage research and development, and improve manufacturing. The study stood

out by further differentiating AI as a technological enabler and a resource for competitive advantage. By examining how AI can reduce costs, increase revenue, and improve asset utilization, the researchers provided a comprehensive framework for understanding technological integration's strategic implications.

Pal's (2023) comprehensive study in the International Journal for Research in Applied Science and Engineering Technology pioneered an in-depth exploration of artificial intelligence's transformative potential in sustainable supply chain management. The study methodically examined how AI improves operational transparency in a study utilizing both qualitative and quantitative research. Pal (2023) categorized and explained the idea of resource optimization as well as carbon reduction through an analysis of predictive analytics, intelligent automation, and tracking machinery. The study's methodology involved systematic data collection and comparative analysis across multiple supply chain contexts, demonstrating AI's potential to address complex sustainability challenges. However, the study revealed the technological promise and challenges of implementing understanding embracing high costs, data privacy and lack of skills. This work is loyal to systematic review by Toorajipour et al., (2021) but it supplies more of an actual outlook on AI’s working mechanism in its practical application.

Mubarik and Khan (2024) research in "Digital Supply Chain and Sustainability Challenges" critically explores the intersection between digital supply chain management and Sustainability. The research provides a wide literature review on the opportunities and limitations of technological appropriation stressing how AI, IoT, and blockchain can increase supply chain visibility and performance. Through elaboration of environmental and socioeconomic concerns, the study raises awareness of the fact that technological advancement in the contemporary complex supply chain environments is a multifaceted phenomenon.

A scholarly article by Goswami et al., (2022) titled Analyzing Technological Opportunities and Implementation Concerns of AI-Enabled Supply Chain Management provides one view of the subject from a theoretical standpoint. The authors do an excellent job of systematically evaluating the use of AI in supply chain management in terms of its application to individual elements of the supply chain lifecycle ranging from demand planning to inventory management. Critically, the study develops a comprehensive framework addressing implementation barriers, including data quality, privacy concerns, and the necessity of domain-specific human expertise. Their approach balances technological potential with pragmatic considerations for responsible AI deployment.

Evaluating AI's Integration and Sustainability Outcomes in International Companies. Comprehensive work by Vaio et al., (2020) in the Journal of Business Research was a groundbreaking study in regards to AI involvement in building sustainability business models. Using bibliometric analysis of 73 papers from 1990 to 2019, the researchers used AI to decompose complex associations between AI, machine learning, and sustainability. The research method used in the study included following a rigorous scientific approach in the review of literature which critically looked at how AI might impact production and consumption consistent with the UN SDGs. Especially important, the concept of Knowledge Management Systems was the most highlighted area of interest in the study where the technological, cultural, and strategic aspects of technology were unveiled. Thus the study was consistent with Nishant et al., (2020) perception but as was previously stated provided a broader historical and institutionalist view.

The outlook of sustainability in AI was critically discussed by Nishant et al., (2020) in the International Journal of Information Management in 2020. They have also extended the literature review by which they assessed the difficulty and the potential to solve problems of the environment and society through artificial intelligence. The researchers, therefore, defined five key issues, which included temporal depletion of data, unpredictable human response, and risks in cybersecurity. Interestingly, the study included a research agenda for the future entailing multilevel synthesis, systems dynamics, and psychological factors. Unlike other research on technological advancement, this work offered a complex, critical, thorough examination of the impact of AI.

Dauvergne (2020) provocative analysis in the Review of International Political Economy offered a critical political and economic perspective that challenged prevailing narratives about AI's sustainability benefits. Using a critical theoretical perspective, the research contended that efficiency enhancements typically lead to a consumer rise instead of positive environmental change. In this context, Dauvergne exposes the hidden costs of integrated technologies and their effects on ecological subordination. It aligned with what Vaio and Nishant had said and brought to strong skepticism the optimism expressed in the technology literature, arguing for the need to go beyond techno-deterministic accounts of social life.

A paper by Goralski and Tan (2020) presented a complex approach to looking at AI and its effects on sustainable development in the International Journal of Management Education. In this paper, the authors investigated the many possible futures of artificial intelligence—from the one where humans and technology are working as one to the one where AI takes over the economy and destroys the environment—and based on multiple cases, provided their insights. Their search

concluded by highlighting management education as an essential function of preparing stewards to steward technological changes significantly.

Rane et al., (2024) research explores artificial intelligence and machine learning's revolutionary impact on logistics and supply chain management, demonstrating how advanced technologies can fundamentally reshape operational paradigms. When analyzing the strategies that are based on AI, the study reveals capabilities of predicting disruption advances, choosing better routes, as well as offering highly accurate demand forecasts. In describing the ways that AI can increase the depth of the supply chain the research also illustrates ways in which further innovations such as blockchain and machine learning can build sturdy traceability tools and help in the action of made well in advance decisions. The study emphasizes AI's transformative applications in autonomous delivery systems, inventory management, and supplier network optimization, offering a comprehensive view of technological innovation's sustainable development potential.

Empirical research level of links between Sustainable Development and AI integration. Kulkov et al., (2023) conducted literature review and aimed at presenting more profound insights about the use of artificial intelligence for sustainable development. The first research question was therefore concerned with identifying best practices through which organizations can adopt AI technologies to enhance Sustainability. Categorizing the results of 57 peer-reviewed articles employing a strict systematic approach to systematic literature analysis, the authors explain that the implementation of AI is multifaceted and occurs at the organizational, technical, and processing levels. The study's methodology distinguished itself through a structured two-stage literature search, enabling a nuanced examination of AI's potential in sustainable development. The findings highlighted three critical dimensions of AI integration: If organizational action plans are organizational, and technical algorithm design is technical, then internal information processing manipulations are intrinsically technical as well. The researchers have come up with tactical frameworks that can be used by organizations tasked with the responsibilities of adopting technologies, specifically enablers including; strategic alignment, infrastructure, and change management.

Srivastava and Maity's (2023) research in urban climate change adaptation represented a groundbreaking global investigation into AI and machine learning's potential for sustainable development. This research differed from prior studies that focused only on case studies of the particular continents; however, this paper also compared several case studies in six continents with the help of articles that were found using SR models with both six-step and five-step searches. The study's unique methodology allowed for a holistic understanding of AI's adaptability across diverse

geographical and environmental contexts. Amphibious and necessarily so, the researchers determined that knowledge of AI implementation for climate change adaptation is contextual. This was a direct contradiction of the general technological solution stressing that adaptation strategies should be closely linked to the opportunities and risks of regional localization. This study established that ideas and technology, sharing of knowledge, and collaboration between countries in putting into practice an integration of AI into climate change adaptation was very important.

Fan et al., (2023) conducted a comprehensive review of Sustainability, providing an extensive exploration of deep learning and artificial intelligence applications across sustainable development goals. The research meticulously mapped AI's potential contributions to 134 of 169 UN sustainable development targets, particularly renewable energy, environmental health, and smart building management. Their approach comprised of the following steps which included conducting a systematic review of the recent developments in the field of AI and Deep Learning. Concerning its applications, the work indicated noteworthy return prospects in areas such as renewable energy resource management, fault identification, and power system stability. However, the researchers also critically pointed to significant issues such as the explainability of the model, scalability of data, and ethically sound use of the model. The recommendations of the authors concerning the improvement of model interpretation, the creation of efficient algorithms, and the solution of privacy-related issues, make the research an objective prognosis of technological advantages and disadvantages.

