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INDUSTRY 4.0 IMPLEMENTATION STRATEGIES TO ENHANCE ENVIRONMENTAL SUSTAINABILITY IN MODERN ENTERPRISES

Doctoral (PhD) dissertation

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Industry 4.0 Implementation Strategies to Enhance Environmental Sustainability in Modern Enterprises

Dissertation to obtain a PhD degree

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I4.0	Fourth Industrial Revolution
Industry 4.0	Fourth Industrial Revolution
IR	Industrial revolution
IR1	First Industrial revolution
IR2	Second Industrial revolution
IR3	Third Industrial revolution
WM	Waste management
SWM	Solid Waste management
ULB	Urban Local Bodies
MSW	Municipal Solid Waste
CE	Circular Economy
EMS	Energy Management System
CHP	Combined Heat and Power
DG	Distributed Generation
AI	Artificial intelligence
ML	Machine learning
IoT	internet of things
3D	Manufacturing three-dimensional manufacturing
AG	Augmented reality
CPS	Cyber-Physical system
VR	Virtual Reality

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Abstract

In today's fiercely competitive business environment, the integration of Industry 4.0 has evolved from an optional approach to an essential strategy for companies seeking to sustain their competitive advantage. With the automation capabilities of IoT, the data management capabilities of AI, and the traceability benefits offered by Blockchain, this imperative has become increasingly apparent. While the interest in Industry 4.0 is widespread, uncertainties surrounding its implementation pose significant challenges. Simultaneously, adherence to environmental sustainability practices has transitioned from an ethical consideration to a mandatory requirement, particularly in developed countries subject to strict local and international regulations.

Our study recognizes the pressing need for companies to address their environmental impact and leverages the transformative potential of Industry 4.0 to achieve this goal without compromising economic and social aspects. Employing a mixed-methods approach, we conducted a quantitative research phase, offering a comprehensive overview of the current Industry 4.0 landscape and its applications for environmental sustainability. This phase involved a questionnaire administered to 205 companies, distinguishing between SMEs and large enterprises. Subsequently, we applied a qualitative study, focusing on a leading information technology company in the Industry 4.0 domain, supplemented by insights from three of its customers.

The mixed-methods approach enabled the creation of a well-structured guide for decision-makers, offering insights on overcoming common challenges and successfully implementing Industry 4.0. Moreover, it shed light on the environmental sustainability objectives achievable through such investments. During our research, these software tools have been used; command-line Astrogrep for literature scanning, Integromat for email automation, SPSS for statistical analysis, and Zotero for referencing, facilitated a comprehensive and methodical research process.

This study contributes a practical resource for decision-makers navigating the complexities of Industry 4.0 implementation, emphasizing its potential to mitigate environmental impact.

1. INTRODUCTION

Industry 4.0 remarks the new era of industrial production, the roots of Industry 4.0 are driven by the time when the manufacturing process was dependant totally on human and animal physical force, the transition from this situation into machinery, new chemical factories, and iron manufacturing processes, development of waterpower, maximizing the use of steam power, and finally, the development of machine tools is considered as the first industrial revolution. The iron and textile sectors also played crucial roles in the first industrial revolution (H. K. Mohajan, 2019). The second revolution was moulded by the introduction of numerous technologies, including internal combustion engines, electricity, chemical industries, alloys, petroleum, as well as advancements in electrical communication and chemical technologies (such as the telegraph, radio, and telephone), alongside the implementation of running water and indoor plumbing. (Gordon, 2000). The third revolution, marked by the integration of digital manufacturing and personal manufacturing, includes the industrialization of the Maker Movement. The term "third industrial revolution" signifies a profound transformation, previously characterized by other authors as an "efficiency revolution," "green capitalism," and a fundamental shift towards a "green industrial revolution." (Bauer et al., 2016). The pivotal question arising is why, despite the third industrial revolution being a promising initiative aimed at assisting organizations in embracing green practices and mitigating environmental impact, the outcomes appear contrary. Over the past few decades, industrial activities have inflicted unprecedented harm on the environment (Hallegraeff, 2010). As per (Parmesan et al., 2022), human activities have emerged as the primary driver behind hundreds of extinctions in the last two centuries, in stark contrast to the natural extinction processes occurring over millions of years. As we navigate the 21st century, human activities continue to reshape the world in unprecedented ways.

Industry 4.0 is no longer a fictional hype that presents repackaged concepts. It is rather a new revolution in manufacturing that is acknowledged by researchers, governments, and industrialists. In May 2022, more than 24.000 papers were available in the SCOPUS database that contained the word Industry 4.0 either in the title, abstract, and/or indexed key words. Since the first industrial revolution in the 18th century, the globe has faced the difficulty of creating more products from limited and decreasing natural resources to fulfil the ever-increasing demand for consumption while minimizing negative environmental and social implications (Müller et al., 2018). The significance of Industry 4.0 is broad, ranging from mass production to satisfying customers through product customization. The adoption rate of Industry 4.0 in the last couple of years has been extremely high (Dev et al., 2020).

In the context of this thesis, "Modern Enterprises" refer to companies that actively integrate various technologies to enhance their operations, regardless of whether they are specifically implementing Industry 4.0 technologies. These enterprises may utilize a range of technologies stemming from both the third and fourth industrial revolutions. The key characteristic of a modern enterprise is its commitment to continuous development and adaptation to meet evolving market needs and to maintain a competitive edge. This includes, but is not limited to, the adoption of advanced manufacturing technologies, digital transformation, and innovative business processes.

There is a trend toward the use of Industry 4.0 for economic purposes only, despite the high potential that the technological facilities have for environmental aspects. Industry 4.0 can play a significant role in balancing the cost/reward of environmental sustainability commitment if presented in the "right way". Transforming the traditional factories into a smart production chain and business processes and deploying smarter devices and machines may present numerous advantages such as manufacturing productivity, resource efficiency, and waste reduction (Tortorella et al., 2019). On the other hand, the development of smart factories and automation will potentially result in a high increase rate of production that would be associated with a high level of energy consumption and resources as well as elevated gas emission and pollution (Beier et al., 2017; X. Liu & Bae, 2018). The primary goal of environmental sustainability is to preserve the earth's environmental systems' equilibrium, the balance of natural resource use and replenishment, and ecological integrity (Glavič & Lukman, 2007). Since previous industrial revolutions resulted in dramatic and rather unanticipated environmental transformations, the sustainability consequences of Industry 4.0 need full academic consideration. The effects of Industry 4.0 and digital transformation on environmental sustainability are predicted to be significant (Kamble et al., 2018; Lopes de Sousa Jabbour et al., 2018).

Given the significant advantages afforded by adopting Industry 4.0 technologies, particularly in an increasingly competitive global environment, it is of great interest to both researchers and practitioners that so many companies are still reluctant to adopt these technologies more broadly (Chiarini et al., 2020; Koh et al., 2019; Tortorella et al., 2019). This resistance is largely justified in the literature; the adoption of industry 4.0 is not trivial, it is rather associated with a chain of challenges and obstacles that needs to be addressed. Even though the integration of Industry 4.0 technologies provide numerous advantages, much work remains (Dalenogare et al., 2018). In 19 different countries, only 14% of CEOs have complete assurance in their companies' ability to adapt to the changes ushered in by Industry 4.0 (Raj et al., 2020) and only four out of ten firms, on average, have made significant headway in the adoption of industry 4.0 (Bauer et al., 2016).

The uncertainty of outcome is playing an important role in this regard as well, and many industrial businesses may undervalue Industry 4.0 technologies (Bai et al., 2020). Efficient and comprehensive assessment methodologies and decision-support systems can assist manufacturing organizations in properly implementing and comprehending Industry 4.0 technology, especially when the larger economic ramifications are considered. These larger ramifications include environmental as well as socioeconomic problems (Frank et al., 2019).

The preponderance of Industry 4.0 implementation case studies concentrates primarily on the economic implications, which do not fully capture the range of possibilities afforded by Industry 4.0, especially in the light of all the challenges associated with Industry 4.0, there is a significant need for successful case studies focusing on the environmental aspects of Industry 4.0, as environmental concerns continue to grow in significance for firms across industries (Zangiacomi et al., 2020). Several researchers have highlighted the possibility and necessity of forging a new trajectory for environmental development (Parajuly & Wenzel, 2017; Sousa-Zomer & Cauchick Miguel, 2018). Even if there is a disconnect between environmental sustainability and I4.0 (Baccarelli et al., 2017), numerous articles underscore its potential to bolster green practices. Notably, it can enhance operational efficiency, streamline data control operations, optimize energy utilization, and reduce waste in processes and machines (Ivanov et al., 2016; Thoben et al., 2017). Taking a closer look at this gap, we've crafted the following scope and research objectives.

1.1 Scope and research objective

This study centers on a comprehensive exploration of Industry 4.0 implementation, aiming to grasp the various variables shaping this revolution, including challenges, technologies employed, the current state of adoption, companies' investment inclinations, hurdles faced during implementation, perceived obstacles, and desired outcomes. The specific emphasis is on the pivotal aspect of environmental sustainability.

