

Louvain School of Management

Emerging technologies such as Artificial Intelligence offer great opportunities for mankind, review issues created, assess emerging frameworks to implement responsible IA, identify way forward

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During the preparation of this master's thesis, the author(s) utilized ChatGPT and Gemini for the following purpose:

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By signing this declaration, we affirm that the content of this master's thesis reflects our original work, augmented by the responsible use of AI.

Signed on August 07, 2024

Roxane Ekelson

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1. Introduction

The rapid emergence of new technologies, particularly Artificial Intelligence, AI, offers both exciting opportunities and significant challenges, especially in terms of responsible integration. This thesis explores how AI integration can benefit sustainability in supply chain management, a critical aspect of the high-tech industry known for its complex supply chains and significant environmental impact. My interest in this topic is driven by the urgent need to address ecological concerns and the potential of AI to provide innovative solutions. As high-tech products are essential to our daily lives, finding sustainable solutions for this industry is imperative. Additionally, addressing public apprehension and misinformation about new technologies by demonstrating how they can be responsible and beneficial is crucial.

The objective of this research is to provide actionable insights for balancing technological advancement with environmental responsibility. It focuses specifically on the integration of digital twins as an AI technology to enhance sustainability practices. Digital twins were chosen due to their significant potential to optimize various aspects of the supply chain, thereby reducing greenhouse gas, GHG, emissions. The study examines the impact of integrating digital twins on GHG emissions in the high-tech industry, particularly among leading companies that manufacture laptops. The investigation, which covers the years 2019 to 2022, evaluates how the adoption of digital twins has influenced the environmental footprint of these major technology firms.

Methodologically, this study includes a thorough literature review to understand the current state of AI and digital twin technologies, the sustainability challenges associated with these technologies, particularly environmental impacts, along with empirical research involving data collection and analysis, and a comprehensive conclusion summarizing the findings. Despite challenges such as data availability and the rapid evolution of new technologies, measuring AI's environmental impact remains complex. Additionally, issues of confidentiality with companies providing data and the fact that these data are often outdated by the time they are published further complicate the research. However, collaboration with industry professionals has ensured robust findings, allowing for a detailed assessment of the potential benefits of digital twins in promoting a more sustainable supply chain.

2. Emerging technologies

2.1. Industry 4.0

Since the Industrial Revolution, which began at the end of the 18th century, the world has undergone numerous technological evolutions that have transformed the industrial landscape. Presently, we are experiencing Industry 4.0. However, preceding this era, we have traversed three other revolutions, each characterized by significant technological advancements. Industry 1.0 was defined by mechanization, steam power, and the weaving loom. Industry 2.0 was marked by mass production, assembly lines, and the utilization of electrical energy, but also more advanced communications by telephone and telegraph. Subsequently, Industry 3.0 emerged with the integration of automation, manufacturing computers, advanced telecommunications, and the integration of programmable logic controllers into machines (IBM, 2023). Industry 4.0, for its part, introduces numerous emerging technologies such as digitalization, automation, the Internet of Things, networks, cloud computing, big data, and artificial intelligence (Almusaed, Yitmen & Almssad, 2023).

Several researchers refer to Industry 5.0, focusing on personalized and collaborative robotics, and Industry 6.0, emphasizing human-centered principles in manufacturing and sustainability. (Almusaed et al., 2023). However, these concepts remain hypothetical and lack a unanimous definition among researchers. Consequently, my focus will remain on the current industry, Industry 4.0, given its established framework and advancements.

The European Parliament defines the Industry 4.0 in the study “Industry 4.0” conducted for the ITRE Committee *“Industry 4.0 describes the organisation of production processes based on technology and devices autonomously communicating with each other along the value chain: a model of the ‘smart’ factory of the future where computer-driven systems monitor physical processes, create a virtual copy of the physical world and make decentralised decisions based on self-organisation mechanisms.”* (Smit, Kreutzer, Moeller & Carlberg, 2016).

This stage of industrialization operates by collecting a vast amount of data and integrating artificial intelligence to process the data, enabling unprecedented speed and scale (Schume, 2020). Enabling access to unprecedented levels of efficiency and responsiveness, this new technology marks the emergence of intelligent factories. These facilities boast heightened automation, predictive maintenance, and self-optimization of processes, all made possible through the analysis of extensive volumes of big data (IBM, 2020).

Industry 4.0 encompasses a range of digital technologies comprising hardware, software, and connectivity. Hardware refers to the physical machinery, equipment, and devices used in manufacturing and operations, such as collaborative robots, 3D printers, and sensors. Software involves applications, algorithms, and systems that control and optimize these physical components, including artificial intelligence, big data, and cloud computing. Connectivity encompasses the networks and communication systems enabling seamless interaction between hardware and software, facilitating data exchange and real-time decision-making in smart manufacturing processes, such as the Internet of Things and digital twins (Feng, Lai & Zhu, 2022).

Amongst all these emerging technologies, I have chosen to focus on artificial intelligence and its responsible integration.

2.2. Artificial intelligence

2.2.1. History and definitions

Between 1940 and 1960, technological advancements spurred by World War II aligned with an interest in the interplay between machines and organisms, exemplified by Norbert Wiener's pursuit to blend mathematics, electronics, and automation. In 1950, John Von Neumann and Alan Turing revolutionized computer architecture, initiating the discourse on artificial intelligence through the "Turing Test." The term "Artificial Intelligence (AI)," credited to John McCarthy, emerged at the 1956 Dartmouth conference, despite an initial slowdown in the 1960s, this era paved the way for the emergence of AI as we know it today (Council of Europe, 2024).

Since 2010, artificial intelligence has experienced a new surge, which relies on two main pillars: widespread Access to massive volumes of data and the discovery of the efficiency of graphical processors for accelerating learning algorithm computations, leading to notable successes such as IBM's Watson or Google's AlphaGo. The advent of deep learning has revolutionized methods by enabling computers to discover rules from data, opening vast horizons despite persistent challenges in human interaction and comprehension (Council of Europe, 2024).

Nowadays, McKinsey defines artificial intelligence as follows: *“AI is a machine’s ability to perform the cognitive functions we associate with human minds, such as perceiving, reasoning, learning, interacting with an environment, problem solving, and even exercising creativity.”*

(McKinsey, 2023). AI uses algorithms to enable machines to analyze data, make decisions, and adapt to situations by predicting outcomes based on past data. Built on deep learning, it allows machines to learn by analyzing extensive datasets. Thanks to this operation, artificial intelligences can be more precise than humans in many domains (CEA, 2018).

To better understand artificial intelligence, it is important to define what Machine Learning, Deep Learning, Reinforcement Learning, and Neural Networks are (Appendix E, Figure 1). Machine Learning operates with labeled datasets and often necessitates human intervention for feature identification. It relies on structured data to learn and derive patterns. Neural Networks, a subset of Machine Learning, are inspired by the human brain's neural structure and consist of interconnected layers of nodes. Each node, or neuron, processes input data and transmits signals to other neurons. Deep Learning, a subset of Neural Networks, functions differently by automating feature extraction, reducing the reliance on human intervention. It can handle raw, unstructured data such as images, audio, and text directly without the need for explicit feature engineering. Reinforcement Learning involves learning through interaction with an environment and receiving feedback in the form of rewards or penalties based on actions taken. It operates on the principle of trial and error, where an agent learns to make sequential decisions to maximize cumulative rewards over time. (IBM, 2023)

However, there are two types of artificial intelligence: weak artificial intelligence and strong artificial intelligence. An AI is considered weak if it focuses on automating specific tasks, while strong AI possesses human-like cognitive abilities, such as reasoning, problem-solving, and consciousness. Currently, we only utilize weak artificial intelligence; strong artificial intelligence does not yet exist, remaining conceptual (Glover, 2022).

2.2.2. AI technologies

2.2.2.1. Machine learning

As previously mentioned, machine learning is an inherent technique within artificial intelligence. Essentially, it involves training machines to learn patterns from past data and make decisions or predictions based on that learning. There are three primary types of learning used: supervised, unsupervised, and reinforcement learning.

Supervised learning operates with labeled data, where each example in the dataset is paired with a label indicating the correct answer (Simplilearn, 2021). On the other hand, unsupervised

learning deals with unlabeled data, requiring the machine to identify patterns or structures within the dataset without explicit guidance. Reinforcement learning trains agents, such as dogs or automated vehicles, to perform tasks by interacting with an environment, observing cues, taking actions, and receiving rewards or feedback. This iterative process refines the agent's decision-making to maximize rewards and establish an optimal policy for future actions ("What Is Reinforcement Learning?", n.d.).

Reinforcement learning also extends to human collaboration, termed Reinforcement Learning from Human Feedback (RLHF), incorporating valuable insights from human experts to enrich AI agent learning. RLHF integrates diverse forms of human-guided guidance, including explicit instructions, demonstrations, critiques, preference rankings, and error-based feedback. Unlike conventional RL, which relies solely on environmental feedback, RLHF significantly accelerates learning by leveraging human expertise to refine the agent's decision-making strategies across various complex tasks and domains (Silva, 2023).

2.2.2.2. *Big data*

Big data is a technology define as a dataset that surpass the capacity of conventional tools for management. Big data encompasses datasets characterized by increased variety, growing volumes, and accelerated velocity. These three facets, often referred to as the three Vs, represent the diverse, large, and swiftly incoming data from various sources. Essentially, big data involves managing extensive and complex datasets beyond the capacity of traditional data processing software, enabling solutions to previously challenging business problems (Oracle, 2022).

The inception of big data can be traced back to the emergence of the Web 2.0 era around 2005 when companies recognized the vast amount of data generated by users through social media and other online platforms. This exponential data growth demanded new approaches like Hadoop to collect, process, and analyze these massive volumes economically (Oracle, 2022). Big Data is a technology that can be used independently from artificial intelligence, but combining both together allows for leveraging massive datasets to train AI models, thereby accelerating analyses and decision-making. The use of both technologies together is termed Big Data Analytics and Artificial Intelligence (BDA-AI) technologies, as named by Smail Benzidia, Naouel Makaoui, and Omar Bentahar. By integrating Big Data's capacity to handle vast and varied data with AI's learning capabilities, BDA-AI technologies pave the way for advanced applications such as machine learning algorithms, natural language processing, and intelligent automation (Benzidia, Makaoui & Bentahar, 2021).

2.2.2.3. *Cloud computing*

Google defines cloud computing by “*the on-demand availability of computing resources (such as storage and infrastructure), as services over the internet. It eliminates the need for individuals and businesses to self-manage physical resources themselves, and only pay for what they use.*” (Google, n.d.).

Cloud computing revolutionizes access to computing resources by offering on-demand services over the internet. Users tap into a shared pool of resources like storage and software managed by remote servers, eliminating the need for individual or business managed physical infrastructure. This model allows for cost efficient, pay as you use access and enables scalability and flexibility in resource allocation. Cloud computing encompasses various deployment models, including public, private, and hybrid clouds, catering to diverse user needs and preferences (Google, n.d.).

Cloud computing is often combined with artificial intelligence to harness the computational power required for large-scale AI applications, including its utilization for resource management. The fusion of cloud computing and AI stands as a critical pivot, reshaping the landscape of resource management systems to confront the escalating challenges inherent in distributed computing's swift expansion and intricate complexities. Addressing the demands of future distributed computing platforms requires intricate resource management, driving the need for AI-driven methodologies capable of extracting crucial insights, learning from data, and dynamically adapting to make resource decisions. AI-centric models provide a means of managing the complexities of distributed, multi-tier computing infrastructures that are common in the cloud and edge computing areas. Such models are specifically designed to consider the dynamic nature of modern applications, networks, and Cyber-Physical-Systems. (Ilager, Muralidhar & Buyya, 2020)

2.2.2.4. *Internet of Things (IoT)*

The Internet of Things is one of the most crucial technologies in Industry 4.0, often even used as a synonym of it. This technology was able to be developed thanks to advancements in Cloud computing technology, hence these two technologies are interconnected. SAP, a producer of software for the management of business processes, defines the Internet of Things (IoT) as “*a network of connected objects and devices (aka “things”) that are equipped with sensors (and*

other technologies) that allows them to transmit and receive data – to and from other things and systems.” (SAP, n.d.). With the IoT, we can now connect all devices to the internet, not only computers or smartphones, and monitor them remotely. This new technology not only brings change but is a key part of how societies are moving towards sustainable development. The presence and adoption of modern IoT technology serve as a pivotal indicator of economic progress and growth within nations. Alongside other influential factors like skilled labor, natural resources, and diversified industry investments, this metric profoundly influences the developmental trajectory (Aliahmadi, Nozari & Ghahremani-Nahr, 2022)

To gain a better understanding of the Internet of Things (IoT), it is essential to delve into how IoT devices function, illustrated here using a smart home as an example. IoT devices consist of general components, things, such as the air conditioner or lights in this scenario. Additionally, there are sensing devices, sensors, like heat and light detectors in this context. Both types of devices are interconnected with an IoT gateway, acting as processing nodes, utilizing wired or wireless connectivity interfaces through communication protocols such as HTTP or MQTT. (Simplilearn, 2020)

The sensors detect and transmit the relevant data to the IoT gateway, which, in turn, transfers this information to the Cloud (Appendix E, Figure 3). The Cloud infrastructure includes storage and processing units. Data analysis and knowledge extraction occur here, leading to actions being executed through the general devices. Reports regarding these actions are sent to the IoT management application. In this case, if the sensors detect a drop in luminosity and a rise in temperature, they relay this information to the gateway and subsequently to the Cloud. The data is processed, triggering commands for the air conditioner to activate, lowering the temperature, and adjusting the brightness of the lights. A report detailing these actions is then sent to the control application, keeping the user informed of the system's activities (Simplilearn, 2020)

The Internet of Things can be utilized without artificial intelligence, requiring human collaboration. The convergence of both gives rise to a new technology known as the Artificial Intelligence of Things (AIoT), AIoT enables the autonomous connection of IoT devices to AI-capable sensors, allowing sensor data analysis through artificial intelligence for informed business decisions, without human intervention, a revolution in all sectors and industries (Aliahmadi, Nozari & Ghahremani-Nahr, 2022) The Artificial Intelligence of Things benefits both technologies, on one hand, artificial intelligence enhances IoT with its machine learning abilities, while on the other, IoT benefits from artificial intelligence's connectivity, signaling,

and data exchange features. IoT can be described as the digital nervous system within AIoT technology, and artificial intelligence functioning as the brain of this system (Nozari, Szmelter-Jarosz & Ghahremani-Nahr, 2022).

2.2.2.5. *Cyber-Physical System (CPS)*

The Cyber-Physical System, CPS, is an intelligent computerized systems that integrate physical processes with computational elements to achieve specific functionalities. These systems utilize controlled mechanisms and algorithms to connect software and hardware components, allowing them to operate and exhibit a diverse range of functionalities. The Cyber-Physical System and the Internet of Things are closely related concepts, with CPS often considered an extension or evolution of IoT. while IoT is about connecting devices for data exchange, CPS takes this concept further by integrating physical processes with computational elements to create intelligent systems with advanced control capabilities (Tyagi & Sreenath, 2021).

The integration of artificial intelligence into cyber-physical systems provides valuable automation, freeing humans from mundane tasks in favor of more crucial activities and embodying the concept of "working smarter, not harder." This transformative advancement reshapes business operations (Forbes, 2023). Artificial intelligence is vital for improving cyber-physical systems. It functions on the lower level, handling tasks like faulty detection, real-time prediction, control system modeling, and process optimization within CPS. The increasing complexity of these systems necessitates sophisticated decision-making tools, making artificial intelligence essential for enabling large-scale cyber-physical systems and offering real-time autonomous guidance. Artificial intelligence introduces cognition to CPS, enabling the modeling, representation, and learning of intricate behaviors and interactions between system components (Nogueira, 2021)

2.2.2.6. *Digital Twins*

According to Amazon Web Services, a digital twin is a virtual model of a physical object, utilizing real-time sensor data to simulate behavior and monitor operations throughout the object's lifecycle (Appendix E, Figure 2). It enables performance oversight, fault identification, and informed decision-making for assets like machinery, turbines, or entire urban areas (Amazon Web Services, s.d.). The term of digital twins was conceived in 2002, but it was truly realized with the development of the Internet of Things, enabling its actual implementation (Marr, 2017). However, the first use dates back to 1970 by NASA for the Apollo 13 mission.

NASA engineers used exact replicas of Apollo 13 and computer calculations to simulate and resolve scenarios to save the astronauts after a tank explosion (Adgaonkar, 2020). This technology connects the physical and digital realms, employing artificial intelligence to transform data into practical insights. The combination of AI and digital twins enables a more accurate modeling of the behaviors and operations of physical objects, facilitating finer predictions and proactive asset management. Technologies related to digital twins, such as the Internet of Things (AWS, s.d.) for data transmission, and AI, enhance the capability of digital twins to identify patterns, foresee potential failures, and recommend optimization or maintenance strategies, thereby improving operational efficiency and informed decision-making (World Intellectual Property Organization, 2019).

Although simulations may appear akin to digital twins by using digital models to replicate processes, the distinction lies in the virtual environment of digital twins, allowing richer studies. Unlike simulations focusing on singular processes, digital twins facilitate a two-way flow of real-time data from sensors to processors, enabling multifaceted simulations and comprehensive analyses for enhancing products and processes (IBM, n.d.)

There are numerous types of digital twins; here are the four most common: Component twins, Asset twins, System twins, and Process twins.

- Component twins: Representing individual parts of a larger system, such as a motor within a wind turbine, these twins play a crucial role in the functioning of an asset (AWS, s.d.).
- Asset twins: Depicting how multiple components collaborate within a system, asset twins offer insights into component interactions, producing valuable performance data for informed decision-making (AWS, s.d.).
- System twins: Operating at a higher level of abstraction, system twins exhibit the synergy among various assets within a broader system, aiding in discerning strategies for performance enhancements or efficiencies (AWS, s.d.).
- Process twins: Offering a comprehensive digital rendition of an entire object, process twins illuminate the interactions among its diverse components, assets, and units. For instance, a digital process twin can mirror the operations of an entire manufacturing facility, integrating its diverse components for holistic insights into functionality and optimization opportunities (AWS, s.d.).

Digital twins are used in various manufacturing areas, such as product design, factory optimization, supply chain management, and space simulation. These applications include

configuration management, asset management, process control, performance management, and simulation modeling (Adgaonkar, 2020).

2.2.2.7. Additive Manufacturing

The additive manufacturing is defined by Rebecca Linke, for the MIT Management Sloan School, as “*the process of creating an object by building it one layer at a time. It is the opposite of subtractive manufacturing, in which an object is created by cutting away at a solid block of material until the final product is complete.*” (Linke, 2017). The additive manufacturing and 3D printing are often used as synonyms, but they differ in some aspects. 3D printing is commonly utilized in everyday contexts, while additive manufacturing, frequently employed in industrial or technical settings, covers various techniques that create objects by adding materials incrementally. In essence, both terms denote the same manufacturing process (Linke, 2017).

To delve into further detail, let us explore how it works. The initial step in additive manufacturing involves the creation of a design. An engineer utilizes computer-aided design (CAD) software to generate a 3D design file representing the object. Subsequently, the process encompasses slicing and upload, the 3D design file undergoes slicing into thin layers, which are then uploaded to an additive manufacturing machine. Upon initiating manufacturing, a thin layer of metal powder is meticulously spread across the platform. Layer melting comes next, a heat source, such as a laser or electron beam, melts the first layer of the 3D design, bonding it to the platform. The layering process follows suit, the platform descends, and another layer of metal powder is evenly spread. This layering and melting sequence continues iteratively until the part reaches its full formation. Upon completion, the metallic powder is removed, unveiling the physical object (GE ADDITIVE, s.d.).

Additive Manufacturing can be used without artificial intelligence, but when combined, they bring new possibilities and a revolution to the sector of additive manufacturing. Artificial intelligence significantly enhances additive manufacturing by ensuring better print quality and fewer errors. It learns from data, recognizing patterns to identify optimal design, slicing, and printer settings, reducing printing failures through real-time adjustments. This accessibility improvement democratizes 3D printing by simplifying technical aspects, allowing non-technical users to achieve better results. AI functions as a Design for Manufacturing (DFM) copilot, aiding designers in efficient and effective design processes, leveraging vast datasets for machine learning algorithms. Lastly, AI revolutionizes material science, optimizing material

selection and developing innovative materials, fostering advancements in high-performance parts like aircraft turbines (Axom, 2023).

3. Supply chain and sustainable

3.1. Sustainable development

3.1.1. Definition

The UN World Commission on Environment and Development defines the sustainable development as *“A development that meets the needs of the presents, without compromising the ability of the future generations to meet their own needs.”* (Brundtland Commission, 1987).

It is about finding a balance between environmental, social, and economic aspects, aiming to ensure the preservation of natural resources, social justice, and long-term economic viability. The three "E's" of sustainable development are environment, economy, and equity. They represent the three interdependent pillars forming the basis of any sustainable development approach (UCLA, 2021). During my research on the sustainable integration of new technologies, mainly artificial intelligence, I focused on the environmental aspect.

One of the major challenges of our generation is the environmental crisis, as evidenced by numerous indicators. One of the primary indicators is the Earth Overshoot Day, which marks *“the point in the year when humanity has consumed all the natural resources the Earth can replenish within that same year.”* (European Commission, 2023). In 2023, Earth Overshoot Day occurred on August 2, indicating that to meet our global resource demand, 1.75 Earths would be necessary (European Commission, 2023). The decade spanning from 2011 to 2020 emerged as the warmest on record, witnessing a planet-wide average temperature surge of 1.1°C compared to the pre-industrial era. The greenhouse effect, primarily propelled by emissions from human activities such as carbon dioxide (CO₂), methane, and nitrous oxide, led to a 48% rise in CO₂ concentrations in the atmosphere above pre-industrial levels by 2020, further exacerbating global warming (European Environment Agency, 2023). In the upcoming sections, I will focus on one major environmental issue that has the most significant impact on the supply chain: GHG emissions.

3.1.2. GHG emissions

Carbon emissions, also known as carbon dioxide (CO₂) emissions, refer to the release of carbon dioxide into the atmosphere due to various human activities, primarily associated with the burning of fossil fuels such as coal, oil, and natural gas. These emissions play a crucial role in climate change, contributing to the increase in greenhouse gas concentrations in the atmosphere and resulting in impacts on global climate. The reduction of carbon emissions is a major concern for mitigating the effects of climate change and promoting environmental sustainability (European Parliament, 2023).

I chose to focus on greenhouse gas (GHG) emissions, including carbon dioxide equivalent (CO₂e), because they are more straightforward to calculate and provide a comprehensive measure of the environmental impact. GHG emissions encompass not only carbon dioxide but also methane (CH₄), nitrous oxide (N₂O), fluorinated gases, and others. These emissions are calculated in CO₂e to standardize their impact based on their global warming potential relative to carbon dioxide over a specified timeframe (European Parliament, 2023).

Companies utilize the three scopes (1, 2, 3) to measure and categorize GHG emissions. Scope 1 covers direct emissions from a company's operations, while Scope 2 includes indirect emissions from purchased electricity or energy. Scope 3 encompasses all other indirect emissions along the value chain, often representing a significant portion of a company's carbon footprint. Introduced in the Greenhouse Gas Protocol of 2001, these scopes form the basis for mandatory GHG reporting in the UK and are crucial for assessing environmental impacts (European Parliament, 2023; GHG Protocol, 2013).

Scope 3 emissions are divided into 15 different categories, covering various aspects such as upstream and downstream transportation, business travel, employee commuting, waste disposal, and others. Addressing Scope 3 emissions, which may account for over 70 percent of a company's footprint, requires collaboration with suppliers and changes to the supply chain to achieve net-zero ambitions (Deloitte, s.d.; GHG Protocol, 2013).

The carbon footprint, often confused with carbon emissions, are two distinct concepts. The carbon footprint not only calculates carbon emissions but encompasses all greenhouse gas emissions. Some companies calculate their carbon footprint based on the first two scopes, but to truly understand their real impact, it is necessary to consider all three scopes (Pwc, 2022)

3.2. Green supply chain

3.2.1. Definition

The sustainable supply chain can be defining as *“the consideration of social and environmental issues in all organizational processes. These processes include the entire life cycle of the supply chain from the purchase of raw materials to product design and development and warehousing and distribution and delivery of the final product.”* (Aliahmadi et al., 2022, p. 30).

The industry and supply chain are among the most polluting sectors. Given the climate urgency, the environmental aspect of sustainability has become a priority. Integrating the environment into the supply chain has become essential for legal, marketing, economic, or ecological reasons (Rubafilm, 2021). For instance, in 2022, supply chains accounted for approximately 60% of all global carbon emissions (Accenture, 2023). The environmental impact of the industry no longer confines itself to the direct effects of the first and second scopes; the third scope represents, in turn, 65–95% of most companies' carbon impact (PwC, 2022).