Thamik and Wu's (2022) investigation critically examined AI's broader societal implications, specifically within electronic markets. Applying the systematic review method, the authors proposed a quadripartite framework of behavioral, cultural, ethical, social, and economic concerns regarding the implementation of AI. In doing so, the study of the article contributed to the enriched knowledge of the nature of technology implementation beyond the technical aspect. The research focused on the areas of concern in AI adoption, including issues concerning consumer privacy, AI prejudices, and job disruptions. Contrary to buoyant perceptions about technology, this study highlighted the call to order regarding AI adoption. The researchers suggested that organizations and governing bodies develop sound security measures and policies to counterbalance negative social consequences, a positive step toward sustainable development in electronic markets.

More so, Bhagat, Naz, and Magda (2022) conducted a bibliometric analysis and recommended AI solutions for sustainable agriculture. The researchers compiled a sample of 465 articles and reviews from 2000 to 2021 to offer a systemic view of the development of AI in agriculture sustainability. Their approach employed sophisticated graphic interfaces, such as VOSviewer and Biblioshiny, to present trends and collaboration patterns. The review established that

the number of papers on the application of AI in sustainable agriculture has increased from 2018 to 2021. On the geographical front, the research pointed out the extensive academic involvement of countries such as China, the USA, India, Iran, and France, among others. The presented bibliometric analysis helped to define the leading research topics and potential areas of cooperation to progress the understanding of the international research network targeted at AI and agricultural Sustainability.

The study conducted by Mutale and Mutono-Mwanza (2024) offers a detailed analysis of Industry 4.0 technologies and their application and implications in an organization. As part of the study, the author collected information through a cross-sectional survey questionnaire with a 100% response rate from employees; a systematic analysis was conducted to identify challenges and opportunities of corresponding Technologies such as the Internet of Things, Blockchain, and Big data analytics. Analytical findings provided research evidence of positive coefficients between Industry 4.0 technologies and important SCM performance indicators such as delivery performance, inventory velocity, and demand forecasting accuracy. The study's most notable contribution lies in its recommendation for targeted workforce skill development, recognizing that technological transformation's success fundamentally depends on the human capacity to effectively adapt and leverage new tools.

Table 1
Authors' findings on Sustainability and Talent Management on the International level

Authors/Date	Research Area	Main Findings
Panigrahi et al. (2023)	Emerging markets, with a focus on SMEs in Asia	The study explores AI-driven supply chain management in SMEs, emphasizing the role of AI-powered chatbots in improving supplier communication, operational efficiency, and demand planning. It argues that SMEs in emerging markets must compete in sustainable markets.
Pawlicka & Bal (2022)	Clothing industry supply chains in Europe	Focused on AI's impact on omni-channel logistics, the research highlights AI's role in improving inventory management and efficient distribution in the European clothing sector. AI implementation reduces costs and enhances resource efficiency, supporting sustainable supply chain finance.
Dash et al. (2019)	Global context in supply chain automation	Highlights AI's role in global supply chains, enabling accurate demand forecasting, reduced R&D cycle times, and better asset utilization. These advancements optimize resources and build resilience, making businesses adaptive to disruptions while supporting sustainability.
Pal (2023)	Global supply chain operations,	This finds out the particular areas of AI in international supply chains based on its focus on predictive analysis and efficient use of resources. It increases operational efficiency and decreases environmental impact although

	including Europe and Asia	factors such as high cost and inadequate human capital limit the adoption of such challenges.
Mubarik & Khan (2024)	Developing regions in Asia and Africa	Explores the major ways Big Data, AI, IoT, and blockchain can enhance supply chain transparency and discuss the sustainability concerns in developing countries. It finds out that in these areas, reliance and regulation are mentioned as significant challenges where the solutions are not typically implemented.
Goswami et al. (2022)	Supply chain networks in developing countries	Initiatives push for the framing of an AI strategy that will assist firms in uplifting their demand planning and inventory management. Peculiarities of the development economies include such difficulties as integrity problems, privacies, and integration problems; however, AI save money and increase the rate of productivity.
Vaio et al. (2020)	Global business models	Through bibliometric analysis, this study explores AI's contribution to sustainability goals in resource-intensive industries worldwide. Collaborative platforms and knowledge management systems are essential for embedding AI into global sustainability-driven business models.
Nishant et al. (2020)	Global societal and environmental impacts	A multilevel approach integrating ethical and technical perspectives is recommended to mitigate risks and harness AI's sustainability potential.
Dauvergne (2020)	Global political and economic perspectives	Challenges the optimism surrounding AI's sustainability benefits. Hidden ecological costs like energy-intensive computation and e-waste are highlighted as global concerns, necessitating a balanced perspective on AI's role in sustainability.
Goralski & Tan (2020)	Global scenarios in sustainable development	It outlines future cases in which AI is likely to have a positive or negative impact on sustainable development globally. Stresses responsible AI governance and management education to create the proper type of environment to prevent the abuses of artificial intelligence while building the symbiosis between humans and artificial intelligence.
Rane et al. (2024)	Logistics and supply chain in North America and Europe	Finds out ideas like disruption prediction, demand forecasting, and blockchain concerning logistics and AI. Discusses the role played by big data analytics for the positive enhancement of sustainability and supply chain decision making in North America and Europe.
Kulkov et al. (2023)	Global organizational and technical dimensions	This paper stresses important factors related to AI deployment in organizations around the world, focusing on frameworks, change management, and interdisciplinary cooperation for linking AI to sustainable development.

Srivastava & Maity (2023)	Urban environments in India and Southeast Asia	This paper examines AI's role in urban climate adaptation strategies, particularly in India and Southeast Asia. It finds out that AI helps predict and mitigate environmental challenges like flooding and air pollution, but global collaboration is necessary to address disparities in AI adoption.
Fan et al. (2023)	Renewable energy and smart infrastructure in Asia and Europe	Explores AI applications in renewable energy optimization and smart infrastructure. Despite advancements, challenges such as ethical concerns and limited scalability hinder the full realization of AI's potential in Asia and Europe.
Thamik & Wu (2022)	Economic and cultural impacts in Asia	Proposes a framework addressing cultural, ethical, and economic concerns around AI in electronic markets across Asia. Highlights risks of privacy violations and job displacement alongside economic opportunities in reshaping markets.
Bhagat, Naz, & Magda (2022)	Precision agriculture in China and India	Focuses on data analysis of AI application potentials in practicing sustainable agriculture, including precision farming, resources efficient use, and crop search in China and India. AI stakeholders' involvement and recommendations are highlighted based on several ideas.
Mutale & Mutono-Mwanza (2024)	Logistics in Zambia and Africa	Finds out how an international company ensures the right deliveries are made on time and reduces inventory through its artificial intelligence techniques. Training of the workforce is a key factor in attaining sustainability in logistics activities in Africa.

