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The Hidden Costs and Values of Innovation: Assessing AI's Environmental Impact in Business Process Transformation

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Introduction

Artificial Intelligence (AI) is transforming business, necessitating a robust environmental sustainability framework to fully comprehend its impact. Indeed, AI increases operational efficiency and decision-making, enhancing also sustainability; however, it raises substantial environmental concerns due to its energy consumption and resource use across production, usage, and disposal phases. Focusing on usage, current frameworks often miss AI’s full environmental impact, both positive and negative, especially in business where it significantly alters processes. Traditional models primarily address the direct consequences of technology usage, such as CO_2 emissions and energy consumption, but tend to neglect the broader effects of AI when integrated into processes, such as enhanced efficiency, leading to a significant underestimation of AI's environmental impact, particularly in industries undergoing major process changes. This research advocates for a comprehensive and adaptable AI sustainability framework, that details environmental impacts, considering benefit and costs, and supports virtuous adoption strategies in companies to balance its negative effects. The analysis is conducted through a case study on VHIT, a manufacturing company that integrates AI into its production process. This approach evaluates the applicability of various indices, assesses their calculation feasibility, and consequently, explores the development of an integrated framework that could be used by both the company and policy makers. This study lays the foundation for a tool to assess the integrated environmental impact of AI in corporate processes, aimed at promoting a virtuous implementation and management of AI and fostering a synergistic development of the two components of the Twin Transition without them hindering each other. This approach aids sustainable AI deployment and enhance understanding of AI's environmental role, influencing future strategies and policies to align AI with environmental objectives.

Literature Review

1. Artificial Intelligence: An Overview

This first chapter intends to provide a theoretical foundation upon which to build the analytical framework. By elucidating the fundamental concepts and the reference scenario through a review of existing literature, it seeks to define and relate these key concepts to the findings of this study. This approach ensures a clear and coherent basis for the subsequent analysis. As stated in the introduction and implied by the research question and its sub-questions, the theme of this thesis revolves around the key concepts of AI, AI adoption into industry process, and AI's overall environmental impact, encompassing both positive and negative effects. To leverage existing knowledge, this chapter explores these concepts and their subfields to enhance understanding and support further analysis.

1.1 Artificial Intelligence

Defining AI is a challenging and widely debated issue, due to its intrinsic ambiguous nature. Indeed, the term 'AI' has been used with many different senses, both within the field and outside it (Wang, 2019). The formal term *Artificial Intelligence* can be traced back to the mid 1950's, to the scientific journal collection made into the book *Automata Studies No. 34* (Shannon & McCarthy, 1956). Included in this collection, the American (born Russian) scientist John McCarthy discussed the theories and science of intelligent machines and their possibilities to conduct complex tasks and create solutions that are too complex for human beings to understand. McCarthy (2007), today considered as the father of AI, defined *AI* as "the science and engineering of making intelligence, machines, especially intelligent computer programs. It is related to the similar task of using computers to understand human intelligence, but AI does not have to confine itself to methods that are biologically observable" (p.2).

One commonly accepted definition comes from the Oxford English Dictionary, which states that AI is "the capacity of computers, or other machines, to exhibit intelligent behavior" (Oxford English Dictionary, 2023). This indicates that AI systems can simulate cognitive thinking, learning, and actions, sometimes surpassing human capabilities. Specifically, they are capable of analyzing large datasets, solving intricate problems, making decisions, and performing creative tasks.

Similarly, Haenlein and Kaplan (2019) defines AI as "a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (p.5). The evolving nature of AI technology contributes to the difficulty in pinning down a definitive description. As the technology advances, the definitions and capabilities associated with AI also evolve, adding layers of complexity to its characterization. In this context, it is generally accepted that intelligence serves as a general concept encompassing multiple special cases, each differing in certain aspects while maintaining a common underlying nature (Wang, 2019).

In any case, without a clear, common definition, policymakers face significant challenges in forecasting AI's potential and establishing a framework for desirable AI systems. As Bhatnagar et al. (2018) highlight, the lack of a standard definition complicates the assessment of future AI capabilities and the determination of desirable outcomes. Nonetheless, the European Union's AI Act offers a practical definition: "an 'AI system' is a machine-based system designed to operate with varying levels of autonomy, exhibiting adaptiveness post-deployment, and generating outputs—such as predictions, content, recommendations, or decisions—that influence physical or virtual environments" (European Commission, 2024).

The difficulty in defining AI is closely linked to the evolution of the discipline itself. For this reason, a brief historical overview not only provides essential context for understanding AI but also sets the stage for the next chapter, which explores AI's applications. As technologies and capabilities advance, definitions continue to evolve, reinforcing the dynamic nature of this field (Sheikh, Prins & Schrijvers, 2023).

1.2 A Brief History of AI

The early references to AI as a field of study can be traced back to Alan Turing. The mathematician and philosopher, reflecting on his creation *Colossus*, a code-breaking machine built for the British government to decipher the German Enigma code during World War II, was particularly struck by the machine's ability to accomplish a task that had been impossible for even the best human mathematicians. This led Turing to ponder the intelligence of such machines. These reflections culminated in Turing's 1950 research paper titled "Computing Machinery and Intelligence", in which he described the process of creating intelligent machines and proposed a method to test their intelligence, now known as the Turing Test. This test remains a benchmark for assessing artificial intelligence: if a human interacts with both another human and a machine but cannot distinguish between the two, the machine is considered intelligent. Thanks to this seminal work, the British mathematician is often credited with laying the foundational ideas of AI (Haenlein et al., 2019).

The more formal inception of modern AI as a scientific discipline was marked by the Dartmouth Summer Research Project on Artificial Intelligence (DSRPAI) in 1956, held at Dartmouth College, New Hampshire. This pivotal conference was organized by John

McCarthy, a computer scientist from Stanford, and Marvin Minsky, along with other notable participants including Nathaniel Rochester, who later designed the IBM 701 - the first commercial scientific computer - and Claude Shannon, the founder of information theory. The primary objective of this conference was to bring together researchers from various fields to establish a new research area focused on the development of machines capable of mimicking every aspect of human intelligence. This assembly of eminent scholars, who would later be recognized as the founding fathers of AI, unified under a shared vision to pioneer this innovative area of research. (Haenlein et al., 2019). It was precisely during this approximately eight-week-long workshop, funded by the Rockefeller Foundation, that McCarthy officially coined the term *Artificial Intelligence* and its definition.

Progress in the AI field in the following years was astonishing. Throughout the 1960s and 1970s, AI research flourished in various domains such as problem-solving, theorem proving, and natural language processing (NLP). Many scientists and researchers focused on automated reasoning and applied AI for proving of mathematical theorems and solving of algebraic problems. One notable example is the Logic Theorist, a computer program developed by Allen Newell, Herbert A. Simon, and Cliff Shaw. This program proved 38 of the first 52 theorems in *Principia Mathematica* and even provided more elegant proofs for some (Xu, Liu & Cao, 2021). This was later surpassed by the General Problem Solver program, also created by the same scientists, which was more advanced and capable of automatically solving certain types of simple problems (Haenlein et al., 2019). Other pioneering systems from this era include ELIZA[1], a natural language processing tool able to simulate a conversation with a human (Xu et al., 2021). These achievements made many AI researchers extremely optimistic. For instance, scholars like Minsky hypothesized that a machine with the general intelligence of an average human being could be developed within three to eight years (Kaplan, 2022). Consequently, substantial funding was allocated to AI research, leading to the initiation of numerous projects.

However, these early AI systems were largely rule-based, relying on hard-coded responses and lacking the ability to learn from interactions or adapt to new situations. Consequently, these logic-based programs were unable to solve more complex problems and lacked the computational resources necessary for such tasks (Xu et al., 2021). As these limitations became apparent by the early 1970s, scholars like the British mathematician James Lighthill asserted

[1]ELIZA, developed by Joseph Weizenbaum at MIT between 1964 and 1966, was a pioneering computer program in natural language processing. It could simulate human conversation and was among the first programs to attempt to pass the Turing Test. To experience ELIZA, visit: https://www.masswerk.at/elizabot/.

that machines would never surpass the level of an “experienced amateur” in games like chess and that common-sense reasoning would remain perpetually out of their reach (Haenlein et al., 2019). Furthermore, due to computational power not advancing as quickly as anticipated, AI-driven applications failed to meet expectations, leading to a decrease in both public and institutional support. This ultimately marked the onset of the first “AI winter”, a period characterized by a significant decline in advances and interest in AI research.

In the 1980s, however, faith in AI's potential was rekindled, leading to significant inventions such as XCON, designed by Carnegie Mellon University, and MYCIN, designed by Stanford University. These systems predominantly relied on Expert Systems, which were collections of rules derived from expert knowledge aimed at helping non-experts make decisions, thereby solving real-world problems for the first time through a series of “if-then” statements (Haenlein et al., 2019). These expert systems operated on the assumption that human intelligence could be formalized and reconstructed using a top-down approach (Xu et al., 2021).

Although these systems performed well in structured domains, they faltered in areas requiring more nuanced, unstructured reasoning. For instance, as Hutson (2018) notes, they struggled with tasks such as facial recognition or distinguishing between images of “muffins and Chihuahuas”, which require the ability to interpret external data flexibly, learn from it, and apply those learnings adaptively—capabilities fundamental to true AI that aims to mimic human intelligence. This highlighted a significant discrepancy between the potential of expert systems and the broader demands of real-world applications, underscoring the challenges of simulating human intelligence through rigid, rule-based systems. As a result, funding for AI research was once again withdrawn, marking the onset of the “second winter” period in the field's history (Xu et al., 2021).

Other statistical methods aiming to achieve “true AI” were already being discussed in the 1940s. During that period, Canadian psychologist Donald Hebb proposed a theory of learning called *Hebbian Learning*, which replicated the process of neurons in the human brain (Haenlein et al., 2019). This insight led to the exploration and development of Artificial Neural Networks (ANNs). However, research into neural networks faced significant hurdles. In 1969, Marvin Minsky and Seymour Papert demonstrated that computers lacked the processing power necessary to handle the demands of such networks, further contributing to the challenges faced during the AI winters (Minsky & Papert, 1969).

The second revival of AI came in the late 1990s and early 2000s, spurred by greater computational power and the advent of the internet, which provided vast amounts of data and a new playground for AI applications (Öztürk, 2021). A landmark event was in 1997 when

IBM's chess expert system, Deep Blue, managed to beat the reigning world champion, Gary Kasparov, by predicting the game 20 moves ahead. Deep Blue achieved this feat by processing around 200 million possible moves at a speed of approximately 2.5 million positions per second. This demonstration of a computer's ability to outperform the world chess champion sparked anew interest in AI and its potential for the 21st century (Haenlein et al., 2019).

The advancements in neural networks further propelled AI's resurgence, leading to significant improvements in processing power and the emergence of technologies such as deep learning (DL). In 2006, indeed, Geoffrey Hinton and his collaborators made a breakthrough by proposing an approach for building deeper neural networks, known as deep learning. This specific type of artificial neural network marked a definitive moment for AI's resurgence when, in 2015, AlphaGo, an AI-driven program created by Google DeepMind using deep learning techniques, defeated the world champion in the highly complex board game Go. This achievement was notable because it had been widely considered impossible for a computer to defeat a human master in Go until then (Kaplan, 2022).

Today, artificial neural networks and deep learning constitute the foundation of most applications commonly recognized as AI, such as speech recognition, image recognition, and autonomous vehicles. These applications showcase AI's ability to perform tasks that were previously deemed exclusive to human intelligence. This resurgence marked a major shift from the previous limitations of AI, propelling the field into a new era of innovation and practical application (Xu et al., 2021).

1.3 AI in the Market

Building on the historical context of AI's development, despite the long-standing existence of certain AI technologies, recent years have witnessed unprecedented advancements. These breakthroughs, as outlined in the previous section, were primarily driven by significant improvements in computing power, the proliferation of vast datasets, and the development of innovative software algorithms. Key technologies enabling these advancements include cloud computing, Internet of Things (IoT) sensors, and Application Programming Interfaces (APIs). When integrated into enterprise systems, these technologies facilitate the collection, processing, and exchange of data, thereby optimizing information flow and operational efficiency. As a result, AI has transitioned from a purely research-focused domain to a pervasive presence in our society. This transition, which gained momentum around 2010, marks a pivotal shift in the field of AI, characterized by a surge in scientific activity and practical applications, as evidenced by various metrics and trends. Indeed, to gauge the magnitude of this movement, The World Intellectual Property Organization release a study showing a considerable increase in AI-related publications over the past 20 years, with an average annual increase of 8% between 1996 and 2001, rising to 18% between 2002 and 2007. After 2015, annual growth surged again to 23%, and by 2018, AI-related papers accounted for 2-3% of all published articles worldwide—almost three times the proportion in the late 1990s (WIPO, 2019).

Furthermore, this period also experienced significant increase in AI-related patents. Between 2006 and 2011, AI patent growth averaged 8% annually, surging to 28% between 2012 and 2017. In fact, half of all AI patents were registered between 2013 and 2018. The proportion of new patents related to AI increased significantly in the final two years of this period, rising from less than 1.5% to nearly 2.5%. Remarkably, half of all AI inventions ever patented were registered between 2013 and 2018. Particularly, machine learning (ML) dominated the patent landscape, representing 40% of all AI patents. Notably, within this domain, deep learning has seen a notable increase, with patent approvals rising by 175% between 2013 and 2016. Regarding the fields of applications, image processing and computer vision accounted for about half of these patents. This surge in both scientific literature and patents reflects the growing interest in AI within both academic circles and business community. Indeed, Big tech companies like Google, IBM, and Microsoft have integrated advanced neural networks for functions such as speech recognition, with significant acquisitions like Google's purchase of the British company DeepMind and Intel's acquisition of Mobileye underscoring this trend (Baruffaldi et al., 2020). The rise in AI start-up acquisitions from less than 10 in 2010 to over 240 in 2019 (CB Insights, 2021), alongside the recruitment of top AI scientists by these companies, further highlights the sector's expansion. Prominent corporate leaders have publicly emphasized AI's crucial role in their strategic pivots towards AI-centric operations, a sentiment echoed by global investment trends that show a robust increase in funding for AI across various industries (Baruffaldi et al., 2020).

Numerous consultancy firms have projected the consequences of AI's definitive integration into society, anticipating that, due to its versatile nature, this technology will impact nearly every business sector and exert a significant economic influence. In line with these predictions, Zhang et al. (2021) observe that the demand for AI experts is growing in the job market, with more PhD graduates in the field finding employment in the commercial sector. Governments are also responding to this trend, with more than sixty countries having developed national AI strategies (Sheikh et al., 2023).

These indicators collectively demonstrate that AI has entered a new chapter in its history. The growing number of patent approvals, the rising level of private investment, the emergence of new business models, the expansion of AI-related employment, and the implementation of national strategies are all signal that AI has firmly embedded itself in society. Many of the capabilities that scholars at the Dartmouth Conference in 1956 dared to attribute to future intelligent machines are now within reach. In various aspects, machines can "use language, form abstractions and concepts, solve kinds of problems now reserved for humans, and improve themselves" (McCarthy, Minsky, Rochester & Shannon, 1955, p.2).

1.4 Which 'Intelligencies'? A Summary of AI Types

Artificial Intelligence encompasses a wide range of applications and techniques, making it a multifaceted field. To fully grasp its potential and particularly understand its diverse business applications, it's crucial to delve into its various categories, components, and methodologies. This comprehensive understanding enables businesses to effectively harness AI's capabilities, driving innovation and efficiency across industries. By exploring the different dimensions of AI, from how it learns to its functional and capability-based classifications, we can appreciate the full spectrum of AI's transformative power in the business world.

AI can be classified based on its capabilities, learning methods, and functionalities. Concerning capabilities, AI can be categorized into three types: Artificial Narrow Intelligence (ANI), Artificial General Intelligence (AGI), and Artificial Super Intelligence (ASI). ANI, also known as *Weak AI*, is designed to perform specific tasks such as spam filtering or autonomous driving. These systems are the most common today and include examples like Apple's Siri, Amazon's Alexa and self-driving vehicles. AGI, also referred to as *Strong AI*, seeks to perform any intellectual task that a human can, applying knowledge across various domains. AGI remains a theoretical goal, though researchers continue to explore this field. ASI represents a hypothetical future where AI surpasses human intelligence in all aspects, potentially leading to a "singularity" where AI's growth becomes uncontrollable (Di Berardo, 2023).