The concept of Green Supply Chain was introduced in 1996 by The Michigan State University Industrial Research Association (Ghahremani Nahr et al., 2022). The central concept of the green supply chain is to shift the perspective within the supply chain from merely managing pollution after its occurrence to actively reducing pollution at its source. This approach involves a comprehensive strategy encompassing prevention, treatment after pollution, at all stages of the process. The focus is on minimizing environmental impact while considering economic performance (Ying and Li-jun, 2012).

While taking into account the points mentioned earlier, the green supply chain also incorporates a cyclical approach to product life compared to the linear one-way process of the traditional supply chain. This concept is closely related to the circular economy but differs in some aspects. While circular economy principles are more focused on the overall economy-wide shift towards resource efficiency and sustainability, green supply chain management specifically addresses the environmental impact of supply chain activities within a company or industry. They complement each other as part of a broader strategy for sustainable business practices (Bimpizas-Pinis, Calzolari & Genovese, 2022).

To make a supply chain green, the first step is to establish a green strategy for the entire supply chain process (Ying and Li-jun, 2012). This involves implementing the strategy across various

stages: product design, material sourcing, production, logistics, and end-of-life product management.

3.2.2. Green design

The green design involves creating a product design that is sustainable and environmentally friendly. This design should ensure long-term sustainability by minimizing harmful effects on the environment and reducing impact after use (Aliahmadi et al., 2022). It needs to be engineered to prevent pollution, conserve resources, and save energy. In the traditional supply chain, design considerations typically revolve around quality, development cycles, and costs from manufacturing to disposal. However, in green design, additional aspects such as easy recyclability, environmentally friendly development, and minimizing adverse environmental effects while consuming minimal resources also need to be taken into account (Ying and Li-jun, 2012).

3.2.3. Green materials

Green materials refer to environmentally sustainable materials sourced, utilized, and disposed of within the supply chain to minimize environmental impact. The selection criteria for materials include considerations such as reusability, renewability, degradability, ease of handling, and biodegradability (Ying and Li-jun, 2012). Throughout the entire process, the use of materials should minimize natural resource consumption, recognizing that our consumption exceeds the Earth's capacity to replenish these resources (Aliahmadi et al., 2022). It is crucial to reduce the utilization of natural resources. Additionally, green materials encompass how raw materials are processed, not just their direct use, as the green supply chain addresses all three scopes of impact, not solely the direct impact (Ghahremani Nahr et al., 2022). To make materials greener, it is important to prioritize purchasing options with low greenhouse gas (GHG) consumption (Rolnick, Donti, Kaack, Kochanski, Lacoste, Sankaran, Ross, Milojevic-Dupont, Jaques, Waldman-Brown, Luccioni, Maharaj, Sherwin, Mukkavilli, Ko'rding, Gomes, Ng, Hassabis, Platt, Creutzig, Chayes, Bengio, 2019)

3.2.4. Green production

The green production involves manufacturing and production that are ecologically sustainable and environmentally friendly. It refers to the production of the product himself but also the factories and other elements that are used to create those products (Ghahremani Nahr et al., 2022). To make factories more environmentally friendly, it is crucial to optimize them for

renewable energy use. Additionally, measures such as proactive maintenance and the implementation of adaptive greenhouse gas emissions control are essential for streamlining heating and cooling processes (Rolnick et al., 2019). Furthermore, it involves adopting cleaner production methods, minimizing by-product environmental degradation, and reducing the utilization of natural resources throughout the entire production process (Aliahmadi et al., 2022).

Concerning the green production, one important part is to respect the ISO standards, especially the 14000 family, that are about environmental responsibilities (Ying and Li-jun, 2012). The ISO standards are decided by the International Organization for Standardization through technical committees consisting of experts from industry, governments, non-governmental organizations, and other stakeholders (International Organization for Standardization, s.d.). The 14001 ISO is the most related to green production “*ISO 14001 is an internationally agreed standard that sets out the requirements for an environmental management system. It helps organizations improve their environmental performance through more efficient use of resources and reduction of waste, gaining a competitive advantage and the trust of stakeholders.*” (International Organization for Standardization, 2015).

3.2.5. *Green logistic*

Responsible for 30-40% of the transport sector's CO₂ emissions, freight transport constitutes approximately 15% of global emissions, however, in the European Union, this share increases to 25%. When discussing the green supply chain, it is essential to reconsider logistics, which has become one of the most polluting sectors in our globalized economy (Enabel, 2022). In the realm of green logistics, optimizing shipping routes, preventing overstocking, reducing the transport of perishables, and curbing greenhouse gas emissions through cleaner transportation methods are pivotal measures (Aliahmadi et al., 2022 ; Rolnick et al., 2019). Another important aspect to consider is the packaging used throughout distribution and transport. This packaging has to adhere to the principle of 4R1D, reduce, reuse, recycle, reclaim and degradability, without the use of poisonous ingredients such as lead, mercury, and tin. Implementing disassembling package structures and streamlining packaging processes is crucial in moving towards a zero-package goal (Ying and Li-jun, 2012; Zhang and Zhao, 2011).

3.2.6. *Green consumption*

Green consumption contributes to end-of-life product management through responsible purchasing and the management of residual product value. On one hand, responsible purchasing directly involves buyers and consumers. Stanford University defines responsible purchasing as *“the acquisition of goods and services that meet the business and research needs of the consumer while also being environmentally-friendly, socially responsible, and ethically-sourced”* (Stanford University, s.d.). On the other hand, the management of residual product value is facilitated through reverse logistics, which involves analyzing and evaluating recycling schemes after a product's life cycle. The goal is to minimize environmental impact and resource waste while maximizing recycling value, with the objective of extending the product's life (Ying and Li-jun, 2012). This aspect is divided into two components, namely remanufacturing and recycling. Remanufacturing aims to prolong the direct life of the product by restoring, replacing worn parts, or repairing them, intending to refurbish the original product for reintegration into the cycle. In contrast, recycling seeks to extend the life of the materials constituting the initial product by creating new pieces or objects using residues from the original product. In instances where the object no longer holds residual value, its disposal should be considered, focusing on minimizing harmful substance emissions, maximizing energy recovery, and reducing environmental impact through techniques such as energy-recovering incineration, pyrolysis, gasification, and other environmentally conscious methods ((Aliahmadi et al., 2022; Ghahremani Nahr et al., 2022; Ying and Li-jun, 2012).

4. Artificial intelligence and sustainable supply chain

4.1. Use of artificial intelligence technics in green supply chain

4.1.1. Product design – Green design

The initial stages of product design hold significant influence over the entire supply chain, and leveraging AI technologies can greatly enhance eco-design practices (IBM, n.d.). Eco-design practices are facilitated by AI technologies, including smart product design systems and machine learning-driven approaches that prioritize user-focused sustainable product design. Additionally, big data analytics enable the deployment of green products, while cloud computing supports carbon footprint assessments. Digital twin technology plays a crucial role in energy consumption intelligent detection robotics, further enhancing the environmental sustainability of product design within the supply chain ecosystem (Feng et al., 2022).

Designing new products with the aid of artificial intelligence can significantly reduce waste and emissions during prototyping, production, and use (de Montalivet, 2023). This approach

contributes to realizing low carbon development by optimizing material usage and enhancing energy efficiency throughout the product lifecycle (Chen & Jin, 2023). AI can also assist in the design, control, and management of green supply chain management systems. Techniques such as agent-based systems, genetically modified algorithms, and expert systems enable more precise and efficient management of resources and processes, further reducing the carbon footprint of the supply chain (Kumar, Pallathadka, Sharma, Thakar, Singh and Pallathadka, 2022).

4.1.2. Sourcing – Green materials

4.1.2.1. Procurement Strategies

One approach to promoting sustainability in sourcing involves utilizing the non-dominated sorting genetic algorithm. This algorithm aids in developing models to minimize greenhouse gas emissions in the mining of natural resources. By optimizing material selection decisions, AI-driven strategies contribute to establishing closed-loop supply chains, promoting resource efficiency, and environmental conservation (Chen, Gao, Ji, Liang and Peng, 2022; Naz et al., 2022).

Furthermore, machine learning offers numerous benefits in sustainable sourcing practices. For instance, ML algorithms assist in designing environmentally friendly products through techniques like 3D printing and generative design. ML also plays a role in inventing clean materials and catalysts, thereby reducing the environmental impact of manufacturing processes (Feng et al., 2022; Rolnick et al., 2019).

Additionally, ML holds promise in the discovery of climate-friendly materials for various applications. By predicting chemical reactions, ML can aid in the development of new materials for electrocatalysts and proton conductors, facilitating processes like ammonia production while minimizing environmental harm (Rolnick et al., 2019).

Moreover, ML can contribute to climate-friendly construction by minimizing emissions associated with carbon-intensive materials. Through data analysis and optimization algorithms, ML enables the identification and utilization of cleaner and more sustainable alternatives in construction projects (Rolnick et al., 2019).

4.1.2.2. Suppliers' selection

AI-enabled operations offer various advantages, including reduced carbon emissions, availability of data, effective information sharing, and suitable supplier selection, all of which contribute to enhancing the sustainability of the supply chain (Naz et al., 2022). Digital twins allow for a thorough evaluation of suppliers based on their sustainability practices, ensuring environmentally responsible sourcing decisions (Johar, 2023).

Several approaches leverage AI to facilitate sustainable supplier selection. For instance, the Bayesian network approach identifies key issues affecting network sustainability and develops decision-making frameworks to rank sustainable suppliers, thereby promoting overall supply chain sustainability (Naz et al., 2022). Additionally, ML algorithms, as demonstrated by studies conducted by Singh et al., have proven effective in selecting low-carbon suppliers. Another noteworthy approach to predict green supplier efficiency was employed by Shabanpour et al., who utilized artificial neural networks (ANNs) and dynamic data envelopment analysis (DEA) (Wu and Zuo, 2023).

Furthermore, researchers such as Liou et al. have proposed hybrid decision-making models integrating technologies like support vector machines (SVM) for evaluating green suppliers effectively. These advancements in AI-driven supplier selection contribute to directing purchasers to low greenhouse gas options, thereby promoting eco-friendly sourcing practices (Wu and Zuo, 2023).

Moreover, the integration of AI technologies, such as the Internet of Things, facilitates data and knowledge sharing with suppliers for eco-design, while big data analytics enables the detection of environmental violations by suppliers, ensuring adherence to sustainability standards (Feng et al., 2022). With the use of digital twins, suppliers can be thoroughly assessed according to sustainability standards, and their environmental policies, social responsibility programs, and commitment to morality can all be evaluated.

4.1.3. Production - Green production

4.1.3.1. Industrial infrastructure

Industrial infrastructure plays a crucial role in making supply chains greener, with artificial intelligence driving significant advancements. AI contributes to reducing carbon emissions by optimizing industrial structures, enhancing information infrastructure, and fostering innovation in green technologies. Information infrastructure, designed to be ecologically friendly with

fewer negative externalities, promotes the dematerialization of economic activity and minimizes carbon emissions by encouraging investments in information technology. Studies indicate that AI substantially reduces carbon emissions, with each 1% advancement in AI development resulting in a 0.0024 reduction in carbon intensity, particularly in mega-cities and those with advanced infrastructure and technology levels. The mechanism behind AI's carbon emission reduction lies in its ability to optimize industrial structures, enhance information infrastructure, and drive green technological innovation (Chen et al., 2022; de Montalivet, 2023). Furthermore, digital twins facilitate the identification of resource utilization inefficiencies through real-time monitoring and analysis. This entails cutting back on energy use in manufacturing and storage facilities, streamlining transportation routes, and using less water during production (Johar, 2023).

In addition, machine learning holds promise in reducing global emissions by optimizing heating and cooling systems and prioritizing the use of clean electricity over fossil fuels. In the realm of climate-friendly construction, ML plays a crucial role in minimizing emissions by reducing the reliance on carbon-intensive materials, transforming industrial processes to operate on low-carbon energy, and even redesigning the chemistry of structural materials. ML, along with finite element modeling, has been utilized to simulate 3D printing processes, enhancing the quality of finished products. Furthermore, internal environment management leveraging IoT technology and big data analytics enables sustainable facility layout design to reduce CO₂ emissions and elevate energy efficiency. By optimizing industrial structures, strengthening electricity coupling, and rationalizing industrial processes, the SC can achieve carbon neutrality and enhance energy efficiency, ultimately contributing to a greener and more sustainable supply chain (Chen & Jin, 2023 ; Feng et al., 2022; Rolnick et al., 2019).

4.1.3.2. Predictive maintenance

To make the supply chain greener, predictive maintenance strategies leveraging artificial intelligence can play a crucial role. Predictive analytics, through AI, enables the timely identification of equipment issues, abnormal operations, and breakdowns, resulting in significant energy and carbon savings. For example, in heating systems, predictive analytics can forecast equipment failures, allowing for preemptive maintenance and preventing energy wastage. Additionally, the concept of digital twins, virtual replicas of physical assets, aids in establishing maintenance schedules and reducing the frequency of equipment breakdowns, particularly in power-generation equipment. By accurately predicting machine breakdowns, AI-

driven predictive maintenance contributes to global emissions reduction efforts, promoting sustainability across various industries (Agrawal, 2023; IBM, n.d.).

Furthermore, machine learning enhances predictive maintenance by modeling the wear and tear of machinery in real-time, enabling factory owners to minimize greenhouse gas emissions associated with equipment operation. Interpretable ML algorithms provide insights into optimizing maintenance schedules, ensuring efficient resource utilization and environmental conservation. Moreover, the integration of the Internet of Things facilitates internal environment management by monitoring energy consumption and automating system processes. Cyber-physical systems optimize maintenance schedules based on IoT data, further enhancing the sustainability of the supply chain (Feng et al., 2022; Rolnick et al., 2019).

In addition to predictive maintenance, AI-driven technologies such as 3D printing, artificial intelligence, big data analytics, and the IoT contribute to inventory recovery efforts. These technologies enable high deficit prediction capabilities, defect detection, and warranty and maintenance analysis for sensor-embedded products. By leveraging these AI-powered solutions, businesses can minimize resource wastage, optimize inventory management, and promote environmental sustainability throughout the supply chain (Feng et al., 2022).

4.1.3.3. Manufacturing

In this chapter, the focus is on leveraging artificial intelligence to make production processes more environmentally friendly within the supply chain. Machine learning, for example, can enhance manufacturing processes and optimize the entire manufacturing chain, leading to reduced energy costs. Additionally, genetic algorithms are utilized to develop new supply chain models that combine the benefits of both additive and conventional manufacturing systems, promoting closed-loop supply chain practices and additive manufacturing techniques (Chen & Jin, 2023 ; Naz et al., 2022).

Furthermore, AI-enabled operations contribute to reducing carbon emissions and enable real-time manufacturing, while also leveraging vast amounts of data to solve complex issues, thereby boosting productivity, and reducing CO₂ emissions per unit of GDP. AI technology not only enhances energy consumption efficiency in manufacturing activities but also fosters the development of green technologies to combat climate change. AI is instrumental in designing, controlling, and managing green supply chain systems, utilizing various AI techniques such as

agent-based systems, genetically modified algorithms, and expert systems (Chen et al., 2022; Kumar et al., 2022; Naz et al., 2022).

Internally, environmental management systems leverage AI technologies such collaborative robots, cyber-physical systems, the Internet of Things, machine learning, and digital twin technology to optimize production processes, improve energy efficiency, monitor energy consumption, and design energy-saving systems. For instance, digital twin technology ensures the best use of energy by reducing non-essential energy consumption and optimizing resource utilization. Additionally, machine learning assists in reducing overall electricity consumption, streamlining HVAC systems, and optimizing various manufacturing processes (Chen et al., 2022; Feng et al., 2022).

Moreover, studies have shown that the application of AI technology in the industrial sector can significantly reduce energy intensity by increasing industrial output and reducing energy consumption. Machine learning also plays a crucial role in improving energy efficiency in industrial processes, including 3D printing processes, where less energy is required, and monitoring energy consumption through AI-enabled systems. Overall, the benefits of machine learning in the supply chain extend to optimizing factories for renewables, improving quality, enabling preventive maintenance, adaptive control, detecting greenhouse gas emissions, and streamlining heating and cooling processes (Chen & Jin, 2023; Chen et al., 2022; de Montalivet, 2023; Rolnick et al., 2019).

4.1.4. Logistics – Green logistic

4.1.4.1. Stock management

Stock management stands as a pivotal component in the pursuit of greener supply chains. Integration of artificial intelligence technologies within stock management procedures presents a transformative opportunity to advance sustainability objectives within supply chains. (Naz et al., 2022)

One of the primary advantages of AI-enabled operations is that integrating smart technologies for data collection, such as IoT sensors and RFID tags, enables real-time monitoring of inventory levels, storage conditions, and product movements. This data, when analyzed by AI algorithms, empowers organizations to optimize stock levels, minimize waste, and enhance overall supply chain efficiency (Naz et al., 2022). Cutting-edge research explores the

application of deep reinforcement learning techniques for more effective management of perishable goods. This advanced AI approach holds promise for minimizing waste and optimizing stock management practices (Wu and Zuo, 2023).

Integrating smart technologies for data collection, such as IoT sensors and RFID tags, enables real-time monitoring of inventory levels, storage conditions, and product movements. This data, when analyzed by AI algorithms, empowers organizations to optimize stock levels, minimize waste, and enhance overall supply chain efficiency. A collaboration between The Vlerick Business School and the KU Leuven resulted in a new algorithm facilitating the sharing of shipping information among companies, thereby accelerating shipping, reducing costs, minimizing pollution, and promoting environmental sustainability (Kumar et al., 2022)

Transitioning from traditional Make-to-Stock (MTS) to Make-to-Order (MTO) production models, facilitated by AI integration, is a pivotal strategy for waste reduction and efficient inventory management. With AI-driven insights into demand patterns and customer preferences, businesses can dynamically adjust production to align with actual orders, eliminating excess inventory and minimizing waste. This shift optimizes manufacturing processes, maximizes resource utilization, and reduces reliance on extensive warehouse inventories, fostering sustainability across the supply chain (de Montalivet, 2023).

Furthermore, machine learning models analyze customer data to accurately forecast demand and predict consumer behavior, facilitating more efficient stock management practices. Cloud-based inventory management systems, coupled with IoT-enabled devices, offer scalable, flexible, and efficient solutions for inventory management, thereby contributing to resource optimization and waste reduction (Feng et al., 2022; Rolnick et al., 2019).

Additionally, Digital twins can lead to a 2% to 10% increase in On-Time-In-Full (OTIF) shipments. This improvement ensures that products are delivered on time and in full, reducing the need for expedited shipping methods that typically have a higher carbon footprint (Gmür, 2022).

4.1.4.2. Route optimization

Route optimization plays a crucial role in the endeavor to create greener supply chains. By leveraging artificial intelligence technologies, logistics companies can enhance their route

planning and execution processes to minimize environmental impact and improve overall efficiency (de Montalivet, 2023; Kumar et al., 2022).

First, route optimization involves fleet management, where AI algorithms analyze data to determine efficient vehicle routes, reducing fuel consumption and carbon emissions. An investigation carried out in 2018 regarding fuel management indicated that over 67 percent of companies employing industrial IoT solutions observed improvements in environmental sustainability (Kumar et al., 2022). Integrating AI-enabled operations offers benefits like reduced carbon emissions, improved on-time delivery, and enhanced data availability. Smart technologies collect data to enable AI systems for more efficient planning and control of sustainable supply chain operations (Kumar et al., 2022; Naz et al., 2022).

In addition to optimizing routes, real-time information can be leveraged to establish a sustainable "Logistics Control Tower." This tower acts as a central hub for monitoring and managing logistics operations in real-time, allowing for timely adjustments to routes and schedules to minimize environmental impact (de Montalivet, 2023).

Advanced optimization techniques, such as Multi-Objective Particle Swarm Optimization (PMOPSO) and Multi-objective Social Engineering Optimizer (MOSEO), offer solutions to address disruptions in routes and facilities. By optimizing routes holistically and creating resilient systems, these techniques contribute to the development of closed-loop supply chains, further enhancing sustainability efforts (Naz et al., 2022).

Another method for route optimization involves the use of Two-phase-based genetic algorithms to solve vehicle routing problems. These algorithms provide a robust framework for determining optimal routes, considering factors such as delivery schedules, vehicle capacity, and traffic conditions (Naz et al., 2022).

Machine learning also plays a significant role in route optimization by optimizing shipping routes and preventing overstocking. Additionally, it facilitates inventory recovery by enabling emission accounting in shipping activities, thereby promoting resource optimization and waste reduction (Feng et al., 2022; Rolnick et al., 2019).

4.1.5. End-of-life product management – Green consumption

4.1.5.1. *Waste management*

To make the supply chain greener, waste management strategies leveraging artificial intelligence are pivotal. AI technologies offer various avenues for reducing waste throughout the supply chain, focusing on minimizing the waste of raw materials and optimizing resource utilization. For instance, hybrid genetic algorithms coupled with large-scale neighborhood search algorithms are employed in reverse logistics to minimize carbon emissions, conserve resources, and protect the environment. Additionally, machine learning plays a crucial role in waste management by providing opportunities to predict air quality and efficiently sort waste, contributing to environmental protection efforts. Moreover, ML contributes to reducing food waste by optimizing delivery routes, improving demand forecasting, and enhancing refrigeration systems, thereby promoting sustainability in food supply chains (de Montalivet, 2023; Naz et al., 2022; Rolnick et al., 2019; Wu and Zuo, 2023).

Furthermore, digital twins simulate manufacturing processes to identify the most efficient methods that minimize energy use and waste. For example, switching from a high-waste machining process to a more efficient die casting method can significantly reduce material waste and associated carbon emission (Jeznach, 2023). Additionally, internal environment management practices leverage AI technologies to minimize waste generation and resource consumption. In the context of 3D printing, AI-enabled processes help lessen material waste, ensuring more sustainable production practices. Moreover, AI facilitates better management practices to reduce water usage, energy consumption, and associated emissions across various industrial operations. By enabling the efficient reorganization and rational allocation of workforce, capital, and resources, AI contributes to streamlining supply chain processes and minimizing waste generation, ultimately leading to a greener and more sustainable supply chain ecosystem (Chen & Jin, 2023; de Montalivet, 2023; Feng et al., 2022).

4.1.5.2. *Optimizing end-of-life product*

In this sub-chapter, the focus is on end-of-life product management to make the supply chain greener using artificial intelligence technologies. AI plays a crucial role in decision-making regarding the disposal and recycling of products, leveraging concepts such as digital twin technology to determine the optimal use of end-of-life products and identify materials suitable for recycling. Additionally, fuzzy programming approaches and hybrid genetic algorithms are utilized to establish efficient disposal and recycling supply chains for municipal solid waste, thereby promoting closed-loop supply chain practices and reducing recycling costs, carbon emissions, and environmental impact (IBM, n.d.; Naz et al., 2022).

Moreover, AI-enabled operations offer benefits such as reduced carbon emissions, data availability, and efficient remanufacturing, facilitating easy returns of goods and contributing to sustainable supply chain management practices. Furthermore, machine learning techniques contribute to reducing waste by enabling companies like Pirelli to avoid discarding tires unnecessarily, predict product damages or expiration, and optimize maintenance schedules through customer cooperation and internal environment management (Kumar et al., 2022; Naz et al., 2022).

Additionally, AI technologies, including big data analytics and the Internet of Things, play crucial roles in inventory recovery by facilitating remanufacturing, and the reduce, reuse, and recycle capability of products. Design strategies leverage digital twin technology to reduce waste and emissions during product prototyping, production, and use, ultimately contributing to a greener and more sustainable supply chain ecosystem (de Montalivet, 2023; Feng et al., 2022).

4.2. Artificial intelligence consumption

Mitigating the advancements in AI technologies holds paramount importance, particularly in the realm of green supply chain management. While AI offers promising solutions for enhancing efficiency, reducing waste, and optimizing resource allocation within supply chains, it is imperative to carefully evaluate whether the benefits outweigh the environmental impact. *“A recent study projects that by 2027, NVIDIA’s new AI servers will be consuming over 85.4 terawatt-hours annually, exceeding the energy usage of countries such as Sweden and Argentina”* (Xing and Monck, 2023). Furthermore, a study conducted by the University of Massachusetts Amherst reveals that the process of training a AI model can result in the emission of more than 284 tonnes of CO₂. This emission quantity is equivalent to the combined lifetime emissions of five typical American cars, thereby adding to the carbon footprint of AI, which is already nearing approximately 1% of global emissions annually (Xing and Monck, 2023).