As an integral part of this expansive exploration, our research methodology involves a mixed-methods approach. A quantitative study casts a wide net over SMEs and large companies, providing a numerical overview of Industry 4.0 trends. Concurrently, a qualitative investigation delves deeply into a singular case study, offering nuanced insights into successful implementation and environmental objectives achieved.

The primary aim is to extract valuable insights from this comprehensive approach, providing decision-makers with a strong understanding of Industry 4.0 adoption.

The main objective is to ultimately provide a practical roadmap to navigate decision-makers through the complexities of Industry 4.0 implementation, providing strategic guidance to address challenges identified in the literature and validated through quantitative study. Subsequently, these challenges will be applied to a case study to assess how the studied company effectively tackled them. The qualitative study will delve into the specifics of how the company overcame these challenges, examining achieved objectives, employed strategies, and utilized technologies, all while aligning its approaches with the imperatives of environmental sustainability.

The study's objective can be delineated into eight sub-objectives that will guide the research.

1.1.1. Research sub-objectives

To achieve our research's main objective and provide decision-makers a coherent and well-structured study as a reference for the industry 4.0 implementation and the use of the technological facilities to mitigate environmental sustainability issues, the following sub-objectives need to be fulfilled relying on the exploration of the literature, quantitative and qualitative studies.

- O.1 Examine the current extent of Industry 4.0 adoption among companies.
- O.2 Assess the motivations for Industry 4.0 investments and evaluate the extent to which these investments prioritize environmental sustainability.
- O.3 Investigate the prevalent technologies used in Industry 4.0 investments.
- O.4 Explore challenges and obstacles preventing companies from investing in Industry 4.0.
- O.5 Differentiate desired objectives from Industry 4.0 between large companies and SMEs. Assess the emphasis on achieving environmental sustainability objectives in each category.

O.6 Analyze a leading company's successful implementation of Industry 4.0.

O.7 Investigate strategies used to overcome common challenges in Industry 4.0 implementation.

O.8 Document the environmental objectives successfully achieved by a company through Industry 4.0 investment.

To fulfill the sub-objectives of the study, the following questions need to answered.

1.1.2. Research sub-Questions

O1:

1. What percentage of companies currently adopt Industry 4.0 practices?
2. What percentage of companies express interest in Industry 4.0 but have not yet adopted it?

O2:

1. What are the primary objectives companies aim to achieve through Industry 4.0 investments?
2. To what extent do environmental sustainability objectives factor into the overall goals of Industry 4.0 investments?

O3:

1. Which technologies dominate the landscape of Industry 4.0 adoption among companies?

O4:

1. What factors contribute to companies' decisions to refrain from Industry 4.0 implementation?
2. What specific challenges and obstacles act as deterrents for companies considering Industry 4.0 investments?

O5:

1. Are there significant differences in objectives between large companies and SMEs in their pursuit of Industry 4.0 adoption?
2. Is there a notable distinction in the emphasis on achieving environmental objectives between large companies and SMEs implementing Industry 4.0 technologies?

O6:

1. What constitutes a successful approach to investing in Industry 4.0?

2. What resources and organizational culture are integral to a company's effective implementation of Industry 4.0 practices?

O7:

1. How did the company under study overcome common obstacles associated with Industry 4.0 investment?
2. What strategies were employed to anticipate potential challenges and successfully navigate them?

O8:

1. What were the overarching objectives achieved through the company's Industry 4.0 investment?
2. Specifically, what objectives were realized concerning environmental sustainability as a result of Industry 4.0 implementation?

These questions are integral for addressing the objectives effectively; however, they will not be explicitly invoked throughout the research process. Instead, the objectives will function as the primary indicators, while the questions will serve as an internal guide.

1.1.3. Research hypothesis

The quantitative part of the study will examine the general state of the industry 4.0 implementation for both SMEs and large companies. This part of the study will focus mainly on the percentages of companies that implement industry 4.0, the challenges encountered during the implementation process, the obstacle that hold the entities that do not invest in industry 4.0, technologies used, the underlying objectives and key differences between large and SMEs in the context of industry 4.0. To achieve that, the following hypothesis emerged:

H01: There is no association between the intention to invest in Industry 4.0 in the future and the type of company (SMEs and large enterprises) at the 0.05 significance level.
H02: There is no significant difference in the overall distribution of technologies used by companies (both current adopters and future investors) between SMEs and large companies at the 0.05 significance level.
H03: There is no significant difference in the overall distribution of challenges faced by companies that do not currently invest in Industry 4.0, whether they wish to invest in the future or not, between SMEs and large companies at the 0.05 significance level.

H04: There is no significant difference in the underlying reasons for investment in Industry 4.0 for environmental sustainability between large companies and SMEs at the 0.05 significance level.

1.2 Research structure

To fulfill the main research objective, the study is guide by eight sub-objectives, each containing one or two questions that need to be answered.
Both quantitative and qualitative methodologies are used to meet the study objectives, as shown in Table 1, each methodology is used for a specific sub-objective/question, the intersections are also visible in Table 1.

Table 1: Study's structure

Research main objective	Sub-Objectives	Number of Questions	Hypothesis	Methodology
Provide decision-makers with a structured guide for successful Industry 4.0 implementation, leveraging advanced technologies to address environmental sustainability issues.	O1 - O2 - O5	6	H01 - H04	Quantitative - Literature review
	O3 - O4	3	H02 - H03	
	O6 - O7 - O8	6		Qualitative

Source: Own research

The definition of Industry 4.0 will be discussed in-depth in the next chapter, but it is relevant to mention that this concept includes different technologies that can differ from an author to the other, for this reason, we scanned 417 articles from the SCOPUS database, which contain the word Industry 4.0 in the title, abstract, and/or in the indexed keywords by the command-line program Astrogrep to find the most common Industry 4.0 technologies. Table 2 shows the most mentioned technologies will guide this research.

Table 2: Number of mentions of each I4.0 technology in the literature

Industry 4.0 technology	Mentions out of 417 papers
Internet of Things (IoT)	252
Cyber-Physical Systems (CPS)	218
AI/ML	81
Simulation	38
Blockchain	30
Augmented reality (AG)	27
Additive manufacturing	23
Digital twin	20
Virtual reality (VR)	20
cloud computing	11
Edge computing	4
Drones	3
Cobots	1

Source: Own research

While CPS has been mentioned in 218 articles, it was not included in the research. The decision is rooted in the challenge of establishing a clear distinction between CPS and IoT in most projects and academic research. The majority of scholars tend to view the two concepts as distinct explanations of the same phenomenon, often using the terms interchangeably, making it difficult to draw a clear-cut line between them (Minerva et al., 2015). Despite this exclusion, the quantitative study will still acknowledge CPS to ensure the accuracy of the responses.

In order to address the objectives of this research, the following literature review first highlights key topics concerning the use of Industry 4.0 technologies to enhance environmental sustainability. This review not only examines existing studies and frameworks but also lays the groundwork for our primary objective: providing a comprehensive guide for decision-makers to successfully implement Industry 4.0 in an environmentally sustainable manner. Each subchapter in the literature review delves into specific aspects of Industry 4.0, discussing its potential impacts and applications.

2. LITERATURE REVIEW

This chapter is dedicated to unpacking the core concepts of our thesis: "industry 4.0" and "environmental sustainability". We will explore industry 4.0 by introducing its key technologies, such as IoT, AI, and Blockchain. Concurrently, we will examine environmental sustainability through its crucial aspects, including energy management, carbon emission reduction, and resource efficiency. Our approach involves categorizing industry 4.0 by technologies and environmental sustainability by aspects, providing a structured analysis of their intersection as shown in Figure 1.

The literature review conducted to inform this study was primarily based on articles sourced from the SCOPUS database, supplemented by relevant sources from other databases such as Springer, Google Scholar, and IEEE. The objective was twofold: first, to establish a clear understanding of the key terms shaping our research, and second, to review existing studies relevant to the integration of industry 4.0 and environmental sustainability.

During the literature review process, the software Astrogrep was employed to systematically extract key technologies associated with industry 4.0 and key aspects related to environmental sustainability.

Furthermore, we presented a detailed overview of the most relevant and up-to-date studies that explore the intersection of industry 4.0 and environmental sustainability. Each technology associated with industry 4.0 was examined separately, providing a clear understanding of its implications for environmental sustainability.

Finally, we addressed the challenges identified in the literature regarding the utilization of industry 4.0 technologies for enhancing environmental sustainability.