The table integrates data from different sources related to various ways in which AI contributes to the enhancement of sustainability in different countries. The collected eleven sources prove a significant correlation between the use of techniques of artificial intelligence and sustainable development, outlining how the use of techniques of artificial intelligence increases supply chain visibility, efficiency of functioning, and rational utilization of resources. In Asia, Africa, Europe, and North America, these papers demonstrate how logistics can benefit from AI, applications of AI in renewable energy, and the use of AI in managing inventory. The other papers examine related connections, more specifically, ethical issues, energy, and challenges of implementation. Case-level studies demonstrate critical logistics optimization and global-level studies prioritize cooperation, management, and proper deployment of artificial intelligence. According to this thorough examination, it is clear that AI has great promise for both sustainability and context-related issues. The study points toward the positive and negative sides of implementing AI. It suggests developing best practices that will harness the positive impact of AI applications while minimizing negative impacts, paying attention to the equities across geo-economic areas and within societies.

2.2. Research model of the influence of AI integration on the Sustainable Development of international organizations

In this subchapter, empirical results of studies are presented. These are drawn from diverse authors within various international contexts and cultures. The studies explore links between AI integration and sustainable development in varied environments and scenarios. The findings of these studies are illustrated and then a research model and hypotheses are presented.

Table 2

Main findings on links

Authors/date	**Research area**	**Main Findings on links**	**Strong/indirect link**
Panigrahi et al. (2023)	India	Explores AI chatbot adoption in SMEs, emphasizing their role in improving customer engagement and supply chain visibility. This fosters sustainability by promoting transparency and innovation, essential for competitive advantages in emerging markets.	**Strong**
Pawlicka & Bal (2022	Poland and Turkey	Focuses on omnichannel logistics and sustainable supply chain financing. AI-enabled systems enhance supplier relationships and resource efficiency, directly contributing to profitability and sustainable performance in the clothing industry.	**Strong**
Pal (2023)	India	AI-driven supply chain practices highlight resource optimization and carbon reduction as core strategies for achieving operational efficiency and environmental goals. The integration demonstrates both innovation and sustainability.	**Strong**
Srivastava & Maity (2023)	Africa, Asia, Australasia, Europe, North America, and South America	AI adapts strategies to regional needs, directly addressing climate adaptation challenges and fostering collaborative approaches to sustainability	**Strong**

Thamik & Wu (2022)		AI adoption indirectly impacts sustainability by improving consumer engagement while posing ethical and cultural challenges in electronic markets.	**Indirect**
Mutale & Mutono-Mwanza (2024)	Zambia	Examines Industry 4.0 technologies, including AI, to enhance SCM metrics such as delivery accuracy and demand forecasting. Workforce skill development is identified as a critical enabler for leveraging technology for sustainable outcomes.	**Strong**
Bhagat et al. (2022)	India, China, USA	Bibliometric analysis reveals the rising importance of AI in sustainable agriculture. Collaborative frameworks and resource-efficient technologies are identified as enablers of ecological and economic sustainability.	**Strong**
Dash et al. (2019)	USA	AI-enabled automation in supply chains supports near-perfect demand forecasts and optimized resource use, directly contributing to competitive advantages and sustainability.	**Strong**
Goswami et al. (2022)	India	AI in supply chain management enhances agility and operational efficiency through real-time data analysis and predictive maintenance. However, challenges such as data quality and privacy require a governance framework for sustainable and competitive outcomes.	**Strong**

The table presents a synthesis of empirical research on the effects of AI integration on sustainable development of international organizations in various geographical areas and industries. The empirical results persistently underline a significant correlation between AI adoption and superior sustainability results, especially in the areas of supply chain management, customer involvement, resource management & optimization, and environmental impact. For example, studies from India (Panigrahi et al., 2023, Pal, 2023, Bhagat et al., 2022, Goswami et al., 2022) reveal the importance of AI in enhancing transparency, innovation, and efficiency in the agricultural and industrial operations. Similarly, research from Poland, Turkey (Pawlicka & Bal, 2022), and Zambia (Mutale & Mutono-Mwanza, 2024) corroborates the contribution of AI to sustainable logistics and workforce development. A global study by Srivastava & Maity (2023) emphasizes AI's flexibility to sustainability challenges in regions. Although various researches show significant direct effects, Thamik & Wu (2022) also point out the presence of indirect effects, concluding that AI enhances

engagement but also presents ethical and cultural challenges. In general, the table shows that AI integration promotes not only economic, but also ecological sustainability, yet a successful launch often relies on complementary components including: skilled human capital and strong data governance. These insights guide the formation of a research model and hypotheses for investigating AI's ability to transform in realizing the global sustainable development goals.