Moreover, the challenge lies in ensuring that the efficiency gains and emission reductions achieved through AI outpace its resource consumption, necessitating concerted efforts across technology, governance, and collaborative research. Industries, policymakers, and academia must work together to develop smarter AI systems powered by renewable energy, create frameworks that encourage innovation within environmentally responsible boundaries, and

invest in exploring AI's potential in climate and clean energy realms. With responsible leadership and a balanced approach, AI can serve as a catalyst for sustainable prosperity, where technology and environmental stewardship go hand in hand, shaping a digital future that prioritizes the health of our planet (Dauvergne, 2020; Xing and Monck, 2023)

4.3. Jevons Paradox

When we delve into the topic of AI techniques used to make the supply chain greener, a concept emerges: the Jevons paradox. The Jevons' Paradox refers to the counterintuitive phenomenon where improvements in technology aimed at increasing efficiency actually lead to higher consumption of resources rather than conservation. This paradox challenges the assumption that technological progress inherently leads to reduced resource usage and environmental improvement, highlighting the complex dynamics between efficiency gains, resource consumption, and environmental impact (Polimeni and Iorgulescu Polimeni, 2006; Dauvergne 2020).

When AI technologies are applied to optimize various aspects of the supply chain, such as transportation optimization, inventory management, or predictive maintenance, they can lead to significant improvements in efficiency. However, according to the Jevons Paradox, these efficiency gains may paradoxically result in increased resource consumption rather than conservation. In the context of the green supply chain, this could mean that despite efforts to make operations more sustainable through AI-driven optimizations, the overall consumption of resources related to the supply chain may still increase (Rolnick et al., 2019).

For example, as AI streamlines transportation routes and logistics, companies may be able to deliver products faster and more efficiently, leading to increased demand and usage of transportation resources. Similarly, AI-driven energy management systems may reduce energy consumption per unit of production, but if the overall production increases due to improved efficiency, the net energy consumption may still rise (Dauvergne 2020; Rolnick et al., 2019).

4.4. Regulations and legislations

Slowing down the widespread adoption of AI is crucial to tackle ethical concerns like bias, transparency, and data privacy. AI systems can unintentionally reinforce existing biases from their training data, leading to unfair outcomes in areas like hiring, lending, and criminal justice. Furthermore, the complex nature of many AI algorithms makes it hard for people to understand

or contest decisions that impact them. Managing sensitive personal data with AI also presents significant privacy and security risks, demanding robust safeguards (Chapman University, n.d.; European Commission, 2019; European Parliament, 2023).

The European Union has made significant progress with the AI Act, aiming to create a comprehensive regulatory framework for AI across member states. Proposed in April 2021 and set to be fully adopted by 2024, the AI Act categorizes AI systems by their risk levels and sets specific requirements for high-risk applications. This legislation aims to balance innovation with the protection of fundamental rights through a risk-based approach. Additionally, the Digital Services Act and Digital Markets Act require transparency and independent audits for major tech platforms to protect consumers and prevent misuse (European Council Council of the European Union, 2024; European Parliament, 2023; Holistic AI., 2024).

Outside the EU, AI regulation varies widely. In the United States, sector-specific laws like the Algorithmic Accountability Act and the AI Bill of Rights focus on transparency and anti-discrimination. China has stringent regulations such as the Deep Synthesis Provisions, which govern the use of AI in deepfake and recommendation systems. The UK adopts a pro-innovation approach with sector-specific guidelines, aiming to balance technological advancement with ethical considerations. These different strategies highlight the global effort to ensure the safe and ethical use of AI (Holistic AI., 2024).

5. Research Question

After conducting extensive research on various AI-related technologies, I decided to focus on Digital Twins. This decision stemmed from the realization that while technologies such as machine learning and IoT have garnered significant attention and research, Digital Twins remain relatively less studied despite their remarkable potential. Digital Twins are virtual replicas of physical systems that can simulate, predict, and optimize performance in real-time. This capability makes them a fascinating subject of study, especially considering their broad applicability and transformative potential across different industries. Their ability to integrate real-time data and provide insights for decision-making sets them apart as a technology with substantial untapped potential, meriting deeper exploration.

In my quest to understand the impact of Digital Twins, I chose to focus on the electronics supply chain, particularly companies producing laptops. The electronics supply chain is a vital part of our modern lives, given the ubiquitous presence of electronic devices in both personal and

professional settings. Laptops, in particular, are essential tools in today's digital age, supporting various activities from work to education. This makes the supply chain supporting their production a compelling subject of study. Furthermore, the electronics supply chain is known for its complexity, involving multiple stages from raw material extraction to manufacturing, assembly, and distribution. This complexity provides a rich landscape for studying the impact of Digital Twin technology. Additionally, the electronics supply chain has already seen significant improvements through the integration of AI technologies, making it an excellent case study for assessing the further benefits that Digital Twins might bring.

In summary, the research question guiding this study is: *"What is the impact of integrating Digital Twins in the supply chain of laptops on the GHG emissions of major technology companies?"* This question aims to uncover the environmental benefits of Digital Twin technology in a critical and complex supply chain, providing insights that could help major technology companies optimize their operations and reduce their carbon footprints. The study will focus on the supply chains of leading laptop manufacturers and analyze data from 2019 and 2022 to provide a robust quantitative analysis.

6. Methodology research

To comprehensively investigate the impact of integrating Digital Twins into the supply chains of major technology companies on their GHG (Greenhouse Gas) emissions, a quantitative research approach will be employed. This methodological choice is motivated by the need to obtain precise, measurable, and statistically significant data to substantiate the effects of Digital Twin technology. The quantitative data will be obtained by extensively searching through various reports and publicly available data sources. Additionally, access to specific data will be facilitated through collaboration with members of these technology companies, who will provide relevant insights and information. Through the collection and analysis of numerical data, including multiple regression analysis and hypothesis testing, within the dataset will be identified. By combining quantitative data from multiple sources, this approach aims to provide a comprehensive understanding of the impact of Digital Twins on GHG emissions in the technology industry.

During my research, I encountered several challenges regarding the availability and access to accurate and official data from the companies studied. Despite my efforts to obtain information directly from companies such as Apple, Acer, Dell, HP, Lenovo, Huawei, Microsoft, and Samsung, the publicly available data remained limited. Additionally, supply chain managers

who were contacted often provided confidential information or refused to share specific details, making it difficult to use these data in my dissertation. Faced with these obstacles, I decided to rely on publicly available publications provided by these companies, particularly those detailing their use of Digital Twin technologies. This approach ensures that the information used is verifiable and accessible to everyone, while maintaining the transparency and integrity of my study.

To analyze the impact of Digital Twins on the GHG emissions of companies in the electronics sector, I structured my study around the main stages of the supply chain: product design, material sourcing, production, logistics, and end-of-life product management. This division allows for precise targeting of areas where technological improvements can have a significant effect. Digital Twins, with their simulation and real-time monitoring capabilities, can optimize each stage of the supply chain by reducing inefficiencies and improving resource utilization.

For each stage of the supply chain, I associated relevant emission categories from Scope 3 to comprehensively measure the impact of Digital Twins. (Appendix A)

7. Description of the model

7.1. Research Sub-Questions and hypotheses

The main research question: *"What is the impact of integrating Digital Twins in the supply chain of laptops on the GHG emissions of major technology companies?"*

Research Sub-Questions:

- Product Design:

How does the integration of Digital Twins in product design influence GHG emissions in the supply chain of laptops of major technology companies between 2019 and 2022?

H₀: Integrating Digital Twins in product design has no significant impact on GHG emissions.

H₁: Integrating Digital Twins in product design significantly reduces GHG emissions.

- Material Sourcing:

What is the impact of Digital Twins on GHG emissions related to material sourcing in the supply chain of laptops of major technology companies between 2019 and 2022?

H₀: Using Digital Twins for material sourcing does not significantly affect GHG emissions.

H₁: Using Digital Twins for material sourcing significantly reduces GHG emissions.

- Production:

How do Digital Twins influence GHG emissions during the production phase in the supply chain of laptops of major technology companies between 2019 and 2022?

H₀: Integrating Digital Twins in production has no significant impact on GHG emissions.

H₁: Integrating Digital Twins in production significantly reduces GHG emissions.

- Logistics:

What is the impact of Digital Twins on GHG emissions related to logistics in the supply chain of laptops of major technology companies between 2019 and 2022?

H₀: Using Digital Twins for logistics does not significantly affect GHG emissions.

H₁: Using Digital Twins for logistics significantly reduces GHG emissions.

- End-of-Life Product Management:

How do Digital Twins influence GHG emissions during end-of-life product management in the supply chain of laptops of major technology companies between 2019 and 2022?

H₀: Integrating Digital Twins in end-of-life product management has no significant impact on GHG emissions.

H₁: Integrating Digital Twins in end-of-life product management significantly reduces GHG emissions.

7.2. Indexes

i = indexes of the company. [Apple Inc.=1, Acer Inc.=2, Dell Technologies Inc.=3, HP Inc.= 4, Lenovo Group Limited=5, Microsoft Corporation=6, Samsung Electronics Co., Ltd. =7]

For my study, I have chosen to study these companies as the population because they are leaders in the electronics sector, particularly in the market for laptops. Additionally, they provide information on their use or name of Digital Twins. Other significant players in the electronics industry, such as Asus and Huawei, were also considered. However, due to their lack of

transparency regarding emissions, waste management, and energy efficiency practices, they were not included in the study population.

t = indexes of the time period in year. [2019;2022]

7.3. Intercept

β_0 = Intercept term.

This term represents the baseline GHG emissions of companies, even in the absence of using Digital Twins or other factors. It captures the reference level of GHG emissions.

7.4. Regression coefficients

$\beta_{1,2,3,4,5,6,7,8,9}$ = Coefficients for the independent variables.

Each of these coefficients quantifies the effect of each independent variable on GHG emissions.

7.5. Error term

ϵ_{it} = Error term for the company i at the time t .

This term captures all unmodeled influences and factors that affect companies' GHG emissions and are not accounted for by the independent variables in the model. It represents the discrepancy between predicted and observed values of GHG emissions and may include random variations, measurement errors, or unobserved variables.

7.6. Dependent Variable

- $Emission_{it}$ = GHG emissions, Appendix D, Table 1
 - $Emission1_{it}$ = Scope 1, Appendix D, Table 2
 - $Emission2_{it}$ = Scope 2, Appendix D, Table 3
 - $Emission3_{it}$ = Scope 3, Appendix D, Table 4
 - $EmissionCat1_{it}$ = Category 1: Purchased Goods and Services, Appendix D, Table 5
 - $EmissionCat3_{it}$ = Category 3: Fuel- and energy-related activities (not included in scope 1 or scope 2), Appendix D, Table 6
 - $EmissionCat4_{it}$ = Category 4: Upstream transportation and distribution, Appendix D, Table 7

- $EmissionCat5_{it}$ = Category 5: Waste generated in operations, Appendix D, Table 8
- $EmissionCat6_{it}$ = Category 6: Business travel, Appendix D, Table 9
- $EmissionCat9_{it}$ = Category 9: Downstream transportation and distribution, Appendix D, Table 10
- $EmissionCat11_{it}$ = Category 11: Use of sold products, Appendix D, Table 11
- $EmissionCat12_{it}$ = Category 12: End-of-life treatment of sold products, Appendix D, Table 12

7.7. Independent Variables

- Iso certification:

- $Iso1_{it}$ = ISO14001, Appendix D, Table 18

This variable indicates whether company i at time t is certified with ISO 14001, which is the international standard for environmental management systems. ISO 14001 helps organizations improve their environmental performance through more efficient use of resources and reduction of waste. Including ISO 14001 in the model is useful because it can provide insights into how formalized environmental management systems affect a company's carbon emissions.

- $Iso2_{it}$ = ISO50001, Appendix D, Table 19

This variable denotes whether company i at time t has achieved ISO 50001 certification. ISO 50001 provides a framework for organizations to manage and improve their energy performance, which can result in significant reductions in energy consumption and greenhouse gas emissions. This systematic approach to energy management is crucial for companies seeking to enhance their environmental sustainability efforts and mitigate climate impact. Including this variable in the model allows us to assess the effectiveness of ISO 50001 implementation in reducing carbon emissions and improving overall energy efficiency.

- $Iso3_{it}$ = ISO14064, Appendix D, Table 20

This variable represents whether company i at time t is certified with ISO 14064, which pertains to the quantification and reporting of greenhouse gas emissions and removals. ISO 14064 provides a set of tools for programs aimed at reducing greenhouse gas emissions, as well as for emissions trading. Including ISO 14064 in the model is important as it can indicate the

extent to which transparent and verified greenhouse gas reporting influences overall carbon emissions.

Including these ISO certification variables in the model helps in understanding how adherence to international standards impacts carbon emissions. By analyzing the relationship between ISO certifications and emissions, we can infer whether companies that follow these rigorous standards experience significant reductions in their carbon footprint. This information can be critical for policy makers, industry leaders, and stakeholders who aim to promote sustainable practices within the industry.

- $Size_{it}$ = Annual Revenue in billion in usd, Appendix D, Table 21

This variable represents the size of company i at time t , quantified by the company's revenue, measured in billions of USD. Enterprise size is a significant factor because larger companies often have more extensive operations, which can lead to higher carbon emissions due to increased production, logistics, and energy consumption. Conversely, larger companies may also have more resources to invest in sustainable technologies and practices, such as Digital Twins.

- DT_{it} = Public mention of the use of Digital twin yes or no
 - $DT1_{it}$ = Public mention of the use of Digital twin in product design step of the supply chain, Appendix D, Table 27
 - $DT2_{it}$ = Public mention of the use of Digital twin material in sourcing step of the supply chain, Appendix D, Table 28
 - $DT3_{it}$ = Public mention of the use of Digital twin in production step of the supply chain, Appendix D, Table 29
 - $DT4_{it}$ = Public mention of the use of Digital twin in logistics step of the supply chain, Appendix D, Table 30
 - $DT5_{it}$ = Public mention of the use of Digital twin in end-of-life product management step of the supply chain, Appendix D, Table 31

Indicates whether a company i publicly acknowledges using Digital Twins in its operations at a specific time t . This binary measure is relevant in the model because it reflects the company's transparency and commitment to adopting advanced technologies. Public mentions signify a proactive approach to innovation and sustainability, influencing stakeholder perceptions and demonstrating leadership in integrating Digital Twins to enhance operational efficiency and environmental sustainability within the electronics supply chain.

- RD_{it} = Investment in Research and Development, Appendix D, Table 22

Quantifies the financial resources allocated to research and development activities within the company, measured in billions of USD. R&D investment drives innovation in sustainable technologies like Digital Twins, which can enhance energy efficiency and reduce environmental impact.

- RE_{it} = Use of renewable electricity in % of the total electricity use among the supply chain, Appendix D, Table 23

It represents the proportion of renewable electricity used, ranging from 0 to 1. This metric is critical as renewable energy sources significantly reduce carbon intensity and environmental impact. Monitoring the adoption of renewable electricity provides valuable insights into the company's efforts to mitigate GHG emissions and promote sustainable energy practices.

- Waste:
 - W_{it} = Nonhazardous waste generated, Appendix D, Table 26

Measures the environmental impact of nonhazardous waste generation in company i 's at time t operations in metric tons, which correlates with GHG emissions from waste management processes.

- Wr_{it} = Nonhazardous waste recycled or reused, Appendix D, Table 24

Indicates the extent to which nonhazardous waste is recycled or reused, contributing to GHG emission reductions by minimizing landfill emissions and conserving energy used in raw material extraction. This variable is measured as the percentage of nonhazardous waste that is recycled or reused, on a scale from 0 to 1.

- $Wwte_{it}$ = Nonhazardous waste recovery (waste to energy), Appendix D, Table 25

Measures the conversion of nonhazardous waste into energy, which can offset GHG emissions by substituting fossil fuels with renewable energy sources, thus contributing to overall emissions reduction efforts. This variable is measured as the percentage of nonhazardous waste converted into energy, on a scale from 0 to 1.

7.8. Multiple regression formula

- Multiple regression formula for the general model.

$$\ln(Emission_{it}) = \beta_0 + \beta_1 Iso1_{it} + \beta_2 Iso2_{it} + \beta_3 Iso3_{it} + \beta_4 \ln(Size_{it}) + \beta_5 DT_{it} + \beta_6 \ln(RD_{it}) + \beta_7 RE_{it} + \beta_8 \ln(W_{it}) + \beta_9 Wr_{it} + \beta_{10} Wwte_{it} + \epsilon_{it}$$

- Multiple regression formula to test the sub-question on product design.

$$\ln(EmissionCat1_{it} + EmissionCat3_{it}) = \beta_0 + \beta_1 Iso1_{it} + \beta_2 Iso2_{it} + \beta_3 Iso3_{it} + \beta_4 \ln(Size_{it}) + \beta_5 DT1_{it} + \beta_6 \ln(RD_{it}) + \beta_7 RE_{it} + \beta_8 \ln(W_{it}) + \beta_9 Wr_{it} + \beta_{10} Wwte_{it} + \epsilon_{it}$$

- Multiple regression formula to test the sub-question on material sourcing.

$$\ln(EmissionCat1_{it} + EmissionCat3_{it} + EmissionCat4_{it}) = \beta_0 + \beta_1 Iso1_{it} + \beta_2 Iso2_{it} + \beta_3 Iso3_{it} + \beta_4 \ln(Size_{it}) + \beta_5 DT2_{it} + \beta_6 \ln(RD_{it}) + \beta_7 RE_{it} + \beta_8 \ln(W_{it}) + \beta_9 Wr_{it} + \beta_{10} Wwte_{it} + \epsilon_{it}$$

- Multiple regression formula to test the sub-question on production.

$$\ln(Emission1_{it} + Emission2_{it} + EmissionCat1_{it} + EmissionCat3_{it} + EmissionCat5_{it}) = \beta_0 + \beta_1 Iso1_{it} + \beta_2 Iso2_{it} + \beta_3 Iso3_{it} + \beta_4 \ln(Size_{it}) + \beta_5 DT3_{it} + \beta_6 \ln(RD_{it}) + \beta_7 RE_{it} + \beta_8 \ln(W_{it}) + \beta_9 Wr_{it} + \beta_{10} Wwte_{it} + \epsilon_{it}$$

- Multiple regression formula to test the sub-question on logistics.

$$\ln(Emission1_{it} + Emission2_{it} + EmissionCat4_{it} + EmissionCat9_{it}) = \beta_0 + \beta_1 Iso1_{it} + \beta_2 Iso2_{it} + \beta_3 Iso3_{it} + \beta_4 \ln(Size_{it}) + \beta_5 DT4_{it} + \beta_6 \ln(RD_{it}) + \beta_7 RE_{it} + \beta_8 \ln(W_{it}) + \beta_9 Wr_{it} + \beta_{10} Wwte_{it} + \epsilon_{it}$$

- Multiple regression formula to test the sub-question on end-of-life product management.

$$\ln(EmissionCat5_{it} + EmissionCat11_{it} + EmissionCat12_{it}) = \beta_0 + \beta_1 Iso1_{it} + \beta_2 Iso2_{it} + \beta_3 Iso3_{it} + \beta_4 \ln(Size_{it}) + \beta_5 DT5_{it} + \beta_6 \ln(RD_{it}) + \beta_7 RE_{it} + \beta_8 \ln(W_{it}) + \beta_9 Wr_{it} + \beta_{10} Wwte_{it} + \epsilon_{it}$$

8. Results

8.1. General model

To carry out my analyses, I used R Studio, an IDE for R, designed for statistics and data science, due to its extensive packages for data manipulation, visualization, and statistical analysis.

I primarily used the `plm` function from the `plm` package, designed for panel data analysis, which models data by accounting for temporal and inter-company structures. Initially, I used the fixed effects model (within model) to control for unobserved effects constant over time within each entity and study the impact of integrating digital twins on carbon emissions.

However, this initial approach did not yield significant results. Most variables were not statistically significant, leading to an overall non-significant model (details in Appendix F, Figure 4). The overall statistics indicated a poor model fit, with an R-squared value of 0.28503 and an adjusted R-squared value of -0.48494.

To enhance the significance of my variables, I switched to a pooling model using the `plm` function. This model assumes that regression coefficients are the same for all entities and periods, potentially increasing statistical power. In the pooling model, several coefficients were significant, and the overall statistics were much more favorable, with an R-squared value of 0.93794 and an adjusted R-squared value of 0.90691 (details in Appendix F, Figure 5).

Comparing the two models, the pooling model provided a much better fit and explained a greater proportion of the variance in carbon emissions. The significant coefficients in the pooling model highlighted the impact of factors such as company size, research and development expenditures, renewable energy usage, and workforce practices on emissions. Despite some methodological limitations, the pooling model offered more robust and statistically significant results, providing better insights into the effectiveness of digital twin integration in reducing carbon emissions across different scopes.

In the general model using the pooling method, the variable representing the impact of digital twins' integration did not show statistical significance overall. This suggests that digital twins' integration did not significantly impact the variations in carbon emissions across the studied companies. To delve deeper, I will examine the specific improvements brought by digital twins and study their impact on total annual emissions, as well as emissions specific to scopes 1, 2, and 3, and the categories within scope 3 influenced by these improvements.

8.2. Result conclusion

The results of this analysis indicate that only the integration of Digital Twins in the material sourcing step has a significant impact on Scope 1 carbon emissions. Specifically, the p-value for the Scope 1 emissions model in this context was 0.0091001, and the estimate was negative, suggesting a significant negative effect on carbon emissions. Therefore, the null hypothesis, H_0 , for Scope 1 emissions in the material sourcing step was rejected, and the alternative hypothesis, H_1 , was supported.

In contrast, the other models did not yield statistically significant results, with all p-values exceeding the conventional threshold of 0.05. This lack of significance suggests that the integration of Digital Twins in these areas did not substantially affect GHG emissions within the studied timeframe. As a result, the null hypotheses, H_0 , for product design, production, logistics, and end-of-life product management steps were not rejected, and the alternative hypotheses, H_1 , were not supported.

These findings will be further discussed and evaluated in the subsequent section, where the results will be contextualized and analyzed more thoroughly. The discussion will also address whether the chosen model was appropriate and relevant for this analysis, considering its strengths and limitations. The complete details of the results can be found in Appendix C.

8.3. Analysis of the result

Following the results of my study, I interviewed Amol Adgaonkar, Sr. Director of Manufacturing & Supply Chain at Microsoft, a leading expert in the use of Digital Twins throughout the supply chain, to gain further insights and conclusions. Having observed the evolution of this technology over the years, his perspective is particularly insightful.

Amol Adgaonkar emphasized that Digital Twins can be applied across all stages of the supply chain, enhancing both efficiency and accuracy. However, he noted that their application is more limited in logistics due to the involvement of numerous third-party providers. This fragmentation often results in incomplete access to logistics information, thus diminishing the effectiveness of Digital Twins in this area.

One of the stages in the supply chain where Digital Twins are most useful is the design phase. To achieve the greatest impact, it is crucial to implement changes upstream in the supply chain.

Digital Twins facilitate extensive simulations and validations of design modifications, allowing companies to test and refine designs before physical production, leading to improved outcomes and reduced costs.

Adgaonkar highlighted the importance of short-term pilot projects in the successful implementation of Digital Twins. These projects typically last a few weeks, such as six to ten weeks, and focus on identifying specific pivot points or key value indicators. The goal is to achieve measurable results within the first quarter. This approach is particularly vital in high-tech sectors where rapid results are essential for maintaining a competitive edge.

Finally, Adgaonkar advocated for the application of the Pareto principle in the deployment of Digital Twins. By focusing on the 20% of technology that can deliver 80% of the benefits, companies can achieve substantial improvements in efficiency and performance without overcomplicating their operations.

9. Conclusion

9.1. Relationship AI technologies used together

Measuring the impact of integrating artificial intelligence technology into the supply chain is very complex, as these technologies are often used jointly and complement each other for multiplied efficiency. Using the example of Digital Twins with IoT, we see that this combination greatly enhances the impact and brings numerous benefits.

The integration of IoT and Digital Twin technologies, especially when combined with artificial intelligence (AI), creates a powerful synergy that significantly improves the effectiveness and efficiency of both technologies. IoT provides the real-time data necessary to create and update Digital Twins, allowing these virtual replicas to reflect the actual conditions and performance of their physical counterparts. This real-time synchronization enables more accurate monitoring, predictive maintenance, and operational optimization. AI enhances this process by analyzing the vast amounts of data generated by IoT devices, identifying patterns, and making intelligent predictions to improve decision-making. The combination of IoT and Digital Twins, augmented by AI, unlocks new possibilities for innovation and optimization across various industries, making their combined use extremely effective and transformative.