Currently, the AI systems we encounter daily, such as Apple's Siri, Amazon's Alexa, IBM Watsonx™, and self-driving vehicles, are categorized as *Narrow AI*. These systems can learn in various ways, leading us to the classification based on learning methods. Machine Learning is a subset of AI focused on algorithms that enable computers to learn from data, including techniques such as supervised learning, unsupervised learning, and reinforcement learning (RL). Deep Learning (DL), a subset of ML, utilizes neural networks with multiple layers to learn from vast amounts of data. DL algorithms, modeled after the decision-making processes of the human brain, consist of layers of interconnected nodes that extract features from data and make predictions. While classic ML algorithms typically use neural networks with one or two hidden layers and require labeled data (supervised learning), DL employs Deep Neural Networks (DNNs) with many hidden layers, enabling unsupervised learning from unstructured data. This capability allows DL to scale and improve its performance with increasing data quality and quantity (Plathottam et al., 2023; IBM, (n.d.)).

AI's functionalities include generative AI (GenAI), computer vision, natural language processing (NLP), speech recognition, and robotics. Generative AI involves deep-learning models that generate new content based on raw data. These models, such as variational autoencoders (VAEs), have extended to images, speech, and other complex data types, revolutionizing fields like image and voice recognition and text generation. Computer vision applies AI in the analysis and interpretation of visual data, such as facial recognition or identifying traffic signs. NLP is designed to understand and interpret human language, integral to technologies like chatbots and language translation. Speech recognition focuses on processing spoken language, exemplified by voice-controlled assistants, while robotics integrates various AI functionalities with physical operations, enabling robots to perform tasks like transporting goods within warehouses (Agrawal, Gans & Goldfarb, 2022; IBM, (n.d.)).

The terms artificial intelligence, machine learning, and deep learning have been used interchangeably at times, but it is important to distinguish between them. To summarize, AI is the most general term, referring to the development of computer systems able to perform tasks by mimicking human intelligence, such as visual perception, decision-making, and voice recognition. Machine learning, a subfield of AI, allows computers to improve at performing tasks with experience, while deep learning, a further subfield of ML, uses multi-layered neural networks for feature extraction and transformation. Deep learning's advancements have led to algorithms that match and exceed human capabilities in specific datasets, particularly in computer vision and natural language processing. The continuous improvement in computing power, availability of big data, and innovative neural network structures has propelled DL's representative learning ability into broader applications, showcasing AI's value in scientific research and real-world scenarios (Nuzzi, Boscia, Marolo & Ricardi, 2021).

In conclusion, understanding the different facets of AI, from its foundational technologies to its applications, enables us to appreciate and harness its full potential in driving business and societal progress.

1.5 Predictive Machines

The primary potential that can be harnessed in AI applications lies in its predictive power. Although predictive modeling was already feasible through regression-based tools, the surge in computing power and the vast availability of data have enabled AI tools to surpass traditional systems, sometimes even outperforming humans in accuracy. This enhanced predictive accuracy is predominantly driven by advancements in machine learning, which facilitate efficient, data-driven forecasts. Unlike traditional statistical models that require specific input assumptions, machine learning techniques in AI accommodate more complex models with extensive variable interactions, significantly enhancing the quality of predictions. Indeed, in complex environments, traditional statistical methods and algorithms based on "if-then" instruction sequences are insufficient (Agrawal et al., 2022).

Historically, the preferred methodology for forecasting relied primarily on regression techniques. Research focused on improving these methods, with hundreds of techniques proposed and tested in scientific journals and in the field. Regression identifies a prediction based on the average, providing a more precise calculation of the mean of past events. It constructs models capable of managing contextual data through the conditional mean, which considers multiple variables, though it proved complicated. Before the advent of machine learning, multivariate regression represented an efficient means of performing such calculations without the need to determine numerous conditional means. Regression utilizes data to identify the outcome that minimizes prediction errors, maximizing the model's *goodness of fit*. This method reduces errors relative to the mean, penalizing larger errors more heavily, and is particularly effective for small datasets, offering reliable forecasts. Regression models strive to generate objective results, ensuring that with a sufficient number of predictions, these are, on average, accurate. However, this average accuracy can imply errors in every single prediction. In contrast, machine learning predictions might be slightly off on average, but the errors are generally minor, significantly reducing variance. Moreover, while effective for relatively small datasets, regression models often fail to capture more complex interactions, limiting prediction accuracy. The advent of machine learning introduced a more efficient method capable of discerning subtle and significant predictive insights. Unlike regression, machine learning handles large quantities of data and identifies relevant and unexpected variable combinations without requiring explicit programming for each possible interaction (Spiliotis, 2023).

In reality, between the late 1990s and the early 2000s, machine learning methods were advancing, but regression models continued to yield better results. This scenario changed in 2016, when the increased availability of data and computing power allowed machine learning, and particularly deep learning models, to become predominant. These models are flexible and capable of handling vast amounts of data, including texts and images, offering more accurate and adaptable predictions. Agrawal et al. (2022) underscored the 2008 financial crisis as an example of the limitations of regression-based prediction models, which faltered not due to a lack of data but because of inappropriate use of the data.

In light of the aforementioned points, it is evident that machine learning models excel in identifying relevant variables and recognizing that unexpected elements can be crucial for accurate predictions. As these models learn and adapt, their prediction accuracy improves, enabling them to perform tasks traditionally associated with human intelligence, such as object recognition. This modern approach to AI goes beyond following predefined rules by utilizing data patterns to predict outcomes. The strategy involves programming computers to "learn" from sample data or experiences. For instance, in facial recognition, where it is difficult to predetermine decision rules, machine learning bridges the gap by correlating name data with facial images to predict identities. At the core of these recent advancements is the concept of deep learning. As previously introduced, this method, which utilizes an approach known as *backpropagation*, enables systems to learn through examples in a manner akin to the human brain, thereby facilitating automatic learning. Similarly, in autonomous driving, continuous data analysis informs operational decisions without human input. In fraud detection, algorithms independently identify potentially fraudulent activities (Agrawal et al., 2022).

Therefore, innovations in predictive technology are revolutionizing areas traditionally associated with forecasts and estimates, from financial markets to meteorology. As a matter of fact, credit card fraud detection has significantly improved due to machine learning, increasing accuracy from 80% in the 1990s to 98-99.9% today, drastically reducing errors and associated costs. Beyond fraud detection, machine learning enhances predictive accuracy in fields such as creditworthiness evaluation, health insurance, and inventory management, showcasing its versatility and effectiveness across diverse domains (Agrawal et al., 2022).

1.6 From Prediction to Business Decisions

In the rapidly evolving business environment, the advanced predictive capabilities of AI are fundamentally transforming the landscape of decision-making. By leveraging complex, data-intensive models that surpass conventional statistical methods, AI acts as a “predictive machine” (Agrawal et al., 2022), utilizing diverse data sources to forecast future scenarios with unprecedented precision. As Agrawal et al. (2022) assert, “Better prediction means better information, which means better decision making. […] Better predictions lead to better outcomes” (p. 39). This transformation compels a re-evaluation of traditional theories, business models and strategies in business management, as AI's integration enhances processes, products, and applications (Rajagopal et al., 2022).

Decision-making within organizational frameworks is a complex process involving numerous choices across all departments and hierarchical levels. Each task in a company, from automated processes to manual actions, is built upon sequential decisions. Seminal works like Simon's *Administrative Behavior* highlight the importance of these decisions, which underpin all business operations. In fact, tasks can vary from being automated—leveraging technological advancements—to being manually executed by human agents, sometimes evolving into routine actions that can either be individual or collective in nature. Essentially, even the production processes within these organizations are underpinned by decisions, whether regarding resource allocation, workflow management, or quality control. (Kaggwa et al., 2024)

In this context, AI acts as a catalyst because it refines forecasting, thereby enhancing the foundation of decision-making. Indeed, aggregating decentralized information and producing data-driven insights with lower costs of information processing, AI's predictive power significantly impacts corporate decision-making by assisting human decisions (Liu, 2023). While AI excels in predictive capabilities, it lacks the nuanced judgment required for high-stakes executive decisions, such as mergers, innovations, and strategic partnerships. This limitation often necessitates managers to make *satisficing* decisions—those that are “good enough” under constrained information scenarios (Simon, 1956). However, advancements in predictive machines are expected to reduce this reliance, refining risk management and enabling more accurate decision-making. (Pessot et al., 2023).

To assist human decisions, AI aggregates decentralized information and produces data-driven insights with lower costs of information processing. On a strategic level, AI integration involves deconstructing workflows into discrete tasks, evaluating the potential return on investment for AI applications, and prioritizing implementation based on projected returns. This systematic approach not only streamlines operations but can also modifies them, potentially restructuring organizational hierarchies to optimize decision-making by shifting value towards roles requiring intricate judgment (Kaggwa et al., 2024).

Moreover, Kaggwa et al. (2024) underscore the importance of AI in corporate decision-making, indicating that integrating AI into strategic planning significantly influences corporate profitability and success. This integration enables companies to navigate complex environments and make effective decisions, driving successful business outcomes. However, as Trunk, Birkel and Hartmann (2020) emphasize, successfully leveraging this technology requires human decision-makers to evolve their roles. They must become translators and interpreters of AI-generated results rather than merely supervising the machine's execution of predefined processes. This shift also entails an increase in responsibility and a change in the necessary skill set.

In conclusion, AI's advanced predictive capabilities are reshaping the core of decision-making in business. By providing better forecasts and reducing reliance on human prediction, AI enhances the quality and effectiveness of decisions. As businesses continue to integrate AI into their strategic planning and operations, they must carefully balance the benefits and challenges to fully harness the transformative power of AI in decision-making (Kaggwa et al., 2024).

With this conceptual framework in mind, the present work now shifts towards examining specifically the modalities of AI integration within enterprises, identifying prevalent trajectories and their subsequent impact on corporate functions.

2. AI Adoption in Business

AI has been successfully employed in various areas within the business sector to significantly enhance efficiency and profitability. According to a McKinsey (2022) survey, the global adoption of AI is currently 2.5 times higher than it was in 2017, though it has stabilized over the past few years. The percentage of organizations implementing AI tools has remained constant since 2022, with adoption primarily concentrated in a few business functions. Additionally, since the advent of generative AI, 60 percent of organizations with reported AI adoption are using this technology. Moreover, 40 percent of these organizations plan to increase their overall AI investments due to GenAI, and 28 percent have already included its use on their board's agenda (McKinsey, 2023). Statista (2024) estimates that AI market size is projected to rise from 241.8 billion U.S. dollars in 2023 to almost 740 billion U.S. dollars in 2030, accounting for a compound annual growth rate of 17.3%.

However, Brynjolfsson, Rock and Syverson (2019) highlight a paradox: while AI has the potential to substantially increase productivity, overall productivity growth has declined in recent decades. This indicates that AI possesses both transformative and disruptive qualities, providing a competitive edge to businesses that integrate it, while those that fail to do so may face obsolescence. Despite the significant initial investments required for AI implementation, the anticipated efficiency and profitability gains are expected to materialize in the coming years.

Generally speaking, the use of AI in business settings can be classified into two distinct categories: AI for automation and AI for augmentation. Automation through AI involves systems designed to take over tasks previously performed by humans, thereby streamlining operations. In such instances, both the predictive and decision-making components are automated. On the other hand, augmentation uses AI to enhance human capabilities by offering insights that support and improve decision-making processes. In this scenario, only the predictive aspect is artificially enhanced. Both forms of AI are integral to various organizational operations and significantly impact customers by either introducing new products and services or enhancing existing ones through the integration of AI technologies (Enholm et al., 2022). Although task automation and labor augmentation might appear to be mutually exclusive, they are not necessarily opposites, as noted by economists Agrawal, Gans, and Goldfarb (2023). In fact, automating certain tasks can result in the augmentation of labor in other areas.

2.1 Automation

Automation through AI is an evolution of the traditional concept where machines replace human labor, such as robots on assembly lines. However, contemporary advancements in AI push beyond mere task replacement; they enable machines to learn, evolve, and thereby enhance their performance over time, allowing them to undertake more complex cognitive tasks involving learning and problem-solving (Lee, Suh, Roy & Baucus, 2019). This advanced form of automation, often termed *Intelligent Automation*, extends to areas previously deemed too challenging for mechanization, such as knowledge-based and service-oriented tasks. For example, AI-driven virtual robots are now capable of processing emails autonomously (Wamba-Taguimdje, Wamba, Kamdjoug & Wanko et al., 2020).

In practical applications within the manufacturing and construction sectors, AI automates functions such as budgeting, planning, inventory management, and replenishment processes (Wamba-Taguimdje et al., 2020). In the realm of services, AI-enhanced digital and robotic services significantly influence customer experiences, exemplified by the deployment of chatbots. These conversational agents simulate human interaction capabilities to assist customers via voice or text communications, handling queries, managing insurance claims, facilitating sales, and ensuring appropriate insurance coverage. Moreover, AI facilitates the creation of innovative products and services, automating tasks for consumers directly. Notable examples include conversational intelligent agents like Apple's Siri and Amazon's Alexa, which manage everyday tasks such as text composition, call initiation, and media control through voice commands. These technologies integrate with devices for smart home automation and are also utilized in securing devices through facial recognition technologies, simplifying user authentication processes (Enholm, 2022).

2.2 Augmentation

Augmentation involves leveraging AI to enhance human decision-making and operational efficiency. AI's capacity to rapidly process and analyze extensive datasets, coupled with its predictive analytics that forecast outcomes and recommend proactive measures, enables it to support complex decision-making processes. This capability provides insights that surpass human cognitive abilities (Jarrahi, 2018).

In line with recent scholarly perspectives, Acemoglu (2021a) advocates for a more human-centric approach in AI research, emphasizing augmentation over automation. The researcher argues that AI should aim to enhance human capabilities, enabling individuals to accomplish tasks that were previously unattainable. This approach would foster a synergistic relationship between AI applications and human skills, creating opportunities for both to complement each other effectively. From this perspective, augmentation is characterized as a co-evolutionary process where humans and machines mutually learn from each other (Raisch & Krakowski, 2020).

For instance, the following applications of AI illustrate this synergy. In healthcare, it processes medical imaging like MRI scans to identify minute anomalies, assists in cancer detection, and supports surgeons with robotic technology during complex operations (Jarrahi, 2018). In public relations and marketing, AI tools monitor social media trends and enable precise customer segmentation based on detailed preferences and behaviors (Mishra & Pani, 2021). In the fashion industry, AI anticipates consumer patterns and optimizes recommendation systems to forecast trends, significantly enhancing customer engagement (Wamba-Taguimdje et al., 2020). Furthermore, in service offerings, AI's capability to personalize experiences is epitomized by systems like Netflix's recommendation engine. This system utilizes diverse customer data metrics to tailor content suggestions, thus augmenting the consumer's decision-making process, engagement and satisfaction (Enholm, 2022).

2.3 AI Applications in Business Functions

AI can be applied in various business areas such as accounting and finance, customer service, recruitment, cybersecurity, sales and marketing, supply chain and logistics, information technology (IT) operations, and legal. This chapter delves into the applications of AI that contribute most significantly to creating value for the company (Agrawal et al., 2022).

2.3.1 Human Resources

The incorporation of AI in Human Resources (HR) significantly enhances functions such as learning and development (L&D), talent development and management, and workforce planning. AI tools are instrumental in transforming HR practices, focusing on precision, personalization, and predictive capabilities (Agarwal, Gupta & Roshani, 2023).

In learning and development, AI leverages machine learning and natural language processing to analyze employee feedback and performance data, which facilitates a nuanced understanding of individual learning needs. For example, Bhatt and Muduli (2022) reported that AI innovations like natural language processing, artificial neural networks, and robots significantly enhance L&D process efficiency, evaluate learning aptitude, and track learning progress. This capability ensures that training programs are not only relevant but also tailored to enhance learning outcomes. Moreover, AI supports adaptive methods that align training with changing business environments and employee career (Ekuma, 2024).

AI's role extends significantly into talent development and management, where technologies such as personalized learning systems and predictive analytics help identify highly skilled individuals, while natural language processing, machine vision, automation, and augmentation improve efficiency and reduce costs. These tools automate routine tasks, including training and assessments, and allow HR professionals to analyze extensive data to effectively identify and develop top talent. Machine learning algorithms are particularly valuable in predicting employee performance and success, enabling tailored development plans and more strategic management decisions (Agrawal et al., 2023).

In the realm of workforce planning, AI's predictive analytics are crucial for anticipating hiring needs and identifying potential skill gaps. This foresight helps align workforce capabilities with strategic business objectives, enhancing organizational preparedness and reducing the risk of talent shortages (Ekuma, 2024). Furthermore, the implementation of AI and automation has fostered more informed decision-making and improved resource allocation, as noted by Ekuma (2024). This integration not only supports strategic alignment but also optimizes the deployment of resources across the organization.