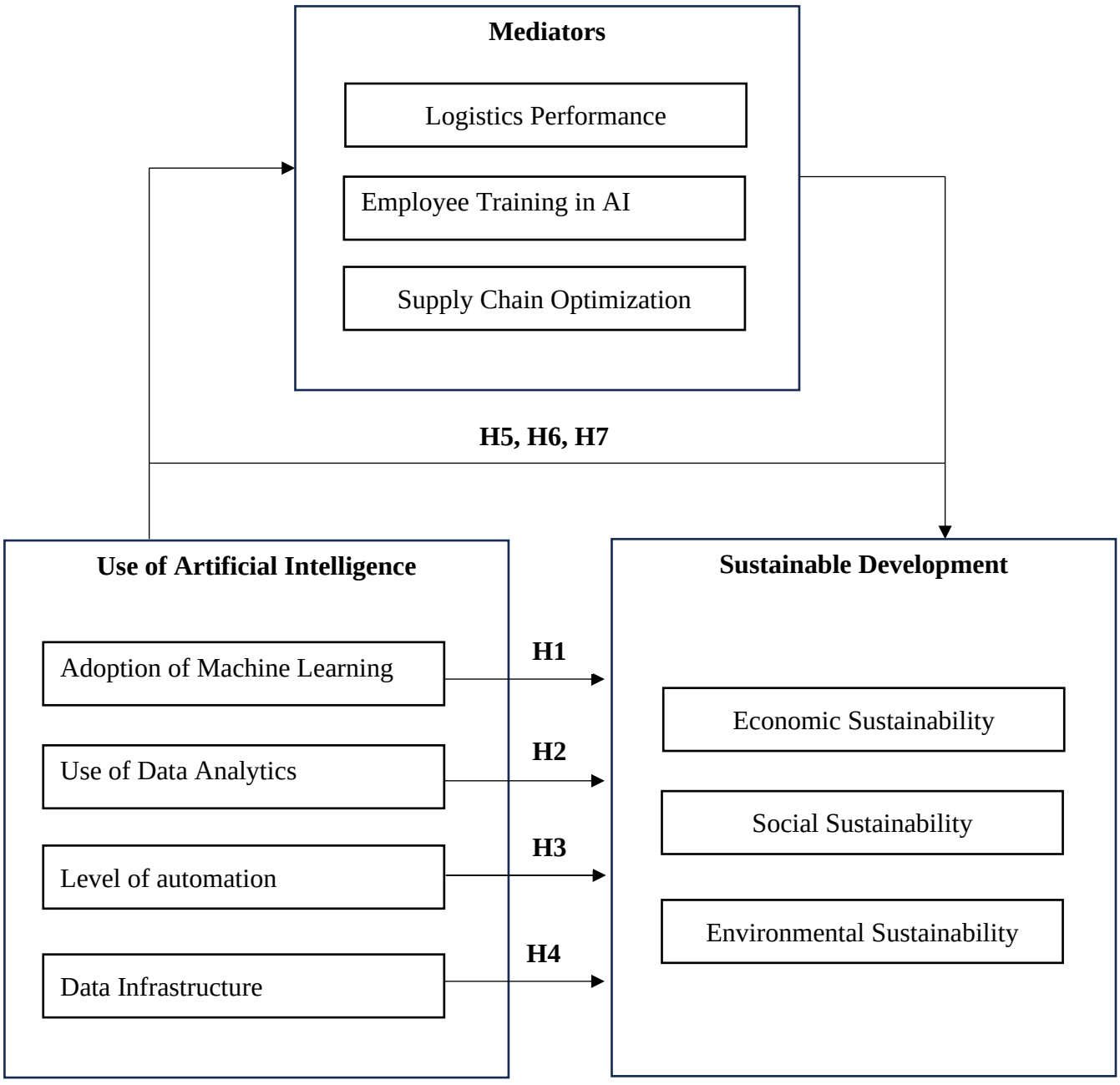


FIGURE 7: RESEARCH MODEL OF THE LINNK BETWEEN THE USE OF ARTIFICIAL INTELLIGENCE AND SUSTAINABLE DEVELOPMENT

The research model illustrated in Figure 6 combines the conceptual connection between Sustainable Development and Artificial Intelligence (AI) in the setting of international organizations.

As illustrated in the research framework, this model highlights three pivotal domains: Artificial Intelligence, Sustainable Development Goals and International Business Management. The framework integrates the theoretical and empirical literature to explain how AI enables change for sustainability in economic, environmental and social domains. Thus, AI is illustrated as a driver of sustainability which supports efficient usage of resources, effective forecasting, and tom product design in terms of sustainability. This alignment can be driven by incorporating of AI solutions in visibility of logistic chains, influences on carbon impact, or improvements in social equity enhancements. Empirical research further reinforces the model by demonstrating AI's potential in fostering operational efficiency, reducing waste, and promoting ethical practices. As combining AI technologies with sustainable business initiatives, the model offers a more holistic solution to address the global challenges by embracing AI adoption in a responsible and inclusive manner. The overall implication highlights the global positioning that multinational corporations must adopt AI as an enabler of sustainable development in the management of risks associated with international operations. Following this conceptualization, specific hypotheses are formulated to further investigate these dynamics:

H1: Adoption of Machine Learning positively influences sustainable development
H2: Use of Data Analytics positively influences sustainable development
H3: Level of automation positively influences sustainable development
H4: Data infrastructure positively influences sustainable development
H5: Logistics performance mediates the relationship between the use of Artificial intelligence and sustainable development
H6: Employee training in AI mediates the relationship between the use of Artificial intelligence and sustainable development
H7: Supply chain optimization mediates the relationship between the use of Artificial intelligence and sustainable development

In conclusion, this chapter analyzed relationships between sustainable development and the integration of AI in international companies. Different research was undertaken by authors from various organizational backgrounds. Specifically, research pertaining to the relationship between AI integration and sustainable development will be evaluated. Research in literature on the links between Sustainable Development and AI integration in international companies revealed that supply chain transparency and innovation potential are enhanced through the contextual use of AI chatbots in emerging markets (Pal (2023) which offers a narrower yet substantial view of technological integration in the context of SMEs, recognizing the context differences in AI implementation at the

company scale (Pawlicka and Bal, 2022) In terms of AI's Integration and Sustainability Outcomes in International Companies, this review found out that the key challenges facing integration are temporal depletion of data, unpredictable human response, and risks in cybersecurity (Dash et al., 2019; Nishant et al., 2020; Vaio et al., 2020). It was also revealed that efficiency enhancements typically lead to a consumer rise instead of positive environmental change (Dauvergne, 2020; Goralski and Tan, 2020). Last but not least, the chapter presents a research model for this study, alongside the study hypotheses that are to be examined empirically by use of quantitative data collection and analysis methods.

3. EMPIRICAL RESEARCH LEVEL OF AI INTEGRATION ON SUSTAINABLE DEVELOPMENT IN AN INTERNATIONAL COMPANY

This chapter presents the research methods, data collection, data analysis, hypothesis testing, and a discussion of the study findings.

3.1. Research methodology

Aim of the research - To examine the link between Sustainable Development and AI integration in an international company.

Objectives of the research:

1. To establish the link between sustainable development & AI integration in international companies.
2. To evaluate the mediating roles of logistic performance, employee training in AI, and Supply chain optimization in the relationship between sustainable development and AI integration in international companies.
3. To provide recommendations on the integration of AI in the facilitation of sustainable development.

Research methods. This study utilized a quantitative study approach from the data collection process through data analysis and interpretation. The data was collected by the use of an online survey that was put together from different authors' questionnaires. The use of quantitative methods allowed the study to put a focus on the specific variables of interests to the study. The use of quantitative research was beneficial because quantitative research generates factual and reliable information that can be generalizable in larger populations as opposed to qualitative research which is not likely to be generalizable (Munther et al., 2024).

Sampling: The convenience sampling method was used to garner participants for the study. This is because the study link was shared via social media pages especially WhatsApp. The link was shared in the work groups so that willing people could participate in the study and complete the questionnaire. According to CBS 2025, multinational companies about 30,000 employees on average. The Pannioto formula was used to compute the sufficient sample size required for the study. Using a sampling error of 0.05, the required sample size was calculated as follows: $n = 1 / (e^2 + 1/N)$; $n = 1 / (0.05^2 + 1/30000)$; $n = 394$. Eventually, the total sample size for this study comprised of 431 participants, which surpassed the lower predicted limit of 394. The questionnaire used to collect data for this study was obtained from existing and already validated surveys as illustrated in the table 3 below:

Table 3

Data collection survey

Variable	Questionnaire item	Source
	Please indicate the importance of each of the following issues/concerns to your organization's supply chain management efforts (1 = low importance, 7 = high importance)	
Supply chain optimization	1. Searching for new ways to integrate SCM activities 2. Creating a greater level of trust throughout the supply chain 3. Establishing more frequent contact with supply chain members 4. Communicating customers' future strategic needs throughout the supply chain 5. Extending supply chains beyond your firm's customers/suppliers 6. Communicating your firm's future strategic needs to suppliers	(Green et al. 2008)
	Please rate your company's performance in each of the following areas as compared to the performance of your competitors (1 = much worse than competition, 7 = much better than competition)	
Logistic performance	1. Delivery speed 2. Delivery dependability 3. Responsiveness 4. Delivery flexibility 5. Order fill capacity	(Green et al. 2008)
	Respond to the following statements by indicating your level of agreement with them based on your company practices (1- strongly disagree, 2 - disagree, 3 - neither agree nor disagree, 4 - agree, 5 - strongly agree)	
Employee training in AI	1. We provide big data analytics training to our own employees 2. Our big data analytics staff has the right skills to accomplish their jobs successfully 3. Our big data analytics staff has suitable education to fulfil their jobs 4. Our big data analytics staff is well trained 5. We continuously coach our employees to make decisions based on data	(Gupta & George, 2016).
Adoption of machine learning	1. My company is using an agile software development process. 2. I know different model stages (e.g. data collection, model training) in Machine Learning. 3. My company's operations depend on machine learning. 4. I know what I can do with machine learning. 5. My company is ready to adapt machine learning.	(Chow & Jakob, 2020)
Use of Data Analytics	1. We have explored or adopted different data visualization tools 2. We have explored or adopted cloud-based services for processing data and performing analytics 3. We have explored or adopted open-source software for big data analytics	(Gupta & George, 2016).