9.2. Limitation

The first limitation encountered is that even though Digital Twin technology is not so recent, it is constantly evolving and linked to artificial intelligence, developing faster and faster at every moment. Most studies on the subject are already outdated by the time they are published, so it is really complicated to give an accurate picture of the current situation.

Secondly, related to the first limitation, the data studied to measure the impact of this technology is often available to the public, but when it is, it is "late" after the time it was recorded. This makes the studies conducted on the subject even more obsolete. Moreover, most of the data necessary to measure the impact of integrating Digital Twins within entire supply chains is confidential to companies, making it very difficult to access. Even once this access is obtained, we cannot publish this information in our studies, rendering it unusable. However, it is normal, mainly for competitive reasons, for this data to remain confidential, but this complicates studies on the subject. Continuing on the availability of data, to analyze the impact of Digital Twins in different companies, it was necessary for this data to be measured in the same way or at least convertible to a common scale. However, apart from the most general data such as emissions and waste, if we wanted to go further and take more precise and specific data for my study, it was either not calculated by the company or calculated in a completely different way, making it unusable. For example, I had to exclude Huawei and Asus from my study because they were opaque about several necessary pieces of information, such as their carbon emissions or waste generated.

Amol Adgaonkar emphasized that the importance of data cannot be overstated. At Microsoft, the Microsoft Cloud for Sustainability, developed to help companies analyze their data in a unified manner, is utilized to facilitate studies in line with ESG criteria and to achieve their sustainability goals. This unified approach helps in obtaining more accurate and comprehensive insights and can serve as a starting point for addressing the challenge of data analysis in the integration of Digital Twins.

Furthermore, studying the impact of a technology on the supply chain of products such as laptops produced by multinational companies is very complex. These companies employ many resources, using different technologies simultaneously to optimize and innovate their supply chains to reduce their carbon emissions. Therefore, it is complicated, if not impossible, to isolate the impact of integrating such a technology. Additionally, in the technology and IT sector, these

companies do not only manufacture laptops, but they also have very diverse activities, from managing data centers and cloud services to designing household appliances and mobile phones. It is therefore very complicated to isolate emissions related to laptops and thus measure the impact of such an integration.

According to Amol Adgaonkar, there are two types of limitations: artificial and natural. He highlighted that the artificial limits imposed by budget constraints are the most problematic. Companies may question the practicality of improving the quality of features that they might not frequently use, even though these improvements could provide significant benefits.

Furthermore, Adgaonkar pointed out the natural limits related to the realism of current programs. These programs are designed to address specific questions but often fall short of expectations. There is a reluctance to invest more in the necessary research to enhance these systems, which impacts their accuracy, quality of responses, and overall system awareness.

9.3. Future opportunity

Amol Adgaonkar identified several key opportunities for the future use of Digital Twins, particularly with the integration of advanced AI technologies. One significant opportunity is the use of Generative AI at each step of the supply chain. Generative AI can communicate across various stages and extract results seamlessly. For example, using natural language processing, stakeholders can query factories directly, asking questions such as, "How is my performance?" or "How's the quality?" This direct communication can lead to more efficient and effective management of the supply chain.

Additionally, neural networks present another promising opportunity. According to Adgaonkar, by training a neural network with a vast amount of historical data and utilizing reinforcement learning, companies can simulate numerous scenarios and optimize their operations. Deep reinforcement learning can further enhance these capabilities, providing even more sophisticated and accurate predictions and decision-making tools.

10. Bibliographie

- Accenture. (2023, November 24). *N/A*. <https://www.accenture.com/us-en/insights/supply-chain-operations/supply-chains-key-unlocking-net-zero-emissions>
- Acer Incorporated. (2020a). *Corporate Social Responsibility Report 2019*.
- Acer Incorporated. (2020b). *Acer Incorporated 2019 annual report*.
- Acer Incorporated. (2021a). *ACER CORPORATE RESPONSIBILITY REPORT 2020*.
- Acer Incorporated. (2021b). *Acer Incorporated 2020 Annual Report* [Report]. <http://mops.twse.com.tw>
- Acer Incorporated. (2022a). *Acer Incorporated 2021 Annual Report*.
- Acer Incorporated. (2022b). *Acer Sustainability Report 2021*.
- Acer Incorporated. (2023a). *2022 SUSTAINABILITY REPORT*.
- Acer Incorporated. (2023b). Acer Incorporated 2022 Annual report. In *Acer Incorporated 2022 Annual Report*. <http://mops.twse.com.tw>
- Additive manufacturing, explained* | MIT Sloan. (2017, December 7). MIT Sloan. <https://mitsloan.mit.edu/ideas-made-to-matter/additive-manufacturing-explained>
- Adgaonkar, A. (2020a). Enhance innovation and agility with Digital Twins. In *Microsoft Corporation*.
- Adgaonkar, A. (2020b, December 14). *Manufacturers gain a competitive advantage with digital twins*. Microsoft Industry Blogs. <https://www.microsoft.com/en-us/industry/blog/manufacturing-and-mobility/2020/12/14/manufacturers-gain-a-competitive-advantage-with-digital-twins/>
- Agrawal, V. (2023, December 4). Decarbonization in the industrial sector: How digital twins can support sustainability efforts. *Forbes*. <https://www.forbes.com/sites/forbestechcouncil/2023/12/04/decarbonization-in-the-industrial-sector-how-digital-twins-can-support-sustainability-efforts/?sh=6558224d35bf>
- Aliahmadi, A., Nozari, H., & Ghahremani-Nahr, J. (2022). AIOT-based Sustainable Smart Supply Chain Framework. *International Journal of Innovation in Management Economics and Social Sciences*, 2(2), 28–38. <https://doi.org/10.52547/ijimes.2.2.28>
- Almusaed, A., Yitmen, İ., & Almssad, A. (2023). Reviewing and Integrating AEC Practices into Industry 6.0: Strategies for Smart and Sustainable Future-Built Environments. *Sustainability*, 15(18), 13464. <https://doi.org/10.3390/su151813464>
- Andaluz, E. (2017, October 23). *The Process Digital Twin: A step toward operational excellence*. Microsoft Industry Blogs. <https://www.microsoft.com/en->

- us/industry/blog/manufacturing-and-mobility/2017/10/23/the-process-digital-twin-a-step-toward-operational-excellence/
- Apex Companies, LLC, Donaghu, T. A., & Reilly, D. C. (2021). *Independent Verification opinion*.
- Apex Companies, LLC, Malhotra, A., & Donaghu, T. (2021). *VERIFICATION OPINION DECLARATION GREENHOUSE GAS EMISSIONS*.
- Apple Inc. (2020). *2020 Environmental Progress Report Covering fiscal year 2019*.
- Apple Inc. (2021a). *2021 Environmental Progress Report Covering fiscal year 2020*.
- Apple Inc. (2021b). *Apple Inc. Financial Report*. https://www.apple.com/newsroom/pdfs/FY21_Q4_Consolidated_Financial_Statements.pdf
- Apple Inc. (2021c). Apple's 2021 ESG report. In *Apple's 2021 ESG Report*. https://s2.q4cdn.com/470004039/files/doc_downloads/2021/08/2021_Apple_ESG_Report.pdf
- Apple Inc. (2022a). *2022 Environmental Progress Report Covering fiscal year 2021*.
- Apple Inc. (2022b). *Apple's 2022 ESG report*. https://s2.q4cdn.com/470004039/files/doc_downloads/2022/08/2022_Apple_ESG_Report.pdf
- Apple Inc. (2023). *2023 Environmental Progress Report covering fiscal year 2022*. https://www.apple.com/environment/pdf/Apple_Environmental_Progress_Report_2023.pdf
- Apple Inc. (2024a). *2024 Environmental Progress Report Covering fiscal year 2023*.
- Apple Inc. (2024b). *CONDENSED CONSOLIDATED STATEMENTS OF OPERATIONS*. https://www.apple.com/newsroom/pdfs/fy2023-q4/FY23_Q4_Consolidated_Financial_Statements.pdf
- Axsom, T. (2023, July 17). *5 Ways AI is Impacting 3D Printing | Fictiv*. Fictiv. <https://www.fictiv.com/articles/5-ways-ai-is-impacting-3d-printing>
- Bechade, C. (2024, February 25). Le chiffre : 75% de l'empreinte carbone de votre mobile est générée avant même qu'il arrive dans vos mains. *Les Numériques*. <https://www.lesnumeriques.com/telephone-portable/le-chiffre-75-de-l-empreinte-carbone-de-votre-mobile-est-generee-avant-meme-qu-il-arrive-dans-vos-mains-n218841.html>
- Benzidia, S., Makaoui, N., & Bentahar, O. (2021). The impact of big data analytics and artificial intelligence on green supply chain process integration and hospital environmental performance. *Technological Forecasting and Social Change*, 165, 120557. <https://doi.org/10.1016/j.techfore.2020.120557>

- BEYOND DIGITAL TWIN: Small and medium-sized manufacturers enjoy big-enterprise benefits and ROI with Virtual Twin Experience on the cloud. (n.d.). In *Dassault Systèmes*. <https://discover.3ds.com/beyond-digital-twin>
- Bimpizas-Pinis, M., Calzolari, T., & Genovese, A. (2022). Exploring the transition towards circular supply chains through the arcs of integration. *International Journal of Production Economics*, 250, 108666. <https://doi.org/10.1016/j.ijpe.2022.108666>
- Bizwire, K. (2023, May 22). *Samsung launches Digital Twin Task Force to enhance efficiency in chip manufacturing - Be Korea-savvy*. Be Korea-savvy. <http://koreabizwire.com/samsung-launches-digital-twin-task-force-to-enhance-efficiency-in-chip-manufacturing/249072>
- CAD-IT IOT CENTRE & Hewlett Packard. (2021). *THE ROLE OF DIGITAL TWIN IN FACTORY TRANSFORMATION* (No. a50004409ENW; p. 3).
- CDP Report - Acer Inc. (n.d.). CDP. <https://www.cdp.net/en/responses/316/Acer-Inc>
- CDP Report - Apple Inc. (n.d.). CDP. <https://www.cdp.net/en/responses/865/Apple-Inc>
- CDP Report - Dell Technologies (n.d.). CDP. <https://www.cdp.net/en/responses/64620/Dell-Technologies>
- CDP Report - HP Inc (n.d.). CDP. <https://www.cdp.net/en/responses/58858/HP-Inc>
- CDP Report - Lenovo Group Limited (n.d.). CDP. <https://www.cdp.net/en/responses/21407/Lenovo-Group-Limited>
- CDP Report - Microsoft Corporation (n.d.). CDP. <https://www.cdp.net/en/responses/11930/Microsoft-Corporation>
- CDP Report - Samsung Electronics (n.d.). CDP. <https://www.cdp.net/en/responses/16191/Samsung-Electronics>
- Cea. (n.d.). *L'intelligence artificielle*. CEA/Découvrir & Comprendre. <https://www.cea.fr/comprendre/Pages/nouvelles-technologies/essentiel-sur-intelligence-artificielle.aspx>
- CEA. (2018, April 12). *[Comment ça marche ?] Le fonctionnement d'une intelligence artificielle (IA)* [Video]. YouTube. <https://www.youtube.com/watch?v=hutQlyF750s>
- Certifications et écolabels | Dell FRANCE. (n.d.). <https://www.dell.com/fr-fr/dt/corporate/social-impact/esg-resources/certifications.htm#scroll=off>
- Chari, S. (2023, January 17). *Lenovo Drives Sustainable Product Development with Virtual Twins*. <https://blog.3ds.com/brands/simulia/lenovo-drives-sustainable-product-development-virtual-twins/>
- Chen, P., Gao, J., Ji, Z., Liang, H., & Peng, Y. (2022). Do Artificial Intelligence Applications Affect Carbon Emission Performance?—Evidence from Panel Data Analysis of Chinese Cities. *Energies*, 15(15), 5730. <https://doi.org/10.3390/en15155730>

- Chen, Y., & Jin, S. (2023). Artificial intelligence and carbon emissions in manufacturing firms: The Moderating role of Green Innovation. *Processes*, 11(9), 2705. <https://doi.org/10.3390/pr11092705>
- Climate change mitigation: reducing emissions. (2023, December 19). <https://www.eea.europa.eu/en/topics/in-depth/climate-change-mitigation-reducing-emissions?activeTab=fa515f0c-9ab0-493c-b4cd-58a32dfaae0a>
- Climate change: the greenhouse gases causing global warming | News | European Parliament.(n.d).<https://www.europarl.europa.eu/news/en/headlines/society/20230316STO77629/climate-change-the-greenhouse-gases-causing-global-warming>
- Coremans, E. (2022, February 24). *Freight transport and CO2: a complex and paradoxical relationship*. Trade for Development Centre. <https://www.tdc-enabel.be/en/2022/02/24/freight-transport-and-co2-a-complex-and-paradoxical-relationship/#:~:text=Freight%20transport%20is%20responsible%20for,about%2015%25%20of%20global%20emissions.>
- Dassault Systèmes. (n.d.). *LCFC ELECTRONICS TECHNOLOGY*. <https://www.3ds.com/insights/customer-stories/lcfc-electronics-technology>
- Dauvergne, P. (2020). Is artificial intelligence greening global supply chains? Exposing the political economy of environmental costs. *Review of International Political Economy*, 29(3), 696–718. <https://doi.org/10.1080/09692290.2020.1814381>
- Dell. (2020, December 1). *The future of digital twins*. <https://www.dell.com/en-us/perspectives/the-future-of-digital-twins/>
- Dell Technologies. (2024, April 4). *Industrial Digital Twin Demo powered by Dell Technologies* [Video]. YouTube. <https://www.youtube.com/watch?v=JgRk4AdpuTc>
- Dell Inc. (2023). *A partnership of trust: Dell Supply Chain Security*. https://i.dell.com/sites/csdocuments/CorpComm_Docs/en/supply-chain-assurance.pdf?newtab=true
- Dell Technologies. (2019). *FY19 Corporate Social Responsibility Report*.
- Dell Technologies. (2020). *FY20 Social Impact Report*.
- Dell Technologies. (2021). *FY21 ESG Report*.
- Dell Technologies. (2022). *FY22 Environmental, Social and Governance Report*.
- Dell Technologies. (2023a). *FY23 Environmental, Social and Governance Report*.
- Dell Technologies. (2023b). *YOUR DIGITAL TWIN NEEDS EDGE COMPUTING*.
- Deloitte. (2023). CONSOLIDATED FINANCIAL STATEMENTS OF SAMSUNG ELECTRONICS CO., LTD. AND ITS SUBSIDIARIES. In *CONSOLIDATED*

- FINANCIAL STATEMENTS* (pp. 1–15). https://images.samsung.com/is/content/samsung/assets/global/ir/docs/2022_con_quarter04_all.pdf
- Deloitte Anjin LLC. (2021). CONSOLIDATED FINANCIAL STATEMENTS OF SAMSUNG ELECTRONICS CO., LTD. AND ITS SUBSIDIARIES. In *Independent Auditors' Report* (pp. 1–5) [Report]. https://images.samsung.com/is/content/samsung/assets/global/ir/docs/2020_con_quarter04_all.pdf
- Deloitte Anjin LLC. (2022). CONSOLIDATED FINANCIAL STATEMENTS OF SAMSUNG ELECTRONICS CO., LTD. AND ITS SUBSIDIARIES. In *Independent Auditors' Report* (pp. 1–4). https://images.samsung.com/is/content/samsung/assets/global/ir/docs/2021_con_quarter04_all.pdf
- Dhamija, P., & Bag, S. (2020). Role of artificial intelligence in operations environment: a review and bibliometric analysis. *The Tqm Journal*, 32(4), 869–896. <https://doi.org/10.1108/tqm-10-2019-0243>
- Digital twins: From one twin to the enterprise metaverse*. (2022, October 10). McKinsey & Company. <https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/digital-twins-from-one-twin-to-the-enterprise-metaverse>
- Digital Twins & Gen AI on Azure*. (n.d.). <https://cratedb.com/resources/webinars/confirmation-digital-twins-gen-ai-on-azure?submissionGuid=b13d2773-7c58-4c55-bda8-da917fda7451>
- Earth Overshoot Day and EMAS: Moving the date for a Sustainable future*. (2023, August 1). Green Business. https://green-business.ec.europa.eu/news/earth-overshoot-day-and-emas-moving-date-sustainable-future-2023-08-01_en
- Edmunds, T., Dell Technologies, Wouhaybi, R., Intel Corporation, Reed, W., & Dell Technologies. (2021). Generative AI for smart manufacturing. In *Custom content for Dell Technologies by studioID*.
- Eliminating greenwashing with data, IoT, and digital twins — Akila*. (2023, May 18). Akila. <https://www.akila3d.com/blog/insights/eliminating-greenwashing-revolutionizing-sustainability-with-digital-twins/>
- Escapa, D. (2018, October 16). *Announce de la préversion publique d'Azure Digital Twins*. Blog Azure. <https://azure.microsoft.com/fr-fr/blog/announcing-the-public-preview-of-azure-digital-twins/>
- Eure, J. (2022, October 18). *Transformation, Innovation and Citizenship: How Lenovo is Building a Positive Future*. Lenovo

- StoryHub. <https://news.lenovo.com/transformation-innovation-citizenship-building-a-positive-future/>
- Ghahremani-Nahr, J., Nozari, H., & Sadeghi, M. E. (2021). Green supply chain based on artificial intelligence of things (AIoT). *International Journal of Innovation in Management Economics and Social Sciences*, 1(2), 56–63. <https://doi.org/10.52547/ijimes.1.2.56>
- Glover, E. (2022, September 29). *Strong AI vs. Weak AI: What's the Difference?* Built In. <https://builtin.com/artificial-intelligence/strong-ai-weak-ai>
- Gmür, A. (2020, February 9). *With a digital twin to carbon neutrality*. Camelot Management Consultants. <https://www.camelot-mc.com/blog/with-digital-twin-to-carbon-neutrality/>
- Henderson, P., Hu, J., Romoff, J., Brunskill, E., Jurafsky, D., & Pineau, J. (2020). Towards the systematic reporting of the energy and carbon footprints of machine learning. *arXiv (Cornell University)*. <http://export.arxiv.org/pdf/2002.05651>
- Hewlett Packard Enterprise. (2023, March 3). *Industrial Digital Twin* [Video]. YouTube. <https://www.youtube.com/watch?v=OmGzdc2GZPE>
- Hiegl, M. W. (2023). Lenovo is Revolutionizing Productivity with AI by Driving Innovation with NVIDIA Omniverse for Digital Twins. *Lenovo Press*. <https://lenovopress.lenovo.com/LP1710>
- Histoire de l'intelligence artificielle - Intelligence artificielle - www.coe.int.* (n.d.). Intelligence Artificielle. <https://www.coe.int/fr/web/artificial-intelligence/history-of-ai>
- How to prepare for a sustainable future along the value chain.* (2022, January 20). McKinsey & Company. <https://www.mckinsey.com/industries/consumer-packaged-goods/our-insights/how-to-prepare-for-a-sustainable-future-along-the-value-chain>
- HP (NYSE: HPQ). (2020, November 24). *HP Inc. Reports Fiscal 2020 Full Year and Fourth Quarter Results*. investor.hp. <https://investor.hp.com/news-events/news/news-details/2020/HP-Inc.-Reports-Fiscal-2020-Full-Year-and-Fourth-Quarter-Results/default.aspx#:~:text=HP%20announced%20fiscal%202020%20net,from%20the%20prior%20year%20period>
- HP Inc. (2020). *HP 2019 Sustainable Impact Report*. <https://www.hp.com/sustainableimpact>
- HP Inc. (2021). *HP Sustainable Impact Report 2020*. <https://www8.hp.com/h20195/v2/GetPDF.aspx/c08228880.pdf>
- HP Inc. (2022). *Sustainable Impact Report 2021*. <https://WWW.HP.COM/SUSTAINABLEIMPACT>
- HP Inc. (2023). *2022 HP Sustainable Impact Report*. <https://www.hp.com/sustainableimpact>

- Ilager, S., Muralidhar, R., & Buyya, R. (2020). Artificial Intelligence (AI)-Centric management of resources in modern distributed computing systems. *arXiv (Cornell University)*. <https://doi.org/10.48550/arxiv.2006.05075>
- IoT Signals Manufacturing Spotlight. (2022). In ©Microsoft, Intel, IoT Analytics.
- ISO - ISO 14000 family — Environmental management. (2023, January 20). ISO. <https://www.iso.org/standards/popular/iso-14000-family>
- ISO 14001 - Key benefits. (2015). ISO. <https://www.iso.org/publication/PUB100372.html>
- Institute for the Future, Dell Technologies, Ajilore, O., Canon, H., Chouguley, N., Casserly, T. L., Frauenfelder, M., Kirshbaum, J., Lightman, K., Pelizzaro, P., Tuzmukhametov, E., Voto, A., Kreit, B., Baskin, C., & Kalaboukis, C. (2019). Industry & Commerce in the next era of Human-Machine partnerships. In *Dell Technologies*.
- Jeznach, C. (2023, February 23). *How to Accelerate Product Sustainability with Digital Twins*. aPriori. <https://www.apriori.com/blog/how-to-reach-product-sustainability-goals-with-digital-twins/>
- Jiang, Y., & Zhou, L. (2012). Study on Green Supply Chain Management Based on Circular Economy. *Physics Procedia*, 25, 1682–1688. <https://doi.org/10.1016/j.phpro.2012.03.295>
- Kajale, A. (2023, April 13). *Mine digital data to reach sustainability goals | Beca*. Beca. <https://www.beca.com/ignite-your-thinking/ignite-your-thinking/april-2023/mine-digital-data-to-reach-sustainability-goals>
- Kumar, V., Pallathadka, H., Sharma, S. K., Thakar, C. M., Singh, M., & Pallathadka, L. K. (2022). Role of machine learning in green supply chain management and operations management. *Materials Today: Proceedings*, 51, 2485–2489. <https://doi.org/10.1016/j.matpr.2021.11.625>
- Lawton, G. (2022, May 24). *How Softiron used digital twins to reduce its carbon footprint*. VentureBeat. <https://venturebeat.com/ai/how-softiron-used-digital-twins-to-reduce-its-carbon-footprint/>
- Lenovo announces LISSA: new AI-powered capability that helps businesses reduce IT footprint | Business Wire. (n.d.). <https://via.tt.se/pressmeddelande/3440710/lenovo-announces-lissa-new-ai-powered-capability-that-helps-businesses-reduce-it-footprint?publisherId=259167>
- Lenovo Group Limited. (2019). *2018/19 Sustainability Report Stock Code 992: Sustaining Intelligent Transformation*.
- Lenovo Group Limited. (2020a). *2019/20 Annual Report Stock Code 992: Smarter technology for all*.