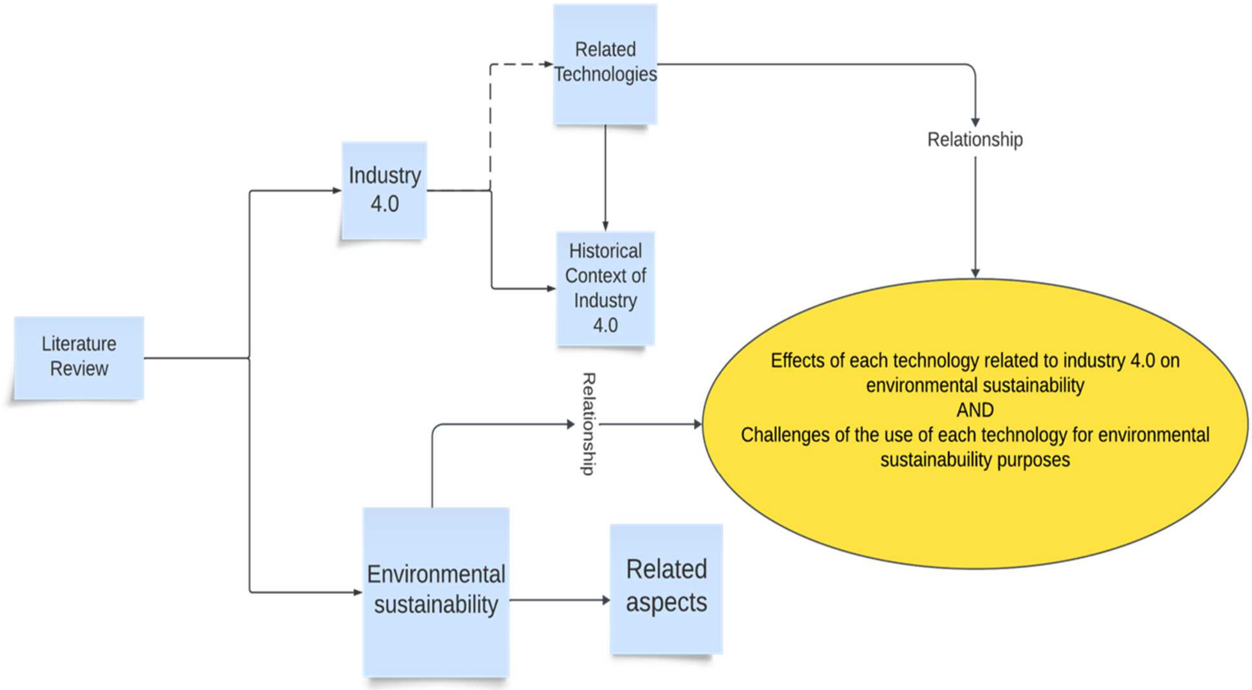


Figure 1: Structure of the Literature Review

Source: Own research

By synthesizing existing research findings, this literature review sets the stage for our subsequent analysis and contributes to a deeper understanding of the opportunities and obstacles in this emerging field.

2.1 Industrial revolutions

The term "industrial revolution" has become ingrained in the English language, widely recognized for its transformative impact on societies. As shown in. Table 3, the roots of the industrial revolution can be traced from the 18th century. While commonly understood in general terms, its precise definition presents a historical challenge. Historians offer three perspectives on this phenomenon. Firstly, it is often portrayed as the rapid expansion of specific industries. Alternatively, it is viewed as a structural transformation in the economy spanning the mid-eighteenth to mid-nineteenth centuries, marked by a significant shift in population from agriculture to manufacturing and mining. Lastly, the industrial revolution can be interpreted as the emergence of an economy that transitioned from sporadic, if any, increases in national income to a continuous and sustained upward trajectory (Agarwal & Agarwal, 2017). In the following sections, we will explore each industrial revolution in detail, revealing their unique characteristics and pivotal changes.

Table 3: First, Second and Third Industrial Revolution overview

	1st Industrial Revolution: approx. 1780	2nd Industrial Revolution: approx. 1890	3rd Industrial Revolution: approx. 1990
Dominant technology and raw material	Steam engine, power loom, iron processing	Electricity, chemistry, combustion engine, assembly line, synthetic materials	ICT, microelectronics, new materials, renewable raw materials, cleaner technology, biotechnology, recycling.
Dominant energy source	Coal	Coal, oil, nuclear power	Renewable energies, energy efficiency
Transport/ communication	Railway, telegraphy	Car, airplane, radio, TV	High-speed railway systems, internet, mobile telecommunication
Society/ state	"Bourgeoisie", freedom of trade, constitutional state	Mass production, mass society, parliamentary democracy, welfare state	Civil society, globalization, global governance
Core countries	UK, Belgium, Germany, France	USA, Japan, Germany	EU, USA, China Japan

Source: (Jänicke & Jacob, 2009)

The Industrial Revolution (IR) was a series of massive socioeconomic developments that occurred in England between the end of the 18th and early 19th centuries (1760-1840) (H. K. Mohajan, 2019). The first industrial revolution was the move from animal and human labor expertise to machinery, innovations in chemical production and manufacturing methods, enhanced water power efficiency, increased use of steam power, and machinery development. The iron and textile sectors were crucial in the first industrial revolution (T. S. Ashton, 1997). Table 4 shows major inventions during this period.

Table 4: First industrial revolution major inventions

Year	Inventor	Invention	relevancy
1563	Rev. William Lee	Stocking Frame	A first crucial step in the mechanization of the textile industry
1708	Jethro Tull	Mechanical Seed Sower	Assisted in the British Agriculture Revolution
1709	Abraham Dabry	Using Coke for smelting iron	A crucial stage in the production of iron as a raw material for the industrial Revolution
1712	Thomas Newcomen	Steam engine	The first device to practically harness steam to produce mechanical work
1733	John kay	Flying Shuttle	Permitted a single weaver to weave wider fabrics, it could be also mechanized, which allowed automatic machine looms
1765	James Hargreaves	The spinning Jenny	Reducing the amount of work needed to produce cloth, with employees able to make eight or more spools at once
1769	Arkwright's	Water powered frame	Designed initially for cotton production and was capable to spin 128 threads at a time, which was a more effective and efficient method than ever.
1775	Watts	Updates of previous steam engine versions	Watt's design saved a high amount of fuel cost compared to the previous design
1787	Cartwright	Power loom	By producing much efficient cloth, the power loom resulted in an increase in the demand and boosted exports, resulted in a growth in industrial employment, albelt low-paid.

Source: (the government of andhra pradesh, 2015)

During the first industrial revolution, there were immense social, political, and economic shifts as shown in Table 5.

Table 5 Patterns of expenditure, residence and employment between 1700-1840 (%)

	1700	1760	1800	1840
Male employment in agriculture	61.2%	52.8%	48.8%	28.6%
Male employment in industry	18.5%	23.8%	29.5%	47.3%
Income from agriculture	37.4%	37.5%	36.1%	24.9%
Income from industry	20%	20%	19.8%	31.5%
Consumption/Income	92.9%	73.6%	76.3%	80.1%
Investment/income	4%	6.8%	8.5%	10.8%
Exports/Income	8.4%	14.6%	15.7%	14.3%
Urban population	17%	21%	33.9%	48.3%

Source: (Crafts, 1994)

These changes included substantial growth in farming and logistics, massive manufacturing of items, international trade expansion, rise in employment, creation of earning sources for women and children, and a shift in the standard of living. As shown in the Figure 2, international GDP has risen significantly since 1800 after hundreds of years of very low growth.

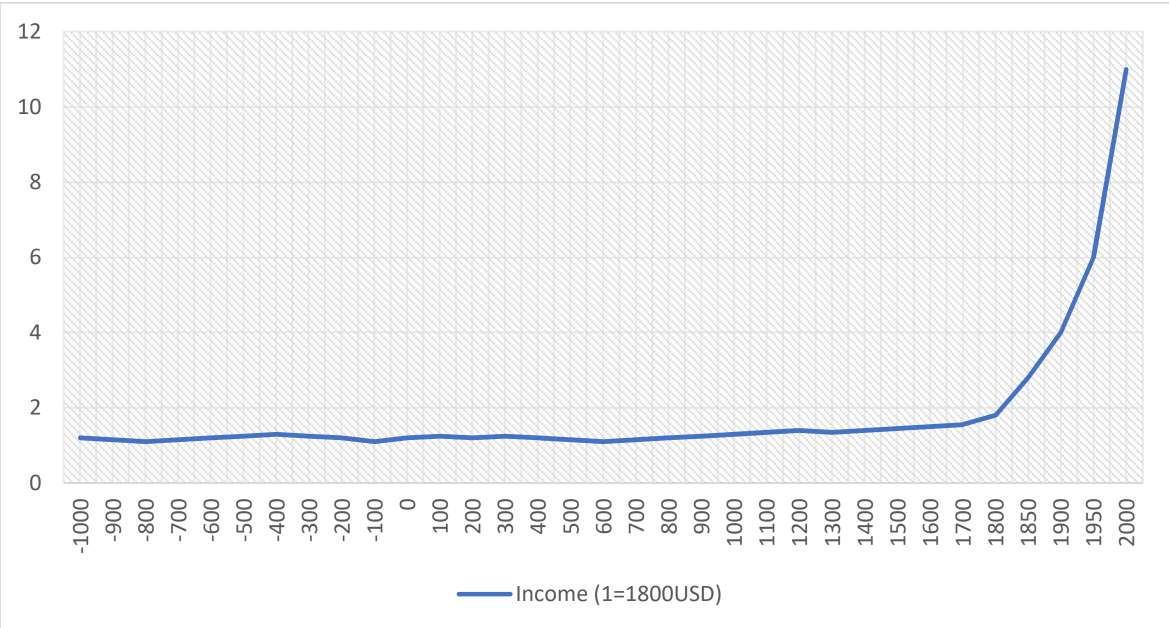


Figure 2: World economic history in one picture. income rose sharply in many countries after 1800.