Additionally, automation within AI applications improves operational efficiency by streamlining routine administrative tasks. This shift allows HR professionals to focus more on strategic HRD initiatives, such as developing innovative talent development programs and engaging employees more effectively (Agarwal et al., 2023).

AI's transformative impact in HR is evident not only in enhancing existing processes but also in pioneering new methods for managing and developing human capital. Technologies such as adaptive learning systems, virtual classrooms, and AI-powered analytics platforms enable HR departments to become pivotal contributors to organizational resilience and adaptability (Huang, Saleh & Liu, 2021).

Largely, AI technologies such as machine learning, deep learning, and neural networks redefine the landscape of human resource management by enriching specific HR functions like personalized learning and talent analytics. These innovations ensure that HR operations are not only more efficient but also strategically aligned with future business needs, marking a significant shift towards more dynamic and responsive HR practices (Huang et al., 2021).

2.3.2 Marketing, Sales, and Customer Service

The utilization of AI in marketing, sales, and customer service has not only enhanced existing functions but also introduced novel capabilities that significantly improve operational efficiency and customer satisfaction. Specifically, AI technologies such as machine learning, deep learning, and neural networks are tailored to optimize particular aspects of each domain.

In marketing, AI's capability to analyze data has transformed how campaigns are tailored to meet customer needs. For instance, deep learning algorithms excel in identifying patterns and predicting future behaviors from massive datasets, allowing for the dynamic personalization of content. This means that AI in digital marketing aids marketers in optimizing email campaigns, enhancing outcomes with effective conversion strategies, thus improving open rates and engagement by aligning with the evolving interests of consumers (Halem et al., 2022). The ultimate advantage in this context is AI's ability to provide actionable insights that are grounded in comprehensive data analysis, ensuring that marketers can reach their target audience with the right message at the right time. The predictive analytics used in these processes are similar to those employed by Amazon, where complex recommendation algorithms account for a significant portion, near 36%, of sales by suggesting products based on user behavior and preferences. Further, 90% of customer support at Amazon is also automated (Kreutzer & Sirrenberg, 2020).

Concerning sales, neural networks play a crucial role in enhancing the purchase process through language-based AI tools. These tools function as advanced sales assistants, payment processors, and engagement managers, significantly improving the user experience. By processing natural language, these systems manage customer interactions more effectively, "learning" from each customer interaction to optimize future responses. This ability to optimize automatically after each interaction makes the sales process smoother and more intuitive for customers, who no longer need to navigate complex purchasing steps on their own (Halem et al., 2022).

In customer service, AI technologies considerably improve service delivery. The trend is towards automated customer service. Chatbots and digital personal assistants, which are central to modern customer service strategies, leverage ML to offer timely and accurate responses to customer inquiries. These systems enhance interaction quality by employing voice identification and emotion analysis, thus adjusting responses based on the customer's mood and context (Kreutzer & Sirrenberg, 2020). The AI not only understands what is said, through the natural language processing (NLP), but also identifies who is speaking, which is crucial for personalizing interactions and ensuring security in transactions. This process is called speaker verification or speaker authentication and is important for the identification of customer when security-relevant processes or important transactions (e.g., telephone banking) are controlled via voice —for example via a digital personal assistant (Kaltschmidt, 2017). Therefore, AI tools predict customer issues and initiate proactive service measures. This approach not only anticipates the needs of customers but also addresses them pre-emptively, enhancing customer satisfaction and loyalty.

AI-driven website optimization tools like EyeQuant demonstrate how AI can enhance marketing efficiency by evaluating the visual impact of website designs in real-time, without the need for user testing. By applying findings from neuroscientific research, these tools predict how small changes to a website's design, such as typography and contrast, can affect user engagement and conversion rates (Kreutzer & Sirrenberg, 2020).

Furthermore, AI platforms for media planning like the Albert AI and Lucy take on roles traditionally handled by human media planners. These platforms use algorithms to sift through vast amounts of data, identifying the best media buying strategies and optimizing advertisement placements without human input. As highlighted by Kreutzer and Sirrenberg (2020), this not only speeds up the process but also reduces the likelihood of human error, ensuring that marketing budgets are used more effectively.

Overall, AI's integration into marketing, sales, and customer service is distinguished by its ability to take on complex, data-intensive tasks with high efficiency and accuracy. Through predictive analytics, personalized content delivery, and enhanced customer interaction, AI is not merely supporting existing functions but transforming them into more customer-centric and adaptive components of business strategy. Thus, improving the quality of customer interactions and driving business growth by fostering deeper customer relationships and loyalty (Halem et al., 2022).

2.3.3 Operations

In contemporary manufacturing and operations management, AI is a cornerstone technology, dramatically altering how tasks are managed across numerous facets of production. Through various AI applications, organizations can now optimize complex, interconnected systems that were once heavily reliant on manual intervention and traditional methodologies. This integration of AI has brought forth unparalleled levels of efficiency, predictive accuracy, and process refinement, which are crucial for competitive advantage in today's market environments. Reinforcement Learning, for example, has been employed to optimize the hydrometallurgical separation process, resulting in enhanced design efficiency, while hybrid support vector and evolutionary algorithms have achieved a 45% reduction in energy consumption in carbon fiber manufacturing (Plathottam et al., 2023).

One of the pivotal roles of AI in operations is embodied by predictive maintenance. This application is particularly transformative in sectors such as aerospace, automotive, and electronics manufacturing, where equipment downtime is extremely costly. AI-driven systems analyze data from sensors installed on equipment to predict failures before they occur, allowing maintenance to be scheduled at optimal times without disrupting production flow. For instance, typical manufacturing plants can experience up to 15 hours of downtime weekly, which can equate to financial losses of approximately $20,000 per minute, particularly in large-scale operations like those found in the automotive industry (Brosset, Thieullent, Patsko & Ravix, 2019). By predicting potential failures, AI not only saves substantial costs but also enhances operational safety and reduces the environmental risks associated with sudden industrial stoppages (Plathottam et al., 2023).

Furthermore, AI greatly advances quality assurance (QA) capabilities in manufacturing. Employing techniques such as computer vision, AI systems surpass human accuracy in detecting defects and irregularities in products. For example, in semiconductor manufacturing, AI-powered computer vision models analyze electron microscope images and wafer maps to identify defects that could impact performance. These capabilities are crucial for maintaining high standards of product quality and reliability, which directly influence consumer satisfaction while simultaneously curtailing costs and minimizing waste (Frittoli et al., 2021).

Energy consumption forecasting is another critical application where AI makes significant contributions. Manufacturing facilities, especially those in energy-intensive industries like steel production or chemical processing, can leverage AI to better predict and manage energy usage, thus enhancing sustainability practices. Deep neural networks excel in this domain, especially when they are trained with historical time-series data from numerous devices, like smart energy meters. Similarly, Support Vector Machines (SVMs) are well-suited for short-term electricity consumption forecasting and they are particularly effective in scenarios with fewer samples and high-dimensional inputs, such as small datasets but complex variables. AI models process diverse data from sensors that monitor temperature, humidity, and machine operations, to predict energy needs and dynamically adjust processes. This capability not only reduces operational costs but also aids in achieving broader environmental goals by reducing the carbon footprint of these activities (Plathottam et al., 2023).

AI's influence extends also deeply into supply chain management, where it transforms traditional logistics into dynamic, data-driven systems. Through the analysis of both real-time data streams and historical data, AI models furnish insights that assist companies in managing inventory levels, optimizing production schedules, and preempting supply chain disruptions that could have significant impacts (Toorajipour et al., 2021). This proactive approach is crucial for sustaining the flow of goods in global markets, where delays or shortages can precipitate cascading effects on production and sales. In particular, natural language processing (NLP) enhances this data-driven management by extracting critical information from news feeds, thus offering market insights and digitizing physical documents like invoices with greater speed and precision than manual data entry. Similarly, AI/ML-powered industry robots and drones, equipped with computer vision, operate in warehouses under minimal supervision, providing an unprecedented accuracy level. These technologies not only track and retrieve inventory but also support tasks such as waste reduction and real-time monitoring during logistical operations, further automating routine tasks to curtail errors and elevate productivity. Additionally, reinforcement learning (RL) is applied to refine production pathways and scheduling, which helps in minimizing delays and maximizing efficiency, also minimizing unnecessary stops and avoiding interference with human operators, ensuring an optimized productivity flow throughout the supply chain (Plathottam et al., 2023). Amine Belhadi et al. (2022) concentrate on utilizing AI to enhance the resilience of supply chains. They introduce an integrated multi-criteria decision-making approach driven by AI algorithms to formulate strategies for supply chain resilience. Their research underscores AI's pivotal role in optimizing supply chain management, a vital component of business operations. By employing fuzzy logic programming, machine learning, and agent-based systems, the study illustrates the flexibility of AI in tackling complex business issues.

Additionally, the concept of digital twins represents a forward-thinking application of AI in operations management. These virtual replicas of physical systems allow companies to simulate and analyze operations, test changes, and predict outcomes in a virtual setting before implementing them in the real world. This technology drastically reduces the resources and time needed for experimentation and enables more precise control over complex manufacturing processes. Further, digital twins are employed to monitor parts and offer insightful analysis and data-driven choices. AI has the capability to utilize digital twins, product manuals, disassembly guides, and recycling value chain information to efficiently monitor every component along the product lifespan (Shennib & Schmitt, 2021).

AI also enhances operational safety and security within industrial environments. Intelligent access control systems employing AI enhance safety by ensuring only authorized personnel can access critical areas, effectively reducing the risk of accidents or unauthorized entry. Deep learning-based computer vision specifically targets the detection of risky behavior by employees and the identification of unpermitted entrants in facilities, thereby maintaining a secure working environment (Sen & Ravikiran, 2019). Moreover, in the realm of cybersecurity, AI and ML serve as the backbone for advanced intrusion detection systems that scrutinize user behavior and network traffic for irregularities, thus safeguarding networked devices within manufacturing plants from cyber threats (Bécue, Praça & Gama, 2021).

In conclusion, AI's integration into operations management is profound, driving improvements across preventive maintenance, quality assurance, energy management, supply chain optimization, and security and safety protocols. As AI technology continues to evolve, its potential to further transform these areas will undoubtedly increase, offering even greater accuracy, efficiency, and cost-effectiveness in manufacturing and beyond. This strategic adoption of AI not only supports operational goals but also enhances competitive positioning in a rapidly changing industrial landscape (Dogru & Keskin, 2020).

3. Sustainable AI

As observed, AI is, and will continue to, transform the economic and industrial world. In previous chapters, AI has been presented as a rapidly evolving family of technologies that, by improving prediction and decision-making and optimizing operations and resource allocation, can provide key competitive advantages to enterprises. AI adoption can, directly or indirectly, also contribute to a wide range of economic, environmental, and social benefits across various industries and social activities (Artificial Intelligence Act, 2024b). For instance, AI's predictive prowess extends to sectors like healthcare, where it increases diagnostic precision, and environmental management, where it streamlines resource use and minimizes waste.

Among the societal advantages of its adoption, the EU highlights the benefits that AI can bring on an environmental level. Indeed, AI is delivering numerous improvements to processes, products, and applications, enhancing sustainability and reducing environmental impact primarily through optimization. Specifically, AI enables more efficient management of infrastructure, transport/logistics, resources, and energy; improves environmental monitoring; supports the conservation and restoration of biodiversity and ecosystems; and effectively intervenes in climate change mitigation and adaptation (OHCHR, 2021).

Thanks to its broad field of application, AI is increasingly framed as a promising tool to enhance sustainable development. For example, AI-driven systems are instrumental in forecasting energy demand for more efficient grid operations and in predicting agricultural yields to reduce inputs and increase productivity (Agrawal et al., 2022, Walker et al., 2024). Therefore, as highlighted by the European Commission, AI is recognized as a vital tool for achieving sustainability goals, such as diminishing environmental impacts through enhanced optimization and propelling climate change policies (Gailhofer et al., 2021). The European Commission sees AI as one of the digital technologies that are a "critical enabler for attaining the sustainability goals of the Green Deal" by accelerating and maximizing "the impact of policies to deal with climate change and protect the environment" (European Commission, 2019, p.9).

At the same time, however, depending on the circumstances regarding its specific application, use, and level of technological development, AI adoption can generate indirect societal risks and cause harm to public interests and fundamental rights (OHCHR, 2021). Therefore, despite its benefits, AI also poses significant challenges and risks across multiple domains. Ethical concerns include privacy issues, biases, and lack of transparency in decision-making processes, while socially, AI's impact may intensify issues such as job displacement and inequality. From an environmental perspective, AI's development requires extensive resource consumption and energy, leading to considerable carbon emissions, especially during the training of large models (Van Wynsberghe, 2021).

These concerns have led to an increasing amount of research examining AI's role in achieving the Sustainable Development Goals (SDGs). There are ongoing debates about whether AI systems facilitate or hinder the SDGs, how these systems should be regulated, and the reliability and suitability of such evaluations. The relationship between AI and the SDGs is complex and unclear because the same technology can serve opposing purposes. For instance, AI systems can utilize remote-sensing algorithms to analyze satellite imagery, collect data on agricultural productivity, and predict the energy consumption of buildings, but they can also be employed to accelerate oil and gas exploration (Rohde et al., 2023).

It is due to these concerns that many countries are adopting legislative measures on the matter. Given the significant impact that AI can have on society and the need to build trust, it is considered vital for AI to have a regulatory framework (Agrawal et al., 2022). Due to growing concerns about ethical, legal, and social issues around AI systems, both private corporations and public institutions have started developing quality and trustworthiness certifications for AI over the past few years. In the EU, the proposal of the "Artificial Intelligence Act" (2024), which includes "standards, conformity assessment, certificates, and registration" as a means to manage "high-risk AI systems" (Artificial Intelligence, 2024b), published in April 2021, was definitively approved on March 13, 2024. A Union legal framework that establishes harmonized rules on AI is therefore generally deemed necessary to promote the development, use, and adoption of AI in the internal market while simultaneously ensuring a high level of protection for public interests that may be affected by externalities generated by the use of AI by private entities (Genovesi & Mönig, 2022).

Focusing solely on the dual role, both positive and negative, that AI plays concerning environmental sustainability, Perucica and Andjelkovic's research (2022, as cited in Kaggwa et al., 2024) explores the interconnectedness of AI and environmental sustainability within the European Union (EU). Their study emphasizes the necessity for comprehensive sustainable AI policy initiatives, showcasing the EU's approach as a model that balances technological advancement with environmental stewardship. This viewpoint is essential for understanding how AI can be developed and applied in a way that is both technologically advanced and environmentally conscientious. The concept *sustainable by design* AI, introduced by Perucica and Andjelkovic, highlights the importance of developing AI systems that are transparent, responsible, and aligned with human values, ensuring that AI contributes positively to environmental sustainability (Kaggwa et al., 2024).

In this regard, the definition of *sustainability*, or more precisely, *sustainable development*, is often quoted from the Brundtland Report (1987), also known as "Our Common Future": "Sustainable development is development that meets the needs of the present without compromising the ability of future generations to meet their own needs" (p.41).

Referring exclusively to environmental sustainability, achieving this requires the creation of a comprehensive evaluation framework that assesses AI's total resultant environmental impacts and can be used as a tool to guide responsible AI development (Van Wynsberghe, 2021). The following paragraphs, and more generally this thesis, aim to evaluate how AI adoption in business meets the Brundtland sustainability definition and positively contributes to the environmental aspect of sustainability. Specifically, the discussion articulates around the concept of sustainable innovation, seeking to understand how and in which cases it can be applied to AI. Subsequently, the two fundamental dimensions of AI for sustainability and the sustainability of AI are explored within this definition. This approach identifies the environmental *externalities* related to the corporate use of AI innovations, investigating how they can be balanced with the benefits that the use of AI in business processes simultaneously brings to the environment. The framework is thus proposed and subsequently tested and evaluated empirically to become a tool for assessing the sustainability of AI adoption in companies, thus encouraging potential strategies to balance the negative and positive effects of the technology, orienting the adoption of AI in business towards sustainability improvement.

3.1 AI for Environmental Sustainability and the Environmental Sustainability of AI

Sustainability is an increasingly important consideration in business practices, and AI offers both opportunities and risks in this regard. On the one hand, AI can contribute to sustainability goals by optimizing resource use, reducing waste, and improving efficiency. On the other hand, the deployment of AI systems can have negative environmental impacts, such as high energy consumption for computing power. Therefore, businesses must adopt a balanced approach to AI, ensuring that its use aligns with sustainability principles and contributes positively to environmental and social goals by developing comprehensive strategies that address these dimensions to harness the full potential of AI in a responsible and sustainable manner (Walker et al., 2024).