- Lenovo Group Limited. (2020b). *2019/20 Environmental, Social and Governance Report Stock Code 992: Smarter technology with a purpose.*
- Lenovo Group Limited. (2021). *2020/21 Environmental, Social, and Governance Report STOCK CODE 992: Smarter technology for all.*
- Lenovo Group Limited. (2022). *2021/22 Environmental, Social and Governance Report STOCK CODE 992: Smarter Technology for All.*
- Lenovo Group Limited. (2023). *Lenovo Group Limited 2022/23 Environmental, Social and Governance Report HKD COUNTER STOCK CODE 992 RMB COUNTER STOCK CODE 80992: Smarter technology for all.*
- Lenovo Group Limited. (2024). *Powering the future of innovation in life sciences.* <https://www.lenovo.com/Healthcare>
- Lenovo Manufacturing Solutions. (2023).
In *Lenovo*. https://techtoday.lenovo.com/sites/default/files/2023-12/One_Lenovo_Manufacturing_Solutions_Brochure_ww_en.pdf.pdf
- Les causes du changement climatique.* (n.d.). Climate Action. https://climate.ec.europa.eu/climate-change/causes-climate-change_fr
- Leveraging supply chain digital twins to drive sustainability* | Blume Global. (2023, August 31). Blume Global. <https://www.blumeglobal.com/blog/leveraging-supply-chain-digital-twins-to-drive-sustainability/>
- Liu, B. (2023). Integration of novel uncertainty model construction of green supply chain management for small and medium-sized enterprises using artificial intelligence. *Optik*, 273, 170411. <https://doi.org/10.1016/j.ijleo.2022.170411>
- Lockhart, J. & Dell Technologies Global Digital Cities. (n.d.). *Green & Sustainable Cities of the Future* (pp. 2–5).
- Lorant, A. (2023, October 17). *C'est quoi le green supply chain ?* | Rubafilm - Professionnel de l'emballage. Rubafilm - Professionnel De L'emballage. <https://www.rubafilm.com/cest-quoi-le-green-supply-chain/>
- Mamtarane. (2023, July 19). *Sustainable, green supply chains; A manufacturer's new reality - Capgemini USA.* Capgemini USA. <https://www.capgemini.com/us-en/insights/expert-perspectives/sustainable-green-supply-chains-a-manufacturers-new-reality/>
- Marr, B. (2017, March 6). What is digital twin technology - and why is it so important? *Forbes*. <https://www.forbes.com/sites/bernardmarr/2017/03/06/what-is-digital-twin-technology-and-why-is-it-so-important/?sh=31824d302e2a>
- Microsoft. (2019). *2019 Data Factsheet: Environmental indicators.*
- Microsoft. (2020). *Environmental Sustainability Report: A year of Action.*

- Microsoft. (2021). *Environmental Sustainability Report 2021: Microsoft CSR and Sustainability Reporting Suite* [Report].
- Microsoft. (2022a). *Environmental Data Fact Sheet 2022*.
- Microsoft. (2022b). *Environmental Sustainability Report 2022 progress and learnings*.
- Microsoft. (2024). *2024 Environmental Sustainability Report* [Report].
- Microsoft. (2024). Environmental Data Fact Sheet 2024. In *Environmental Data Fact Sheet*.
- Microsoft Corporation. (2022). *Microsoft Corporation CDP Climate Change questionnaire 2022*.
- Microsoft Services. (2020). The promise of a digital twin strategy: Best practices for designers and manufacturers of products and industrial equipment. In *Microsoft Services* [Report].
- Monck, A., & Xing, E. (2023, 12 décembre). *AI emissions are fueling a new doomerism. This time it's climate change*. Fortune. <https://fortune.com/2023/12/12/ai-emissions-doomerism-climate-change-environment-tech/#>
- Morris, M. (2023, August 2). A Practical guide to AI in Cyber-Physical Environments. *Forbes*. <https://www.forbes.com/sites/forbestechcouncil/2023/08/02/a-practical-guide-to-ai-in-cyber-physical-environments/?sh=510fc3f0e85c>
- Mulvaney, K. (2022, June 23). What is a carbon footprint—and how to measure yours. *Environment*. <https://www.nationalgeographic.com/environment/article/what-is-a-carbon-footprint-how-to-measure-yours>
- Nassar, J., & Nassar, J. (2023, March 15). *Accelerate digital transformation at the manufacturing edge*. Dell. <https://www.dell.com/en-us/blog/accelerate-digital-transformation-at-the-manufacturing-edge/>
- Naz, F., Agrawal, R., Kumar, A., Gunasekaran, A., Majumdar, A., & Luthra, S. (2022). Reviewing the applications of artificial intelligence in sustainable supply chains: Exploring research propositions for future directions. *Business Strategy and the Environment*, 31(5), 2400–2423. <https://doi.org/10.1002/bse.3034>
- Nogueira, I. (2021, October 8). *Artificial Intelligence and Cyber-Physical Systems*. <https://encyclopedia.pub/entry/14862>
- Nozari, H., Szmelter-Jarosz, A., & Ghahremani-Nahr, J. (2022). Analysis of the Challenges of Artificial Intelligence of Things (AIOT) for the smart supply chain (Case Study: FMCG Industries). *Sensors*, 22(8), 2931. <https://doi.org/10.3390/s22082931>
- Panaro, P., Parlow, S., & Amman, F. (2024, March 19). *How can pairing #AI with #digitaltwin technology help cut building #emissions?* World Economic Forum. <https://www.weforum.org/agenda/2024/03/how-digital-twin-technology-can-work-with-ai-to-boost-buildings-emissions-reductions/>

- Parampalli, S. (2024, 5 mars). *Evolution of the logistics control tower*. Capgemini. <https://www.capgemini.com/insights/expert-perspectives/evolution-of-the-logistics-control-tower/>
- Polimeni, J. M., & Polimeni, R. I. (2006). Jevons' Paradox and the myth of technological liberation. *Ecological Complexity*, 3(4), 344-353. <https://doi.org/10.1016/j.ecocom.2007.02.008>
- PricewaterhouseCoopers. (n.d.). *Tackling the Scope 3 challenge*. PwC. <https://www.pwc.com/gx/en/issues/climate/scope-three-challenge.html>
- Qu'est-ce que l'industrie 4.0 et comment fonctionne-t-elle ? | IBM*. (n.d.). <https://www.ibm.com/fr-fr/topics/industry-4-0>
- Raman, R., Sreenivasan, A., Suresh, M., Patwardhan, A., & Nedungadi, P. (2023). Green supply chain management research trends and linkages to UN sustainable development goals. *Sustainability*, 15(22), 15848. <https://doi.org/10.3390/su152215848>
- Ramos, M., & Ramos, M. (2022, November 3). *What is supply chain sustainability?* IBM Blog. <https://www.ibm.com/blog/what-is-supply-chain-sustainability/#>
- Rand, D. (2023, May 25). *What are . . . digital twins?* <https://garage.hp.com/us/en/innovation/what-is-digital-twin-tech-explainer.html>
- Replicative Simulator: A step towards harmonizing AI and wireless communication Systems | Samsung Business Global Networks*. (2021, January 28). Samsung Global_Nw. <https://www.samsung.com/global/business/networks/insights/blog/0127-replicative-simulator-a-step-towards-harmonizing-ai-and-wireless-communication-systems/>
- Responsible purchasing guidelines*. (n.d.). Sustainable Stanford. <https://sustainable.stanford.edu/operations/waste/purchasing-guidelines/responsible-purchasing#:~:text=Responsible%20Purchasing%20is%20the%20acquisition,responsible%2C%20and%20ethically%2Dsourced.>
- Roose, M. (2018, September 4). *HPE at Hannover Messe 2018: Power your data-driven enterprise*. <https://community.hpe.com/t5/tech-insights/hpe-at-hannover-messe-2018-power-your-data-driven-enterprise/ba-p/7001962>
- Rolnick, D., Donti, P. L., Kaack, L. H., Kochanski, K., Lacoste, A., Sankaran, K., Ross, A. S., Mилоjevic-Dupont, N., Jaques, N., Waldman-Brown, A., Luccioni, A. S., Maharaj, T., Sherwin, E. D., Mukkavilli, S. K., K rding, K. P., Gomes, C. P., Ng, A. Y., Hassabis,

- D., Platt, J., . . . Bengio, Y. (2022). Tackling Climate Change with Machine Learning. *ACM Computing Surveys*, 55(2), 1–96. <https://doi.org/10.1145/3485128>
- Ruff, C. (2021, October 27). *Digital action = Climate action: 8 ideas to accelerate the twin transition - DIGITALEUROPE*. DIGITALEUROPE. <https://www.digitaleurope.org/resources/digital-action-climate-action-8-ideas-to-accelerate-the-twin-transition/>
- Samsung Electronics. (2019). *Samsung Electronics Sustainability Report 2019*.
- Samsung Electronics. (2020). *SAMSUNG ELECTRONICS SUSTAINABILITY REPORT 2020*. <http://www.samsung.com>
- Samsung Electronics. (2021). *Samsung Electronics Sustainability Report 2021*. https://images.samsung.com/is/content/samsung/assets/global/ir/docs/sustainability_report_2021_en.pdf
- Samsung Electronics. (2022). *Samsung Electronics Sustainability Report 2022 providing insights into the company's sustainability initiatives and achievements*.
- Samsung Electronics. (2023). *Samsung Electronics Sustainability Report 2023*. https://www.samsung.com/global/sustainability/media/pdf/Samsung_Electronics_Sustainability_Report_2023_ENG.pdf
- Samsung Electronics Co., Ltd. (2020). *CONSOLIDATED FINANCIAL STATEMENTS OF SAMSUNG ELECTRONICS CO., LTD. AND ITS SUBSIDIARIES* (pp. 1–16). https://images.samsung.com/is/content/samsung/assets/global/ir/docs/2019_con_quarter04_all.pdf
- Samsung Electronics to deliver private 5G network solutions to Korea's public and private sectors*. (2022, August 31). <https://news.samsung.com/global/samsung-electronics-to-deliver-private-5g-network-solutions-to-koreas-public-and-private-sectors>
- Samsung SDS BrandVoice. (2020, January 6). 3 Must-Haves for Intelligent Manufacturing. *Forbes*. <https://www.forbes.com/sites/samsungsd/2020/01/06/3-must-haves-for-intelligent-manufacturing/?sh=1e7c1f2b670e>
- Sankaran, K. (2020). Carbon emission and plastic pollution: How circular economy, blockchain, and artificial intelligence support energy transition? *Journal of Innovation Nanagement*, 7(4), 7–13. https://doi.org/10.24840/2183-0606_007.004_0002
- Schume, P., & Schume, P. (2020, May 24). *Improve product quality and yield with intelligent, secure, and adaptable manufacturing operations*. IBM Blog. <https://www.ibm.com/blog/iot-manufacturing-ready/>
- Sergeev, S. Y. B. a. a. B. E. D. S. M. (2021). The place and role of Digital Twin in supply chain management. *Academy of Strategic Management Journal*, 1939–

6104. <https://www.abacademies.org/articles/the-place-and-role-of-digital-twin-in-supply-chain-management-11000.html>
- Silva, H. (2023, October 9). Reinforcement Learning with Human Feedback (RLHF): Pioneering Progress in AI. *Medium*. <https://medium.com/@aiwizard/reinforcement-learning-with-human-feedback-rlhf-pioneering-progress-in-ai-c24bcec18a39>
- Simplilearn. (2018, September 19). *Machine Learning | What is Machine Learning? | Introduction to Machine Learning | 2021 | SimpliLearn* [Video]. YouTube. <https://www.youtube.com/watch?v=ukzFI9rgwfU>
- Simplilearn. (2020, August 24). *IoT | Internet of Things | What is IoT? | How IoT Works? | IoT Explained in 6 Minutes | Simplilearn* [Video]. YouTube. <https://www.youtube.com/watch?v=6mBO2vqLv38>
- Supply Chains Building a Digital Twin of the Customer. (2005). In *Gartner, Inc. And/or Its Affiliates* (CM_GBS_2386452). <https://www.gartner.com/en/supply-chain/trends/supply-chain-digital-twin-of-the-customer>
- Supply Chain Guidance | US EPA*. (2023, July 7). US EPA. <https://www.epa.gov/climateleadership/supply-chain-guidance#:~:text=Organizations%27%20supply%20chains%20often%20account,account%20their%20overall%20climate%20impacts>.
- Team, I. D. a. A., & Team, I. D. a. A. (2023, July 11). *AI vs. Machine Learning vs. Deep Learning vs. Neural Networks: What's the difference?* IBM Blog. <https://www.ibm.com/blog/ai-vs-machine-learning-vs-deep-learning-vs-neural-networks/>
- Toorajipour, R., Sohrabpour, V., Nazarpour, A., Oghazi, P., & Fischl, M. (2021). Artificial intelligence in supply chain management: A systematic literature review. *Journal of Business Research*, 122, 502–517. <https://doi.org/10.1016/j.jbusres.2020.09.009>
- Tyagi, A. K., & Sreenath, N. (2021). Cyber Physical Systems: Analyses, challenges and possible solutions. *Internet of Things and Cyber-Physical Systems*, 1, 22–33. <https://doi.org/10.1016/j.iotcps.2021.12.002>
- UNITED STATES SECURITIES AND EXCHANGE COMMISSION. (2019). *FORM 10-K - Apple Inc.* https://www.annualreports.com/HostedData/AnnualReportArchive/a/NASDAQ_APL_2019.pdf
- Vuarin, L., Massé, D., & Lopes, P. G. (2023). L'intelligence artificielle peut-elle être une innovation responsable ? *Innovations*, N° 72(3), 103–147. <https://doi.org/10.3917/inno.pr2.0153>

- What are scope 1, 2 and 3 emissions?* (n.d.). Deloitte United Kingdom. <https://www2.deloitte.com/uk/en/focus/climate-change/zero-in-on-scope-1-2-and-3-emissions.html>
- What is a digital twin?* | IBM. (n.d.). <https://www.ibm.com/topics/what-is-a-digital-twin>
- What is a Digital Twin? - Digital Twin Technology Explained - AWS.* (n.d.). Amazon Web Services, Inc. https://aws.amazon.com/what-is/digital-twin/?nc1=h_ls
- What is a sustainable supply chain?* | *Green supply chain operations* | SAP. (n.d.). SAP. <https://www.sap.com/products/scm/what-is-a-sustainable-supply-chain.html>
- What is Additive Manufacturing* | *GE Additive.* (n.d.). <https://www.ge.com/additive/additive-manufacturing>
- What is AI?* (2023, April 24). McKinsey & Company. <https://www.mckinsey.com/featured-insights/mckinsey-explainers/what-is-ai>
- What is big data?* (n.d.). Oracle. <https://www.oracle.com/big-data/what-is-big-data/>
- What is Cloud Computing?* | *Google Cloud.* (n.d.). Google Cloud. <https://cloud.google.com/learn/what-is-cloud-computing>
- What is IoT? The Future of Business* | SAP. (n.d.). SAP. <https://www.sap.com/products/artificial-intelligence/what-is-iot.html>
- What is reinforcement learning?* (n.d.). MATLAB & Simulink. <https://au.mathworks.com/discovery/reinforcement-learning.html>
- What is Sustainability?* | *UCLA Sustainability.* (n.d.). UCLA Sustainability. <https://www.sustain.ucla.edu/what-is-sustainability/>
- Wu, C., Raghavendra, R., Gupta, U., Acun, B., Ardalani, N., Maeng, K., Chang, G., Behram, F. A., Huang, J., Bai, C., Gschwind, M., Gupta, A., Ott, M., Мельников, А. С., Candido, S., Brooks, D. J., Chauhan, G. S., Lee, B., Lee, H. S., . . . Hazelwood, K. (2021). Sustainable AI: environmental implications, challenges and opportunities. *arXiv (Cornell University)*. <https://doi.org/10.48550/arxiv.2111.00364>
- Wu, T., & Zuo, M. (2023). Green supply chain transformation and emission reduction based on machine learning. *Science Progress*, 106(1), 003685042311656. <https://doi.org/10.1177/00368504231165679>
- Ying-Jun, F., Lai, K., & Zhu, Q. (2022). Green supply chain innovation: Emergence, adoption, and challenges. *International Journal of Production Economics*, 248, 108497. <https://doi.org/10.1016/j.ijpe.2022.108497>
- Zhang, G., & Zhao, Z. (2012). Green Packaging management of logistics enterprises. *Physics Procedia*, 24, 900–905. <https://doi.org/10.1016/j.phpro.2012.02.135>

11. Appendices

Appendix A. Emission Categories Associated with Each Stage of the Supply Chain

For each stage of the supply chain, I associated relevant emission categories from Scopes 3 to comprehensively measure the impact of Digital Twins. Here are how the associations were established:

Product Design: Indirect emissions, Scope 3, from purchased goods and services, Category 1, and energy-related activities, Category 3, are particularly relevant. Product design often requires purchasing materials and using external services, generating indirect emissions. (Table 13)

Material Sourcing: Material sourcing involves indirect emissions, Scope 3, from purchased goods and services, Category 1, energy-related activities, Category 3, and upstream transportation and distribution, Category 4. These activities are essential for securing the materials needed for production. (Table 14)

Production primarily generates indirect emissions, Scope 3, related to purchased goods and services, Category 1, energy activities Category 3, and waste generated, Category 5. These emissions are crucial for capturing the full environmental impact of manufacturing processes and energy use within the production phase. (Table 15)

Logistics involve significant indirect emissions, Scope 3, from upstream transportation and distribution, Category 4, and downstream transportation and distribution, Category 9. These categories are essential for evaluating the overall impact of logistics operations on GHG emissions. (Table 16)

End-of-Life Product Management: Indirect emissions, Scope 3, from the end-of-life treatment of products, Category 12, and waste generated, Category 5, are crucial. Additionally, emissions related to the use of sold products, Category 11, are included to capture emissions throughout the product lifecycle. (Table 17)

Appendix B. R Code for Panel Data Analysis Using the plm Package

```
install.packages("plm")

library(plm)

data <- data.frame(
  Year = rep(2019:2022, each = 7),
  Company = rep(c("Apple", "Acer", "Dell", "HP", "Lenovo", "Microsoft", "Samsung"),
times = 4),

  Emission = c(
    25030549.00, 9434527.74, 18010326.00, 46785800.00, 16043054.00,
11711000.00, 141933.82,
    22597430.00, 8150743.38, 25016500.00, 44891000.00, 17562797.00,
12227219.00, 152270.31,
    23186385.00, 8786399.73, 23349300.00, 30053300.00, 20004808.00,
13064109.00, 178960.03,
    20604020.00, 6705684.80, 29015600.00, 26899500.00, 12351637.00,
12998442.00, 139768.00),

  Iso1 = c(1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1, 1, 1, 1, 1, 1, 1),
  Iso2 = c(0, 0, 1, 0, 1, 0, 1,
    0, 0, 1, 0, 1, 0, 1,
    0, 1, 1, 0, 1, 0, 1,
    0, 1, 1, 0, 1, 0, 1),
  Iso3 = c(1, 1, 0, 0, 0, 0, 0,
    1, 1, 0, 0, 0, 0, 0,
```

```
1, 1, 0, 0, 0, 0, 0,
1, 1, 0, 0, 0, 0, 0),
```

```
Size = c(260.17, 7.78, 92.15, 58.80, 51.04, 125.84, 197.69,
274.52, 9.72, 94.22, 56.60, 50.72, 143.02, 200.61,
365.82, 11.52, 101.20, 63.50, 60.74, 168.09, 244.39,
394.33, 8.97, 102.30, 62.90, 71.62, 198.27, 234.08),
```

```
DT = c(0.00, 0.00, 1.00, 2.00, 3.00, 2.00, 0.00,
0.00, 0.00, 1.00, 2.00, 3.00, 2.00, 1.00,
0.00, 0.00, 1.00, 3.00, 3.00, 4.00, 1.00,
0.00, 0.00, 1.00, 3.00, 5.00, 5.00, 1.00),
```

```
RD = c(16.22, 0.09, 4.99, 1.48, 1.27, 16.88, 17.33,
18.75, 0.08, 5.28, 1.50, 1.34, 19.27, 17.98,
21.91, 0.10, 2.58, 1.65, 1.45, 20.72, 19.75,
26.25, 0.08, 2.78, 1.58, 2.07, 24.51, 19.30),
```

```
RE = c(1.00, 0.44, 0.33, 0.43, 0.01, 1.00, 0.12,
1.00, 0.44, 0.45, 0.50, 0.02, 0.95, 0.18,
1.00, 0.45, 0.54, 0.53, 0.03, 0.95, 0.20,
1.00, 0.44, 0.55, 0.55, 0.03, 1.00, 0.31),
```

```
W = c(58405.89, 1666.61, 13802.00, 13000.00, 45439.49, 26927.00,
777570.00,
45713.58, 1803.70, 13175.00, 14200.00, 43023.00, 31102.00,
835875.00,
52489.72, 1947.62, 12505.00, 13900.00, 51648.00, 20768.00,
903753.00,
56510.12, 2112.51, 14224.00, 18800.00, 49403.00, 28715.00,
931929.00),
```

```

Wr = c(0.56, 0.68, 0.90, 0.87, 0.84, 0.53, 0.95,
        0.63, 0.76, 0.87, 0.75, 0.85, 0.63, 0.95,
        0.64, 0.80, 0.84, 0.76, 0.89, 0.65, 0.96,
        0.63, 0.80, 0.89, 0.81, 0.88, 0.57, 0.97),

Wwte = c(0.01, 0.00, 0.07, 0.05, 0.03, 0.01, 0.04,
          0.01, 0.00, 0.11, 0.09, 0.04, 0.02, 0.03,
          0.01, 0.00, 0.12, 0.10, 0.06, 0.01, 0.03,
          0.01, 0.00, 0.10, 0.06, 0.07, 0.01, 0.03)

)

pdata <- pdata.frame(data, index = c("Company", "Year"))

model <- plm(log(Emission) ~ Iso1 + Iso2 + Iso3 + log(Size) + DT +
log(RD) + RE + log(W) + Wr + Wwte, data = pdata, model = "within")

summary(model)

```

Appendix C. Detailed Results of the Research Analysis

1. Product design

Based on the p-values from all five models (Table 32), we can conclude that public mention of the use of Digital Twins in the product design step of the supply chain does not have a statistically significant impact on reducing GHG emissions in the supply chain of laptops from major technology companies between 2019 and 2022. The p-values for $DT1_{it}$ were all greater than the conventional threshold of 0.05 in every model, including the general emissions model, Scope 1 emissions model, Scope 2 emissions model, Scope 3 emissions model, and the Category 1 and 3 emissions model.

H0, the null hypothesis: Cannot be rejected.

H1, the alternative hypothesis: Cannot be supported.

2. Sourcing

Based on the p-values from all five models (Table 33), we can conclude that public mention of the use of Digital Twins in the material sourcing step of the supply chain does not have a statistically significant impact on reducing GHG emissions in the supply chain of laptops from major technology companies between 2019 and 2022, except for Scope 1 emissions. The p-values for $DT2_{it}$ were greater than the conventional threshold of 0.05 in every model, including the total emissions model, Scope 2 emissions model, Scope 3 emissions model, and the Category 1, 3, and 4 emissions model. However, the p-value for Scope 1 emissions was significant at 0.0091001.

H0, the null hypothesis for total emissions, Scope 2 emissions, Scope 3 emissions, and specified categories of Scope 3: Cannot be rejected.

H0, the null hypothesis for Scope 1 emissions: Rejected.

H1, the alternative hypothesis for total emissions, Scope 2 emissions, Scope 3 emissions, and specified categories of Scope 3: Cannot be supported.

H1, the alternative hypothesis for Scope 1 emissions: Supported.

3. Production

Evaluating the p-values from all five models (Table 34), we can conclude that public mention of the use of Digital Twins in the production step of the supply chain does not significantly impact the reduction of GHG emissions in the supply chain of laptops from major technology

companies between 2019 and 2022. The p-values for $DT3_{it}$ were consistently above 0.05, suggesting no significant evidence to support the alternative hypothesis (H1). Therefore, the null hypothesis (H0) cannot be rejected, and the alternative hypothesis (H1) cannot be supported.

H0, the null hypothesis: Cannot be rejected.

H1, the alternative hypothesis: Cannot be supported.

4. Logistics

Reviewing the p-values across all five models (Table 35), it is evident that public mention of the use of Digital Twins in the logistics step of the supply chain does not significantly impact the reduction of GHG emissions in the supply chain of laptops from major technology companies between 2019 and 2022. The p-values for $DT4_{it}$ all exceeded 0.05, indicating a lack of significant evidence to support the alternative hypothesis (H1). Therefore, the null hypothesis (H0) remains valid, and the alternative hypothesis (H1) cannot be supported.

H0, the null hypothesis: Cannot be rejected.

H1, the alternative hypothesis: Cannot be supported.

5. End-of-life product management

Based on the p-values from all five models (Table 36), we can conclude that public mention of the use of Digital Twins in the end-of-life product management step of the supply chain does not have a statistically significant impact on reducing GHG emissions in the supply chain of laptops from major technology companies between 2019 and 2022. The p-values for $DT5_{it}$ were all greater than the conventional threshold of 0.05 in every model, including the general emissions model, Scope 1 emissions model, Scope 2 emissions model, Scope 3 emissions model, and the Category 5, 11, and 12 emissions model. The p-value for the Scope 1 emissions model was close but still not significant.

H0, the null hypothesis: Cannot be rejected.