	4. We integrate external data with internal to facilitate high-value analysis of our business environment	
Level of automation	**On a scale of 1 - 10, rate your company's operations based on the following options:** 1. Human considers alternatives, makes and implements decision. 2. Computer offers a set of alternatives which human may ignore in making decision. 3. Computer offers a restricted set of alternatives, and human decides which to implement. 4. Computer offers a restricted set of alternatives and suggests one, but human still makes and implements final decision. 5. Computer offers a restricted set of alternatives and suggests one, which it will implement if human approve. 6. Computer makes decision but gives human option to veto prior to implementation. 7. Computer makes and implements decision, but must inform human after the fact. 8. Computer makes and implements decision, and informs human only if asked to. 9. Computer makes and implements decision, and informs human only if it feels this is warranted. 10. Computer makes and implements decision if it feels it should, and informs human only if it feels this is warranted.	(Frohm et al., 2008)
Data Infrastructure	1. We have explored or adopted new forms of databases such as Not Only SQL (NoSQL) for storing data. 2. We have access to very large, unstructured, or fast-moving data for analysis 3. We integrate data from multiple internal sources into a data warehouse or mart for easy access 4. We continuously assess and improve the business rules in response to insights extracted from data 5. We consider data a tangible asset	(Gupta & George, 2016).
Economic sustainability	1. The firm has developed long-term strategic plans for its economic growth 2. The economic growth of the firm spreads to the local communities around it 3. The firm has adopted to use of new technologies to increase work efficiencies 4. The use of modern technologies is to cut operational costs 5. The firm growth is an aspect of proper planning 6. The firm continuous invests in research and development programs 7. The strategic team comes up with annual smart agenda for growth and development	(Mbuthia, 2022)
Environmental sustainability	1. The firm has installed measures to protect the environment 2. Managers encourage adoption of recycling strategies 3. The firm has put measures for proper resource management 4. All staff are encouraged to stop the degradation of the environment 5. Renewable energy sources like solar is used in the organization	(Mbuthia, 2022)

	6. There are measures to protect the natural eco-systems 7. The firm has adopted to bio-diversity measures	
Social sustainability	1. The firm designed a healthy working environment for all its staff 2. There are measures that ensure equal opportunities to all staff 3. The firm engages in CSR for community growth and development 4. Employees are empowered through training and educational programs 5. The firm encourages inclusivity of all persons 6. The firm promotes the well-being of its staff	(Mbuthia, 2022)

3.2. Data analysis and discussion of the results

The data was collected via Google Forms and downloaded upon reaching a workable sample size. Having collected the data, it was cleaned on Microsoft Excel before being imported to SPSS for data analysis and evaluation. A total of 431 respondents participated in this study by completing the survey.

Most of the study participants were female (49.9%, *n* = 215) while 30.6% (*n* = 132) were male participants and 19.5% (*n* = 84) of the participants identified with other gender orientations.

Table 4

Gender distribution of respondents

		Frequency	Percent	Valid Percent
Valid	Male	132	30.6	30.6
	Female	215	49.9	49.9
	Other	84	19.5	19.5
	Total	431	100.0	100.0

There was a fair distribution of the study participants on age groups with most of the study participants aging between 26 and 35 years (46.9%, *n* = 202), 37.6% (*n* = 162) between 36 and 11.4%, (*n* = 49) between 18 and 25 years old. Only 4.2%, (*n* = 18) of the participants were aged 46 years and above.

Table 5

Distribution of participants by Age Range

		Frequency	Percent	Valid Percent
Valid	18 - 25 years	49	11.4	11.4
	26 - 35 years	202	46.9	46.9
	36 - 45 years	162	37.6	37.6
	46 years and older	18	4.2	4.2
	Total	431	100.0	100.0

Working duration

Most of the study participants had between two- and five-years' experience working in their current organization (41.3%, *n* = 178), followed by those with six months two two-years' experience working in their current organization (28.8%, *n* = 124). On the other hand, 18.8% (*n* = 81) of the participants had six to ten years' experience. Only 6.3% (*n* = 27) of the participants had less than six months' experience and 4.9% (*n* = 21) with more than 10 years' experience.

Table 6

Duration of working in the current organization

		Frequency	Percent	Valid Percent
Valid	Less than six months	27	6.3	6.3
	six months to 2 years	124	28.8	28.8
	2 - 5 years	178	41.3	41.3
	6 - 10 years	81	18.8	18.8
	More than 10 years	21	4.9	4.9
	Total	431	100.0	100.0

3.3. Reliability Analysis

The reliability of the variable constructs was evaluated using the Cronbach's alpha coefficient, and all the variables met an acceptable level of internal consistency as indicated in table 7 below. According to Raharjanti et al. (2022), a Cronbach's alpha reliability of 0.6 and above is considered to be acceptable internal consistency. The dependent variable, sustainable development (α = 0.839) had the highest level of reliability, followed by Level of automation (α = 0.800), Employee training

in AI (α = 0.769), Data infrastructure (α = 0.734), Adoption of machine learning (α = 0.714), Supply chain optimization (α = 0.651), Use of data analytics (α = 0.619), and Logistics performance (α = 0.612) respectively. Table 7 illustrates the reliability analysis results.

Table 7

Reliability analysis

Variable	**Cronbach's alpha coefficient**	**Number of items**
Adoption of machine learning	0.714	5
Use of data analytics	0.619	4
Level of automation	0.800	10
Data infrastructure	0.734	5
Logistics performance	0.612	5
Employee training in AI	0.769	5
Supply chain optimization	0.651	6
Sustainable development	0.839	20

3.4. Descriptive Statistics

The descriptive statistics (minimum, maximum, mean, standard deviation, skewness, and kurtosis) for the variables of the study were evaluated and presented in table 8. Notably, the mean values for all the variables were greater than the average values. This shows that the responses to the survey questions were leaning towards the positive angles. It is important to note that all variables were computed by averaging the respective survey items, except for the 'Level of automation' variable, which was computed by summing up the survey items for the variables as directed by the authors of the scale (Frohm et al., 2008).

Table 8

Descriptive statistics of the study variables

	Minimum	Maximum	Mean	Std. Deviation
	Statistic	Statistic	Statistic	Statistic
Supply chain optimization	1.50	6.33	3.9768	.87359
Logistic performance	1.00	6.60	4.0111	.91054
Employee training in AI	1.00	5.00	3.1937	.63384
Adoption of machine learning	1.20	5.00	3.1596	.59247

Use of Data Analytics	1.00	5.00	3.1642	.60942
Level of automation	13.00	95.00	53.5963	13.08823
Data Infrastructure	1.40	5.00	3.3114	.59848
Economic sustainability	1.57	5.00	3.2698	.57782
Environmental sustainability	1.29	5.00	3.1936	.58199
Social sustainability	1.00	5.00	3.1756	.61683

The descriptive statistics revealed interesting insights pertaining to the variables. The levels of automation seemed to be relatively high, followed by sustainable chain development and logistics performance in comparison to the other variables.