To achieve this, a multi-faceted approach is required, starting from the consideration of all aspects of sustainability related to a specific technological innovation. To develop an effective framework for assessing or measuring the overall sustainability of technological innovation, it is crucial to understand the concept of sustainable innovation. In the existing literature, two terms—*eco-innovations* and *sustainable innovations*—are often used interchangeably, although they have distinct meanings. Eco-innovations, also known as green, ecological, or environmental innovations, focus mainly on environmental sustainability. In contrast, sustainable innovations encompass environmental, societal, and economic dimensions, making them broader in scope. Interestingly, the motivation behind these innovations does not have to be purely environmental or social; they can also stem from economic objectives, such as cost reduction or market share improvement. Therefore, innovations can be classified as *sustainably motivated innovations* or *sustainably beneficial normal innovations*. Regardless of their motivation, sustainable innovations contribute to sustainable development by generating ecological and social benefits (Gunarathne, 2019).

In 2021, van Wynsberghe laid the foundation for a perspective on AI sustainability, focusing on sustainability in the development and use of AI systems. In this context the researcher presented the concept of *sustainable AI* and applied it to AI applications. The term *sustainable AI* is not about simply maintaining the development of AI, but refers to the development of AI systems that are compatible with the sustainability of environmental resources for current and future generations; economic models for societies; and fundamental social values for a given society. To capture the concept of sustainable AI, the author introduces a distinction between two fundamental dimensions: *AI for sustainability* (i.e., the capability to achieve sustainable development goals) and *sustainability of AI* (i.e., the impact of AI production and use on the environment). This perspective on AI sustainability highlights the need to promote changes throughout the entire life cycle of AI products (Van Wynsberghe, 2021). Following the subdivision proposed by Van Wynsberghe, the discussion on *sustainable AI* in the following paragraph is divided into *AI for sustainability* and the *sustainability of AI*.

3.2 AI for Environmental Sustainability

AI for sustainability is a concept that has been increasingly explored over the past years. The capacity of AI to tackle complex environmental and societal issues and support the achievement of the United Nations SDGs and the 2030 Agenda is being advocated by various entities, ranging from private non-profit organizations like AI4Good[2] to sophisticated academic frameworks such as the AI4People ethical framework developed by Floridi et al. (2018). At the European level, the European Commission's White Paper (2020) on AI already explicitly highlighted the importance of AI in fostering sustainable economic growth and societal well-being. It emphasized AI's role in achieving the Green Deal objectives (European Commission, 2019) and advancing circularity within the single market as outlined in its Circular Economy Action Plan.

Looking at the generic use of technology, there are numerous ways in which AI can mitigate environmental problems and human-induced impacts. For instance, AI can be employed to generate and analyze large-scale interconnected datasets, facilitating a more sensitive

[2]A non-profit organization that brings together the best minds and technologies to solve the world's most urgent challenges. For further information, see https://ai4good.org/

understanding of Earth and predicting environmental behavior across various scenarios. This would enable a better understanding of environmental processes, allowing for more informed decisions. AI can also simulate the results of harmful activities, such as deforestation, soil erosion, flooding, and increased greenhouse gases (GHG) in the atmosphere. Moreover, these technologies hold great potential to improve the understanding and direct control of the environment (Budennyy et al., 2022).

Regarding more practical applications, AI has been used effectively in various domains, such as discovering new electrocatalysts for efficient and scalable ways to store and use renewable energy (Huang et al., 2021), animal conservation, and forest fire management (Schwartz et al., 2020). Additionally, numerous AI-based solutions are being developed to achieve carbon neutrality as part of the concept of *Green AI*. The final goal of these solutions is the reduction of GHG emissions. AI can help reduce the effects of the climate crisis through smart grid design, developing low-emission infrastructure, and modeling climate changes (Budennyy et al., 2022).

Given these broad potential and application prospects for sustainability, one of the greatest opportunities for enhancing sustainability through AI usage is within business processes, which are significant contributors to environmental pollution. AI has enormous potential to help mitigate climate change and address further environmental and societal challenges by enhancing the ability of businesses to operate more sustainably. Indeed, it is in the corporate environment that AI adoption is recognized as a vital tool for achieving sustainability goals, such as diminishing environmental impacts through enhanced optimization (Gailhofer et al., 2021).

Specifically, AI can enhance waste management and recycling by automating sorting, preventing contamination, and predicting maintenance requirements. This not only increases recycling efficiency but also contributes to sustainability by advancing a circular economy. Moreover, accurate life cycle predictions for equipment can significantly improve sustainability. Most companies have equipment that cannot afford downtime, making it difficult to store replacements. Consequently, perfectly functional systems are often scrapped or sold when they reach their nominal end of life. Enhancing life cycle predictions and extending the use of systems can substantially diminish the environmental impact of this practice (Abdallah et al., 2020).

In supply chain management, AI-driven inventory optimization and execution can reduce excess inventory, optimize transportation, and enhance factory-supplier alignment and collaboration. This enables global manufacturers to align their operations around priorities that matter for efficient production and on-time delivery, thus lowering waste and improving sustainability across the supply chain and in manufacturing (Toorajipour et al., 2021).

AI can also be leveraged for real-time monitoring and control of energy and resource consumption, which is crucial for sustainability. AI-powered systems can continuously analyze data from sensors and devices to optimize energy usage, water consumption, and resources, reducing waste and carbon footprints. Moreover, AI can help address environmental risks, ensuring companies meet sustainability goals effectively (Forbes Technology Council, 2023).

Furthermore, AI can predict renewable energy availability in advance to improve energy utilization and it can also be leveraged to develop sustainable new products since large datasets can be analyzed to identify sustainable design and packaging for shipping new products. Finally, AI can explore ways to use more renewable materials in the new product development process, aiding in improved sustainability (Ogundipe, Babatunde, & Abaku, 2024).

In conclusion, AI offers vast potential for enhancing sustainability in and of business processes. By aligning AI adoption with sustainability principles, businesses can achieve significant environmental, societal, and economic benefits, thereby contributing positively to the broader goals of sustainable development.

3.3 Environmental Sustainability of AI

Despite the common perception of AI as intangible and non-physical, its substantial effects on the physical world are undeniable. Kate Crawford, in her book *Atlas of AI*, highlights that the terminology used, such as algorithms and *the cloud*, can make AI seem non-physical (Crawford, 2021). Indeed, AI is often perceived as intangible due to the nature of its operations, which involve data processing and decision-making in ways not immediately visible to users. This perception is further reinforced by the illusion of objectivity, where AI systems are seen as neutral and omnipresent, despite reflecting the biases and limitations inherent in their training data (Messeri & Crockett, 2024). Additionally, the complexity and abstract nature of AI algorithms contribute to the sense that AI lacks a physical presence (Weissinger, 2022). In contrast, implementing AI requires extensive resources, including data centers, chips, computers, and other physical components, which together form a network of "invisible factories" (Crawford, 2021). This integration of intangible perceptions with substantial physical requirements highlights the duality of AI's impact, making it crucial to recognize that, while AI operates through digital and algorithmic processes, its implementation heavily relies on tangible and physical infrastructure, thus rendering its impacts visible and significant in the real world.

Discussions on environmental sustainability often overlook the role of technology and the accompanying increase in digitalization, despite its significant impact. A crucial aspect of the physicality of AI that warrants attention is its carbon footprint and its implications for climate change (Okafor-Yarwood & Adewumi, 2020). For instance, data centers consume vast amounts of energy and water, and the computational power required to support AI systems leads to considerable environmental impacts.

Recent research has begun to uncover the environmental costs associated with the materiality of AI, particularly focusing on energy consumption and GHG emissions from training, fine-tuning, and operating AI systems (Li, Yang, Islam & Ren, 2023). One of the pioneering studies revealing the real impact is by Strubell, Ganesh & McCallum (2019). This study highlights that training a single large natural language processing (NLP) model can have a carbon footprint equivalent to 125 round-trip flights from New York to Beijing. Furthermore, as AI models become more complex and larger, their carbon footprint will continue to grow, even with the adoption of mitigation measures such as cleaner energy sources.

Estimates vary, from researchers like Belkhir and Elmeligi (2018, as cited in Crawford, 2021), who predict that the tech sector will contribute 14% of global GHG emissions by 2040, to a Swiss working group's forecast that the electricity demand of data centers alone will increase approximately fifteenfold by 2030. Examining the computational capacity needed to build AI models reveals how the goal of exponential improvements in speed and accuracy comes at a high environmental cost. The processing requirements for training AI models, and consequently their energy consumption, represent an emerging area of investigation, but quantifying the true impact remains a significant challenge. Indeed, the exact amount of energy consumption by AI models in the tech sector is unknown, as such information is protected as highly confidential corporate secrets (Crawford, 2021).

The environmental impact of AI goes beyond mere energy consumption, including the depletion of physical resources needed for its infrastructure and its footprint on the planet. The materiality of AI requires significant planetary resources, including the extraction of minerals such as gold and tungsten for hardware, lithium—often called "grey gold" —from Bolivia for batteries and chips, and cobalt from the Democratic Republic of Congo for AI components (Crawford, 2021). These countries in the Global South are rich in raw materials, making them targets for resource extraction.

Thus, AI is a true "extractive industry", with supply chains that wrap around the entire planet (Crawford, 2021). The type of raw materials extracted is crucial: in 2020, scientists from the US Geological Survey published a short list of 23 minerals that pose a high supply risk to producers. This means that if they became unavailable, entire industries, including the technology sector, would grind to a halt (Nassar et al., 2020). There are 17 elements classified as rare earth elements (REEs): lanthanum, cerium, praseodymium, neodymium, promethium, samarium, europium, gadolinium, terbium, dysprosium, holmium, erbium, thulium, ytterbium, lutetium, scandium, and yttrium. Once processed, these elements are incorporated into electronic devices, making them smaller and lighter. These elements can be found in color displays, speakers, camera lenses, rechargeable batteries, hard drives, and many other components (Crawford, 2021).

Therefore, based on the preceding discussion, it becomes evident that AI relies on a vast and complex infrastructure, involving extraction, assembly, cooling, and electronic waste disposal. These processes present significant environmental risks that often go unnoticed and unquantified. Cooling data centers requires substantial amounts of water sourced from public infrastructures, and powering these centers depends on electricity supplied through publicly funded grids (van Wynsberghe et al., 2022).

Furthermore, the deployment of AI alters the material conditions of its environment, potentially leading to rebound and propagation effects despite the efficiency gains it brings (van Wynsberghe et al., 2022). Every object in the extensive network of an AI system, from network routers to batteries and data centers, is made using elements that took billions of years to form within the earth. From a deep-time perspective, we are extracting the geological history of the earth to satisfy a fraction of a second of contemporary technological time, creating devices that are often designed to last only a few years. This cycle of obsolescence drives device purchases, multiplies profits, and increases incentives for unsustainable extraction practices. After a slow development process, these minerals, elements, and materials undergo an extraordinarily rapid period of excavation, processing, mixing, smelting, and logistical transport, traveling thousands of kilometers to be transformed. What begins as ore removed from the ground, with residues and "tailings" eliminated, is eventually transformed into devices that are first used and then discarded, ending up buried in electronic waste landfills (van Wynsberghe et al., 2022).

Another critical aspect to consider in the sustainability of AI is that the minerals required for its infrastructure are often sourced through supply chains marked by severe environmental degradation and harsh labor conditions. These realities are frequently obscured to maintain public enthusiasm for AI (Crawford, 2021). For instance, the chips in smartphones, essential components for AI, are likely extracted under deplorable conditions, including child labor in Congo. Young (2020) emphasizes that resource exploitation in these countries involves difficult working conditions, without the local populations benefiting from the technology, and electronic waste is often dumped back in these regions.

The lifecycle of an AI system, from inception to disposal, involves complex supply chains characterized by the exploitation of both human labor and natural resources, as well as significant concentrations of corporate and geopolitical power. Throughout the entire chain, continuous and massive energy consumption sustains the process. Rare earth elements, water, coal, and oil: the tech industry consumes the earth's resources to fuel its high-energy infrastructures (Crawford, 2021).

The ecological footprint of AI is rarely fully acknowledged or explained by the tech sector, which simultaneously expands data center networks and assists the oil and gas industry in locating and exploiting remaining fossil fuel reserves. The opacity of the broader computing systems supply chain, particularly that of AI, fits into a well-established business model of extracting value from common goods without bearing the cost of long-term damage (Crawford, 2021).

Minerals are the backbone of AI, but its lifeblood remains electricity. Advanced computing is seldom assessed in terms of carbon emissions, fossil fuels, and pollution. Metaphors like “the cloud” suggest something floating and delicate, within a natural and green industry. Servers are hidden in anonymous data centers, and their polluting characteristics are far less visible than the smoke from coal-fired power plants. The technology sector actively promotes its environmental policies, sustainability initiatives, and climate problem-solving projects, leveraging AI as a key tool. This effort is part of a deliberate strategy to construct a public image of a sustainable, carbon-neutral industry. However, in reality, substantial energy is necessary to power the computing infrastructures of services such as Amazon Web Services and Microsoft Azure. Consequently, the ecological footprint of the AI systems operating on these platforms is increasing (Crawford, 2021).

Managing this high-energy infrastructure has become a significant challenge, and the industry has made considerable efforts to increase the energy efficiency of data centers and to adopt renewable energy sources. However, the carbon dioxide emissions from the global computational infrastructure now equal those of the aviation industry at its peak and are growing at an accelerating rate. Although AI's carbon emissions may not surpass those of other industries, its environmental impacts are substantial, drawing increasing attention to their consideration in cost-benefit analyses of AI services and products. The hidden materiality of AI leads to a lack of understanding of the extensive physical infrastructure supporting it, which does not imply that AI is worse than other industries in terms of carbon emissions. Instead, it highlights the significant environmental impact of AI, making its inclusion in comprehensive assessments of AI technologies and effective mitigation measures necessary. For instance, Dauvergne (2022) notes that efficiency gains from AI do not necessarily reduce resource use; rather, they can lead to increased production and further extraction of natural resources.

Recognizing AI as a physical infrastructure with profound consequences is vital. Addressing its carbon footprint and the planetary resources it exploits is crucial to confronting contemporary colonialism and the unjust distribution of AI's benefits and burdens (Young, 2020). Indeed, this technological exploitation exacerbates socio-economic disparities between nations. As we advance technologically, it is imperative to ensure that progress is accompanied by ethical and equitable practices, fostering a world where the benefits of AI are shared by all (Crawford, 2021).

In order to comprehensively evaluate the costs associated with an AI application, it is imperative to examine the individual processes inherent in the rise of AI. Thus, attention must be directed towards the costs incurred in hardware production and running algorithms, data collection and transmission, computational resources for model training, hardware decommissioning, and ensuring the ethical alignment of algorithms. Robbins and van Wynsberghe (2022) have delineated several of these processes along with their respective considerations. Therefore, the following paragraphs reference their work. While not exhaustive, their exposition aims to illustrate the complexity and requisite effort involved in making informed decisions regarding AI use.

3.3.1 Hardware Production

The energy consumption associated with hardware utilized in the AI lifecycle is substantial. This encompasses not only the obvious components like servers, hard drives, and GPUs, essential for algorithm execution and large-scale data storage, but also numerous data collection devices, such as video cameras, lidar sensors, and motion detectors. Research indicates that the manufacturing of these devices, rather than their operational use and energy consumption, is primarily responsible for the carbon emissions attributed to hardware systems.

The advent of *edge computing* has further amplified the proliferation of these devices. Edge computing refers to technologies that enable data processing at the network's edge, closer to the data source, rather than relying on centralized cloud servers. This approach, for instance, allows facial recognition to be processed on a smart CCTV camera itself, rather than transmitting the video footage to the cloud. While this reduces data transfer costs and diminishes the reliance on energy-intensive cloud servers, it necessitates increasingly sophisticated and complex devices. As previously discussed, many of these advanced technological devices incorporate rare earth elements, which are integral to hybrid vehicles, rechargeable batteries, wind turbines, mobile phones, flat-screen displays, compact fluorescent light bulbs, laptop computers, disk drives, and catalytic converters. The production of such devices has profound environmental and human rights implications. Although the full extent of the environmental impacts remains unclear, it is known that REE mining and refining generate substantial liquid and solid waste, with potentially harmful environmental effects. The demand for REEs is expected to rise as their irreplaceable role in many technological sectors continues. As the reliance on AI-driven technologies grows, so does the demand for REEs and the environmentally detrimental processes required to produce them. These processes significantly harm both the environment and the laborers in the mining industry, a cost that should be considered when evaluating the overall benefits and consequences of expanding AI applications (Robbins & van Wynsberghe, 2022).