Source: (MALANI, 2023)

These developments didn't come with no cost, as the IR resulted in unsafe labor conditions, air and water pollution, and a rise in child labor. It significantly increased tensions between the working and middle classes (Galbi, 1997).

2.1.1. Second industrial revolution

The second Industrial Revolution occurred between 1870 and 1914, while some major developments can be traced back to the 1850s (Mokyr & Strotz, 1998). During this period, Henry Ford introduced the moving assembly line, revolutionizing mass production. This era witnessed the invention of key technologies, the development of Electric motors, water wheels and turbines and Steam is showed in Figure 3, but this period also witnessed other inventions such as railways, iron steamships, telephones, internal combustion engines, electricity, electric light bulbs, automobiles, radios, airplanes, and computers.

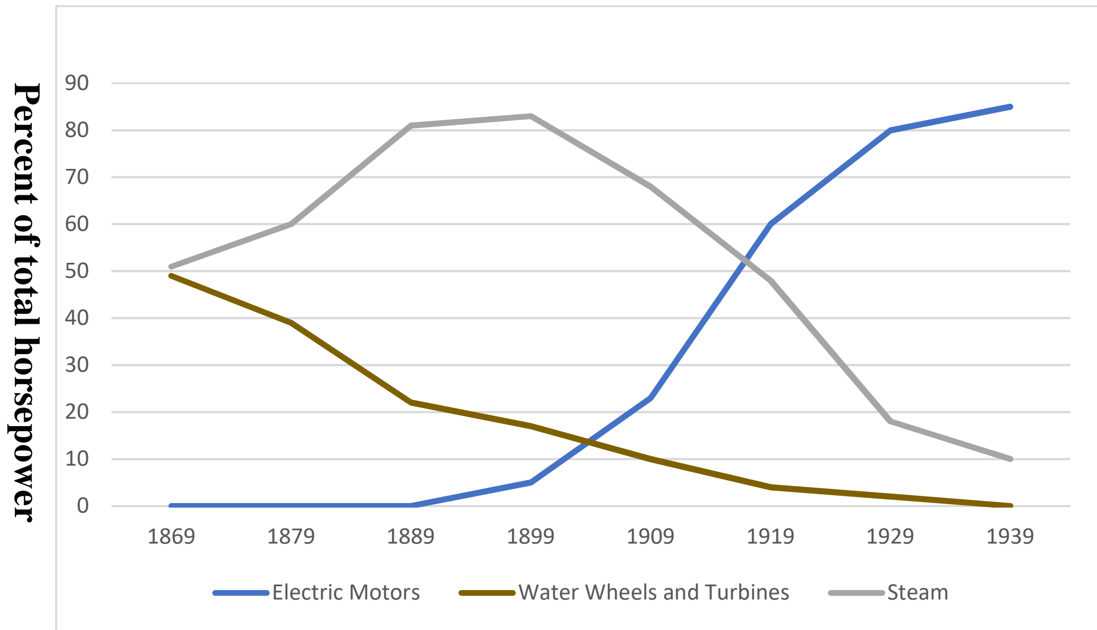


Figure 3: Sources of mechanical Drive in U.S manufacturing Establishments. 1869-1939

Source: (Atkeson & Kehoe, 2001)

Throughout the first and second Industrial Revolutions (IR1&2), prices decreased, yet the quality of items notably improved (Atkeson & Kehoe, 2001). As a consequence, the second Industrial Revolution expanded upon the relatively limited and localized successes of the first, encompassing a significantly broader range of activities and goods. Living standards and purchasing power experienced substantial growth as new technologies permeated the daily lives of the middle and working classes to an unprecedented extent (Mokyr & Strotz, 1998). Table 6 presents the main patent of electric invention.

Table 6: ***Basic patent in the development of electric inventions***

Patent N°	Year	Patentee	Invention
US N°. 132	1837	Davenport	DC-motor
US N° 295.454	1888	Sprague	DC-motor (railway applications)
US N°. 494.978	1892	Crocker/Wheeler	DC-motor (machine applications)
GB N°. 806	1855	S.Hjorth	Dynamo-Electric generator
GB N°. 3.394	1886	S.A. Varley	Dynamo-Electric Generator
GB N°. 261	1867	W.Siemens	Dynamo-Electric Generator
US N°. 292.079	1884	Jonas Wenström	Dynamo-Electric machine
US N°. 381.968	1888	Nicola Tesla	Two-phase induction motor
US N°. 390.439	1888	Charles Bradley	Two-phase induction motor
US N°. 427.978	1890	M. Dobrovolsky	Three-phase induction motor
Fr N°. 112.024	1876	Pavel Jablochkoff	Electric-Arc light
US N°. 223.898	1880	Th. Edison	Incandescent Lamp

Source: (van der Kooij, 2017)

However, it took several decades from the onset of this revolution for measurable productivity growth to manifest. According to the standard model of growth, this delay appears counterintuitive. Historians posit that the delay can be attributed to the inefficient transmission of new technologies across production plants and the ongoing learning curve within factories even after the implementation of these new technologies (David, 1990) .

Significant issues emerged with the second industrial revolution surpassing anything observed previously. This shift transpired as the importance of manufacturing economies of scale escalated. Some of these challenges were primarily physical, exemplified by the proportional relationship between the cost of constructing containers and cylinders in the chemical industry, where costs relate to surface area and capacity correlates with volume (Scranton, 1997).

2.1.2. Third industrial revolution

The Third Industrial Revolution (IR3) commenced in the 1950s, reached its zenith in the late 1990s during the dot-com era (Taalbi, 2019), and is presently ongoing in 2024, at the time this thesis is written, marking a transitional phase from the third to the fourth industrial revolution. IR3 is recognized as a shift from mechanical and analogue electrical technologies to digital electronics, exemplified in innovations like green buildings, electric cars, and distributed manufacturing (H. Mohajan, 2021).

It is also termed "The Digital Revolution", as it is grounded in energy transition, digital technology, and the internet (Bojanova, 2014). In recent years, the world has evolved from an information society to a knowledge society, and subsequently to a ubiquitous knowledge society (Anderson, 2012). IR3 is propelled by the opportunities offered by nanotechnology, intelligent systems, 3D printing, and robots in both industrial production and home services which contributed to a spike in the global GDP as shown in Figure 4. Microelectronics and the internet are the core technologies of IR3 (Taalbi, 2019). During this period, the integration of digital production and personal manufacturing commenced, contributing to the enhanced efficiency of the global economy (Troxler, 2013). In the 1970s, pivotal inventions like the modern computer, lean manufacturing, the internet, and biotechnology emerged, shaping the trajectory of IR3 (Taalbi, 2019).

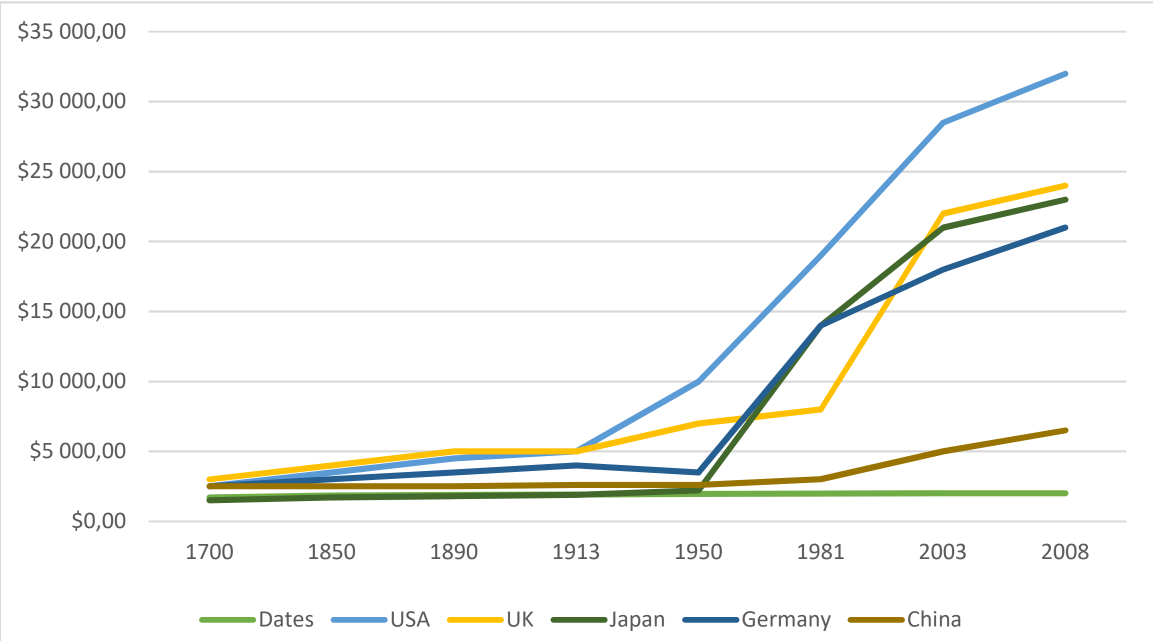


Figure 4*: GDP Per Capita (Inflation adjusted)*

Source: (Maddison, 2008)

The third industrial revolution is seen as the industrialization of the Maker Movement, by two main aspects, first, manufacturers are progressively employing digital tools and equipment for both the design and production of items, facilitating seamless sharing and collaboration on concepts across different times and locations. Subsequently, with the capability to transfer files directly to machines for production (direct digital manufacturing), manufacturers can harness pooled manufacturing resources on a larger scale than any individual maker could afford (Anderson, 2012). Table 7 provides more details about the timeline of the third industrial revolution.