Correlation Analysis

A Pearson Correlation test was conducted to establish the association between the independent variables of the study and the dependent variable (sustainable development). All the independent variables were significantly and positively associated to the dependent variable. Logistics performance was most highly correlated with sustainable development ($r = 0.664$, $p < .001$), and of all the independent variables, use of data analytics was least highly correlated with sustainable development ($r = 0.574$, $p < .001$). Table 9 depicts the correlation analysis results for the study variables.

Table 9
Correlation Analysis

Correlations									
		Supply chain optimization	Logistic performance	Employee training in AI	Adoption of machine learning	Use of Data Analytics	Level of automation	Data Infrastructure	Sustainability
Supply chain optimization	Pearson Correlation	1	.593**	.480**	.559**	.536**	.607**	.503**	.615**
	Sig. (2-tailed)		<.001	<.001	<.001	<.001	<.001	<.001	<.001
	N	431	431	431	431	431	431	431	431
Logistic performance	Pearson Correlation	.593**	1	.532**	.553**	.531**	.565**	.540**	.664**
	Sig. (2-tailed)	<.001		<.001	<.001	<.001	<.001	<.001	<.001

	N	431	431	431	431	431	431	431	431
Employee training in AI	Pearson Correlation	.480**	.532**	1	.486**	.499**	.524**	.463**	.592**
	Sig. (2-tailed)	<.001	<.001		<.001	<.001	<.001	<.001	<.001
	N	431	431	431	431	431	431	431	431
Adoption of machine learning	Pearson Correlation	.559**	.553**	.486**	1	.541**	.556**	.477**	.595**
	Sig. (2-tailed)	<.001	<.001	<.001		<.001	<.001	<.001	<.001
	N	431	431	431	431	431	431	431	431
Use of Data Analytics	Pearson Correlation	.536**	.531**	.499**	.541**	1	.570**	.480**	.575**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001		<.001	<.001	<.001
	N	431	431	431	431	431	431	431	431
Level of automation	Pearson Correlation	.607**	.565**	.524**	.556**	.570**	1	.574**	.660**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001		<.001	<.001
	N	431	431	431	431	431	431	431	431
Data Infrastructure	Pearson Correlation	.503**	.540**	.463**	.477**	.480**	.574**	1	.632**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001		<.001
	N	431	431	431	431	431	431	431	431
Sustainability	Pearson Correlation	.615**	.664**	.592**	.595**	.575**	.660**	.632**	1
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	
	N	431	431	431	431	431	431	431	431
**. Correlation is significant at the 0.01 level (2-tailed).									

The correlation test revealed that the independent variables move in the same direction with the dependent variable. An increase in any of these variables (Logistics performance, adoption of machine learning, level of automation, data infrastructure, use of data analytics) corresponds to an increase in sustainable development and vice versa.

3.5. Hypothesis Testing

H1: *Adoption of Machine Learning positively influences sustainable development*

H2: *Use of Data Analytics positively influences sustainable development*

H3: *Level of automation positively influences sustainable development*

H4: *Data infrastructure positively influences sustainable development*

A multiple linear regression test was conducted to determine the predictors of sustainable development. The predictor variables included Data Infrastructure, Use of Data Analytics, Adoption of machine learning, Level of automation, while sustainable development was the dependent variable. The resulting model was statistically significant: F (4, 426) = 153.05, $p < .001$. The adjusted R square effect was .586, which means that the predictor variables explained approximately 58.6% of the variance in sustainable development.

Table 10
Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.768[a]	.590	.586	.33231	.590	153.047	4	426	<.001
a. Predictors: (Constant), Data Infrastructure, Adoption of machine learning, Use of Data Analytics, Level of automation									

Individually, all the predictor variables: Data Infrastructure (β = .292, $p < .001$), Use of Data Analytics (β = .158, $p < .001$), Adoption of machine learning (β = .213, $p < .001$), Level of automation (β = .284, $p < .001$) were found to significantly and positively predict sustainable development. This means that higher levels of AI integration result in more sustainable development and vice versa. H1, H2, H3, and H4 were therefore accepted based on the significant findings.

Table 11
Standardized and unstandardized coefficients table from regression

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.769	.107		7.175	<.001

	Adoption of machine learning	.186	.035	.213	5.308	<.001
	Use of Data Analytics	.134	.034	.158	3.904	<.001
	Level of automation	.011	.002	.284	6.583	<.001
	Data Infrastructure	.252	.034	.292	7.382	<.001
a. Dependent Variable: Sustainability						

H5: *Logistics performance mediates the relationship between the use of Artificial intelligence and sustainable development*

H6: *Employee training in AI mediates the relationship between the use of Artificial intelligence and sustainable development*

H7: *Supply chain optimization mediates the relationship between the use of Artificial intelligence and sustainable development*

The mediator variables were then added to the model in order to determine their mediating roles (or lack thereof). On adding these three mediator variables (logistics performance, employee training in AI, and supply chain optimization) to the model, the adjusted R squared increased by 0.057 (from 0.586 to 0.643), an indication that by adding the mediator variables to the model the model's effectiveness in predicting sustainable development increased by 5.7%.

Table 12

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.806[a]	.649	.643	.30850	.649	111.651	7	423	<.001
a. Predictors: (Constant), Supply chain optimization, Employee training in AI, Data Infrastructure, Use of Data Analytics, Adoption of machine learning, Logistic performance, Level of automation									

Observing the outcome of the mediator variables individually, logistic performance was significant (β = .210, p < .001). Employee training in AI (β = .152, p < .001), and supply chain optimization (β = .106, p = .01) were also significant in the model, thus indicating that employee

training in AI and supply chain optimization were significant mediators of the relationship between the use of Artificial intelligence and sustainable development.

The beta coefficient values of all the independent variables in the model reduced upon adding the mediator variables to the model: adoption of machine learning (from, β = .213 to β = .111) use of data analytics (from, β = .158 to β = .072), level of automation (from, β = .284 to β = .176), and data infrastructure (from, β = .292 to β = .207). Notably, although the use of data analytics was significant in the initial model, it was not significant in this mediation model. This shows that the even though the mediators mediated the relationship between other independent variables (adoption of machine learning, use of data analytics, level of automation, and data infrastructure) and sustainable development, the relationship between data analytics and sustainable development was explained the most by the mediator variables in the model. Based on these findings, H5, H6, and H7 are therefore accepted.

Table 13
Standardized and unstandardized coefficients table from mediation

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.630	.103		6.147	<.001
	Adoption of machine learning	.097	.034	.111	2.827	.005
	Use of Data Analytics	.061	.033	.072	1.830	.068
	Level of automation	.007	.002	.176	4.143	<.001
	Data Infrastructure	.178	.033	.207	5.428	<.001
	Logistic performance	.119	.023	.210	5.103	<.001
	Employee training in AI	.124	.030	.152	4.071	<.001
	Supply chain optimization	.063	.024	.106	2.586	.010
a. Dependent Variable: Sustainability						

3.6. Evaluation of the research results

The findings of this study revealed that the adoption of machine learning, use of data analytics, level of automation, and data infrastructure positively influence sustainable development. The more a company adopts machine learning and data analytics, the more likely they are to uphold and maintain sustainable development practices. In addition, the findings of this study imply that higher levels of automation and intensified data infrastructure result in increased adoption of sustainable development practices.