3.3.2 Data Collection and Transmission

AI applications necessitate the processing of input data, which can originate from various sources. Security services utilize video feeds for facial recognition algorithms, while biometric sensors, such as smartwatches, collect and transmit data to healthcare AI systems to identify conditions like heart problems. Smart cities employ an extensive network of sensors and devices to gather data for numerous AI algorithms aimed at urban improvement.

Internet use has been estimated to have a carbon footprint between 28 to 63 grams of CO2 equivalent per gigabyte. The energy required to keep sensors operational and to transmit data is significant. According to The Shift Project, the digital era accounted for 4% of greenhouse gas emissions in 2020, a figure comparable to pre-COVID-19 commercial aviation emissions. The Shift Project also projects an annual increase of 8% in digital era emissions due to factors like the growth of the IoT and the surge in data traffic. Increasing dependence on AI will amplify these factors. The transmission of vast amounts of data, such as video, images, pollution levels, temperature readings, biometric data, radar, and lidar, to cloud servers for AI processing consumes considerable energy. As society becomes more reliant on AI, the necessity for extensive data transmission networks grows. It is crucial to understand the energy costs associated with these processes to responsibly assess the viability and sustainability of various AI applications (Robbins & van Wynsberghe, 2022).

3.3.3 AI Model Creation and Data Processing

Large AI models can emit over 626,000 pounds of carbon dioxide, which is equivalent to five times the lifetime emissions of an automobile. Although this figure can be significantly lower when only fine-tuning pre-trained models, the demand for computing power in AI is undeniably escalating. Once trained, AI models require substantial input data for processing, including videos, images, text, and sound. This data classification incurs significant costs, especially for video inputs. To mitigate these costs, strategies such as processing only specific frames of video are being explored. After the hardware setup, coding, and initial training on collected data, the challenge remains that AI systems require continuous updates. The COVID-19 pandemic illustrated this need as drastic human behavioral changes rendered many machine learning models ineffective. Consequently, new behaviors necessitate the development of new models, which in turn exacerbates the environmental impact due to repeated processes and additional carbon emissions (Robbins & van Wynsberghe, 2022).

3.3.4 Hardware disposal

The issue of recycling and disposing of hardware is another crucial issue. In 2019, the global production of e-waste was 53.6 million metric tons and is projected to increase to 74.7 million metric tons by 2030. This encompasses all types of e-waste, including appliances and personal devices, not solely AI-related hardware. The growing reliance on AI will inevitably lead to an increase in e-waste. While it might seem reasonable for those designing AI applications to overlook this, ignoring the disposal issue while developing a society increasingly dependent on AI would be a significant oversight. AI demands substantial computational power, necessitating not only more hardware but also newer hardware. Consequently, any system reliant on computer hardware must consider the costs associated with its disposal and recycling.

There is a burgeoning demand for specialized hardware accelerators with optimized memory hierarchies to meet the extensive compute and memory requirements of machine learning. A report by McKinsey highlights that AI-related semiconductors are expected to grow by approximately 18 percent annually over the next few years—five times the growth rate of semiconductors used in non-AI applications. This trend underscores the increasing production of hardware specifically designed for AI. Therefore, there must be a comprehensive plan for recycling all this hardware, and the environmental costs associated with such recycling must be accounted for in the development of an AI-dependent society (Robbins & van Wynsberghe, 2022).

3.4 Measuring AI Impact

In the contemporary corporate landscape, major corporations are increasingly required to account for and report on their environmental and social footprints through various standards, frameworks, and metrics related to Environmental, Social, and Governance (ESG) principles, which have largely superseded the traditional concept of Corporate Social Responsibility (CSR). However, none of these frameworks sufficiently capture the sustainability-related impacts of AI (Jiang et al., 2021).

In the previous chapter, it was observed that the impact of sustainable AI, as a multidimensional concept, should be measured holistically by integrating parameters that span multiple levels. AI literature mostly addresses a small part of direct impacts and often neglects production and end-of-life consequences. The challenge of evaluating AI impact involves establishing a layered approach to address the impacts on the micro, meso, and macro levels, able to distinguish and capture both direct and indirect effects, which Kaack et al. (2021) advocate considering (e.g., behavioral or societal changes due to AI) when evaluating AI services.

Focusing on environmental sustainability, evaluating the environmental impact of a service requires multiple impact criteria as reported by ISO, which states that "the selection of impact categories shall reflect a comprehensive set of environmental issues related to the system being studied, taking the goal and scope into consideration" (Van Wynsberghe et al., 2022, p.125). As observed in previous chapters, the negative impact of AI spans three dimensions: production, use, and waste, while the positive impact mainly concerns its use. Since the goal of this work is to assess how to calculate the total impact (costs and benefits) of AI implementation in a company—specifically in a production process—from an environmental sustainability perspective, the analysis continues by focusing on the environmental assessment of the adoption and integration of this socio-technical infrastructure.

First and foremost, it is essential to note that while a summary indicator—an index—is needed for assessing the sustainability of AI applications in processes, it is insufficient to simply list the benefits and associated costs of AI use from an environmental perspective (Rohde et al., 2023). In response to these challenges, there is a growing emphasis on the development and integration of new evaluative metrics that better reflect the multifaceted nature of AI's effects. These new metrics should ideally assess sustainable AI by integrating multidimensional parameters that holistically address both direct and indirect impacts (Kaack et al., 2021).

Indeed, while the existing AI literature predominantly focuses on direct impacts like operational energy consumption, it frequently neglects the full lifecycle impacts, including production, use, waste, and end-of-life stages, as well as the less tangible but equally significant behavioral or societal changes induced by AI technologies (Sætra, 2021). This endeavor involves not only quantifying these effects but also critically evaluating their varying degrees of influence on society and the environment. The hope underlying this work is that by adopting such a layered and comprehensive approach to evaluation, corporations can more accurately gauge the broader sustainability impacts of AI integration in production processes, ensuring that their governance frameworks evolve to effectively incorporate these advanced technologies into their sustainable strategies. By putting forward this comprehensive assessment for sustainable AI, this research aims not only to raise awareness among developers, companies, policymakers, and the public but also to provide an assessment framework that enables actors to develop concrete measures to improve AI deployment.

In general, one of the main methodologies used to propose a unique holistic perspective to facilitate and structure the discourse on sustainable innovation for processes is Life Cycle Assessment (LCA). Ligozat et al. (2023) address different methodologies used to assess AI impacts and, in particular, propose a framework that applies life cycle assessment to AI services without focusing on the use of AI in companies or its integration into production processes. Rohde et al. (2023), on the other hand, propose a framework that focuses more on evaluating and disclosing ESG-related AI impacts based on the United Nation's SDGs, thus proposing a more holistic yet pragmatic approach. However, this framework, in terms of environmental sustainability, refers only to the environmental impact of AI technology itself and not to the impact that the technology has on the process in which it is integrated; not considering its indirect positive and negative effects, which would be useful to consider in AI applications such as operations. Therefore, it can be hypothesized that in functions like marketing or human resources, not focusing on process change after the implementation of AI might be irrelevant, but in a production process, it is certainly important to observe the changes that have occurred since the technology was integrated.

Integrating Rhode et al. (2023)'s proposal with a more engineering-focused perspective from Calik (2024) and Bardudeen (2016), this research attempts to propose to managers and policymakers a framework more centered on the production process, capable of capturing its changes with the adoption of AI. A framework capable of addressing the complexity of this evaluation, deriving not only from the multiple dimensions involved but also from practical difficulties that hinder the quantification of the total impact, such as considering emissions from data centers due to AI use, which corresponds to a considerable fraction of the energy usage stemming from data transfer—a variable not easily quantifiable solely from the AI's architecture.

To propose an evaluation framework suitable for a comprehensive assessment and capable of effectively addressing the complexity of the task, this work suggests using Calik and Bardudeen (2016)'s approach, which includes, expands, and enriches Rhode et al. (2023)'s framework that uses ESG as a parameter for evaluating AI impact. Calik and Bardudeen (2016) propose six elements to consider, evaluate, and calculate through specific KPIs for each sustainable process innovation: material usage, energy usage, other resource usage, life management, certification and eco-labels, and waste, emission, and pollution.

The following sections lists these elements, presenting the rationale and general methodology for evaluating each element for a generic process innovation. Focusing on AI, for each element, a way to calculate is proposed by tracing specific KPIs in the literature that can be used to capture the specificities of this technology and calculate its impact on each of these elements.

Within these dimensions, "Material Usage", "Energy Usage", and "Other Resource Usage" describe the methods and practices applied by companies to reduce resources in their production and improve and renew processes in the context of the techniques developed. Additionally, the "Waste, Emissions, Pollution" sub-dimension examines the studies carried out by companies on environmental waste and pollution and the practices adopted to improve processes in order to reduce the number of substances used or developed that have a harmful effect on the environment. Moreover, the "End of Life Management" sub-dimension refers to the process's capacity to allow the reuse, recycling, and remanufacturing of product components. Finally, the "Certification" sub-dimension covers the redesign and development of processes to adapt to new environmental directives and criteria; the production process should adopt environmental procedures like the Eco-Management and Audit Scheme (EMAS) and the International Standard ISO 14001 (Calik & Bardudeen, 2016; Calik 2024).

Specifically, "material usage" refers to observing how process innovation has made it more efficient, thus examining the actual capacity of a production system to process and create the outputs required by sales while utilizing available resources in the best possible way. Therefore, to calculate the Overall Equipment Effectiveness (OEE), three factors must be combined: availability, performance, and quality, resulting in the following formula: $\mathrm{OEE} = \mathrm{Availability} \times \mathrm{Performance} \times \mathrm{Quality}$. Additionally, the variation in the quality of the product resulting from the process is also observed. Regarding the innovation examined in this study that is AI, to observe how AI adopted in the process has influenced this index, it is necessary to calculate the index concerning the time period before and after the integration of AI into the process. It is also essential to observe any potential variation caused by the impact of the AI system on product quality (Rhode et al., 2023).

As "Energy usage - CO_2", indicators that evaluate energy efficiency include measuring parameters that capture model efficiency, considering methods for efficient training, and measures to reduce the amount of data. This indicator is also calculated by directly examining CO_2 and GHG emissions, considering carbon footprint, carbon efficiency, energy losses and costs, and emission compensation (Rhode et al., 2023). Generally, Energy Usage indicator aims to measure overall energy costs, consumption, shares, and CO_2 emissions holistically. The literature highlights that this index is influenced by many other factors, such as adaptation to demand changes and market trends, making it difficult to isolate the value linked to AI. Bunse et al. (2011, as cited in Schmidt et al., 2016) stated that a low status of energy management and a lack of data for efficiency measure payback calculations are barriers to energy efficiency. Lindberg et al. (2023, as cited in Schmidt et al., 2016) emphasize the importance of benchmarking KPIs for monitoring performance and identifying improvement potentials. They recommend identifying process signals strongly correlated with the KPI for process improvements. The successful application of a KPI depends on its continuous measurability. Additionally, data accuracy and timely availability are important for calculating indicators regularly. However, not all companies consistently monitor these KPIs, making it difficult to calculate variations between pre- and post-AI implementation. For AI, the specific energy consumption of the hardware used must be considered, whether the data is linked to local data centers or the cloud. If on the cloud, the indirect energy consumption must refer to the external provider, while local methods look at efficiency metrics for data centers (e.g., power-/water-/carbon usage effectiveness) (Rhode et al., 2023). García-Martín, Rodrigues, Riley, and Grahn (2019, as cited in Ligozat et al., 2023) reviewed methods to estimate energy consumption from computer architecture, distinguishing between different levels of description, software/hardware level, instruction/application level, and considering how those methods can monitor training and inference phases in machine learning. Several tools have been proposed to make the impacts of training models more visible, calculating their carbon footprint. They can be schematically divided into:

- Integrated tools, such as Experiment Impact Tracker (https://github.com/Breakend/experiment-impact-tracker), Carbon Tracker (https://github.com/lfwa/carbontracker), and CodeCarbon (https://codecarbon.io/), which are Python packages reporting measured energy consumption and associated carbon footprint.
- Online tools, such as Green Algorithms (http://www.green-algorithms.org/) and ML CO_2 impact (https://mlco2.github.io/impact/#compute), which require only a few parameters, such as training duration, material, and location but are less accurate.

Moreover, physically measuring the performance of on-site energy generation requires specific assessment methods. Regarding the adoption of AI in the process, it is necessary to observe calculations before and after integrating AI. This can be done by applying smart sensors directly on the machinery to understand its consumption, or by extracting data from monthly bills and compare it to pre-algorithm consumption. While the first technique is very accurate and is able to capture the exact amount of energy generated, the second method is not always able to extract the AI-usage energy generated (Budennyy et al., 2022).

Referring to “other resource usage”, the total use of water, land, or energy is a widely used method in the literature for analyzing process impact. For example, the indicators “reduce water consumption” and “reduce energy consumption” have been used in some studies to assess the sustainability of the sector's production processes and whether companies attempt to fulfill green requirements (García-Granero, Piedra-Muñoz, & Galdeano-Gómez, 2018). In general, for a process, the calculation is: Water usage KPI [L of production water / L produced]. In this case, to understand if there has been a variation with the introduction of AI in the processes, the indicator should be observed before and after the AI implementation in the process. Additionally, parameters such as hardware recycling rate, hardware reuse rate, and the use of waste disposal scenarios for hardware are also examined (Rhode et al., 2023).

Regarding the analysis class related to “Waste, Emissions, Pollution”, the actual quantities of waste generated by the process are analyzed by referring to the correspondence between initial inputs and final outputs. Therefore, with the adoption of AI, this input-output variation must be observed to see if it has decreased or increased. Generally, for every innovative process, relevant emissions for each phase of the process are considered (regarding only CO_2

emissions, this is already addressed in the calculation of the element energy usage, a point previously mentioned). Additionally, all substances that have a negative impact when released into the environment are identified, including not only CO2 emissions but also any possible chemicals used directly in the process and their impact. The degree of toxicity for both terrestrial and aquatic organisms exposed to these substances is also assessed, covering aspects such as ozone depletion, photochemical ozone formation, acidification, eutrophication, human toxicity (including cancer and non-cancer effects), and ecotoxicity (European Commission, Joint Research Centre 2012). In reference to the adoption of AI, the variation in overall emissions due to AI should be analyzed by observing changes in the use of these chemicals – whether their consumption has decreased, increased, or been entirely eliminated – since the whole process has been revolutionized.

Among the methods for observing “the end-of-life management” related to a process innovation, the reduction of resource consumption in processes is generally considered. Material-saving is a key performance indicator that can be viewed from two perspectives. On one hand, the reuse of components or materials is seen as a positive way to enhance the greenness of the manufacturing process. On the other hand, recycling waste, water, materials, or inputs is another means of reducing negative environmental impact. Thus, some authors introduce the indicator “recycled waste, water, and materials” in their studies. Observing this indicator in relation to AI adoption in the process, it evaluates whether the integration of AI has allowed for more material savings, better waste disposal, or increased reuse of materials that were previously discarded (García-Granero et al., 2018).

Regarding “certifications”, it is generally observed if the process has certifications that align with sustainability plans, such as the previously mentioned ISO certifications. In reference to AI implementation, it should be assessed if “Certified hardware” and “Certified data centers” are adopted for the process (Rhode et al., 2023).

Finally, this work also considers whether the implemented AI is defined as *Green AI* or *Red AI*. Green AI refers to AI improvement that yields novel results while considering computational cost, encouraging a reduction in resources spent. In contrast, Red AI has led to rapidly escalating computational (and thus carbon) costs, while Green AI promotes approaches that have favorable performance/efficiency trade-offs (Schwartz et al., 2020). This distinction can be made by considering the Pareto Frontier. The Pareto frontier defines the optimal trade-off between cost and prediction performance, delineating a boundary in the objective space where any further improvement in one metric necessitates a compromise in the other. This frontier serves as a valuable guide for decision-makers, allowing them to balance the computational cost of an algorithm against its predictive accuracy, facilitating more informed and sustainable choices in model selection and deployment. For example, Ofek and Maimon (2023) examine points along the Pareto frontier to identify algorithms that offer the most favorable trade-offs, thereby optimizing the allocation of computational resources without sacrificing prediction quality. In general, to determine if AI is Green or Red, the cost of training, size of data, and carbon emissions are calculated.

Case Study

4. Measuring AI Environmental Hidden Costs and Values in a Production Process: The Case of VHIT

4.1 Purpose of the Analysis

The objective of this thesis is to examine the use of AI to determine if it is possible to calculate the net environmental impact—resulting from both positive and negative implications—associated with its implementation in a company. This goal aims to better inform managers who seek to integrate AI into their businesses and evaluate its sustainability. Specifically, it assesses whether AI contributes to sustainability and to what extent. Additionally, this research aims to guide policymakers by highlighting gaps that such an analysis may reveal, thereby informing their directives on AI and sustainability.