Table 7: Timeline and Key Phases of the Third Industrial Revolution

		Innovations	
1950s-1970s	Introduction of digital computing and early automation.	Transistor (1947), integrated circuits (1959), and early mainframe computers.	Began the shift from mechanical and analog electronic technology to digital electronics.
1970s-1990s	Expansion of information and communication technologies (ICT).	Microprocessors (Intel 8080, 1974), personal computers, and the Internet.	Widespread adoption of personal computing and the early internet, leading to global communication networks.
1990s-2010s	Digital revolution and globalization.	Internet commercialization, mobile phones, and the World Wide Web.	Transformation of industries through digital technologies, global supply chains, and increased connectivity.
2010s-present	Advanced digitalization and the beginning of the Fourth Industrial Revolution.	Cloud computing, big data, artificial intelligence, and Internet of Things (IoT).	Enhanced automation, data-driven decision-making, and smart technologies integrating into daily life.

Source: (Lolich et al., 2019; Patnaik & Bhowmick, 2019)

2.1.3. Fourth industrial revolution

The term "Industry 4.0" made its debut in Germany in April 2011 during the Hannover Fair (Drath & Horch, 2014). Since then, it has garnered increasing attention, particularly after being designated as one of the ten initiatives in the "High-Tech Strategy 2020" action plan in March 2012 (Liao et al., 2017) . Its objective is to develop cutting-edge technologies that will ensure the future sustainability of Germany's industrial economy. In April 2013, (Kagermann et al., 2013) released the final report of the "Industry 4.0" Working Group, outlining the vision, integrative features, priority areas for action, and sample applications for the fourth industrial revolution.

Since December 2011, the United Kingdom (UK) has initiated a two-year project named "Future of Manufacturing" aimed at portraying a long-term and strategic vision for its manufacturing industry until 2050. Consequently, the Foresight Programme of the Government Office for Science published the final project report in October 2013(Liao et al., 2018). In April 2016, the Department for Business, Energy, and Industrial Strategy launched a National Innovation Plan (NIP) to support and cultivate innovation. The updated Delivery Plan of the "Innovate UK" agency has allocated approximately a quarter of its annual budget to projects related to Manufacturing and Materials, considering them a fundamental component of this NIP (Innovate, 2016).

Many other countries have launched their own strategies to keep up with the new revolution. In France in September 2013, The French President inaugurated the initial phase of "La Nouvelle France Industrielle," a strategic review outlining 34 sector-based initiatives that serve as France's industrial policy goals (Raffour, 2016) . in Spain, the Ministry of Industry, Energy, and Tourism (MINETUR) announced "Industria Conectada 4.0" in July 2015 (Buisán & Valdéz, 2017). In the Netherlands, a report on the definition of "Smart Industry" was released during the Hannover Messe in April 2014, which provides an overview of the Dutch smart industry strategy (Sotirov & Storch, 2018).

The attention given to the fourth industrial revolution by leaders of various countries effectively demonstrates the potential of technological advancements that have emerged and continue to evolve since the last decade.

As this revolution is still in its infancy, a precise definition of its aspects remains elusive, Table 8 shows couple of key difference between today’s manufacturing and Industry 4.0.

Table 8: comparison of today's manufacturing and Industry 4.0 manufacturing

		Today's Manufacturing	Industry 4.0 manufacturing
Component (e.g., sensor)	Key attributes	Precision	Independency in taking action based on automated predictions.
	Key technologies	Smart sensors for defect detection	Monitoring degradation and estimating the remaining usable life
Machine (e.g., controller)	Key attributes	Performance and Producibility (quality and output).	Autonomous decision-making relying on personal forecasts and contrast with stock information.
	Key technologies	Monitoring and diagnostics based on prevailing conditions.	Recording operational time coupled with anticipatory health monitoring.
Manufacturing System (e.g., manufacturing execution systems	Key attributes	Efficiency and overall equipment performance.	Autonomous configuration, upkeep, and organization.
	Key technologies	Efficient operations: minimizing work and waste.	Production systems that require minimal maintenance and adapt autonomously.

Source: (Skapinyecz et al., 2018)

In the literature, contradictory results are frequently encountered, leading to varied interpretations. Table 9 shows a broad definition of the most common industry 4.0 technologies. In the following paragraph, we will present the most commonly cited presentation and definition of Industry 4.0.

Table 9: Definitions of Industry 4.0 Technologies

Industry 4.0 Technologies	Description
Artificial Intelligence (Al)	The system recognizes complex patterns, processes data, draws conclusions, and makes decisions. A system that could evolve in the future and be genuinely autonomous in its reasoning and thinking, as well as capable of improving itself completely independently of people.
Big Data	The sophisticated process of studying huge and diverse data sets (Big Data) to reveal information such as undetected trends, unrecognized correlations, customer preferences, and other pertinent insights can help organizations make informed decisions.
Blockchain	Computing services (servers, storage, databases, networking, software, analytics, and intelligence) are delivered via the internet (the "cloud").
The Internet of things (loT)	A collection of interconnected computing devices, mechanical and digital machinery, items, animals, or people with unique identifiers (UIDs) and the ability to send data over a network without requiring human-to-human or human-to-computer interaction.
Additive manufacturing	The technique for creating things using computer-assisted, layer-by-layer material addition, as well as the industrial application of 3D printing technology.
Virtual reality (VR)	Virtual reality is an artificial, computer-generated simulation or recreation of a real-world scene or situation.
Augmented reality (AR)	AR is a technology that adds computer-generated extras to an existing reality to make it more meaningful by allowing users to interact with it.
Autonomous Vehicle	An autonomous, driverless vehicle capable of moving and navigating without human intervention

Source: (Prisecaru, 2016)

Although many countries have different titles for the Fourth Industrial Revolution, undoubtedly, the first mention of it occurred in 2011 at the Hanover Fair in Germany. Industry 4.0 is characterized by the use of information and communication technology in business processes (Milošević et al., 2022). Its technical foundation is the Internet of Things, which enables communication, connections, and control among physical items, people, systems, and IT (Huber et al., 2022; Oberländer et al., 2018; L. D. Xu et al., 2018). In the context of Industry 4.0, IoT is frequently referred to as the "industrial internet", "The Internet of Things (IIoT)" or "cyber-physical systems (CPS)" (Duan & Da Xu, 2021). Since IoT forms the core of Industry 4.0, numerous other technologies, including Blockchain, simulation, additive manufacturing, and artificial intelligence, play pivotal roles in supporting various industries, ultimately enhancing performance and productivity (Turkyilmaz et al., 2021).

In such a configuration, machines and equipment become linked to a single cloud and avoid centralized control systems. Furthermore, they have complete autonomy to make quick decisions when unexpected events occur (Alcácer & Cruz-Machado, 2019). When utilized individually, each technology can offer advantages, but it is their collective integration that holds the transformative potential to revolutionize and elevate traditional manufacturing methods (Issa et al., 2018).

Three prominent definitions of Industry 4.0 have been identified in the literature to date (Huber et al., 2022). (Cohen et al., 2019; Oesterreich & Teuteberg, 2016) defined I4.0 as the process of incorporating digital technology into the manufacturing industry. For (Kagermann, 2015; Vaidya et al., 2018), it is a new paradigm for industrial production with a focus on the process outcome, and the last one is a mixture of these two points of view (i.e. transformation process and its outcome), which makes I4.0 an umbrella term for innovative manufacturing technology and emerging concepts in manufacturing.

- *Internet of things*

In 1989, there were approximately 100,000 hosts connected to the Internet (H’obbes’ Zakon, 2000), and the World Wide Web (WWW) debuted a year later at CERN using the initial and sole site at the time. A decade after Tom Berners-Lee launched the World Wide Web, a whole new world of possibilities began to emerge when scientist from the Massachusetts Institute of Technology's (MIT) goes by the name Kevin Ashton, mentioned the concept Internet of Things (K. Ashton, 2009).