H1: Adoption of Machine Learning positively influences sustainable development

Confirmed. The finding that the adoption of machine learning has a positive influence on sustainable development aligns with most of the findings in the theoretical literature that was reviewed in relation to machine leaning and sustainable development. In their finding, Sachs (2015) and Harari (2017) attributed the use of Artificial Intelligence machine learning to a positive impact on up to 79% of the SDG goals by offering better access to technology and efficient service delivery. Although according to the UN Economic and Social Council (2019), machine learning can have a negative impact and risks on 35% of the SDGs in terms of privacy violation and environmental pollution, this percentage is relatively smaller and is still consistent with the findings of this study.

H2: Use of Data Analytics positively influences sustainable development

Confirmed. Data analytics was found to have a positive influence on sustainable development. This is in line with the findings of Restrepo (2018) who found that data analytics powered applications have a fit for 70% and many of those are often related to the development goals such as, economic development (SDG 8), infrastructure and innovation (SDG 9) and inequality (SDG 10). In addition, Acemoglu and Restrepo (2018) had also pointed out that AI data analytics can stimulate productivity growth and lead to economic growth as data analysis enhances resource utilisation and improves industrial productivity.

H3: Level of automation positively influences sustainable development

Confirmed. The finding that the level of automation has a positive influence on sustainable development also aligns with the findings in literature such as of Dash et al. (2019). The author had found out that AI-enabled automation supports near-perfect demand forecasts and optimized resource use, directly contributing to competitive advantages and sustainability.

H4: Data infrastructure positively influences sustainable development

Confirmed. This study found out that a well-structured data infrastructure within the working of an facilitates better sustainable development outcomes. This aligns with the finding of Fan et at. (2023) that the adoption of machine learning has a positive influence on sustainable development. Fan et at. (2023) however cautioned that despite advancements, challenges such as ethical concerns and limited scalability hinder the full realization of AI's potential in Asia and Europe.

H5: Logistics performance mediates the relationship between the use of Artificial intelligence and sustainable development

Confirmed. This study found logistics performance to mediate the relationship between the use of Artificial intelligence and sustainable development. These findings align with the findings in literature. In their study, Rane et al., (2024) explored artificial intelligence and machine learning's revolutionary impact on logistics and supply chain management, demonstrating how advanced technologies can fundamentally reshape operational paradigms. The authors found out that AI's transformative applications in autonomous delivery systems, inventory management, and supplier network optimization, offering a comprehensive view of technological innovation's sustainable development potential.

H6: Employee training in AI mediates the relationship between the use of Artificial intelligence and sustainable development

Confirmed. The finding of this study that Employee training in AI mediates the relationship between the use of Artificial intelligence and sustainable development was not very consistent with literature review findings. Studies in literature had indicated that there are adverse effects of bias in the labour market in relation to the use of AI in posting job vacancies (Dalenberg, 2018). This was an indication that training data calls for ethical design and use of data for AI.

H7: Supply chain optimization mediates the relationship between the use of Artificial intelligence and sustainable development

Confirmed. This study found out that finding that Supply chain optimization mediates the relationship between the use of Artificial intelligence and sustainable development. This study was consistent with the findings of Panigrahi et al. (2023) that supply chain transparency and innovation potential are enhanced through the contextual use of AI chatbots in emerging markets. The findings were also consistent with Pal (2023)’s study which indicated that supply chain integration in the context of SMEs facilitates the implementation of companies’ sustainable goals. Goswami et al. (2022)’s study had also indicated that AI in supply chain management enhances agility and operational efficiency through real-time data analysis and predictive maintenance.

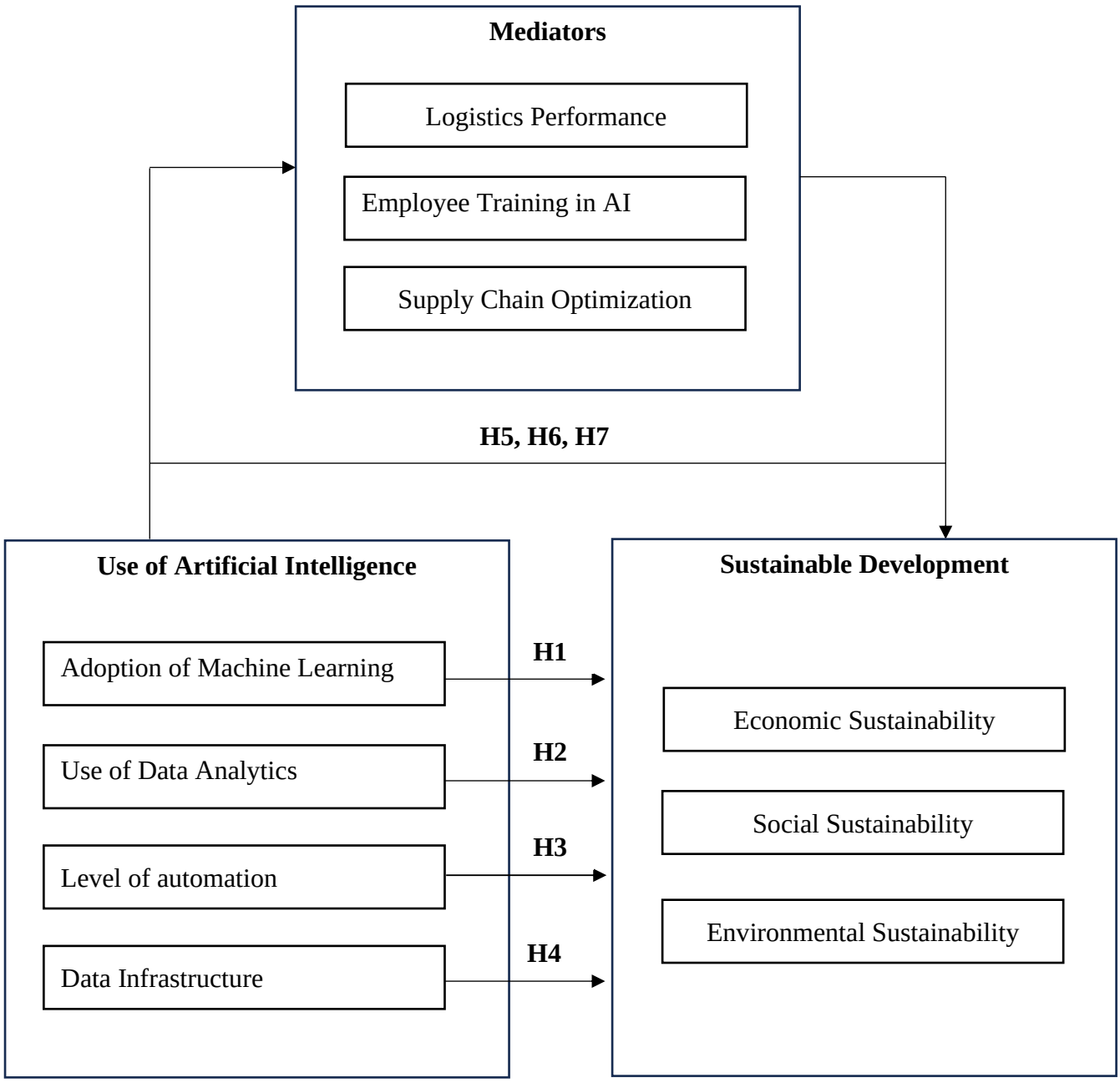


FIGURE 8: THE EMPIRICALLY TESTED RESEARCH MODEL OF THE LINK BETWEEN THE USE OF ARTIFICIAL INTELLIGENCE AND SUSTAINABLE DEVELOPMENT

The above research model reflects the findings of this study. The model remains the same since all the seven hypotheses of the study were approved.