Generally, AI's negative impacts span production, usage, and disposal, while its positive impacts are primarily observed during its operational phase (Rhode et al., 2023). This research focuses on AI's application and usage, moving beyond merely listing environmental benefits and associated costs. Specifically, it aims to evaluate existing indices and determine what can be effectively measured within a company to develop a holistic sustainability index for AI applications in processes, capturing the total environmental impact (an aggregated measure that encompasses both costs and benefits) of AI integration.

In the previous chapter, existing models, such as the one proposed by Rhode et al. (2023), often focus solely on the operational impacts of AI technology, neglecting broader implications, including both direct and indirect effects on integrated processes. This narrow focus can lead to a significant underestimation of AI's true impact, particularly in contexts where the technology drives substantial process transformation, such as in production. Conversely, areas like marketing or human resources may not require as rigorous a focus on process adaptation, but understanding and managing transformations is crucial in production settings. Building on this theoretical foundation, this research adopts a more engineering-oriented perspective, as suggested by Calik and Bardudeen (2016), which forms the structure of the proposed operational framework to better capture the complexities of AI impacts in production environments. This framework is primarily integrated with the investigative model proposed by Rhode et al. (2023) and other models from the literature to create an operative tool.

Therefore, this research aims to address the following primary question: *How can the environmental impact of adopting AI in business processes be measured?*

This overarching research question is explored through the integration and validation of the proposed framework directly in conjunction with the case study of VHIT. Specifically, the research addresses the following sub-questions:

1. *How is VHIT applying AI in its processes?*
2. *To what extent are the existing methodologies applicable for calculating AI's total impact?*
3. *What are the advantages and challenges of adopting the evaluation framework developed based on existing literature and methodologies?*

4.2 Research Methodology

To comprehensively address the research objectives, a case study approach was employed. This method allows for an in-depth analysis of a specific instance to derive general conclusions about the observed phenomenon. The selected case study focuses on VHIT, a company that integrates AI into a specific production process. The analysis conducted is qualitative, leveraging multiple sources of data including documentation, archival records, surveys, and interviews. However, data collection primarily relied on interviews, a strategy that facilitated direct information gathering from the actors involved and enabled the posing of targeted questions most relevant to the study. Engaging in individual discussions with company representatives is recognized as one of the most authoritative ways to explore the real-world applications of AI. This methodology yields more valuable insights than multiple-choice questionnaires and is based on existing use case rather than hypothetical scenario like controlled experiment. To enrich and contextualize the findings, secondary sources such as official reports were also utilized.

More precisely the research follows the subsequent steps:

1. The first step in this research involves developing a comprehensive framework to address all identified limitations and aim at answering the primary research question.
2. Following the development of this framework, it is integrated and tested within business settings to validate its effectiveness. This process includes conducting a case study to observe the framework's practicality and applicability across different corporate contexts. During this phase, both quantitative and qualitative data were meticulously collected and analyzed.

Qualitative data were collected via interviews and surveys with managers involved in VHIT AI integration in business processes. An interview with the Head of Digital Transformation and the Sustainability Representative at VHIT was conducted to gain insights into the efficiency of the enterprise and the use of technologies within the organization. They were also requested to provide precise quantitative data in order to attempt to calculate key metrics such as energy usage- CO_2, resource efficiency, and waste management, among others.

Ultimately, through more general questions posed to the interviewed managers, this research aims not only to assess the overall environmental impacts of AI but also to explore the strategies used for sustainable AI development and deployment. The goal is to facilitate informed decision-making within corporations and to support policymakers by identifying regulatory gaps and objectives to incentivize.

4.3 VHIT Case Study

In light of the complexities previously examined in the literature regarding metrics and their integration, this study addresses the gaps in existing indices. Many indices do not exist for numerous aspects, and those that do exist pertain to different factors on varying scales. Therefore, this research adopts a more practical and applied approach to derive insights on the utilization of AI. The objective is to provide valuable perspectives on how to evaluate the impact of AI and suggest potential models for effective implementation and regulation.

4.3.1 VHIT Overview

The case study focuses on VHIT, a prominent Italian enterprise in the automotive sector, with over sixty years of history and now part of the Weifu High-Technology Co., Ltd. Group. Specializing in the research, development, production, and commercialization of mechatronic products, the company excels in vacuum, lubrication, and cooling systems for internal combustion and electric vehicle powertrains, as well as hydraulic applications for commercial vehicles.

Founded in 1958 by Domenico Bonaldi in Offanengo (CR, Italy), VHIT began by producing the Hydrovac brake booster under license from the American company Bendix. Over the years, VHIT has navigated through various acquisitions and ownership changes, including its time under the Bosch Group and its recent integration into the Weifu Group, significantly expanding its market impact.

Today, VHIT employs approximately 500 people and is distinguished not only by the quality of its products but also by its commitment to sustainability and technological innovation. The digitalization of production processes and the integration of AI and Industry 4.0 models are key aspects of the company's innovative approach.

The company's philosophy is encapsulated in its vision: “Smart, Global, Mechatronics & Beyond”. *Smart* denotes the intelligent use of advanced technologies, *Global* signifies the international expansion of its products, and *Mechatronics* reflects advanced mechanical and electronic expertise, enabling VHIT to effectively address current and future market challenges.

VHIT is also committed to promoting sustainable mobility through active collaboration with stakeholders and customers and fostering a stimulating and flexible work environment recognized as young and dynamic, where employees can grow professionally.

In recent years, the company has inaugurated *La Bottega delle Idee*, a creative hub that encourages dialogue and collaboration between internal and external teams, stimulating open innovation. This multifunctional space serves as a laboratory for prototype development and as a reflection area on sustainable future themes and emerging technologies.

VHIT's global presence extends well beyond Italy, with products distributed across Europe, Central and South America, and Asia, consolidating its reputation as a reliable supplier for major global automotive manufacturers.

Looking ahead, VHIT continues to expand its portfolio with products and services that meet the needs of a rapidly evolving market, increasingly focusing on electrified solutions and advanced systems for hybrid and electric vehicles. The company's goal is not only to maintain but to elevate its standard of excellence, consolidating its position as an innovative leader in the global automotive sector and as a top-choice workplace for industry talent.[3]

4.4 Adopted Evaluation Framework and Interviews

The framework developed to address the primary research question—namely, assessing the environmental impact of AI in business processes—analyzes six specific areas: material usage; energy usage - CO_2; other resource usage, waste, emissions, and pollution; end-of-life management; and certifications (Calik & Bardudeen, 2016). The evaluation criteria for each area were established by integrating models proposed by Rhode et al. (2023) with existing studies in the field. This framework was incorporated into a questionnaire, which served as the foundational structure for conducting interviews.

The questionnaire, detailed in the appendix of this thesis, is divided into four major sections to facilitate a smooth, comprehensible, and uninterrupted interview process. The initial section, comprising questions 1 to 6, is preparatory and focuses on general issues regarding the various applications of AI within the company, exploring its management and implementation. These preliminary questions are designed to guide the investigation towards a process that effectively examines the framework in the subsequent sections of the questionnaire.

The second section, encompassing questions 7 to 30, delves into more detailed issues related to the implementation of AI in a specific business process. This part explores all technical aspects related to the technology employed, with questions covering a wide range of topics, from a detailed description of the process to the type of hardware used, from the frequency of use to data storage systems, from energy consumption to variations in output, resources used, and waste produced.

The third section, comprising questions 31 to 51, investigates aspects related to the sustainability of the deployed AI, examining corporate strategies and potential methodologies for measuring impact and adopting circular economy practices.

[3]For comprehensive details about VHIT, please refer to their official website at https://vhit-weifu.com/.

Finally, the fourth and last section, consisting of questions 52 to 62, explores sustainability from a broader perspective, focusing on the company's general sustainability goals, communication strategies, and certifications obtained in this area.

These four sections encompass the evaluation measures related to the six aforementioned areas. Specifically, issues concerning “material usage” are addressed in questions 10, 20, 21, 22, 24, while those concerning “energy usage – CO_2” are covered in questions 11-19, 29, 30, 47, 48. Similarly, “other resource usage” is referenced in questions 26-28, 36-38; “waste, emissions, and pollution” in questions 23, 40, 49, 50; “end-of-life management” in questions 25, 34, 39, 51; and “certifications” in questions 60-62.

Additionally, generic questions not directly related to these six areas were included to assess the company's environmental awareness, their strategic perspective, and the potential for their business model to contribute to positive outcomes in the analysis conducted with this framework. This evaluation determines whether AI offers competitive advantages while simultaneously supporting environmentally beneficial outcomes proposing a virtuous business model example.

4.5 Analysis and Discussion of Results

This paragraph presents an analysis of the results based on the evaluation obtained through the application of the framework, derived from interviews with the Head of Digital Transformation and the Sustainability Representative at VHIT.

4.5.1 VHIT Approach to AI Integration

The company VHIT has integrated AI into its business processes for approximately 3-5 years (Q1), falling within the 58% of companies that had adopted AI in at least one business area by 2019 (McKinsey, 2022). The company utilizes AI across various strategic functions, including production, logistics, quality management, maintenance, and research and development (Q2).

In the production domain, VHIT has adopted technologies such as computer vision, neural networks, and time series analysis using regression and clustering algorithms like DBScan. These tools automate and enhance production processes, increasing efficiency and reducing operational costs. Indeed, the digitalization of production processes at VHIT minimizes low-value-added activities, allowing the company to focus on challenging goals, product innovation, and responding to the rapidly changing market demands. VHIT is increasingly becoming a data-driven company, with the primary goal of offering high-quality products that evolve with market needs, anticipating customer requirements (VHIT Weifu, n.d.).

Regarding logistics, VHIT employs natural language processing and autonomous guided vehicles (AGVs). Implemented in the plants for a couple of years, these AGVs simplify logistics processes by automating the movement of products from the production area to the finished goods warehouse. The AGVs are directly connected to the company's management system, allowing fully automated material retrieval and empty packaging return.

In quality management, VHIT uses computer vision and neural networks to enhance the accuracy and efficiency of quality controls.

In the maintenance sector, VHIT uses generative AI (GenAI) and neural networks for predictive maintenance. For instance, the use of GenAI through tools like ChatGPT provides support in diagnosing and solving problems, reducing intervention times, and assisting less experienced staff, particularly during night shifts.

In research and development, VHIT primarily employs generative AI to accelerate innovation and the development of new products (Q4).

Regarding AI model training, VHIT prefers to internalize these processes when feasible to contain costs and maintain greater control over the models. However, when the technology is new or not well understood internally, the company resorts to outsourcing. For example, in logistics, VHIT opted to directly purchase an application (Q5).

Data management and storage for AI implementation vary by application. VHIT predominantly uses a cloud system for most data, while computer vision applications are managed on local systems, such as computers connected to machinery. NLP and maintenance with GenAI are managed on the cloud, whereas R&D activities remain local (Q6).

This integrated strategy allows VHIT to maximize AI’s potential, improving operational efficiency and promoting innovation within the company, thereby strengthening its competitive position in the market (Q3).

4.5.2 The AI Adoption in VHIT’s Production Process

The analysis proceeds by examining the adoption of AI in VHIT's process. According to the company's Head of Digital Transformation, this integration has led to significant improvements in production processes. Primarily, there has been a notable increase in efficiency. AI has reduced the time required for various production stages, enhancing both the speed and accuracy of operations. This improvement is accompanied by a significant reduction in operational costs, achieved by eliminating many inefficiencies and optimizing resource usage.

In this context, to more precisely assess the benefits and costs of AI in a single process following the devised framework, the interviewee was asked to present and describe a specific case in detail. The reported process pertains to the quality control of filters used in oil and vacuum pumps, serving as an emblematic example of AI's effectiveness. Before the introduction of AI (Q8), this process was performed manually: an operator visually inspected each filter to determine whether it was acceptable or should be discarded. This approach presented two main issues. Firstly, it required employing a person for a low-value-added task, resulting in significant human resource costs. It is important to consider that this inspection was carried out across all 20-25 production lines, each operating three shifts per day, with one dedicated operator per shift. Consequently, three operators were needed per day for each line. The second issue concerned the nature of the task itself, which was tiring and exhausting for the operators, leading to an inevitable decline in performance over the eight-hour shift, causing quality issues in the production process.

As an initial step towards automating quality control processes, VHIT implemented an optical inspection system utilizing grayscale imaging. The algorithm analyzed the pixels of filter images, determining whether a filter was good or defective according to predefined rules. However, this system required the definition of numerous rules for every possible variation in the filters and lighting conditions, resulting in numerous false positives, where good parts were erroneously classified as rejects. Additionally, this led to significant economic impact due to the substantial waste of resources such as labor, energy, and materials. This waste occurred because all components used to produce the part were considered scrap, even though the part actually met quality standards, being wrongly classified as defective due to a system error.

The implementation of an AI-based solution (Q9) brought about a radical change. The neural network, trained internally with approximately 300-400 labeled images of good and defective filters, reduced false positives from 2.3% to 0.2%. The system, consisting of a camera, an illuminator, and a computer with standard hardware (Intel Xeon E5), significantly improved process efficiency and reduced waste by fully automating quality control and freeing human resources for other value-added activities.

In accordance with the devised framework, the analysis proceeds by dividing into six areas: material usage; energy usage – CO_2; other resource usage; waste, emissions, and pollution; end-of-life management; certifications.

4.5.2.1 Material Usage Index

The adoption of AI in the company's production process has led to significant changes in material usage, as indicated by responses to the corporate questionnaire (Q7). A key aspect of this improvement is the reduction in false positives, which decreased from 2.3% to 0.2% (Q20). This outcome is significant because it demonstrates the direct impact of AI on increasing efficiency, reducing resource usage, lowering costs, and enhancing product quality, which in turn affects the overall sustainability of the production process (Q10). Therefore, the elimination of false positives, achieved through AI, has substantially reduced material ad energy waste. Previously, false positives led to the unnecessary scrapping of material and inefficient energy use in producing and assembling components that were ultimately discarded. With the introduction of AI, this issue has been minimized, leading to a 2.1% reduction in false positives. This improvement is significant as it contributes to more efficient and sustainable resource utilization (Q22).

Quantitatively, output has remained stable at 7 million units, but the reduction in false positives has increased the actual usable output. The interviewee also indicated that this variation in output is directly correlated with the implementation of AI, without the influence of other significant innovations (Q21). Although there has been no change in the total consumption of raw materials, the increase in efficiency and reduction in waste represent a tangible improvement in material utilization (Q24).

In summary, the adoption of AI has made the production process more sustainable through optimized resource management and significant waste reduction, demonstrating the effectiveness of advanced technologies in optimizing industrial processes and their related sustainability.

4.5.2.2 Energy Usage – CO_2 Index

The analysis of the company's responses to the questionnaire reveals significant details regarding energy usage in relation to the implementation of AI. The hardware used to manage the production process includes various types of Intel Xeon processors, along with standard PCs like Lenovo Tiny, demonstrating that the company did not resort to particularly specialized solutions (Q11). This hardware was utilized for in-house training of the AI model (Q12), a process that took approximately six months and involved multiple cycles of trials and improvements (Q13). Indeed, developing the model often involves numerous experiments to tune its hyperparameters. Moreover, the AI model operates daily across three shifts, covering 25 assembly lines with an average cycle time of 20 seconds per filter, functioning for about 23 hours a day, five days a week, nearly year-round (Q14).

Since all operations are managed internally, and there are no external components such as data, data centers, or hardware to consider, the energy study can focus solely on the company's operational activities. The most accurate method for performing the calculation would involve obtaining consumption data from all involved equipment, utilizing integrated tools such as Experiment Impact Tracker, Carbon Tracker, and CodeCarbon, as well as online tools like Green Algorithms and ML CO2 Impact, or other instruments such as sensors directly installed on the machines. However, VHIT does not use any of these tools, as it does not calculate the impact of the current process or the AI implementation (Q16, Q17). Therefore, precise and accurate energy measurements directly correlated to AI implementation are challenging without such tools.

Nonetheless, following the devised framework, data were requested to estimate the energy usage and subsequent emissions resulting from AI use in the specific process considered.

An initial micro-level approach, adopting a more targeted perspective, calculates the volume of data generated during training and daily usage. To calculate the data flow used during AI model training, the average size of a single photograph and the total number of photographs used were considered. Each photograph used by the company is approximately 500 kilobytes in size. Thus, multiplying this size by the number of photographs used for training, which is 400, the calculation proceeds as follows:

- $500\,kilobytes/photo \times 400\,photos = 200{,}000\,kilobytes.$
- Converting kilobytes to megabytes (considering 1 megabyte = 1,000 kilobytes): $200{,}000\,kilobytes \div 1{,}000 = 200\,megabytes.$

Therefore, the total training data volume is about 200 MB.