In 2009, a report on the European IoT action plan was issued by the Commission of the European Communities, highlighting the considerable significance of the IoT among European policymakers, commercial and industry collaborators, and researchers (Espinoza et al., 2020). In recent years, various global standard initiatives have emerged to deliberate on and define issues related to the IoT, aiming to establish a consensus on standard technologies applicable to IoT projects. For instance, oneM2M, initiated in 2012, serves as a global standard initiative encompassing machine-to-machine and IoT technologies. It addresses requirements, architecture, application programming interface (API) specifications, as well as security solutions and interoperability challenges (Hassan & Madani, 2017). Additionally, in 2015, the European Commission established the Alliance for the Internet of Things (AIOTI) to promote interaction and collaboration among IoT stakeholders. The convergence of cloud computing, the reduction in size and cost of sensors and microcontrollers, and the ubiquitous presence of digital connectivity have collectively played a role in materializing the IoT, ensuring its relevance for the foreseeable future (Sundmaeker et al., 2010).

The Internet of Things (IoT) is a network of connected devices that can sense, act, and communicate with one another and with their surrounding environment (also known as smart things or smart items). Furthermore, IoT enables the sharing of data as well as the autonomous response to real/physical world events by initiating processes and producing services, with or without direct human involvement (Schoder, 2018). For (Atzori et al., 2010), the fundamental notion of IoT revolves around the widespread existence of diverse things or objects in our surroundings, including Radio-Frequency IDentification (RFID) tags, sensors, actuators, mobile phones, and more. Through distinctive addressing schemes, these entities can interact and collaborate with one another to achieve shared objectives. Another definition proposed by IERC website, assert that IoT is a dynamic global network framework with self-adjusting capabilities, built on standardized and interoperable communication protocols. Here, tangible and virtual entities, referred to as 'entities,' encompass distinct identities, physical traits, and virtual characteristics. They employ intelligent interfaces and seamlessly integrate into the information network (ERC Cluster SRIA, 2014).

The ultimate objective of IoT systems is to establish synergy among diverse systems, ensuring seamless interoperability and automatic communication to deliver innovative services to users. Consequently, standardization becomes imperative to guarantee that IoT platforms facilitate reliable interoperability among distinct systems (Hassan & Madani, 2017). While the transformative impact of IoT is anticipated across various sectors of the economy and society, it will also generate a substantial volume of data. This not only introduces fresh challenges related to data management, processing, and transmission but, more importantly, raises concerns about data security. Hence, in addition to standardization

for interoperability, there is a need for security standards to safeguard individuals, businesses, and governments utilizing IoT systems (Dahmen-Lhuissier, 2020).
Reports from Vodafone in both 2016 and 2019 indicate that companies embracing the IoT allocate approximately 24% of their average IT budgets to IoT investments, aligning with expenditures on cloud computing or data analytics (Vodafone, 2016, 2019). According to the latest update from the Worldwide Semi-annual Internet of Things Spending Guide by the International Data Corporation (IDC, 2019), the United States and China are anticipated to be the global frontrunners in IoT spending for 2019, with projected figures of $194 billion and $182 billion, respectively, constituting nearly half of the global expenditure (Torchia et al., 2017). In contrast, data availability in Europe is notably limited compared to the U.S., posing challenges for analysis in this region. As per IDC, Germany is expected to lead in Europe in 2019, surpassing $35 billion in spending, followed by France and the U.K., each exceeding $25 billion (Torchia et al., 2017). Furthermore, when breaking down the data projections by region, it becomes apparent that Asia/Pacific, North America, and Western Europe take the forefront in the IoT business, particularly in the number of connected devices as shown in Table 10.

Table 10: Worldwide IoT installed base, connected devices by region, in billions, 2013–2020.

Region	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
Asia/Pacific	2.8	3.6	4.4	5.4	6.4	7.6	8.9	10.1
Central/Eastern Europe	0.3	0.3	0.4	0.5	0.6	0.7	0.8	0.8
Latin America	0.2	0.2	0.3	0.2	0.4	0.4	0.5	0.6
Middle/East Africa	0.3	0.4	0.4	0.5	0.5	0.7	0.7	0.8
North America	3.1	3.8	4.5	5.2	5.9	6.5	7	7.5
Western Europe	2.4	3.1	3.7	4.5	5.4	6.3	7.3	8.3
Total	9.1	11.4	13.7	16.3	19.2	22.2	25.2	28.1

Source: (Statista, 2020)

Nevertheless, additional investment in IoT is deemed necessary to fully realize its potential (European Commission, 2020). Several challenges must be addressed, including the implementation of privacy and security measures to safeguard the data generated by the IoT, the enhancement of infrastructure to further advance the technology, (Want et al., 2015) collaboration among stakeholders to advocate for optimal policies and regulations

(Vermesan & Friess, 2014), and the cultivation of IoT skills crucial for navigating this transformative technological landscape (Van Ark & O'Mahony, 2016), among other considerations. However, it is unlikely that any of these challenges will overshadow the potential benefits offered by the IoT.

- *Artificial intelligence*

AI has garnered significant interest from scientists, businesses, and governments. Over the last 20 years, there has been a 6-fold increase in global AI research papers per year (Razack et al., 2021). Additionally, at least 26 governments have launched national AI strategies in the last 4 years, and daily articles in both the business and lay press talk about AI's future applications and impact (Harrison et al., 2021). Artificial intelligence (AI) refers to machines' ability to execute cognitive activities similar to those of humans. Automation can enhance physical processes like item manipulation, perception, solving problems, making choices independently, and creativity (Benbya & Leidner, 2018). AI is often regarded as the most crucial and disruptive new technology for large organizations (Willetts et al., 2020). The advent of artificial intelligence (AI) stands out as a remarkable innovation in the scientific world, captivating the interest of nearly every discipline in academic research. Scholars are harnessing AI to address the challenge of predicting protein structures, with the potential to bring about significant advancements in the field of biological sciences. (Jumper et al., 2021). In addition, AI plays a crucial role in predicting renewable energy availability for optimizing energy consumption efficiency. (Shin et al., 2021). It is also instrumental in discovering innovative electrocatalysts to develop scalable and effective approaches for storing and utilizing renewable energy (Zitnick et al., 2020). The substantial research and notable accomplishments in applying AI across diverse domains have greatly heightened its significance.

Artificial neural networks (ANN), support vector machines (SVM), genetic algorithms (GA), and fuzzy logic (FL) are AI models but can also be considered synonyms for Artificial intelligence (Chambers et al., 2018; H. Hong et al., 2018; Lesnik & Liu, 2017; Zhang et al., 2019). Machine learning and deep learning, on the other hand, are different concepts, but they are often used interchangeably with AI. Machine learning is a computer program that learns and performs progressively better over time in connection with a specific set of tasks and performance measures (Jordan & Mitchell, 2015) . This is accomplished by using algorithms that repeatedly learn from training data that is particular to the situation at hand.

This enables computers to discover intricate patterns and hidden insights without requiring them to be explicitly programmed (Janiesch et al., 2021). While machine learning methods typically have fewer hidden layers, deep learning, on the other hand, often involves several hidden layers arranged in deeply nested network designs. As for processing text, pictures, videos, voice, and audio data, deep learning consistently outperforms ML methods, particularly excelling in areas with big and high-dimensional data (LeCun et al., 2015). Both machine learning (ML) and deep learning (DL) are integral aspects of AI, allowing the development of programs that autonomously learn from past data, accumulate knowledge from experience, and continuously enhance their learning behavior to make predictions based on fresh data (Holzinger et al., 2019). To clarify the relationship between these concepts, as shown in figure 5, Deep Learning is a subset of Machine Learning, which, in turn, is a subset of Artificial Intelligence expressed as DL ⊂ ML ⊂ AI (Goodfellow et al., 2016).

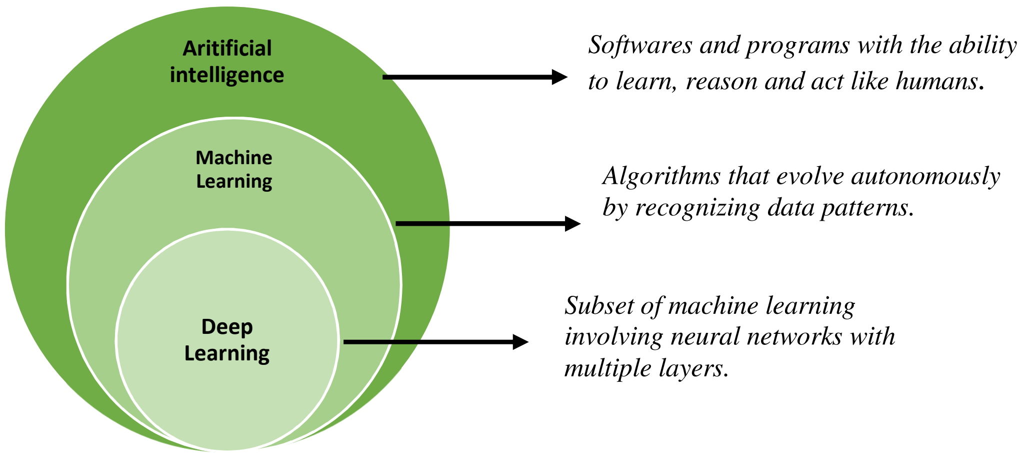


Figure 5: The intersection of DL, ML and AI

Source: Own research

The application of AI in the context of environmental sustainability has garnered significant attention from both researchers and practitioners. AI possesses the potential to mitigate human emotion bias and address knowledge asymmetries, two critical challenges hindering the progress of environmental sustainability (Cullen-Knox et al., 2017). Generally speaking,

innovations in digital technology promote the environment, human health, and the entire food chain (Weersink et al., 2018).
One of the critical factors that enhanced the popularity of AI is that it reached even individuals. Most readers of this thesis have likely interacted with AI in some capacity and understand its power, in contrast to other industry 4.0 technologies, which are typically only accessible to large corporations due to their complexity.