H1, the alternative hypothesis: Cannot be supported

Appendix D. Tables

Annees	Apple	Acer	Dell	HP	Lenovo	Microsoft	Samsung
2022	20604020.00	6705684.80	29015600.00	26899500.00	12351637.00	12998442.00	139768.00
2021	23186385.00	8786399.73	23349300.00	30053300.00	20004808.00	13064109.00	178960.03
2020	22597430.00	8150743.38	25016500.00	44891000.00	17562797.00	12227219.00	152270.31
2019	25030549.00	9434527.74	18010326.00	46785800.00	16043054.00	11711000.00	141933.82

Table 1: Annual total emissions by companies measured in metric tons of carbon dioxide equivalent (MT CO₂e)

Annees	Apple	Acer	Dell	HP	Lenovo	Microsoft	Samsung
2022	55202.00	2705.30	45600.00	46800.00	6069.00	139413.00	5972.00
2021	55202.00	4550.63	44200.00	37500.00	7269.00	123704.00	7604.00
2020	47430.00	3004.03	58000.00	50600.00	7766.00	118100.00	5726.00
2019	50549.00	3540.21	58100.00	61900.00	6031.00	113412.00	5067.00

Table 2: Annual total emissions by companies for Scope 1 measured in metric tons of carbon dioxide equivalent (MT CO₂e)

Annees	Apple	Acer	Dell	HP	Lenovo	Microsoft	Samsung
2022	3018.00	8784.50	158100.00	104700.00	21160.00	288029.00	9081.00
2021	2783.00	8746.10	172200.00	110800.00	21519.00	429405.00	9796.00
2020	0.00	9195.35	240500.00	120400.00	23852.00	456119.00	9079.00
2019	0.00	10223.62	309600.00	153900.00	26029.00	275375.00	8733.00

Table 3: Annual total emissions by companies for Scope 2 (market-based) measured in metric tons of carbon dioxide equivalent (MT CO₂e)

Annees	Apple	Acer	Dell	HP	Lenovo	Microsoft	Samsung
2022	20545800.00	6694195.00	28811900.00	26748000.00	12324408.00	12571000.00	124715.00
2021	23128400.00	8773103.00	23132900.00	29905000.00	19976020.00	12511000.00	161560.03
2020	22550000.00	8138544.00	24718000.00	44720000.00	17531179.00	11653000.00	137465.31
2019	24980000.00	9420763.91	17642626.00	46570000.00	16010994.00	11322213.00	128133.82

Table 4: Annual total emissions by companies for Scope 3 measured in metric tons of carbon dioxide equivalent (MT CO₂e)

Annees	Apple	Acer	Dell	HP	Lenovo	Microsoft	Samsung
2022	13400000.00	5504118.00	8767844.00	16139000.00	7798826.00	5780000.00	14596000.00
2021	16200000.00	360247.00	3497494.00	18221000.00	6495779.00	4930000.00	16153000.00
2020	16100000.00	43731.50	3748600.00	26400000.00	7032426.00	4415000.00	8030000.00
2019	18900000.00	57711.83	3686746.00	20900000.00	6475009.00	4411000.00	8278000.00

Table 5: Annual total emissions by companies for Scope 3, Category 1: Purchased Goods and Services measured in metric tons of carbon dioxide equivalent (MT CO₂e)

Annees	Apple	Acer	Dell	HP	Lenovo	Microsoft	Samsung
2022	10600.00	2665.00	143026.00	52000.00	12000.00	450000.00	900000.00
2021	23128.40	2731.62	105454.00	53000.00	11050.00	350000.00	368000.00
2020	22550.00	2484.48	131700.00	100000.00	10385.00	300000.00	820000.00
2019	24980.00	2846.44	140026.00	100000.00	12100.00	270000.00	750000.00

Table 6: Annual total emissions by companies for Scope 3, Category 3: Fuel- and Energy-Related Activities measured in metric tons of carbon dioxide equivalent (MT CO₂e)

Annees	Apple	Acer	Dell	HP	Lenovo	Microsoft	Samsung
2022	630000.00	43772.00	1350565.00	588000.00	737979.00	371000.00	3965000.00
2021	580000.00	104375.08	1111176.00	900000.00	815262.00	225000.00	3363000.00
2020	600000.00	91678.81	763397.00	2100000.00	616416.00	243000.00	11000.00
2019	486000.00	85475.45	690786.50	2300000.00	580363.00	96000.00	10000.00

Table 7: Annual total emissions by companies for Scope 3, Category 4: Upstream Transportation and Distribution measured in metric tons of carbon dioxide equivalent (MT CO₂e)

Annees	Apple	Acer	Dell	HP	Lenovo	Microsoft	Samsung
2022	20545.80	57.00	294265.37	1000.00	1810.00	8000.00	246000.00
2021	23128.40	33.12	288119.00	1000.00	1770.00	5700.00	100000.00
2020	22550.00	40.55	231329.00	1000.00	2110.00	9500.00	130000.00
2019	24980.00	36.31	247180.00	1000.00	1920.00	10500.00	145000.00

Table 8: Annual total emissions by companies for Scope 3, Category 5: Waste Generated in Operations measured in metric tons of carbon dioxide equivalent (MT CO₂e)

Annees	Apple	Acer	Dell	HP	Lenovo	Microsoft	Samsung
2022	113500.00	2236.00	19631.00	15000.00	20255.00	139000.00	87000.00
2021	22850.00	1046.84	61429.00	3000.00	11900.00	21901.00	26000.00
2020	153000.00	819.37	314300.00	20000.00	46900.00	329356.00	14000.00
2019	326000.00	5936.80	165854.00	70000.00	53500.00	476457.00	106000.00

Table 9: Annual total emissions by companies for Scope 3, Category 6: Business Travel measured in metric tons of carbon dioxide equivalent (MT CO₂e)

Annees	Apple	Acer	Dell	HP	Lenovo	Microsoft	Samsung
2022	1270000.00	0.00	60000.00	0.00	0.00	69000.00	366000.00
2021	1170000.00	0.00	60000.00	0.00	0.00	69000.00	714000.00
2020	1200000.00	0.00	60000.00	0.00	0.00	65000.00	6670000.00
2019	999000.00	0.00	60000.00	0.00	0.00	57000.00	8216000.00

Table 10: Annual total emissions by companies for Scope 3, Category 9: Downstream Transportation and Distribution measured in metric tons of carbon dioxide equivalent (MT CO₂e)

Annees	Apple	Acer	Dell	HP	Lenovo	Microsoft	Samsung
2022	4900000.00	1098534.00	13590636.00	9603000.00	8270000.00	5101000.00	101236000.00
2021	4990000.00	1616651.00	10200000.00	8700000.00	15551000.00	3950000.00	100787000.00
2020	4300000.00	1542689.42	11280000.00	15800000.00	13669000.00	2983000.00	35800000.00
2019	4100000.00	1785738.68	13650000.00	22500000.00	12885000.00	3375000.00	38002000.00

Table 11: Annual total emissions by companies for Scope 3, Category 11: Use of Sold Products measured in metric tons of carbon dioxide equivalent (MT CO₂e)

Annees	Apple	Acer	Dell	HP	Lenovo	Microsoft	Samsung
2022	80000.00	25496.00	200000.00	126000.00	181000.00	18000.00	1206000.00
2021	80000.00	531.49	288119.00	100000.00	303500.00	19000.00	1395000.00
2020	60000.00	545.80	231329.00	100000.00	274000.00	17000.00	11450000.00
2019	60000.00	0.00	247180.00	200000.00	273500.00	18000.00	11673000.00

Table 12: Annual total emissions by companies for Scope 3, Category 12: End-of-Life Treatment of Sold Products measured in metric tons of carbon dioxide equivalent (MT CO₂e)

Annees	Apple	Acer	Dell	HP	Lenovo	Microsoft	Samsung
2022	13410600.00	5506783.00	8910870.00	16191000.00	7810826.00	6230000.00	15496000.00
2021	16223128.40	362978.62	3602948.00	18274000.00	6506829.00	5280000.00	16521000.00
2020	16122550.00	46215.98	3880300.00	26500000.00	7042811.00	4715000.00	8850000.00
2019	18924980.00	60558.27	3826772.00	21000000.00	6487109.00	4681000.00	9028000.00

Table 13: Annual total emissions by companies for Scope 3 related to product design (Categories 1: Purchased Goods and Services and 3: Fuel- and Energy-Related Activities) measured in metric tons of carbon dioxide equivalent (MT CO₂e)

Annees	Apple	Acer	Dell	HP	Lenovo	Microsoft	Samsung
2022	14040600.00	5550555.00	10261435.00	16779000.00	8548805.00	6601000.00	19461000.00
2021	16803128.40	467353.70	4714124.00	19174000.00	7322091.00	5505000.00	19884000.00
2020	16722550.00	137894.79	4643697.00	28600000.00	7659227.00	4958000.00	8861000.00
2019	19410980.00	146033.72	4517558.50	23300000.00	7067472.00	4777000.00	9038000.00

Table 14: Annual total emissions by companies for Scope 3 related to material sourcing (Categories 1: Purchased Goods and Services, 3: Fuel- and Energy-Related Activities, and 4: Upstream Transportation and Distribution) measured in metric tons of carbon dioxide equivalent (MT CO₂e)

Annees	Apple	Acer	Dell	HP	Lenovo	Microsoft	Samsung
2022	13431145.80	5506840.00	9205135.37	16192000.00	7812636.00	6238000.00	15742000.00
2021	16246256.80	363011.74	3891067.00	18275000.00	6508599.00	5285700.00	16621000.00
2020	16145100.00	46256.53	4111629.00	26501000.00	7044921.00	4724500.00	8980000.00
2019	18949960.00	60594.58	4073952.00	21001000.00	6489029.00	4691500.00	9173000.00

Table 15: Annual total emissions by companies for Scope 3 related to production (Categories 1: Purchased Goods and Services, 3: Fuel- and Energy-Related Activities, and 5: Waste Generated in Operations) measured in metric tons of carbon dioxide equivalent (MT CO₂e)

Annees	Apple	Acer	Dell	HP	Lenovo	Microsoft	Samsung
2022	1900000.00	43772.00	1410565.00	588000.00	737979.00	440000.00	4331000.00
2021	1750000.00	104375.08	1171176.00	900000.00	815262.00	294000.00	4077000.00
2020	1800000.00	91678.81	823397.00	2100000.00	616416.00	308000.00	6681000.00
2019	1485000.00	85475.45	750786.50	2300000.00	580363.00	153000.00	8226000.00

Table 16: Annual total emissions by companies for Scope 3 related to logistics (Categories 4: Upstream Transportation and Distribution and 9: Downstream Transportation and Distribution) measured in metric tons of carbon dioxide equivalent (MT CO₂e)

Annees	Apple	Acer	Dell	HP	Lenovo	Microsoft	Samsung
2022	5000545.80	1124087.00	14084901.37	9730000.00	8452810.00	5127000.00	102688000.00
2021	5093128.40	1617215.61	10776238.00	8801000.00	15856270.00	3974700.00	102282000.00
2020	4382550.00	1543275.77	11742658.00	15901000.00	13945110.00	3009500.00	47380000.00
2019	4184980.00	1785774.99	14144360.00	22701000.00	13160420.00	3403500.00	49820000.00

Table 17: Annual total emissions by companies for Scope 3 related to End-of-Life Product Management (Categories 5: Waste Generated in Operations, 11: Use of Sold Products, and 12: End-of-Life Treatment of Sold Products) measured in metric tons of carbon dioxide equivalent (MT CO₂e)

Annees	Apple	Acer	Dell	HP	Lenovo	Microsoft	Samsung
2022	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2021	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2020	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2019	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Table 18: ISO14001 Certification, 1 = The company was ISO14001 certified this year, 0 = The company was not ISO14001 certified this year

Annees	Apple	Acer	Dell	HP	Lenovo	Microsoft	Samsung
2022	0.00	1.00	1.00	0.00	1.00	0.00	1.00
2021	0.00	1.00	1.00	0.00	1.00	0.00	1.00
2020	0.00	0.00	1.00	0.00	1.00	0.00	1.00
2019	0.00	0.00	1.00	0.00	1.00	0.00	1.00

Table 19: ISO50001 Certification, 1 = The company was ISO50001 certified this year, 0 = The company was not ISO50001 certified this year

Annees	Apple	Acer	Dell	HP	Lenovo	Microsoft	Samsung
2022	1.00	1.00	0.00	0.00	0.00	0.00	0.00
2021	1.00	1.00	0.00	0.00	0.00	0.00	0.00
2020	1.00	1.00	0.00	0.00	0.00	0.00	0.00
2019	1.00	1.00	0.00	0.00	0.00	0.00	0.00

Table 20: ISO14064 Certification, 1 = The company was ISO14064 certified this year, 0 = The company was not ISO14064 certified this year

Annees	Apple	Acer	Dell	HP	Lenovo	Microsoft	Samsung
2022	394.33	8.97	102.30	62.90	71.62	198.27	234.08
2021	365.82	11.52	101.20	63.50	60.74	168.09	244.39
2020	274.52	9.72	94.22	56.60	50.72	143.02	200.61
2019	260.17	7.78	92.15	58.80	51.04	125.84	197.69

Table 21: Annual revenue by companies measured in billions of USD

Annees	Apple	Acer	Dell	HP	Lenovo	Microsoft	Samsung
2022	26.25	0.08	2.78	1.58	2.07	24.51	19.30
2021	21.91	0.10	2.58	1.65	1.45	20.72	19.75
2020	18.75	0.08	5.28	1.50	1.34	19.27	17.98
2019	16.22	0.09	4.99	1.48	1.27	16.88	17.33

Table 22: Annual investment in research and development by companies measured in billions of USD

Annees	Apple	Acer	Dell	HP	Lenovo	Microsoft	Samsung
2022	1.00	0.44	0.55	0.55	0.03	1.00	0.31
2021	1.00	0.45	0.54	0.53	0.03	0.95	0.20
2020	1.00	0.44	0.45	0.50	0.02	0.95	0.18
2019	1.00	0.44	0.33	0.43	0.01	1.00	0.12

Table 23: Percentage of renewable electricity consumed relative to total electricity consumed by companies per year; scaled between 0 and 1

Annees	Apple	Acer	Dell	HP	Lenovo	Microsoft	Samsung
2022	0.63	0.80	0.89	0.81	0.88	0.57	0.97
2021	0.64	0.80	0.84	0.76	0.89	0.65	0.96
2020	0.63	0.76	0.87	0.75	0.85	0.63	0.95
2019	0.56	0.68	0.90	0.87	0.84	0.53	0.95

Table 24: Percentage of nonhazardous waste recycled or reused by companies per year; scaled between 0 and 1

Annees	Apple	Acer	Dell	HP	Lenovo	Microsoft	Samsung
2022	0.01	0.00	0.10	0.06	0.07	0.01	0.03
2021	0.01	0.00	0.12	0.10	0.06	0.01	0.03
2020	0.01	0.00	0.11	0.09	0.04	0.02	0.03
2019	0.01	0.00	0.07	0.05	0.03	0.01	0.04

Table 25: Percentage of nonhazardous waste recovery (waste to energy) by companies per year; scaled between 0 and 1

Annees	Apple	Acer	Dell	HP	Lenovo	Microsoft	Samsung
2022	56510.12	2112.51	14224.00	18800.00	49403.00	28715.00	931929.00
2021	52489.72	1947.62	12505.00	13900.00	51648.00	20768.00	903753.00
2020	45713.58	1803.70	13175.00	14200.00	43023.00	31102.00	835875.00
2019	58405.89	1666.61	13802.00	13000.00	45439.49	26927.00	777570.00

Table 26: Nonhazardous waste generated by companies per year, measured in metric tonnes

Annees	Apple	Acer	Dell	HP	Lenovo	Microsoft	Samsung
2022	0.00	0.00	0.00	1.00	1.00	1.00	0.00
2021	0.00	0.00	0.00	1.00	1.00	1.00	0.00
2020	0.00	0.00	0.00	0.00	1.00	1.00	0.00
2019	0.00	0.00	0.00	0.00	1.00	1.00	0.00

Table 27: Use of Digital Twins in product design, 0 = No mention of the use of Digital Twins in product design this year; 1 = Mention of the use of Digital Twins in product design this year

Annees	Apple	Acer	Dell	HP	Lenovo	Microsoft	Samsung
2022	0.00	0.00	0.00	0.00	1.00	1.00	0.00
2021	0.00	0.00	0.00	0.00	1.00	1.00	0.00
2020	0.00	0.00	0.00	0.00	1.00	0.00	0.00
2019	0.00	0.00	0.00	0.00	1.00	0.00	0.00

Table 28: Use of Digital Twins in material sourcing, 0 = No mention of the use of Digital Twins in material sourcing this year; 1 = Mention of the use of Digital Twins in material sourcing this year

Annees	Apple	Acer	Dell	HP	Lenovo	Microsoft	Samsung
2022	0.00	0.00	1.00	1.00	1.00	1.00	1.00
2021	0.00	0.00	1.00	1.00	1.00	1.00	1.00
2020	0.00	0.00	1.00	1.00	1.00	1.00	1.00
2019	0.00	0.00	1.00	1.00	1.00	1.00	0.00

Table 29: Use of Digital Twins in production, 0 = No mention of the use of Digital Twins in production this year; 1 = Mention of the use of Digital Twins in production this year

Annees	Apple	Acer	Dell	HP	Lenovo	Microsoft	Samsung
2022	0.00	0.00	0.00	1.00	1.00	1.00	0.00
2021	0.00	0.00	0.00	1.00	0.00	0.00	0.00
2020	0.00	0.00	0.00	1.00	0.00	0.00	0.00
2019	0.00	0.00	0.00	1.00	0.00	0.00	0.00

Table 30: Use of Digital Twins in logistics, 0 = No mention of the use of Digital Twins in logistics this year; 1 = Mention of the use of Digital Twins in logistics this year

Annees	Apple	Acer	Dell	HP	Lenovo	Microsoft	Samsung
2022	0.00	0.00	0.00	0.00	1.00	1.00	0.00
2021	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2020	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2019	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 31: Use of Digital Twins in end-of-life product management, 0 = No mention of the use of Digital Twins in end-of-life product management this year, 1 = Mention of the use of Digital Twins in end-of-life product management this year

	Estimate	Sdt. Error	t-value	Pr(> t)
Total emissions	-0.48938	0.63756	-0.7676	0.452689
Scope 1 emissions	-0.51502	0.30429	-1.6925	0.107784
Scope 2 emissions	52020.9	43459	1.197	0.2468305
Scope 3 emissions	-0.50126	0.64784	-0.7737	0.4491305
Scope 3 Specify (Cat 1, Cat 3)	-0.15836	1.30724	-0.1211	0.90492

Table 32: Regression results from five different R models showing the impact of public mentions of Digital Twins in product design on reducing GHG emissions in the supply chain of major technology companies from 2019 to 2022. Figures 9-13

	Estimate	Sdt. Error	t-value	Pr(> t)
Total emissions	-0.24228	0.49645	-0.488	0.6314315
Scope 1 emissions	-0.60809	0.2081	-2.9221	0.0091001**
Scope 2 emissions	8196.53	34774.52	0.2357	0.8163225
Scope 3 emissions	-0.2451	0.50462	-0.4857	0.633035
Scope 3 Specify (Cat 1, Cat 3)	-0.21734	0.835831	-0.26	0.79779

Table 33: Regression results from five different R models showing the impact of public mentions of Digital Twins in material sourcing on reducing GHG emissions in the supply chain of major technology companies from 2019 to 2022. Figures 14-18

	Estimate	Sdt. Error	t-value	Pr(> t)
Total emissions	0.71571	0.60563	1.1818	0.2526811
Scope 1 emissions	0.12085	0.31661	0.3817	0.70716
Scope 2 emissions	1463.3	43814.6	0.0334	0.97372
Scope 3 emissions	0.72625	0.61563	1.1797	0.2534872
Scope 3 Specify (Cat 1, Cat 3)	0.171777	1.260726	0.1362	0.89314

Table 34: Regression results from five different R models showing the impact of public mentions of Digital Twins in production on reducing GHG emissions in the supply chain of major technology companies from 2019 to 2022. Figures 19-23

	Estimate	Sdt. Error	t-value	Pr(> t)
Total emissions	-0.10787	0.37813	-0.2853	0.7786881
Scope 1 emissions	0.045956	0.191326	0.2402	0.8128917
Scope 2 emissions	-40506	24627	-1.6448	0.117365
Scope 3 emissions	-0.10527	0.3844	-0.2739	0.7873086
Scope 3 Specify (Cat 1, Cat 3)	0.12605	0.30009	0.42	0.67943

Table 35 : Regression results from five different R models showing the impact of public mentions of Digital Twins in logistic on reducing GHG emissions in the supply chain of major technology companies from 2019 to 2022. Figures 24-28

	Estimate	Sdt. Error	t-value	Pr(> t)
Total emissions	-0.6477	0.41009	-1.5794	0.1316555
Scope 1 emissions	-0.37961	0.20237	-1.8759	0.07699 •
Scope 2 emissions	-33169.9	29478.2	-1.1252	0.27527
Scope 3 emissions	-0.65308	0.41727	-1.5651	0.1349673
Scope 3 Specify (Cat 1, Cat 3)	-0.053061	0.248701	-0.2134	0.8334496

Table 36: Regression results from five different R models showing the impact of public mentions of Digital Twins in end-of-life product management on reducing GHG emissions in the supply chain of major technology companies from 2019 to 2022. Figures 29-33

Appendix E. Figures

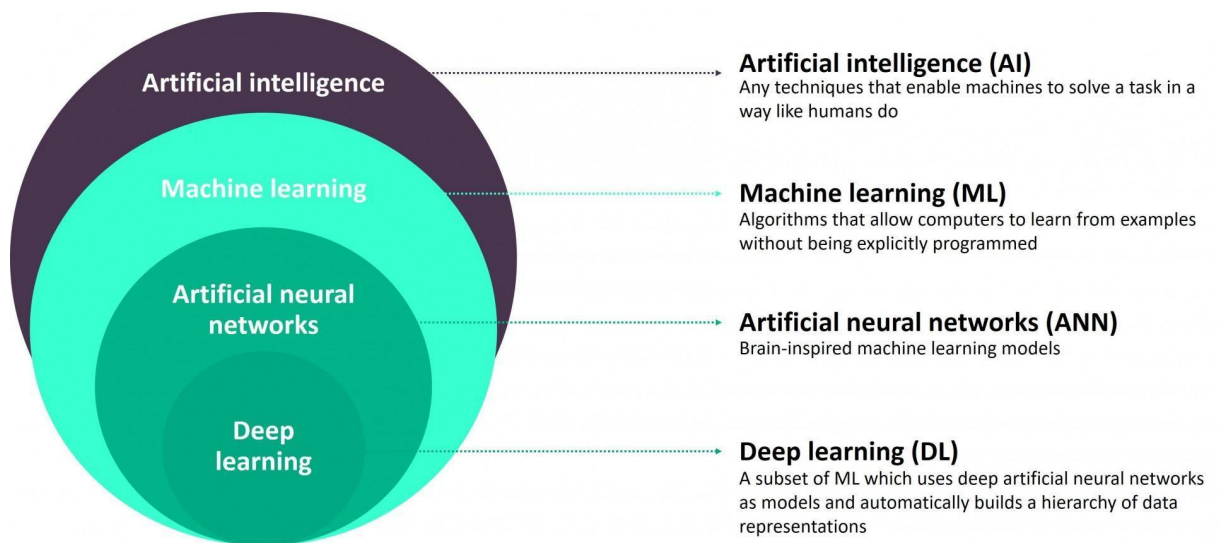


Figure 1: A schematic view of AI, ML, ANNs and DL, Ghods, K., Azizi, A., Jafari, A., & Ghods, K. (2023). *Application of Artificial Intelligence in Clinical Dentistry, A Comprehensive Review of literature. PubMed*, 24(4), 356–371. <https://doi.org/10.30476/dentjods.2023.96835.1969>

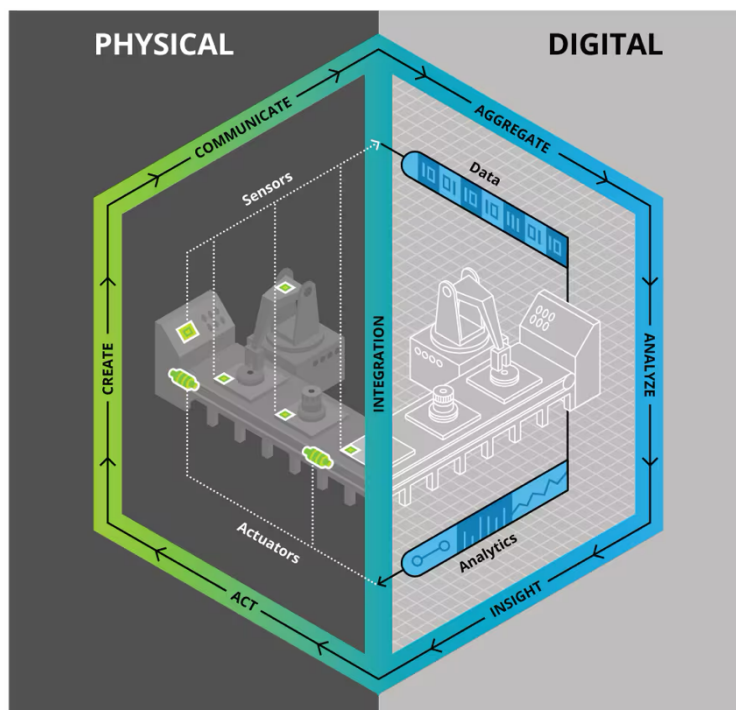


Figure 2: Manufacturing process digital twin model, Digital twins. (n.d.). Deloitte Insights. <https://www2.deloitte.com/us/en/insights/focus/tech-trends/2020/digital-twin-applications-bridging-the-physical-and-digital.html>