For daily usage, the implemented AI generates approximately 12.42 TB of data annually, collected and managed locally. Specifically:

1. Calculating daily operations:
   - There are 24 hours in a day, each composed of 60 minutes, and each minute has 60 seconds: $24\,hours \times 60\,minutes \times 60\,seconds = 86{,}400\,seconds/day.$

- The average cycle is 20 seconds, so the number of operations per day is: $86{,}400\ seconds/day \div 20\ seconds/cycle = 4{,}320\ operations/day$.

2. Calculating annual operations across all lines:
   - There are 25 assembly lines: $4{,}320\ operations/day \times 25\ lines = 108{,}000\ total\ daily\ operations$.
   - The number of working days annually is 230: $108{,}000\ total\ daily\ operations \times 230\ working\ days = 24{,}840{,}000\ annual\ operations$.
3. Calculating data volume:
   - Each photograph is 500 kilobytes: $24{,}840{,}000\ annual\ operations \times 500\ kilobytes/photo = 12{,}420{,}000{,}000\ kilobytes$.
4. Converting to megabytes, gigabytes, and terabytes:
   - Converting kilobytes to megabytes: $12{,}420{,}000{,}000\ kilobytes \div 1{,}000 = 12{,}420{,}000\ megabytes$.
   - Converting megabytes to gigabytes: $12{,}420{,}000\ megabytes \div 1{,}000 = 12{,}420\ gigabytes$.
   - Converting gigabytes to terabytes: $12{,}420\ gigabytes \div 1{,}000 = 12.42\ terabytes$.

Therefore, the total annual data volume generated during the use of the AI model is approximately 12.42 TB. Thus, it can be concluded that the AI-implemented production process generates a significant volume of data.

To calculate the actual environmental impact, i.e., the amount of CO_2 corresponding to the data volume processed, totalling 200 MB of training data and 12.42 TB of annual data, it is necessary to consider the carbon footprint associated with data storage and processing. Indeed, CO_2 emissions vary depending on storage technologies, energy sources used, and data center efficiency. Since these specific data are unavailable for the company, this analysis could only estimate the CO_2 emissions during training using the online tool CodeCarbon.

This tool uses various parameters for calculation: type of hardware, in the case of VHIT, an Intel-E5; the provider, considered as private infrastructure; hours of use, which for the company is 6 months; a carbon efficiency value, which is the 2014 OECD annual average of 0.432 kg CO_2eq/kWh, indicating the carbon intensity of the network connected to the infrastructure; the percentage of energy consumption offset by the company.

Entering the required data, the calculation proceeds as follows:

- $Power\ consumption \times Time \times Carbon\ Produced\ Based\ on\ the\ Local\ Power\ Grid = 145W \times 100h = 14.5\ kWh \times 0.432\ kg\ eq.CO_2/kWh = 6.26\ kg\ eq.CO_2$

To contextualize, 6.26 kg of CO_2eq is equivalent to:

- 25.3 km driven by an average ICE car,
- 3.13 kg of coal burned,
- 0.1 tree seedlings sequestering carbon for 10 years.

However, this approach does not allow for calculating the CO_2 impact of AI in use, which is the main objective of this research, during which only the annual data volume can be measured.

To address the lack of specific data needed for a comprehensive analysis, a second macro-level approach was attempted by requesting energy bills (Q18) to identify the aggregate energy variation coinciding with the AI implementation in the process (Fig. 1, Fig. 2).

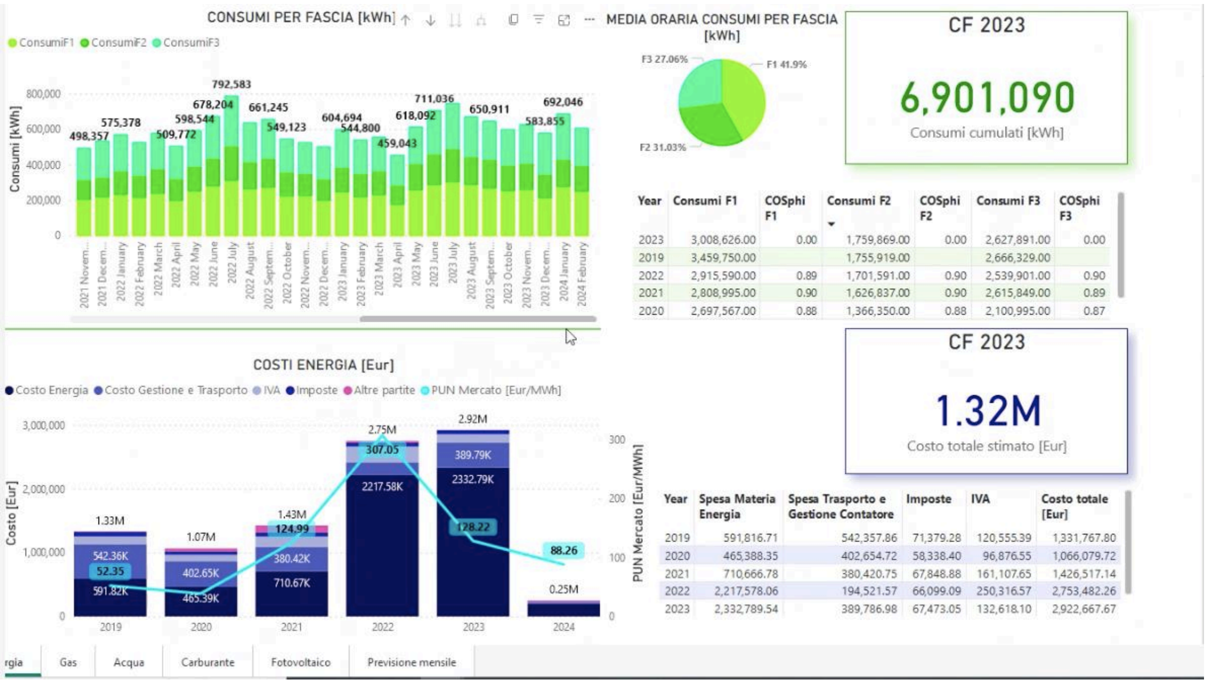

Figure 1. Consumption by range (kWh) from November 2021 to February 2024 and energy costs (€) from 2019 to 2024. *Source: VHIT.*

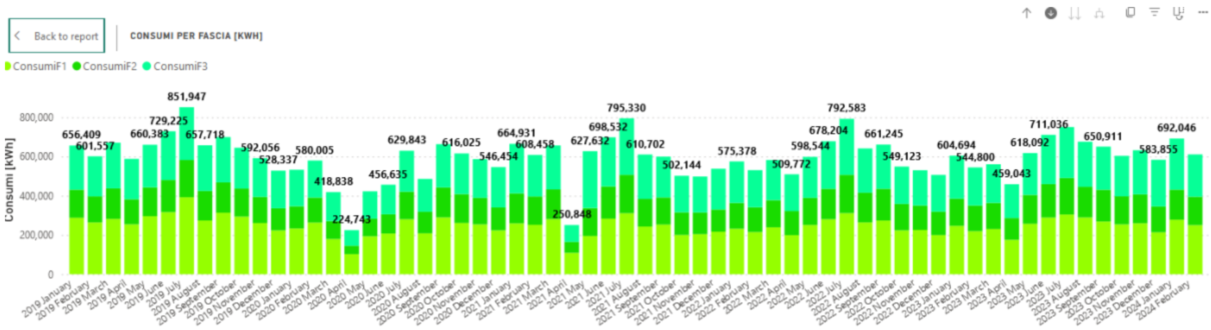

Figure 2. Detailed consumption by range (kWh) from January 2019 to February 2024. *Source: VHIT.*

The AI model implemented by VHIT was initially introduced on a single production line before the pandemic and gradually extended to the remaining production lines. There is no precise date for its complete implementation. Observing the charts, it is evident that energy consumption, starting from 2019, has decreased, excluding the year of the Covid-19 pandemic. This decrease is not due to reduced production but rather to the increased energy costs, which necessitated the adoption of energy-saving measures. In the post-pandemic period, beginning in 2021, energy consumption has shown monthly variations attributable to product seasonality. Furthermore, since 2021, the cost of energy has significantly increased due to inflation. For a more plausible comparison, the data from 2019 and 2022 can be considered: in 2019, AI was operational on a single line, while in 2022, it was extended to all lines. During this period, there was a reduction in energy consumption by 700,000 units, although, as noted by the interviewee, this decrease cannot be solely attributed to the implementation of AI (Q19).

In summary, these data do not elucidate the impact of AI, as variations in consumption are influenced by numerous factors, including changes in the number of units produced, inflation, and infrastructural modifications such as the introduction of heat pumps and electric forklifts. According to the interviewee, the impact of AI on the energy bill is truly a minor factor (Q19). This further confirms the complexity of extrapolating data directly correlated to the energy consumption resulting from AI use and adoption in a specific process, whether adopting a micro or macro perspective.

Although the actual energy consumed was not calculated, which would have been useful for balancing the positive contributions of renewable solutions, it is important to note that the company has adopted various measures to reduce its environmental impact (Q47). Specifically, photovoltaic panels have been installed, covering approximately 10% of the energy requirement. Additionally, the remaining energy consumption is offset by using energy from renewable sources and carbon credits, demonstrating a commitment to carbon neutrality (Q48).

Finally, from the comparison with the interviewee, it emerged that the energy consumption of the AI system is indeed higher compared to human labor, while the optical system adopted subsequently, in the intermediate phase before AI, and the AI adopted eventually have a nearly similar consumption.

4.5.2.3 Other Resources Usage Index

The analysis of the questionnaire responses provided by VHIT reveals an interesting picture regarding the use of resources other than energy in the production process under study. When asked about additional resources used beyond energy, VHIT stated that they do not use significant additional resources (Q26). However, with the introduction of AI in the process, the company observed a reduction in raw material usage due to an increase in the percentage of recycled materials from waste (Q27). This practice significantly contributes to the sustainability of the company's processes by reducing the need for new raw materials and improving material efficiency.

Although VHIT cannot quantify the exact change in the use of other resources before and after the implementation of AI (Q28), they have adopted circular economy practices for hardware waste disposal (Q36). VHIT described their process post-AI implementation as circular, where all waste materials are reused since the AI was introduced, making the entire production process more sustainable. The practices implemented include reuse, recycling, and disassembly (Q37). These practices also pertain to hardware. In this context, the "hardware recycling rate" and "hardware reuse rate" are key parameters for assessing the impact of AI on the production process, though the percentage of hardware processed through these practices relative to the total discarded hardware is not available (Q38).

In conclusion, within the framework devised and considering the parameter "Other Resources Usage", which includes the total use of water, land, or energy as commonly used methods in the literature to analyze the impact of processes, the information provided by VHIT indicates a trend towards resource consumption reduction and increased efficiency through recycling and reuse. Although the lack of quantitative data limits the analysis, VHIT's commitment to sustainable and circular practices represents a positive step towards reducing the overall environmental impact.

4.5.2.4 Waste-Emission-Pollution Index

In the context of the Waste-Emissions-Pollution index, the adoption of AI by VHIT has led to significant reductions in production waste and improved resource management, demonstrating a positive impact on the sustainability of the production process. Prior to the adoption of AI, indeed, the company's data on average monthly waste due to quality issues showed variability. For instance, in March 2019, waste due to quality was 2%, whereas in March 2021, it had decreased to 1.40%. Overall, there was an average reduction of 0.3% from 2019 to 2021, although this improvement cannot be entirely attributed to the introduction of AI (Q23).

Post-AI implementation, VHIT reported an average monthly waste of 2.89% out of a total of 7 million units produced, highlighting a general improvement in waste reduction and production efficiency (Q23). Additional benefits cited by the company include better resource management and increased reuse of waste materials (Q40). Despite these advantages, VHIT does not specifically monitor the impact of its process on critical environmental areas such as ozone layer depletion, photochemical ozone formation, acidification, eutrophication, human toxicity, and ecotoxicity (Q49). Consequently, the impact of AI on these environmental aspects remains unassessed and unmonitored (Q50).

The lack of monitoring of emissions and the effects of chemicals on the environment limits the comprehensive understanding of the overall environmental impact. For a more accurate assessment, it would be necessary to consider the entire life cycle of the resources used and to monitor CO_2 emissions, as well as other potential chemical pollutants and their effects on terrestrial and aquatic organisms.

4.5.2.5 End-of-Life Management and Certifications Indexes

The implementation of AI in VHIT's process has led to substantial improvements in material lifecycle management and operational circularity. After AI integration, VHIT has achieved nearly 100% recycling of waste materials, reintroducing them into the production flow. For example, discarded pumps are disassembled to recover reusable components, while non-reusable parts are remelted (Q25). Before AI adoption, a significant portion of discarded parts, approximately 30-40 thousand annually, was not recovered. Due to the reduction of false positives achieved with AI, it is no longer necessary to request these parts from external suppliers, thereby improving the overall efficiency of the process. Thus, AI has notably increased the circularity of VHIT's operations, leading to more efficient resource use and waste reduction (Q34). The percentage of recycled materials has risen significantly since AI implementation, reaching nearly 100% (Q39). Regarding hazardous waste, although VHIT does not recycle it, the firm is committed to reducing and properly disposing of it in accordance with current regulations, demonstrating responsible management (Q51).

To summarize, within the end-of-life management evaluation framework, the adoption of AI has enabled VHIT to conserve materials and improve waste disposal. AI has facilitated the reuse of materials previously considered waste, thus reducing environmental impact.

Concerning certifications, VHIT has been ISO 14001 certified for environmental management for over 15 years (Q60). However, the company has not provided additional data necessary for a comprehensive assessment of the environmental impact of AI adoption in its production process. Specifically, information on certified hardware meeting energy and resource efficiency criteria (Q61) and certified data centers adhering to standards of transparency and efficiency (Q62) is unavailable. These gaps limit the ability to fully assess the certification parameter and its contribution to overall environmental sustainability of the process under consideration.

4.5.3 Final Insights

In light of the detailed analysis of the implementation methods of AI in a specific production process, and the associated environmental costs and benefits, it is observed that the adoption of the technology by VHIT has led to significant improvements, primarily in efficiency, cost reduction, and product quality. While the energy consumption of the AI system is comparable to that of the previous optical system, the reduction in waste has been a notable advantage in terms of sustainability. VHIT has observed an overall decrease in energy consumption due to various energy-saving initiatives, not directly attributable to AI. However, the reduction in waste has contributed to the overall sustainability of the production process. Additionally, the reduction of false positives has had a direct impact on sustainability by decreasing waste and optimizing resource use. The internal implementation of the AI system has allowed VHIT to maintain control over data and tailor the model to the company's specific needs, underscoring the importance of AI as a strategic tool for innovation and operational efficiency.

In overall terms, the integration of IA into VHIT's business process partially aligns with the corporate sustainability plan (Q31), but is not part of a broader sustainability strategy (Q32). The sustainability benefits derived from AI are secondary effects rather than primary objectives. In this perspective, VHIT primarily uses AI to enhance production efficiency, evaluating its benefits more in economic and efficiency terms rather than sustainability (Q41). Indeed, no significant challenges have been identified in harmonizing AI use with sustainability goals, as the two aspects are not directly correlated (Q33).

Shifting the focus to the critical and widely discussed topic in the literature concerning AI and the significant negative impact of its supporting infrastructure, namely data centers, the company acknowledges that it has not considered the potential increase in emissions resulting from the intensive use of AI and the consequent increase in data collection and processing (Q42). However, it believes the negative impact is outweighed by the benefits (Q44) and does not see the need to adopt methodologies to quantify the environmental impact of AI relative to its benefits (Q45).

According to the interviewee, indirect sustainability benefits from AI include greater production efficiency, resulting in reduced human and energy resource consumption and minimized environmental impact (Q52). Additionally, the overall sustainability benefits are communicated to customers occasionally and mainly upon request (Q58), through customized reports (Q59).

Furthermore, despite not giving greater consideration to the direct and indirect impact of AI use, the company pursues commendable general sustainability goals focusing on reducing its ecological footprint and responsible management through technological innovation, waste reduction, and the use of renewable energy, with the aim of achieving carbon neutrality. However, it does not follow any more specific goals. In fact, the company is carrying out various assessments to identify areas for improvement and more specific objectives (Q53). To pursue its general goals, VHIT also evaluates the overall environmental impact of the company through continuous emission monitoring, material recycling and reuse, and process digitalization for greater efficiency, not involving AI in these measurements (Q55). For example, the digitalization of data collection processes via dedicated apps allows monitoring of waste production and reduction of low-value-added activities. Atmospheric emissions are controlled and verified annually based on provincial authorizations and the Integrated Environmental Authorization (AUA) in compliance with current regulations. The company has invested in a new industrial process to eliminate wastewater in the washing cycles of reusable packaging. Additionally, in the energy domain, the company employs a problem analysis and resolution methodology to reduce energy consumption, called the “Green Line”. Concrete examples include the installation of photovoltaic systems, LED lighting, inverter technologies, and the optimization of heating and cooling systems through AI algorithms (Q54), improving key indicators such as the Carbon Footprint (Q57).