- *Additive manufacturing*

The initial method of systematically building a three-dimensional object through computer-aided design (CAD) originated as rapid prototyping, formulated in the 1980s for the production of models and prototype components (Wong & Hernandez, 2012). Developed to materialize the concepts envisioned by engineers, rapid prototyping stands as one of the early additive manufacturing (AM) processes (Wohlers, 2012). This approach facilitates the generation of printed parts, extending beyond mere models. Key contributions of this process to product development include notable advancements in time and cost efficiency, human interaction, and consequently, the product development cycle (Grimm, 2004). This process has brought significant advancements to product development, including reductions in time and costs, enhanced human interaction, and consequently, improvements in the product development cycle. Additionally, it provides the capability to fabricate nearly any shape, which could be exceedingly challenging through traditional machining methods(Ashley, 1991).

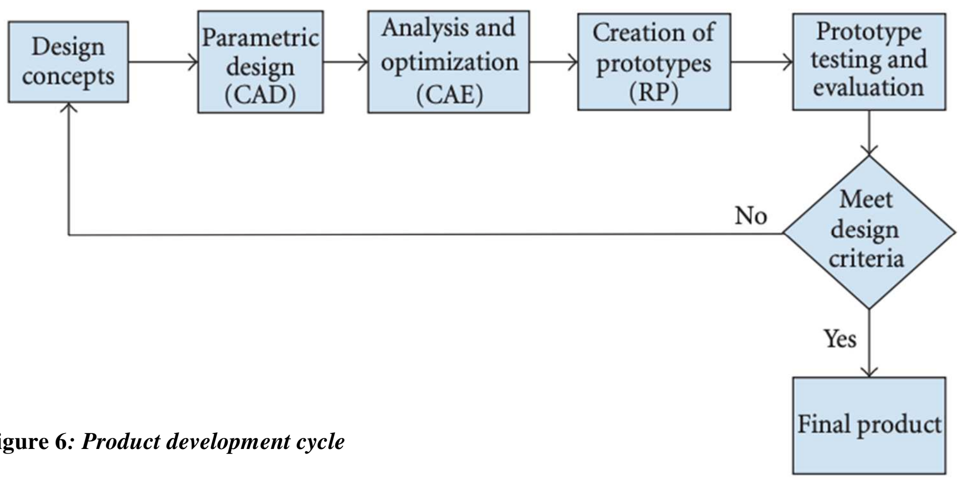


Figure 6*: Product development cycle*

Source: (Noorani, 2006)

The process of product development through rapid prototyping is outlined in Figure 6. It is evident that expediting model creation saves a significant amount of time and allows for the testing of numerous models.

Currently, rapid prototyping technologies extend beyond model creation. Leveraging the advantages of plastic materials, it is now possible to produce finished products. Initially developed to broaden the scope of situations tested in the prototyping process (Wohlers, 2012), these technologies are now referred to by various names such as 3D printing and others. However, they all trace their origins back to rapid prototyping (Noorani, 2006).

Additive manufacturing (AM) can be defined as a technique that blends materials through processes such as fusion, binding, or solidification, involving substances like liquid resin and powders (Abdulhameed et al., 2019). It constructs parts layer by layer using 3D CAD modeling. Various terms, such as 3D printing (3DP), rapid prototyping (RP), direct digital manufacturing (DDM), rapid manufacturing (RM), and solid freeform fabrication (SFF), are employed to describe AM processes (Zeltmann et al., 2016). These processes manufacture components based on 3D computer data or Standard Tessellation Language (STL) files, which encompass information about the object's geometry. AM proves highly beneficial in scenarios requiring low production volumes, intricate designs, and frequent design modifications (Y. Li et al., 2017). It enables the production of complex parts by overcoming the design constraints associated with traditional manufacturing methods (Huang et al., 2013). While AM offers numerous advantages, its applications remain somewhat limited due to issues such as lower accuracy and longer build times compared to CNC machines. Unlike CNC machining, AM divides the part into cross-sections with a resolution equivalent to the process, eliminating the same constraints (S. Yang & Zhao, 2015). Nonetheless, accuracy and build time can be enhanced through proper part orientation. Optimized part orientation not only improves accuracy but also reduces building time and support volume, thereby minimizing part production costs (Karunakaran et al., 2010).

The literature reveals that numerous researchers and academicians predominantly employ a functional framework for classifying additive manufacturing (AM) (Bandyopadhyay & Bose, 2019). This framework encompasses various categories such as material, AM technologies, AM material preparation, layer creation technique, phase changes in AM, patterning energy, phenomena of creating primitive geometry, support mechanisms, and AM applications (Gardan, 2017), as illustrated in Table 11. The primary classifications of AM are contingent upon the material utilized and the applied technology. The preparation of these materials before actual fabrication exhibits variations.

Table 11*: Different AM methods and their characteristics*

Raw Material	Material preparation	Layer creation technique	Phase change	Typical materials	Applications
Liquid	Liquid resin in a vat. Liquid polymer in jet	Laser scanning/light projection	Photopolymerization Solidification by cooling	UV curable resin and ceramic suspension UV curable acrylic plastic and wax	Prototypes, casting patterns, and soft tooling Prototypes and casting patterns
Filament/paste	Liquid droplet in nozzle. Filament melted in nozzle	On-demand droplet deposition	Solidification by freezing	Water Thermoplastics and waxes	Prototypes and casting patterns
Powder	Paste in nozzle. Powder in bed	Continuous extrusion Laser scanning	Full melting	Ceramic paste Thermoplastics, waxes, metal powder, and ceramic powder Metal	Functional parts. Prototypes, casting patterns, and metal and ceramic preform (to be sintered and infiltrated)
Solid sheet	Laser cutting	Feeding and binding of sheets with adhesives	–	Polymer, metal, ceramic, and other powders Paper, plastic, and metal	Prototypes, casting shells, and tooling. Prototypes and casting models

Source: (Abdulhameed et al., 2019)

The phenomenon of layer creation can also differ based on the technological methods employed (Abdulhameed et al., 2019). Following the creation of a layer, phases can be categorized as full melting, partial melting, or solidification phases. Furthermore, the application of these parts, whether for prototyping or as final products, varies depending on the technology employed (Abdulhameed et al., 2019).

- *Blockchain*

Blockchain allows for direct peer-to-peer transfers of digital assets, unlike older techniques that require intermediaries (Aste et al., 2017). Blockchain technology was initially developed to support the popular cryptocurrency Bitcoin that was introduced in 2008 and implemented in 2009 by an unknow person or a group of people go by the name of Nakamoto (Nakamoto, 2008). Consequently, it has had significant expansion in the capital market, hitting $10 billion in 2016 (Salah et al., 2019). Blockchain is a block sequence that uses a public ledger as shown in Table 12, to store all completed transactions. It is an append-only data structure maintained by nodes that do not fully trust one another. The blockchain is a log of organized transactions, with nodes agreeing on blocks containing numerous transactions and serves as a solution for decentralized transaction management in databases. Nodes maintain clones of data and agree on transaction execution order (Dinh et al., 2018).

Table 12*: Distributed Ledgers Examples*

Data Model	Number of ledgers	Owner	Example
Accounts	One	Administrator	Financial firms employ traditional ledgers.
Assets	Many	Group of users	Private ledgers are typically employed within financial institutions or among small groupings of organizations, such as global financial services.
Coins or accounts	One	Any user	Crypto-currencies such as Bitcoin or Ethereum.

Source: (Dinh et al., 2018)

While Bitcoin stands out as the most renowned application of blockchain, its potential extends far beyond cryptocurrencies. With its capacity to facilitate payments without the need for banks or intermediaries, blockchain finds application in various financial services such as digital assets, remittance, and online payments (Peters et al., 2015).