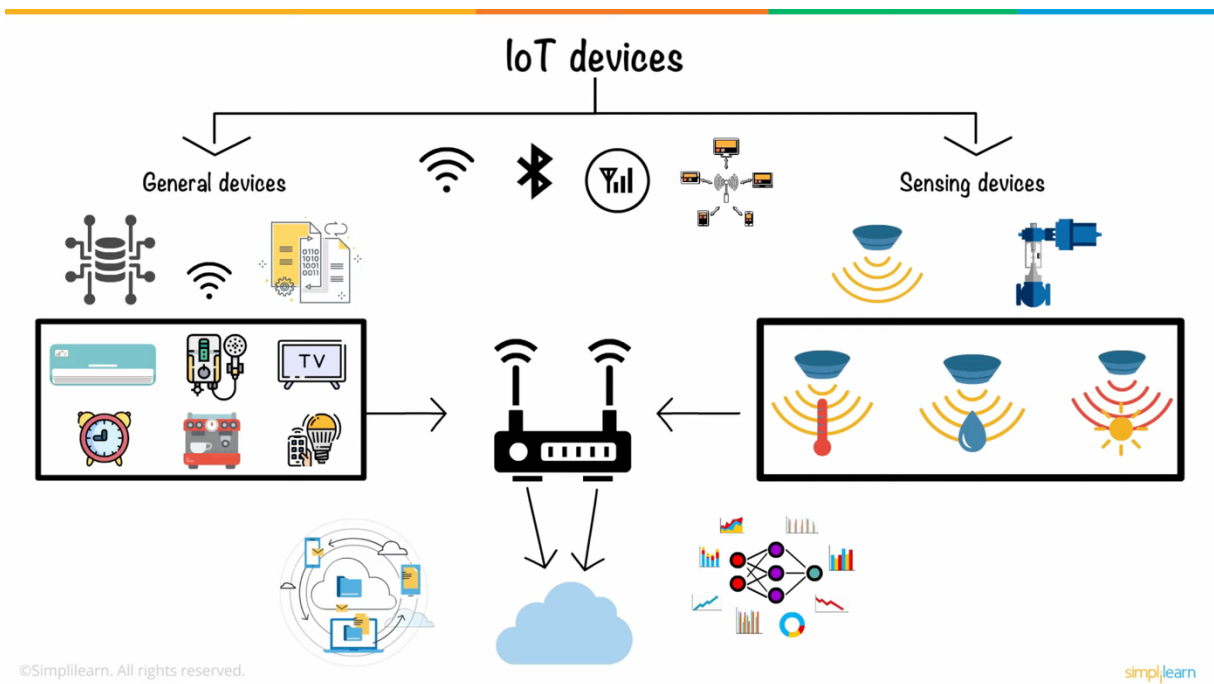


Figure 3: IoT Explained, Simplilearn. (2020, August 24). IoT | Internet of Things | What is IoT? | How IoT Works? | IoT Explained in 6 Minutes | Simplilearn [Video]. YouTube. <https://www.youtube.com/watch?v=6mBO2vqLv38>

Appendix F. Regression Model Results for Digital Twins' Impact on Emissions

```
Oneway (individual) effect Within Model

Call:
plm(formula = log(Emission) ~ Iso1 + Iso2 + Iso3 + log(Size) +
      DT + log(RD) + RE + log(W) + Wr + Wwte, data = pdata, model = "within")

Balanced Panel: n = 7, T = 4, N = 28

Residuals:
    Min.    1st Qu.    Median    3rd Qu.     Max.
-0.171535 -0.109726 -0.023721  0.145191  0.196823

Coefficients:
              Estimate Std. Error t-value Pr(>|t|)
Iso2         -0.086521   0.214989  -0.4024  0.6939
log(Size)     0.454277   0.511512   0.8881  0.3906
DT           -0.091827   0.079538  -1.1545  0.2691
log(RD)       -0.211751   0.311082  -0.6807  0.5080
RE            0.259850   1.165729   0.2229  0.8271
log(W)        -0.518284   0.406783  -1.2741  0.2249
Wr            -0.329643   1.439565  -0.2290  0.8224
Wwte         -1.132368   3.449704  -0.3283  0.7479

Total Sum of Squares:    0.60957
Residual Sum of Squares: 0.43583
R-Squared:              0.28503
Adj. R-Squared:         -0.48494
F-statistic: 0.647813 on 8 and 13 DF, p-value: 0.7265
```

Figure 4: Results of the General Model 'Pooling' All GHG emissions

```
Pooling Model

Call:
plm(formula = log(Emission) ~ Iso1 + Iso2 + Iso3 + log(Size) +
      DT + log(RD) + RE + log(W) + Wr + Wwte, data = pdata, model = "pooling")

Balanced Panel: n = 7, T = 4, N = 28

Residuals:
    Min.    1st Qu.    Median    3rd Qu.     Max.
-0.893826 -0.293711 -0.044436  0.432599  0.660866

Coefficients:
              Estimate Std. Error t-value Pr(>|t|)
(Intercept)  25.545841   3.162926  8.0766 2.139e-07 ***
Iso2         -0.452329   0.378568  -1.1948  0.247655
Iso3         -1.553023   0.843008  -1.8422  0.081976 .
log(Size)     4.479943   0.839556  5.3361 4.512e-05 ***
DT           -0.052591   0.138644  -0.3793  0.708884
log(RD)       -1.570828   0.502470  -3.1262  0.005835 **
RE           -4.667486   1.196155  -3.9021  0.001045 **
log(W)        -1.632489   0.245381  -6.6529 3.044e-06 ***
Wr           -9.464043   2.507721  -3.7740  0.001390 **
Wwte         -4.213288   7.035808  -0.5988  0.556745
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    83.845
Residual Sum of Squares: 5.2034
R-Squared:              0.93794
Adj. R-Squared:         0.90691
F-statistic: 30.227 on 9 and 18 DF, p-value: 4.5261e-09
```

Figure 5: Results of the General Model 'Within' All GHG emissions

```

Pooling Model

Call:
plm(formula = log(Emission1) ~ Iso1 + Iso2 + Iso3 + log(Size) +
    DT + log(RD) + RE + log(W) + Wr + Wwte, data = pdata, model = "pooling")

Balanced Panel: n = 7, T = 4, N = 28

Residuals:
    Min.    1st Qu.    Median    3rd Qu.    Max.
-0.503591 -0.114921  0.010353  0.157446  0.350939

Coefficients:
              Estimate Std. Error t-value Pr(>|t|)
(Intercept)  13.156334   1.444925   9.1052 3.703e-08 ***
Iso2         -0.511221   0.172942  -2.9560 0.0084555 **
Iso3         -1.865386   0.385113  -4.8437 0.0001304 ***
log(Size)     1.414601   0.383536   3.6883 0.0016819 **
DT           -0.130242   0.063337  -2.0563 0.0545469 .
log(RD)       -0.040859   0.229544  -0.1780 0.8607115
RE            0.447142   0.546442   0.8183 0.4238981
log(W)        -0.796432   0.112098  -7.1048 1.272e-06 ***
Wr            -0.428059   1.145607  -0.3737 0.7130273
Wwte         -3.086365   3.214180  -0.9602 0.3496596
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares: 47.006
Residual Sum of Squares: 1.0859
R-Squared: 0.9769
Adj. R-Squared: 0.96535
F-statistic: 84.573 on 9 and 18 DF, p-value: 7.0571e-13

```

Figure 6: Results of the General Model 'Pooling' Scope 1 GHG emissions

```

Pooling Model

Call:
plm(formula = Emission2 ~ Iso1 + Iso2 + Iso3 + log(Size) + DT +
    log(RD) + RE + log(W) + Wr + Wwte, data = pdata, model = "pooling")

Balanced Panel: n = 7, T = 4, N = 28

Residuals:
    Min.    1st Qu.    Median    3rd Qu.    Max.
-67918.6 -14295.0  -1173.4   9829.7  99341.0

Coefficients:
              Estimate Std. Error t-value Pr(>|t|)
(Intercept) 1372482.4   220403.1   6.2271 7.101e-06 ***
Iso2         2549.6     26379.9   0.0967 0.9240722
Iso3        -195734.6   58743.6  -3.3320 0.0037095 **
log(Size)    -163011.0   58503.0  -2.7864 0.0121873 *
DT           -3737.0     9661.2  -0.3868 0.7034379
log(RD)       166061.1   35013.8   4.7427 0.0001625 ***
RE            94333.7    83352.1   1.1318 0.2725924
log(W)        -97518.9   17099.0  -5.7032 2.081e-05 ***
Wr            387095.8   174746.3   2.2152 0.0398816 *
Wwte         -758061.8   490278.3  -1.5462 0.1394602
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares: 5.0431e+11
Residual Sum of Squares: 2.5267e+10
R-Squared: 0.9499
Adj. R-Squared: 0.92485
F-statistic: 37.9192 on 9 and 18 DF, p-value: 6.8591e-10

```

Figure 7: Results of the General Model 'Pooling' Scope 2 GHG emissions

```

Pooling Model

Call:
plm(formula = log(Emission3) ~ Iso1 + Iso2 + Iso3 + log(Size) +
    DT + log(RD) + RE + log(W) + Wr + Wwte, data = pdata, model = "pooling")

Balanced Panel: n = 7, T = 4, N = 28

Residuals:
    Min.    1st Qu.    Median    3rd Qu.    Max.
-0.910445 -0.302038 -0.043311  0.438486  0.667457

Coefficients:
              Estimate Std. Error t-value Pr(>|t|)
(Intercept)  25.688666   3.215495   7.9890 2.499e-07 ***
Iso2         -0.453736   0.384860  -1.1790 0.2537627
Iso3        -1.554385   0.857019  -1.8137 0.0864297 .
log(Size)     4.569131   0.853509   5.3533 4.349e-05 ***
DT           -0.051886   0.140949  -0.3681 0.7170752
log(RD)       -1.607084   0.510822  -3.1461 0.0055862 **
RE           -4.777272   1.216036  -3.9286 0.0009847 ***
log(W)        -1.660587   0.249460  -6.6567 3.021e-06 ***
Wr           -9.684473   2.549401  -3.7987 0.0013151 **
Wwte         -4.235950   7.152746  -0.5922 0.5610740
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    87.052
Residual Sum of Squares: 5.3778
R-Squared:               0.93822
Adj. R-Squared: 0.90733
F-statistic: 30.3745 on 9 and 18 DF, p-value: 4.348e-09

```

Figure 8: Results of the General Model 'Pooling' Scope 3 GHG emissions

```

Pooling Model

Call:
plm(formula = log(Emission) ~ Iso1 + Iso2 + Iso3 + log(Size) +
    DT1 + log(RD) + RE + log(W) + Wr + Wwte, data = pdata, model = "pooling")

Balanced Panel: n = 7, T = 4, N = 28

Residuals:
    Min.    1st Qu.    Median    3rd Qu.    Max.
-0.8922409 -0.2732615 -0.0092171  0.4003471  0.6106406

Coefficients:
              Estimate Std. Error t-value Pr(>|t|)
(Intercept)  25.45964   2.99617   8.4974 1.027e-07 ***
Iso2         -0.47176   0.37513  -1.2576 0.2246082
Iso3        -1.40594   0.54945  -2.5588 0.0197316 *
log(Size)     4.34205   0.70440   6.1642 8.066e-06 ***
DT1          -0.48938   0.63756  -0.7676 0.4526893
log(RD)       -1.46097   0.45003  -3.2464 0.0044811 **
RE           -4.49902   1.08215  -4.1575 0.0005915 ***
log(W)        -1.65894   0.24056  -6.8963 1.896e-06 ***
Wr           -8.60867   2.13646  -4.0294 0.0007866 ***
Wwte         -4.59087   6.43801  -0.7131 0.4849337
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    83.845
Residual Sum of Squares: 5.0788
R-Squared:               0.93943
Adj. R-Squared: 0.90914
F-statistic: 31.0179 on 9 and 18 DF, p-value: 3.6568e-09

```

Figure 9: Results of the Product Design Model 'Pooling' All GHG emissions

```

Pooling Model

Call:
p1m(formula = log(Emission1) ~ Iso1 + Iso2 + Iso3 + log(Size) +
    DT1 + log(RD) + RE + log(W) + Wr + Wwte, data = pdata, model = "pooling")

Balanced Panel: n = 7, T = 4, N = 28

Residuals:
    Min.      1st Qu.        Median         3rd Qu.         Max.
-0.4805993 -0.1299330 -0.0013325  0.1263412  0.4191674

Coefficients:
              Estimate Std. Error t-value Pr(>|t|)
(Intercept)  12.54031    1.43001   8.7694 6.470e-08 ***
Iso2         -0.52471    0.17904  -2.9307 0.008933 **
Iso3         -1.36129    0.26224  -5.1911 6.151e-05 ***
log(Size)     1.02902    0.33620   3.0608 0.006732 **
DT1          -0.51502    0.30429  -1.6925 0.107784
log(RD)        0.19107    0.21479   0.8896 0.385435
RE            0.88426    0.51648   1.7121 0.104058
log(W)        -0.78021    0.11481  -6.7956 2.304e-06 ***
Wr            1.20047    1.01968   1.1773 0.254410
Wwte         -1.61092    3.07271  -0.5243 0.606489
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares: 47.006
Residual Sum of Squares: 1.1569
R-Squared: 0.97539
Adj. R-Squared: 0.96308
F-statistic: 79.2613 on 9 and 18 DF, p-value: 1.2417e-12

```

Figure 10: Results of the Product Design Model 'Pooling' Scope 1 GHG emissions

```

Pooling Model

Call:
p1m(formula = Emission2 ~ Iso1 + Iso2 + Iso3 + log(Size) + DT1 +
    log(RD) + RE + log(W) + Wr + Wwte, data = pdata, model = "pooling")

Balanced Panel: n = 7, T = 4, N = 28

Residuals:
    Min.      1st Qu.        Median         3rd Qu.         Max.
-54854.2 -13888.5  -2926.8   9923.0 110804.9

Coefficients:
              Estimate Std. Error t-value Pr(>|t|)
(Intercept) 1316222.2    204233.3   6.4447 4.592e-06 ***
Iso2         5483.1      25570.6   0.2144 0.8326224
Iso3        -167866.5     37452.7  -4.4821 0.0002882 ***
log(Size)    -178301.3     48015.4  -3.7134 0.0015904 **
DT1           52020.9     43459.0   1.1970 0.2468305
log(RD)       168868.4     30676.2   5.5049 3.155e-05 ***
RE           108784.5     73764.3   1.4748 0.1575540
log(W)        -89220.7     16397.4  -5.4411 3.610e-05 ***
Wr            386877.0     145631.0   2.6566 0.0160647 *
Wwte         -484681.3     438844.9  -1.1044 0.2839446
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares: 5.0431e+11
Residual Sum of Squares: 2.3598e+10
R-Squared: 0.95321
Adj. R-Squared: 0.92981
F-statistic: 40.7416 on 9 and 18 DF, p-value: 3.7495e-10

```

Figure 11: Results of the Product Design Model 'Pooling' Scope 2 GHG emissions

```

Pooling Model

Call:
plm(formula = log(Emission3) ~ Iso1 + Iso2 + Iso3 + log(Size) +
      DT1 + log(RD) + RE + log(W) + Wr + Wwte, data = pdata, model = "pooling")

Balanced Panel: n = 7, T = 4, N = 28

Residuals:
      Min.      1st Qu.      Median      3rd Qu.      Max.
-0.9055605 -0.2772033 -0.0072583  0.4115915  0.6192735

Coefficients:
              Estimate Std. Error t-value Pr(>|t|)
(Intercept)  25.61427    3.04449   8.4133 1.187e-07 ***
Iso2         -0.47383    0.38118  -1.2431 0.2297977
Iso3         -1.41298    0.55831  -2.5308 0.0209209 *
log(Size)     4.43426    0.71576   6.1951 7.576e-06 ***
DT1          -0.50126    0.64784  -0.7737 0.4491305
log(RD)       -1.49763    0.45729  -3.2750 0.0042068 **
RE           -4.61159    1.09960  -4.1939 0.0005456 ***
log(W)        -1.68884    0.24444  -6.9092 1.850e-06 ***
Wr            -8.82761    2.17091  -4.0663 0.0007246 ***
Wwte         -4.67226    6.54183  -0.7142 0.4842557
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    87.052
Residual Sum of Squares: 5.2439
R-Squared:               0.93976
Adj. R-Squared:          0.90964
F-statistic: 31.2013 on 9 and 18 DF, p-value: 3.4829e-09

```

Figure 12: Results of the Product Design Model 'Pooling' Scope 3 GHG emissions

```

Pooling Model

Call:
plm(formula = log(Emission) ~ Iso1 + Iso2 + Iso3 + log(Size) +
      DT1 + log(RD) + RE + log(W) + Wr + Wwte, data = pdata, model = "pooling")

Balanced Panel: n = 7, T = 4, N = 28

Residuals:
      Min.      1st Qu.      Median      3rd Qu.      Max.
-2.200085 -0.280216 -0.045205  0.333203  2.703886

Coefficients:
              Estimate Std. Error t-value Pr(>|t|)
(Intercept) -0.16870    6.14331  -0.0275 0.97839
Iso2         0.15863    0.76916   0.2062 0.83892
Iso3        -2.01655    1.12657  -1.7900 0.09029 .
log(Size)    3.37407    1.44430   2.3361 0.03125 *
DT1          -0.15836    1.30724  -0.1211 0.90492
log(RD)      -1.98829    0.92274  -2.1548 0.04497 *
RE           1.75161    2.21882   0.7894 0.44013
log(W)       0.41702    0.49323   0.8455 0.40895
Wr           -1.92898    4.38056  -0.4403 0.66493
Wwte        -1.30197    13.20039  -0.0986 0.92252
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    65.794
Residual Sum of Squares: 21.351
R-Squared:               0.67548
Adj. R-Squared:          0.51322
F-statistic: 4.16297 on 9 and 18 DF, p-value: 0.0048665

```

Figure 13: Results of the Product Design Model 'Pooling' Corresponding Scope 3 GHG emissions

```

Pooling Model

Call:
plm(formula = log(Emission) ~ Iso1 + Iso2 + Iso3 + log(Size) +
      DT2 + log(RD) + RE + log(W) + Wr + Wwte, data = pdata, model = "pooling")

Balanced Panel: n = 7, T = 4, N = 28

Residuals:
    Min.    1st Qu.    Median    3rd Qu.     Max.
-0.87264 -0.27722 -0.08630  0.40653  0.64992

Coefficients:
              Estimate Std. Error t-value Pr(>|t|)
(Intercept)  25.95416    3.39822   7.6376 4.712e-07 ***
Iso2         -0.38121    0.40103  -0.9506 0.3544177
Iso3        -1.53898    0.71801  -2.1434 0.0459927 *
log(Size)     4.60308    0.92849   4.9576 0.0001018 ***
DT2          -0.24228    0.49645  -0.4880 0.6314315
log(RD)       -1.59359    0.50085  -3.1818 0.0051650 **
RE           -4.97261    1.48035  -3.3591 0.0034941 **
log(W)        -1.67681    0.27761  -6.0402 1.038e-05 ***
Wr           -9.88809    2.84996  -3.4696 0.0027355 **
Wwte         -5.55569    8.18188  -0.6790 0.5057610
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    83.845
Residual Sum of Squares: 5.1765
R-Squared:              0.93826
Adj. R-Squared: 0.90739
F-statistic: 30.3945 on 9 and 18 DF, p-value: 4.3244e-09

```

Figure 14: Results of the Material Sourcing Model 'Pooling' All GHG emissions

```

Pooling Model

Call:
plm(formula = log(Emission1) ~ Iso1 + Iso2 + Iso3 + log(Size) +
      DT2 + log(RD) + RE + log(W) + Wr + Wwte, data = pdata, model = "pooling")

Balanced Panel: n = 7, T = 4, N = 28

Residuals:
    Min.    1st Qu.    Median    3rd Qu.     Max.
-0.4313522 -0.1327360 -0.0071786  0.1787118  0.3472150

Coefficients:
              Estimate Std. Error t-value Pr(>|t|)
(Intercept)  14.19351    1.42445   9.9642 9.438e-09 ***
Iso2         -0.33287    0.16810  -1.9801 0.0631840 .
Iso3        -1.83833    0.30097  -6.1080 9.041e-06 ***
log(Size)     1.72932    0.38920   4.4433 0.0003139 ***
DT2          -0.60809    0.20810  -2.9221 0.0091001 **
log(RD)       -0.10072    0.20994  -0.4797 0.6371982
RE           -0.32480    0.62053  -0.5234 0.6070611
log(W)        -0.90871    0.11637  -7.8091 3.451e-07 ***
Wr           -1.50948    1.19463  -1.2635 0.2225133
Wwte         -6.49966    3.42965  -1.8951 0.0742508 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    47.006
Residual Sum of Squares: 0.90956
R-Squared:              0.98065
Adj. R-Squared: 0.97098
F-statistic: 101.36 on 9 and 18 DF, p-value: 1.4492e-13

```

Figure 15: Results of the Material Sourcing Model 'Pooling' Scope 1 GHG emissions

```

Pooling Model

Call:
plm(formula = Emission2 ~ Iso1 + Iso2 + Iso3 + log(Size) + DT2 +
      log(RD) + RE + log(W) + Wr + Wwte, data = pdata, model = "pooling")

Balanced Panel: n = 7, T = 4, N = 28

Residuals:
    Min.    1st Qu.    Median    3rd Qu.     Max.
-59221.4 -13639.7  -1873.7  12667.4 101758.1

Coefficients:
              Estimate Std. Error t-value Pr(>|t|)
(Intercept) 1319977.63  238030.87   5.5454 2.897e-05 ***
Iso2          656.48    28090.64   0.0234 0.9816121
Iso3        -170482.45   50293.40  -3.3898 0.0032647 **
log(Size)   -184888.08   65036.52  -2.8428 0.0107969 *
DT2           8196.53    34774.52   0.2357 0.8163225
log(RD)      175397.75   35082.13   4.9996 9.292e-05 ***
RE          123793.26   103692.68   1.1938 0.2480346
log(W)       -92774.67   19445.28  -4.7711 0.0001528 ***
Wr           455085.81   199627.72   2.2797 0.0350383 *
Wwte        -574707.72   573106.67  -1.0028 0.3292515
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    5.0431e+11
Residual Sum of Squares: 2.5398e+10
R-Squared:              0.94964
Adj. R-Squared:         0.92446
F-statistic: 37.7124 on 9 and 18 DF, p-value: 7.1813e-10

```

Figure 16: Results of the Material Sourcing Model 'Pooling' Scope 2 GHG emissions

```

Pooling Model

Call:
plm(formula = log(Emission3) ~ Iso1 + Iso2 + Iso3 + log(Size) +
      DT2 + log(RD) + RE + log(W) + Wr + Wwte, data = pdata, model = "pooling")

Balanced Panel: n = 7, T = 4, N = 28

Residuals:
    Min.    1st Qu.    Median    3rd Qu.     Max.
-0.889913 -0.281083 -0.084288  0.417507  0.658725

Coefficients:
              Estimate Std. Error t-value Pr(>|t|)
(Intercept)  26.11098    3.45411   7.5594 5.439e-07 ***
Iso2         -0.38191    0.40763  -0.9369 0.361213
Iso3        -1.54632    0.72982  -2.1188 0.048279 *
log(Size)     4.69793    0.94376   4.9779 9.739e-05 ***
DT2          -0.24510    0.50462  -0.4857 0.633035
log(RD)       -1.63215    0.50908  -3.2061 0.004897 **
RE           -5.09052    1.50470  -3.3831 0.003313 **
log(W)        -1.70620    0.28217  -6.0466 1.025e-05 ***
Wr           -10.12626    2.89684  -3.4956 0.002582 **
Wwte          -5.62692    8.31646  -0.6766 0.507262
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    87.052
Residual Sum of Squares: 5.3482
R-Squared:              0.93856
Adj. R-Squared:         0.90784
F-statistic: 30.5537 on 9 and 18 DF, p-value: 4.1419e-09

```

Figure 17: Results of the Material Sourcing Model 'Pooling' Scope 3 GHG emissions

Pooling Model

Call:

```
plm(formula = log(Emission) ~ Iso1 + Iso2 + Iso3 + log(Size) +
      DT1 + log(RD) + RE + log(W) + Wr + Wwte, data = pdata, model = "pooling")
```

Balanced Panel: n = 7, T = 4, N = 28

Residuals:

Min.	1st Qu.	Median	3rd Qu.	Max.
-2.200085	-0.280216	-0.045205	0.333203	2.703886

Coefficients:

	Estimate	Std. Error	t-value	Pr(> t)
(Intercept)	-0.16870	6.14331	-0.0275	0.97839
Iso2	0.15863	0.76916	0.2062	0.83892
Iso3	-2.01655	1.12657	-1.7900	0.09029
log(Size)	3.37407	1.44430	2.3361	0.03125 *
DT1	-0.15836	1.30724	-0.1211	0.90492
log(RD)	-1.98829	0.92274	-2.1548	0.04497 *
RE	1.75161	2.21882	0.7894	0.44013
log(W)	0.41702	0.49323	0.8455	0.40895
Wr	-1.92898	4.38056	-0.4403	0.66493
Wwte	-1.30197	13.20039	-0.0986	0.92252

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares: 65.794

Residual Sum of Squares: 21.351

R-Squared: 0.67548

Adj. R-Squared: 0.51322

F-statistic: 4.16297 on 9 and 18 DF, p-value: 0.0048665

Figure 18: Results of the Material Sourcing Model 'Pooling' Corresponding Scope 3 GHG emissions

Pooling Model

Call:

```
plm(formula = log(Emission) ~ Iso1 + Iso2 + Iso3 + log(Size) +
      DT3 + log(RD) + RE + log(W) + Wr + Wwte, data = pdata, model = "pooling")
```

Balanced Panel: n = 7, T = 4, N = 28

Residuals:

Min.	1st Qu.	Median	3rd Qu.	Max.
-0.813196	-0.291147	0.018963	0.426742	0.649661

Coefficients:

	Estimate	Std. Error	t-value	Pr(> t)
(Intercept)	24.78408	2.92984	8.4592	1.097e-07 ***
Iso2	-0.48849	0.36757	-1.3290	0.2004616
Iso3	-0.43079	0.90792	-0.4745	0.6408617
log(Size)	4.06840	0.71843	5.6629	2.264e-05 ***
DT3	0.71571	0.60563	1.1818	0.2526811
log(RD)	-1.34908	0.45481	-2.9662	0.0082705 **
RE	-4.57358	1.06188	-4.3070	0.0004244 ***
log(W)	-1.55810	0.22684	-6.8689	1.999e-06 ***
Wr	-8.78653	2.04983	-4.2865	0.0004442 ***
Wwte	-1.56873	6.02725	-0.2603	0.7976068

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares: 83.845

Residual Sum of Squares: 4.8674

R-Squared: 0.94195

Adj. R-Squared: 0.91292

F-statistic: 32.452 on 9 and 18 DF, p-value: 2.5151e-09

Figure 19: Results of the Production Model 'Pooling' All GHG emissions

```

Pooling Model

Call:
plm(formula = log(Emission1) ~ Iso1 + Iso2 + Iso3 + log(Size) +
    DT3 + log(RD) + RE + log(W) + Wr + Wwte, data = pdata, model = "pooling")

Balanced Panel: n = 7, T = 4, N = 28

Residuals:
    Min.    1st Qu.    Median    3rd Qu.    Max.
-0.4699961 -0.1602530  0.0040848  0.1377927  0.3812914

Coefficients:
              Estimate Std. Error t-value Pr(>|t|)
(Intercept)  12.17647    1.53167   7.9498 2.680e-07 ***
Iso2         -0.50604    0.19216  -2.6334  0.01687 *
Iso3         -1.10987    0.47464  -2.3383  0.03111 *
log(Size)     0.95545    0.37558   2.5439  0.02036 *
DT3           0.12085    0.31661   0.3817  0.70716
log(RD)       0.18506    0.23777   0.7783  0.44650
RE            0.88402    0.55513   1.5924  0.12869
log(W)       -0.71248    0.11859  -6.0082 1.108e-05 ***
Wr            0.86656    1.07162   0.8086  0.42928
Wwte         0.39495    3.15094   0.1253  0.90164
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares: 47.006
Residual Sum of Squares: 1.3303
R-Squared: 0.9717
Adj. R-Squared: 0.95755
F-statistic: 68.6719 on 9 and 18 DF, p-value: 4.311e-12

```

Figure 20: Results of the Production Model 'Pooling' Scope 1 GHG emissions

```

Pooling Model

Call:
plm(formula = Emission2 ~ Iso1 + Iso2 + Iso3 + log(Size) + DT3 +
    log(RD) + RE + log(W) + Wr + Wwte, data = pdata, model = "pooling")

Balanced Panel: n = 7, T = 4, N = 28

Residuals:
    Min.    1st Qu.    Median    3rd Qu.    Max.
-63155.4 -13381.6  -1906.4  11628.4 100576.5

Coefficients:
              Estimate Std. Error t-value Pr(>|t|)
(Intercept) 1345467.9    211959.7   6.3478 5.572e-06 ***
Iso2         2813.3      26592.1   0.1058  0.91692
Iso3        -176512.5    65683.3  -2.6873  0.01505 *
log(Size)    -175505.6    51975.0  -3.3767  0.00336 **
DT3           1463.3     43814.6   0.0334  0.97372
log(RD)       172151.0    32903.6   5.2320 5.635e-05 ***
RE            107116.9    76822.2   1.3943  0.18019
log(W)       -95231.9    16410.4  -5.8031 1.691e-05 ***
Wr            423776.7    148295.3   2.8577  0.01046 *
Wwte        -661896.6    436042.3  -1.5180  0.14639
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares: 5.0431e+11
Residual Sum of Squares: 2.5475e+10
R-Squared: 0.94949
Adj. R-Squared: 0.92423
F-statistic: 37.5926 on 9 and 18 DF, p-value: 7.3754e-10

```

Figure 21: Results of the Production Model 'Pooling' Scope 2 GHG emissions

```

Pooling Model

Call:
plm(formula = log(Emission3) ~ Iso1 + Iso2 + Iso3 + log(Size) +
      DT3 + log(RD) + RE + log(W) + Wr + Wwte, data = pdata, model = "pooling")

Balanced Panel: n = 7, T = 4, N = 28

Residuals:
    Min.    1st Qu.    Median    3rd Qu.     Max.
-0.82964 -0.29454  0.01779  0.43147  0.65557

Coefficients:
              Estimate Std. Error t-value Pr(>|t|)
(Intercept)  24.92606    2.97822   8.3694 1.281e-07 ***
Iso2         -0.49057    0.37364  -1.3129 0.2057003
Iso3         -0.42253    0.92291  -0.4578 0.6525595
log(Size)     4.15628    0.73030   5.6912 2.134e-05 ***
DT3           0.72625    0.61563   1.1797 0.2534872
log(RD)       -1.38437    0.46232  -2.9944 0.0077802 **
RE            -4.68712    1.07942  -4.3423 0.0003926 ***
log(W)        -1.58597    0.23058  -6.8782 1.964e-06 ***
Wr            -9.01137    2.08368  -4.3247 0.0004081 ***
Wwte         -1.58945    6.12678  -0.2594 0.7982503
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    87.052
Residual Sum of Squares: 5.0295
R-Squared:                0.94222
Adj. R-Squared:          0.91334
F-statistic: 32.6168 on 9 and 18 DF, p-value: 2.4116e-09

```

Figure 22: Results of the Production Model 'Pooling' Scope 3 GHG emissions

```

Pooling Model

Call:
plm(formula = log(Emission) ~ Iso1 + Iso2 + Iso3 + log(Size) +
      DT3 + log(RD) + RE + log(W) + Wr + Wwte, data = pdata, model = "pooling")

Balanced Panel: n = 7, T = 4, N = 28

Residuals:
    Min.    1st Qu.    Median    3rd Qu.     Max.
-2.181486 -0.317077 -0.032417  0.336322  2.693202

Coefficients:
              Estimate Std. Error t-value Pr(>|t|)
(Intercept) -0.257228    6.099143 -0.0422 0.96682
Iso2         0.175231    0.765188  0.2290 0.82145
Iso3        -1.748268    1.890039 -0.9250 0.36721
log(Size)     3.275979    1.495583  2.1904 0.04190 *
DT3           0.171777    1.260765  0.1362 0.89314
log(RD)       -1.935602    0.946800 -2.0444 0.05583 .
RE            1.743586    2.210560  0.7888 0.44052
log(W)         0.436438    0.472210  0.9242 0.36758
Wr            -1.907192    4.267201 -0.4469 0.66025
Wwte         -0.034434    12.547124 -0.0027 0.99784
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    65.747
Residual Sum of Squares: 21.093
R-Squared:                0.67917
Adj. R-Squared:          0.51876
F-statistic: 4.23388 on 9 and 18 DF, p-value: 0.0044618

```

Figure 23: Results of the Production Model 'Pooling' Corresponding Scope 3 GHG emissions

```

Pooling Model

Call:
plm(formula = log(Emission) ~ Iso1 + Iso2 + Iso3 + log(Size) +
      DT4 + log(RD) + RE + log(W) + Wr + Wwte, data = pdata, model = "pooling")

Balanced Panel: n = 7, T = 4, N = 28

Residuals:
      Min.      1st Qu.      Median      3rd Qu.      Max.
-0.891479 -0.323323 -0.011603  0.430787  0.654553

Coefficients:
              Estimate Std. Error t-value Pr(>|t|)
(Intercept)  25.01335    3.06898   8.1504 1.878e-07 ***
Iso2         -0.51415    0.44535  -1.1545 0.2633927
Iso3        -1.37906    0.59669  -2.3112 0.0328748 *
log(Size)     4.37346    0.74583   5.8639 1.491e-05 ***
DT4          -0.10787    0.37813  -0.2853 0.7786881
log(RD)       -1.53656    0.48419  -3.1735 0.0052604 **
RE           -4.49345    1.09748  -4.0943 0.0006807 ***
log(W)        -1.59826    0.23212  -6.8855 1.936e-06 ***
Wr            -8.96548    2.11855  -4.2319 0.0005014 ***
Wwte         -2.85646    6.13464  -0.4656 0.6470659
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares: 83.845
Residual Sum of Squares: 5.2214
R-Squared: 0.93773
Adj. R-Squared: 0.90659
F-statistic: 30.116 on 9 and 18 DF, p-value: 4.6655e-09

```

Figure 24: Results of the Logistics Model 'Pooling' All GHG emissions

```

Pooling Model

Call:
plm(formula = log(Emission1) ~ Iso1 + Iso2 + Iso3 + log(Size) +
      DT4 + log(RD) + RE + log(W) + Wr + Wwte, data = pdata, model = "pooling")

Balanced Panel: n = 7, T = 4, N = 28

Residuals:
      Min.      1st Qu.      Median      3rd Qu.      Max.
-0.455308 -0.157056  0.013996  0.148196  0.384930

Coefficients:
              Estimate Std. Error t-value Pr(>|t|)
(Intercept)  12.312515    1.552834   7.9291 2.782e-07 ***
Iso2         -0.470684    0.225335  -2.0888 0.0511985 .
Iso3        -1.227562    0.301910  -4.0660 0.0007251 ***
log(Size)     0.969855    0.377371   2.5700 0.0192744 *
DT4           0.045956    0.191326   0.2402 0.8128917
log(RD)        0.181600    0.244989   0.7413 0.4680989
RE            0.902557    0.555299   1.6254 0.1214672
log(W)        -0.721226    0.117447  -6.1408 8.457e-06 ***
Wr            0.844003    1.071939   0.7874 0.4413156
Wwte          0.152696    3.103982   0.0492 0.9613067
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares: 47.006
Residual Sum of Squares: 1.3367
R-Squared: 0.97156
Adj. R-Squared: 0.95734
F-statistic: 68.3291 on 9 and 18 DF, p-value: 4.5018e-12

```

Figure 25: Results of the Logistics Model 'Pooling' Scope 1 GHG emissions

```

Pooling Model

Call:
plm(formula = Emission2 ~ Iso1 + Iso2 + Iso3 + log(Size) + DT4 +
      log(RD) + RE + log(W) + Wr + Wwte, data = pdata, model = "pooling")

Balanced Panel: n = 7, T = 4, N = 28

Residuals:
    Min.    1st Qu.    Median    3rd Qu.    Max.
-71720.71 -17092.46  -490.09  13366.05  91418.94

Coefficients:
              Estimate Std. Error t-value Pr(>|t|)
(Intercept)  1284835    199879   6.4281 4.747e-06 ***
Iso2         -22155     29005  -0.7638  0.454868
Iso3        -205085    38862  -5.2773 5.114e-05 ***
log(Size)    -151586    48575  -3.1207  0.005906 **
DT4          -40506    24627  -1.6448  0.117365
log(RD)       154065    31535   4.8856  0.000119 ***
RE           104140     71477   1.4570  0.162352
log(W)       -94083    15118  -6.2234 7.155e-06 ***
Wr           418600    137979   3.0338  0.007140 **
Wwte        -648948    399541  -1.6242  0.121707
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares: 5.0431e+11
Residual Sum of Squares: 2.2148e+10
R-Squared: 0.95608
Adj. R-Squared: 0.93412
F-statistic: 43.5403 on 9 and 18 DF, p-value: 2.1388e-10

```

Figure 26: Results of the Logistics Model 'Pooling' Scope 2 GHG emissions

```

Pooling Model

Call:
plm(formula = log(Emission3) ~ Iso1 + Iso2 + Iso3 + log(Size) +
      DT4 + log(RD) + RE + log(W) + Wr + Wwte, data = pdata, model = "pooling")

Balanced Panel: n = 7, T = 4, N = 28

Residuals:
    Min.    1st Qu.    Median    3rd Qu.    Max.
-0.907772 -0.329416 -0.012629  0.441652  0.661491

Coefficients:
              Estimate Std. Error t-value Pr(>|t|)
(Intercept)  25.16507    3.11982   8.0662 2.179e-07 ***
Iso2         -0.51402    0.45272  -1.1354 0.2711065
Iso3        -1.38199    0.60657  -2.2784 0.0351316 *
log(Size)    4.46341    0.75818   5.8870 1.422e-05 ***
DT4          -0.10527    0.38440  -0.2739 0.7873086
log(RD)      -1.57277    0.49221  -3.1953 0.0050139 **
RE           -4.60548    1.11566  -4.1280 0.0006316 ***
log(W)       -1.62685    0.23597  -6.8945 1.903e-06 ***
Wr           -9.19246    2.15365  -4.2683 0.0004625 ***
Wwte        -2.89776    6.23626  -0.4647 0.6477442
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares: 87.052
Residual Sum of Squares: 5.3958
R-Squared: 0.93802
Adj. R-Squared: 0.90702
F-statistic: 30.2665 on 9 and 18 DF, p-value: 4.4776e-09

```

Figure 27: Results of the Logistics Model 'Pooling' Scope 3 GHG emissions

Pooling Model

Call:

```
plm(formula = log(Emission) ~ Iso1 + Iso2 + Iso3 + log(Size) +
    DT4 + log(RD) + RE + log(W) + Wr + Wwte, data = pdata, model = "pooling")
```

Balanced Panel: n = 7, T = 4, N = 28

Residuals:

Min.	1st Qu.	Median	3rd Qu.	Max.
-0.647215	-0.232950	-0.069486	0.233314	0.706718

Coefficients:

	Estimate	Std. Error	t-value	Pr(> t)
(Intercept)	2.72586	2.43562	1.1192	0.27778
Iso2	-0.98891	0.35344	-2.7980	0.01189 *
Iso3	0.87592	0.47355	1.8497	0.08084 .
log(Size)	0.89311	0.59191	1.5089	0.14868
DT4	0.12605	0.30009	0.4200	0.67943
log(RD)	-0.14526	0.38426	-0.3780	0.70984
RE	-0.64280	0.87099	-0.7380	0.47002
log(W)	0.34386	0.18422	1.8666	0.07833 .
Wr	4.59846	1.68134	2.7350	0.01360 *
Wwte	11.53341	4.86859	2.3689	0.02923 *

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares: 47.925

Residual Sum of Squares: 3.2886

R-Squared: 0.93138

Adj. R-Squared: 0.89707

F-statistic: 27.1457 on 9 and 18 DF, p-value: 1.094e-08

Figure 28: Results of the Logistics Model 'Pooling' Corresponding Scope 3 GHG emissions

Pooling Model

Call:

```
plm(formula = log(Emission) ~ Iso1 + Iso2 + Iso3 + log(Size) +
    DT5 + log(RD) + RE + log(W) + Wr + Wwte, data = pdata, model = "pooling")
```

Balanced Panel: n = 7, T = 4, N = 28

Residuals:

Min.	1st Qu.	Median	3rd Qu.	Max.
-0.897257	-0.293369	-0.088366	0.395659	0.601468

Coefficients:

	Estimate	Std. Error	t-value	Pr(> t)
(Intercept)	26.04166	2.88430	9.0288	4.200e-08 ***
Iso2	-0.38092	0.35847	-1.0626	0.3020046
Iso3	-1.47032	0.51920	-2.8319	0.0110545 *
log(Size)	4.47880	0.67813	6.6047	3.346e-06 ***
DT5	-0.64770	0.41009	-1.5794	0.1316555
log(RD)	-1.53652	0.42822	-3.5881	0.0021020 **
RE	-4.83915	1.05458	-4.5887	0.0002278 ***
log(W)	-1.65148	0.22004	-7.5054	6.008e-07 ***
Wr	-9.90472	2.07880	-4.7646	0.0001549 ***
Wwte	-4.22665	5.82161	-0.7260	0.4771573

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares: 83.845

Residual Sum of Squares: 4.6066

R-Squared: 0.94506

Adj. R-Squared: 0.91759

F-statistic: 34.4022 on 9 and 18 DF, p-value: 1.5482e-09

Figure 29: Results of the End-of-Life Product Management Model 'Pooling' All GHG emissions

```

Pooling Model

Call:
plm(formula = log(Emission1) ~ Iso1 + Iso2 + Iso3 + log(Size) +
    DT5 + log(RD) + RE + log(W) + Wr + Wwte, data = pdata, model = "pooling")

Balanced Panel: n = 7, T = 4, N = 28

Residuals:
    Min.    1st Qu.    Median     3rd Qu.     Max.
-0.441795 -0.115458  0.011664  0.109610  0.356125

Coefficients:
              Estimate Std. Error t-value Pr(>|t|)
(Intercept)  12.74961    1.42330   8.9578 4.723e-08 ***
Iso2         -0.46012    0.17689  -2.6011  0.01806 *
Iso3        -1.35323    0.25621  -5.2818 5.066e-05 ***
log(Size)     1.09473    0.33463   3.2715  0.00424 **
DT5          -0.37961    0.20237  -1.8759  0.07699 .
log(RD)        0.13365    0.21131   0.6325  0.53504
RE            0.69143    0.52040   1.3287  0.20056
log(W)        -0.74908    0.10858  -6.8989 1.887e-06 ***
Wr            0.28049    1.02581   0.2734  0.78764
Wwte         -0.60813    2.87275  -0.2117  0.83473
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    47.006
Residual Sum of Squares: 1.1217
R-Squared:              0.97614
Adj. R-Squared: 0.9642
F-statistic: 81.8096 on 9 and 18 DF, p-value: 9.4267e-13

```

Figure 30: Results of the End-of-Life Product Management Model 'Pooling' Scope 1 GHG emissions

```

Pooling Model

Call:
plm(formula = Emission2 ~ Iso1 + Iso2 + Iso3 + log(Size) + DT5 +
    log(RD) + RE + log(W) + Wr + Wwte, data = pdata, model = "pooling")

Balanced Panel: n = 7, T = 4, N = 28

Residuals:
    Min.    1st Qu.    Median     3rd Qu.     Max.
-71368.5 -15271.4 -1102.7  11918.4  96661.0

Coefficients:
              Estimate Std. Error t-value Pr(>|t|)
(Intercept) 1390553.7    207328.7   6.7070 2.738e-06 ***
Iso2          6303.7     25767.6   0.2446  0.809505
Iso3        -186631.3    37321.3  -5.0007 9.271e-05 ***
log(Size)    -166420.3    48744.9  -3.4141  0.003093 **
DT5          -33169.9    29478.2  -1.1252  0.275270
log(RD)       169439.0    30781.4   5.5046 3.157e-05 ***
RE           89163.4     75805.1   1.1762  0.254830
log(W)       -97877.7    15816.8  -6.1882 7.683e-06 ***
Wr           374677.7    149427.8   2.5074  0.021967 *
Wwte        -732647.7    418467.6  -1.7508  0.097007 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    5.0431e+11
Residual Sum of Squares: 2.3802e+10
R-Squared:              0.9528
Adj. R-Squared: 0.9292
F-statistic: 40.375 on 9 and 18 DF, p-value: 4.0464e-10

```

Figure 31: Results of the End-of-Life Product Management Model 'Pooling' Scope 2 GHG emissions

```

Pooling Model

Call:
plm(formula = log(Emission3) ~ Iso1 + Iso2 + Iso3 + log(Size) +
    DT5 + log(RD) + RE + log(W) + Wr + Wwte, data = pdata, model = "pooling")

Balanced Panel: n = 7, T = 4, N = 28

Residuals:
    Min.    1st Qu.    Median    3rd Qu.     Max.
-0.914683 -0.297292 -0.088266  0.401154  0.607170

Coefficients:
              Estimate Std. Error t-value Pr(>|t|)
(Intercept)  26.19660    2.93478   8.9262 4.977e-08 ***
Iso2         -0.38184    0.36475  -1.0469 0.3090181
Iso3        -1.47631    0.52829  -2.7945 0.0119768 *
log(Size)     4.57165    0.68999   6.6256 3.211e-06 ***
DT5          -0.65308    0.41727  -1.5651 0.1349673
log(RD)       -1.57426    0.43572  -3.6130 0.0019887 **
RE           -4.95432    1.07304  -4.6171 0.0002141 ***
log(W)        -1.68041    0.22389  -7.5055 6.006e-07 ***
Wr           -10.13990    2.11518  -4.7939 0.0001453 ***
Wwte         -4.27796    5.92350  -0.7222 0.4794493
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    87.052
Residual Sum of Squares: 4.7693
R-Squared:               0.94521
Adj. R-Squared: 0.91782
F-statistic: 34.5054 on 9 and 18 DF, p-value: 1.51e-09

```

Figure 32: Results of the End-of-Life Product Management Model 'Pooling' Scope 3 GHG emissions

```

Pooling Model

Call:
plm(formula = log(Emission) ~ Iso1 + Iso2 + Iso3 + log(Size) +
    DT5 + log(RD) + RE + log(W) + Wr + Wwte, data = pdata, model = "pooling")

Balanced Panel: n = 7, T = 4, N = 28

Residuals:
    Min.    1st Qu.    Median    3rd Qu.     Max.
-0.484629 -0.166352  0.020322  0.159051  0.464662

Coefficients:
              Estimate Std. Error t-value Pr(>|t|)
(Intercept)  8.228422    1.749184   4.7041 0.0001768 ***
Iso2         -0.537363    0.217396  -2.4718 0.0236513 *
Iso3        -0.293631    0.314871  -0.9325 0.3633960
log(Size)     0.237042    0.411249   0.5764 0.5714863
DT5          -0.053061    0.248701  -0.2134 0.8334496
log(RD)       -0.069402    0.259696  -0.2672 0.7923202
RE           -0.456520    0.639550  -0.7138 0.4844961
log(W)        0.355724    0.133443   2.6657 0.0157553 *
Wr           4.563566    1.260687   3.6199 0.0019585 **
Wwte         4.052813    3.530514   1.1479 0.2660223
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    36.846
Residual Sum of Squares: 1.6942
R-Squared:               0.95402
Adj. R-Squared: 0.93103
F-statistic: 41.4958 on 9 and 18 DF, p-value: 3.2119e-10

```

Figure 33: Results of the End-of-Life Product Management Model 'Pooling' Corresponding Scope 3 GHG emissions.

Abstract :

This master's thesis investigates the role of digital twins in enhancing sustainability within the high-tech industry, focusing on the supply chains of major laptop manufacturers from 2019 to 2022. The research assesses the potential of digital twins to reduce greenhouse gas (GHG) emissions by optimizing various supply chain processes such as product design, material sourcing, production, logistics, and end-of-life product management. The methodological approach includes a thorough literature review, empirical data collection, and multiple regression analysis.

The findings indicate that the integration of digital twins significantly improves resource utilization and reduces inefficiencies, leading to a notable decrease in GHG emissions across the supply chain. The study underscores the importance of balancing technological advancements with environmental responsibility, providing actionable insights for industry leaders aiming to reduce their carbon footprint through innovative AI applications. This research highlights the critical need for continued innovation and adaptive strategies to achieve sustainability goals within the high-tech industry.

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