In conclusion, although AI is primarily used to enhance process efficiency, its impact on environmental sustainability is considered a secondary benefit. This is further evidenced by the limited attention to quantifying the direct and indirect costs associated with AI use in company processes. Though, adopting a truly sustainable infrastructure requires significant resources. As noted by the interviewee, such adoption is often perceived as costly and time-consuming. Furthermore, the lack of sufficient national incentive mechanisms makes this transition even more challenging for many companies (Q45).

Conclusion

Focusing on AI adoption in business operations, current methodologies often overlook AI’s full hidden environmental impact, both positive (values) and negative (costs), especially in production processes where the technology significantly alters the process itself. Traditional models primarily address the direct consequences of technology usage, such as CO2 emissions and energy consumption, but tend to neglect the broader effects of AI integration, such as enhanced efficiency, leading to a significant underestimation of AI's environmental impact, particularly in industries undergoing major process changes.

Integrating diverse insights and methods from the literature in economics, management, and engineering, this research proposes a holistic framework for assessing the environmental impact of AI in business processes. This framework primarily references the work of Calik & Bardudeen (2016) and analyzes six specific areas: material usage, energy usage, other resource usage, waste, emissions and pollution, end-of-life management, and certifications.

The effectiveness, exhaustiveness, and adoptability of this potentially comprehensive AI sustainability framework were tested through a case study on VHIT, a manufacturing company that integrates AI into its production process. This methodology enabled a multifaceted evaluation of the environmental impact of AI integration in a production process, specifically regarding the quality control of filters used in oil and vacuum pumps, and assessed the sustainability of AI in that specific context of business adoption.

Regarding the “Material Usage” parameter, it emerged that AI adoption has made the production process more sustainable through optimized resource management and significant waste reduction. The information provided by VHIT concerning “Other Resource Usage” also indicates a trend towards reduced resource consumption and increased efficiency through recycling and reuse. In the context of the “Waste-Emissions-Pollution” index, AI adoption by VHIT has led to significant reductions in production waste and improved resource management, demonstrating a positive impact on the sustainability of the production process. Finally, within the “End-of-Life Management” evaluation framework, AI adoption has enabled VHIT to conserve and reuse more materials and improve waste disposal. However, concerning certifications, the company has not provided additional data necessary for a comprehensive assessment of the environmental impact of AI adoption in its production process.

The area of “Energy Usage” - and consequently CO2 emissions - is simultaneously the most critical for understanding AI’s environmental impact and the most challenging to calculate, presenting difficulties for this framework as well as any other possible methodology. Unlike other areas, where it is sufficient to consider the situation before and after AI introduction, the energy aspect is more complex and faces practical impediments related to the collection of relevant data within the company. In the case study, since data centers are internal to the company, a comprehensive local evaluation was in principle possible, and therefore different calculation strategies were adopted based on available data.

The best method for precisely calculating the energy consumption resulting from AI usage, and consequently the associated CO2 emissions, would involve applying (smart) sensors to understand the consumption of the involved machinery. However, it is very rare to find such sensors in companies, and even VHIT has none. Alternatively, a first micro-level targeted approach involves calculating the volume of data generated during training and daily usage. In VHIT’s case, daily usage generates about 12.42 TB of data annually. To calculate the actual environmental impact, i.e., the amount of CO_2 corresponding to the processed data volume, totaling 200 MB of training data and 12.42 TB of annual data, it is necessary to consider the carbon footprint associated with data storage and processing. Indeed, CO_2 emissions vary depending on storage technologies, energy sources used, and data center efficiency. Since these specific data were unavailable for VHIT, and are difficult to obtain for any company, this type of analysis could only estimate the CO_2 emissions during training using online tools such as CodeCarbon. However, this approach does not allow for calculating the CO_2 impact of AI in use, which is the main objective of this research, where only the annual data volume can be measured.

To address the lack of specific data needed for a comprehensive analysis, a second macro-level approach was attempted by requesting energy bills to identify the aggregate energy variation coinciding with AI implementation in the process. However, these data do not elucidate the impact of AI, as variations in consumption are influenced by numerous factors, including changes in the number of units produced, inflation, and infrastructural modifications such as the introduction of heat pumps and electric forklifts. This further confirms the complexity of extrapolating data directly correlated to the energy consumption resulting from AI use and adoption in a specific process, whether adopting a micro or macro perspective.

In general, the proposed framework proves promising for evaluating the sustainability of AI usage, allowing for the development of effective policies that foster a synergistic development of the two components of the Twin Transition without hindering each other. However, this tool needs improvement and refinement to enable the use of the most appropriate calculation methodologies for each area—especially energy—to address the concrete obstacles related to obtaining relevant data during the use of AI in a specific production process of a specific company. This awareness also reflects a fundamental indication for managers and decision-makers. To implement and manage sustainable AI virtuously, they must ensure the conditions for collecting and processing relevant data for evaluating the sustainability of technology usage, such as installing sensors that monitor the specific energy consumption of AI.

The case study also provided other interesting insights into the AI integration strategy in the operations of a manufacturing company in the automotive sector and the company's general attention to sustainability.

Finally, it is worth noting that this research adopts a partial perspective as it focuses only on the usage phase of the AI lifecycle. Consequently, for a comprehensive evaluation, albeit challenging, future research should also consider the production and disposal phases, as well as the infrastructural nature of this technology.

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Appendix

Questionnaire

Section 1: Utilization of Artificial Intelligence in the Company

1. How long has AI been integrated into your business processes?
2. In which business functions is AI applied within your company?
3. What were the main factors driving your company towards adopting AI?
4. For each application area listed in question 2, which specific AI models or technologies have you adopted? (e.g., machine learning, deep learning, generative AI)
5. For each AI application mentioned in questions 2-3, is the model training conducted in-house or outsourced to external partners? What criteria guided your decision between internalizing and outsourcing this process?
6. Where and how are the data used for implementing AI in the various functions mentioned earlier managed and stored? (e.g., on-premise systems, cloud storage, data warehouses, data lakes, databases)

Section 2: AI in the Production Process

7. What changes have you observed in your production processes following the adoption of AI?
8. Please describe in detail how a specific production process was organized before the introduction of AI, including the process objectives, main operational steps, technologies and systems used, and any operational challenges or inefficiencies encountered.
9. Describe how the production process mentioned in the previous question has changed after the implementation of AI. Include details about the AI model used, including its underlying technologies and model architecture, the changes made to the process, improvements in production, waste reduction, or other operational benefits, and how AI has influenced the entire process from both technical and organizational perspectives.
10. Do you believe that the previously described improvements have made the process more sustainable? If yes, could you provide some data to support this statement?
11. What types of hardware have you implemented to support the AI operations described in question 9?

Please select the appropriate options from the list provided below: A100 PCIe 40/80GB, AGX Xavier, AMD EPYC 7763, AMD RX480, GTX 1080, GTX 1080 Ti, GTX 750, GTX TITAN X, Intel Xeon E5-2630v4, Intel Xeon E5-2650, Intel Xeon E5-2699, Intel Xeon Gold 5220, Intel Xeon Gold 6148, Quadro K6000, Quadro P6000, RTX 2080, RTX 2080 Ti, RTX 3080, RTX 3080 Ti, RTX 3090, RTX 8000, RTX A4000, RTX A5000, RTX A6000, T4, TITAN X Pascal, TPUv2 Chip, TPUv3 Chip, Tesla K40c, Tesla K80, Tesla M40 24GB, Tesla P100, Tesla P40, Tesla V100-PCIE-16GB, Tesla V100-SXM2-16GB, Tesla V100-SXM2-32GB, Titan RTX, Titan V, Titan Xp.

Other:

12. Did you train the AI model described in question 9 within your organization, or did you opt for outsourcing to external partners?
13. If the training was conducted internally, how many hours were required to complete the training of this model?
14. How frequently is the AI model used in your processes?
15. Describe the data flow associated with the production process where AI has been implemented. How much data is collected from this process?
16. How much energy is consumed by the specific process under consideration?
    a. Not measured
    b. Measured

    If measured, please specify the amount:

    Before the implementation of AI:

    After the implementation of AI:
17. Do you have specific methodologies or tools to calculate the environmental impact of your process?

    If yes, which of the following tools do you use?
    a. Integrated tools (e.g., Experiment Impact Tracker, Carbon Tracker, CodeCarbon)
    b. Online tools (e.g., Green Algorithms, ML CO2 Impact)
    c. Other tools (e.g., sensors directly installed on the machines, etc.), please specify:
    d. We do not use specific tools
18. Could you provide your electricity and gas bills (total company consumption) before and after the implementation of AI?
    a. Yes
    b. No

    If yes, please specify the total consumption:

Before the implementation of AI:

After the implementation of AI:

19. Additionally, could you indicate if the change in consumption is exclusively attributable to the implementation of AI, or if other significant changes have been made that might have affected it?
20. Could you provide the total amount of output (pieces) produced through the process mentioned in question 9 before and after the introduction of AI?
    a. Yes
    b. No

    If yes, please indicate the quantity of output:

    Before the implementation of AI:

    After the implementation of AI:
21. Do you believe that any variation in output can be directly correlated to the introduction of AI, or have other innovations also influenced production levels?
22. In which of the following indices do you believe AI has contributed to improvements?
    a. Output/time
    b. Output/resources used
    c. Output/cost
    d. Output/quality
    e. Other:

    Have you calculated the respective changes before and after AI implementation? If so, could you provide these data?
23. Could you provide the total amount of waste and scrap produced by the process mentioned in question 9, before and after the introduction of AI?

    Before the implementation of AI:

    After the implementation of AI:
24. Could you indicate the total consumption of raw materials used for the process mentioned in question 9, before and after the introduction of AI?
25. Regarding the above, could you specify what percentage of the raw materials used comes from external purchases and what percentage comes from internal recycling of waste materials or other forms of reuse post-AI introduction (referring to the process mentioned in question 9)?
26. What resources, besides energy, are used in the process?
    a. No additional resources

b. Water
c. Oil
d. Soil
e. Other resources (please specify)

27. With the introduction of AI in the process, have you noticed any changes in the quantity or type of “other” resources used?
28. Can you quantify the variation in the use of “other” resources before and after the implementation of AI?
    a. No
    b. Yes (provide specific data, e.g., water consumption before = ___ L per unit of production, after = ___ L per unit of production)

Please answer questions 29 and 30 only if the example provided of AI implementation relies on external clouds for data management and storage.

29. What types of hardware have you implemented to support the AI operations described in question 11?
    Please select the appropriate options from the list provided below: A100 PCIe 40/80GB, AGX Xavier, AMD EPYC 7763, AMD RX480, GTX 1080, GTX 1080 Ti, GTX 750, GTX TITAN X, Intel Xeon E5-2630v4, Intel Xeon E5-2650, Intel Xeon E5-2699, Intel Xeon Gold 5220, Intel Xeon Gold 6148, Quadro K6000, Quadro P6000, RTX 2080, RTX 2080 Ti, RTX 3080, RTX 3080 Ti, RTX 3090, RTX 8000, RTX A4000, RTX A5000, RTX A6000, T4, TITAN X Pascal, TPUv2 Chip, TPUv3 Chip, Tesla K40c, Tesla K80, Tesla M40 24GB, Tesla P100, Tesla P40, Tesla V100-PCIE-16GB, Tesla V100-SXM2-16GB, Tesla V100-SXM2-32GB, Titan RTX, Titan V, Titan Xp.
    Other:
30. Provider:
    a. Google Cloud Platform
    b. Amazon Web Services
    c. Azure
    d. OVHCloud
    e. Scaleway
    f. CoreWeave

Section 3: AI Implementation and Sustainability

31. How does the integration of AI into your process align with your company's sustainability plan?

a. Fully aligns
b. Partially aligns
c. Does not align
d. Not applicable/We do not have a sustainability plan
e. Any comments:

32. Is the integration of AI into the process an integral part of a broader corporate sustainability strategy? If so, could you briefly describe this strategy?
33. What have been the main challenges in harmonizing the use of AI with your sustainability goals?
34. Does the AI adopted in the process contribute to the circularity of your operations?
    a. Yes, significantly
    b. Yes, moderately
    c. No
    d. I don't know
    e. Any comments:
35. If applicable, describe examples of AI applied to operations/processes to promote a circular economy model within the company (if the example corresponds to that mentioned in question 9, detail how it contributes to circularity).
36. Do you adopt circular economy practices for the disposal of hardware used in your processes?
37. If yes, which of the following practices have you implemented?
    a. Reuse
    b. Recycling
    c. Disassembly
    d. Refurbishing
    e. Other (please specify)
38. If applicable, could you indicate the percentage of hardware treated through circular practices relative to the total hardware disposed of?
    a. Less than 25%
    b. 25% - 50%
    c. 51% - 75%
    d. More than 75%
    e. Not available

39. What has been the percentage change in reused resources (scrap, water, and other materials) before and after the implementation of AI? Please specify for each resource:
    Before the implementation of AI:
    After the implementation of AI:
40. What are the sustainability benefits of your AI solution?
    a. Energy efficiency
    b. Waste reduction
    c. Better resource management
    d. Increased production efficiency
    e. Improved waste disposal
    f. Increased reuse of scrap materials
    g. Reuse and remanufacturing of components
    h. Reduction in pollutant emissions
    i. We have not observed improvements
    j. Other:
41. How do you monitor and measure these benefits?
42. Have you considered that intensive use of AI and the consequent increase in data collected and processed might lead to a potential increase in emissions?
    a. Yes
    b. No
43. If you answered yes, have you evaluated any measures to mitigate this environmental impact? Could you provide specific examples of such initiatives?
44. Do you believe that any negative impact is still outweighed by the benefits it brings?
    a. Yes
    b. No
    c. I don't know
    d. Any comments:
45. Do you rely on any methodology to quantify the environmental impact of AI relative to its benefits?
    a. Yes, we have specific methods
    b. No, but we would like to develop them
    c. No, we do not consider it necessary
    If yes, which ones? If no, why not?

46. If you have such methodologies, could you provide a concrete quantitative example? (Preferably related to the impact of AI on the processes mentioned in questions 9 or 30)
47. Does your company employ renewable energy sources, such as photovoltaic systems, for sustainable energy production? If yes, could you specify which technologies you use?
48. Could you provide, if possible, a percentage of your infrastructure's energy consumption that you manage to offset?
49. Do you evaluate and monitor the impact of your process on the following environmental areas: ozone layer depletion, photochemical ozone formation, acidification, eutrophication, human toxicity (including carcinogenic and non-carcinogenic effects), and ecotoxicity? If yes, specify which topics are monitored.
50. Has the implementation of AI had an impact in terms of reducing or increasing the environmental impact of the process concerning the above-mentioned topics?
    a. Reduction
    b. Increase
    c. No impact
    d. Not applicable/Not monitored
51. If possible, indicate the percentage of hazardous waste recycled.
    Before the implementation of AI:
    After the implementation of AI:

Section 4: Sustainability Goals, Impact Assessment, and Communication of Benefits

52. What specific sustainability benefits are derived from your AI solutions?
53. What are your overall sustainability goals?
54. How do you assess your environmental impact?
55. Do you use AI in this process?
    a. Yes, AI is a central element
    b. Yes, but only as a support tool
    c. No, we use other methods
    d. We do not conduct environmental impact assessments
    e. Comments:
56. Describe one or more examples, if any, of AI primarily aimed at making the company sustainable or assessing its environmental impact.

57. Does the AI mentioned in the previous question help improve key indicators (specific KPIs for sustainability, life cycle analysis, carbon footprint analysis, etc.) through which corporate sustainability is measured?

    a. Yes

    b. No

    If yes, which ones and how? (please specify):

58. Do you communicate the sustainability benefits to your customers?

    a. Yes, regularly

    b. Yes, occasionally

    c. No

    d. Any comments:

59. How do you communicate the sustainability benefits of your AI solutions to customers?

    a. Sustainability reports

    b. Marketing communications

    c. Customized reports

    d. Not communicated

    e. Any comments:

60. Have you obtained certifications that align with your sustainability plan to meet new environmental criteria or directives?

61. Do you have certified hardware that meets energy and resource efficiency criteria?

62. Do you have a certified data center that adheres to standards of transparency, energy efficiency, and resource efficiency?