In summary, the findings of this study revealed that the Adoption of Machine Learning positively influences sustainable development, the use of Data Analytics positively influences sustainable development, the Level of automation positively influences sustainable development, Data infrastructure positively influences sustainable development, Logistics performance mediates the relationship between the use of Artificial intelligence and sustainable development and that training in AI mediates the relationship between the use of Artificial intelligence and sustainable development.

Supply chain optimization was also found to mediate the relationship between the use of Artificial intelligence and sustainable development Notably, most of the hypotheses' results were consistent with the findings in literature. This was except for employee raining in AI whereby studies in literature had indicated that there are adverse effects of bias in the labour market in relation to the use of AI in posting job vacancies.

CONCLUSION

1. The theoretical analysis of the study unveiled the link between sustainable development & AI integration in international companies. The theoretical analysis showed that the incorporation of Artificial Intelligence (AI) into global enterprises has the potential to significantly enhance sustainable development. Artificial Intelligence (AI) enhances overall business operations, lowers waste, and maximizes resource utilization - all of which contribute to environmental sustainability. Businesses can better control their environmental impact and assume leadership roles in fostering a greener economy by utilizing AI for data analysis and prediction purposes. AI not only improves the environment but also social and economic sustainability of an organization. It facilitates the creation of environmentally sustainable new goods and services that satisfy consumer demands and, by automating repetitive operations, improves employee job satisfaction. AI therefore encourages diversity and equitable development in all areas.
2. The analytical chapter provided a critical analysis of the relationships between sustainable development and the integration of AI in international companies and envisioning the use of AI in enhancing sustainable management initiatives. This study also strengthens the capability of AI in Environmental, Social, and Economic aspects; While, empirical findings of Panigrahi et al. (2023) and Dash et al. (2019) reveal positive impacts of AI solutions in supply chain management and operational excellence. Studies also underscored AI's dual impact, noting the potential to reduce environmental degradation through optimized resource utilization while acknowledging risks such as increased energy consumption in data processing, as noted by Vinuesa et al. (2018). Furthermore, comprehensive analyses, such as those by Vaio et al. (2020), illustrate AI's role in enabling organizations to align business strategies with UN Sustainable Development Goals, fostering resilience and competitive advantage. In synthesizing these insights, the conclusions emerging support the assertion that the adoption of AI in the sustainable developmental frameworks presents a sound vector for international firms in combating global challenges. However, it also underscored the need to promote ethical adoption and use of artificial intelligence and implement right policies to avoid the negative impacts the advancement in technology brings in support of sustainable development goals and corporate success in the era of globalization.
3. The empirical research of this study explored seven study hypotheses with a view of examining the link between Sustainable Development and AI integration in an international company. The findings of this study revealed that the adoption of machine learning, use of data analytics, level of automation, and data infrastructure positively influence sustainable development. The more a company adopts machine learning and data analytics, the more likely they are to uphold and maintain sustainable development practices. Furthermore, the findings of this study imply that

higher levels of automation and intensified data infrastructure result in increased adoption of sustainable development practices. It was also found out that logistics performance, employee training, and supply chain optimization mediate the relationship between AI and sustainable development. Based on these findings, it is imperative for international companies to harness the aspects of adoption of machine learning, use of data analytics, level of automation, and data infrastructure as primary elements to facilitate sustainable development. Logistics performance, employee training in AI, and supply chain optimization are also key elements to maximize because they help explain how the use of AI relates with sustainable development.

SANTRAUKA

Aktualumas o: Dirbtinis intelektas yra pagrindinis efektyvumo ir išteklių optimizavimo komponentas, kuris puikiai dera su tvaraus vystymosi pagrindais, kuriuose akcentuojamas atsakingas išteklių naudojimas. Dirbtinis intelektas mažina poveikį aplinkai, nes optimizuoja tiekimo grandines ir sunaudoja mažiau energijos, naudodamas tokias taikomąsias programas kaip prognozavimo analizė. Taip tarptautinės korporacijos tampa etiškos verslo praktikos lyderėmis ir taip pat prisideda prie aplinkos tvarumo. Dirbtinis intelektas papildomai remia inovacijas tvarumo srityje, suteikdamas įmonėms galimybę kurti ekologiškus produktus ir spręsti pasaulines problemas. Tai, kaip jis skatina įtrauktį ir socialinį poveikį, įrodo sprendimų, kuriais sprendžiamos socialinės problemos tarptautinėse korporacijose, kūrimas.

Mokslinė problema - nustatyti pagrindinius dirbtinio intelekto integracijos rodiklius, turinčius įtakos tvariam vystymuisi tarptautinėje įmonėje.

Disertacijos objektas - darnaus vystymosi ir dirbtinio intelekto integracijos sąsajos tarptautinėje įmonėje.

Disertacijos tikslas - ištirti Darnaus vystymosi ir AI integracijos tarptautinėje įmonėje ryšį.

Disertacijos uždaviniai:

1. Teoriniame lygmenyje rasti ryšį tarp Darnaus vystymosi ir AI integracijos tarptautinėse įmonėse.
2. Empiriniame lygmenyje įvertinti AI integracijos tyrimo sąsajas su darniu vystymusi tarptautinėje įmonėje.
3. Išanalizavus teorinį ir empirinį tyrimo lygmenis, suprojektuoti AI poveikio tarptautinės įmonės darniam vystymuisi tyrimo modelį.

Aufbau und Umfang der Arbeit. Die vorliegende Arbeit besteht aus einem Einleitungsteil, der einen kurzen Überblick über die gesamte Studie gibt, gefolgt von einem Kapitel über die theoretischen Aspekte des Zusammenhangs zwischen nachhaltiger Entwicklung und KI-Integration in einem internationalen Unternehmen, einem Kapitel über die empirische Forschungsebene der KI-Integration zur nachhaltigen Entwicklung in einem internationalen Unternehmen und einem weiteren über die empirische Forschungsebene der KI-Integration zur nachhaltigen Entwicklung in einem internationalen Unternehmen.

Diese Masterarbeit besteht also aus einer Einleitung, 3 Teilen und Schlussfolgerungen. Die Hauptaspekte der Studie werden auf 50 Seiten, einschließlich 8 Abbildungen und 13 Tabellen, beschrieben. Für die Studie wurden insgesamt 87 Literaturquellen herangezogen.

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