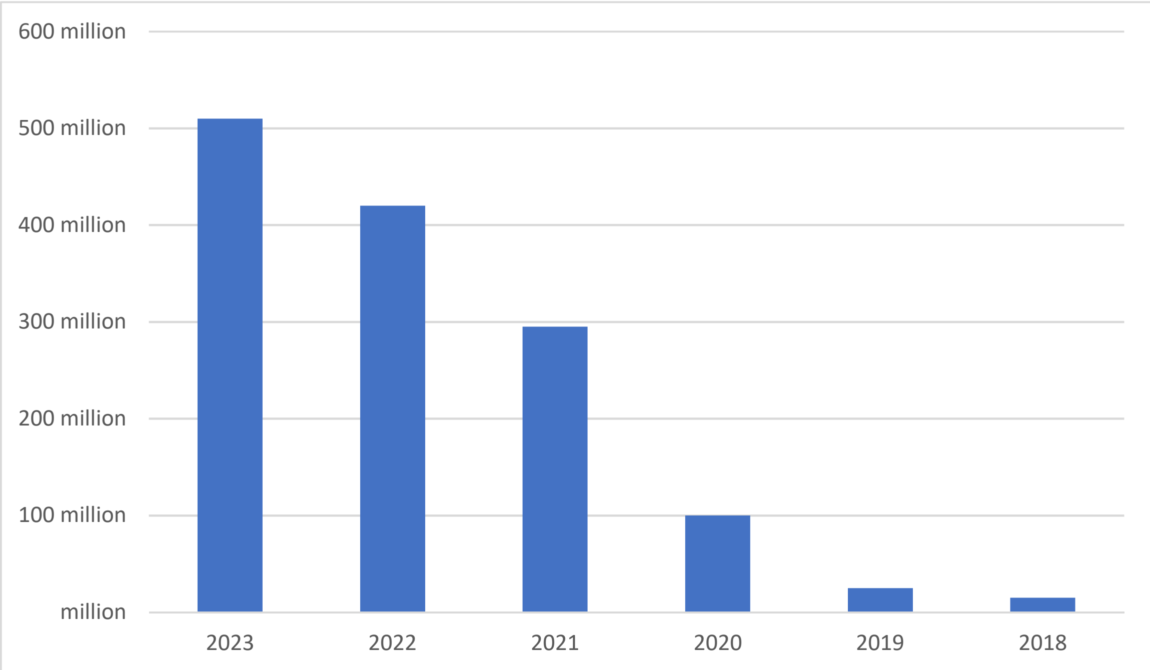


Figure 7***: Number of Cryptocurrency users***

Source: (Rohit, 2024)

Evolving beyond its initial association with cryptocurrencies, blockchain has become a versatile technology that has permeated diverse industries as shown in the Figure 7, including finance, healthcare, government, manufacturing, and distribution(Al-Jaroodi & Mohamed, 2019).

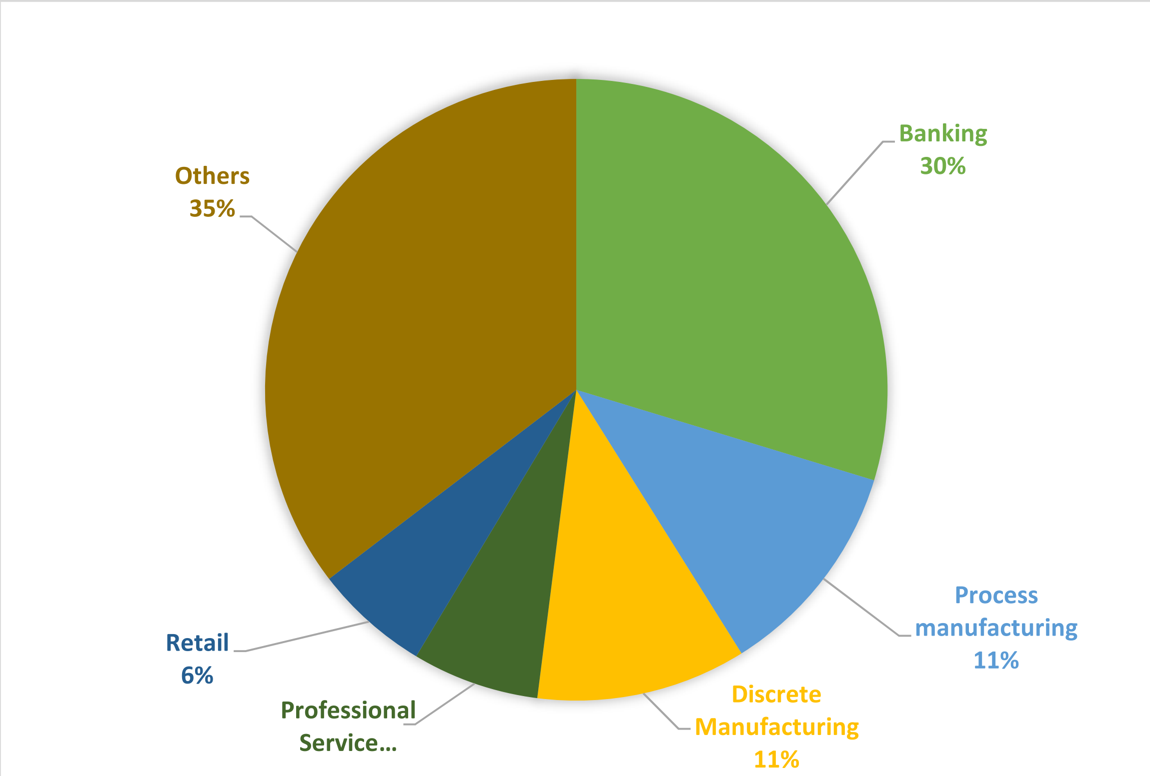


Figure 8*: Distribution of blockchain market value per sector*

Source: (Rohit, 2024)

Positioned as an innovator, blockchain is anticipated to bring about transformative changes in a wide array of applications, ranging from supply chain management (goods transfer) and the sale of digital media (art) to remote services delivery (travel and tourism) and decentralized platforms, exemplified by the shift of computing to data sources and distributed credentialing (Casino et al., 2019). The applications of blockchain continue to expand, encompassing areas such as distributed resources (power generation and distribution), crowdfunding, electronic voting, identity management, and governance of public records (Monrat et al., 2019), all thanks to Ethereum that supports decentralized, replicated programs referred to as smart contracts (Buterin, 2014). More crucially, industry demand has begun to push the creation of new blockchain platforms tailored for secure private settings with verified participants. Private (or permissioned) blockchain systems differ from public (or permissionless) networks, which can be joined and left by anybody (Dinh et al., 2018). Hyperledger is one of the most prominent private blockchain platforms (Sharma et al., 2020). Since node credentials are known in private contexts, most blockchains use one of the algorithms from the extensive literature on distributed consensus (X. B. Wu et al., 2019).

Due to the nascent stage of the technology, there exist vulnerabilities that expose users to cybercrime, with 51% attacks being among the most well-known security issues associated with blockchain (P. Li et al., 2018). In a 51% attack, one or several malicious entities attain majority control of a blockchain's hashrate. By wielding this majority hashrate, they can reverse transactions to execute double-spends and impede other miners from confirming blocks (Dabbagh et al., 2021).

Another method compromising the integrity of a blockchain network is Selfish Mining, employed by mining pools to unjustly boost block rewards (Göbel et al., 2016). While it is conventionally believed that malicious nodes possessing over 51% of computing power can take control of the blockchain network, (Eyal & Sirer, 2018) have proposed a blockchain network that remains vulnerable even if someone attempts to manipulate it with a small fraction of hashing power. More research is needed to develop industrial applications that fully utilize blockchain technology and meet its intended purposes. Open challenges include security, privacy, scalability, energy, integration with other systems, and legislative considerations (Monrat et al., 2019).

- *Simulation*

From its initiation, simulation has found applications across various sectors, encompassing manufacturing, services, defense, healthcare, and public services. It stands as the second most widely employed technique in the field of operations management, with 'Modelling' being the foremost choice (Aebersold, 2016). The introduction and progression of computers have fundamentally reshaped its utility, facilitating the adoption of practical simulation tools and techniques (Negahban & Smith, 2014).

The appropriateness, relevance, and suitability of simulation techniques are crucial considerations in real-world applications, especially given the growing imperative to address the complexities inherent in entire enterprises and the challenges associated with diverse layers of decision-making within a system (Jahangirian et al., 2010). In numerous business environments, it is apparent that changes at one management level can significantly impact others. While tools are available for each level, a deeper understanding is required regarding the relationships between different organizational layers and the methods for connecting simulation tools pertaining to each layer, enabling the comprehensive management of the system as a whole (Shanton & Goldman, 2010).

Concerning techniques, discrete event simulation (DES) emerges as the most prevalent method in manufacturing and business as shown in Figure 9, according to (Jahangirian et al., 2010), it was being utilized in over 40% of the reviewed papers at the time when their research was written. It has found application across various industries for a broad range of operational management purposes, including scheduling, production planning, inventory control, process engineering, inventory management, supply chain management (SCM), and project management (Jahangirian et al., 2010). This indicates that DES proves suitable for tactical and operational decision-making levels. Additionally, DES is well-suited for detailed process analyses, resource utilization, queuing, and relatively short-term analyses. These findings align with previous research conducted by (Kellner et al., 1999)

System dynamics (SD) stands out as the second most commonly employed simulation technique in manufacturing and business, boasting a popularity rate exceeding 15%(Jahangirian et al., 2010). Its utilization has been concentrated in areas such as policy and strategy development, project management, SCM, and knowledge management.

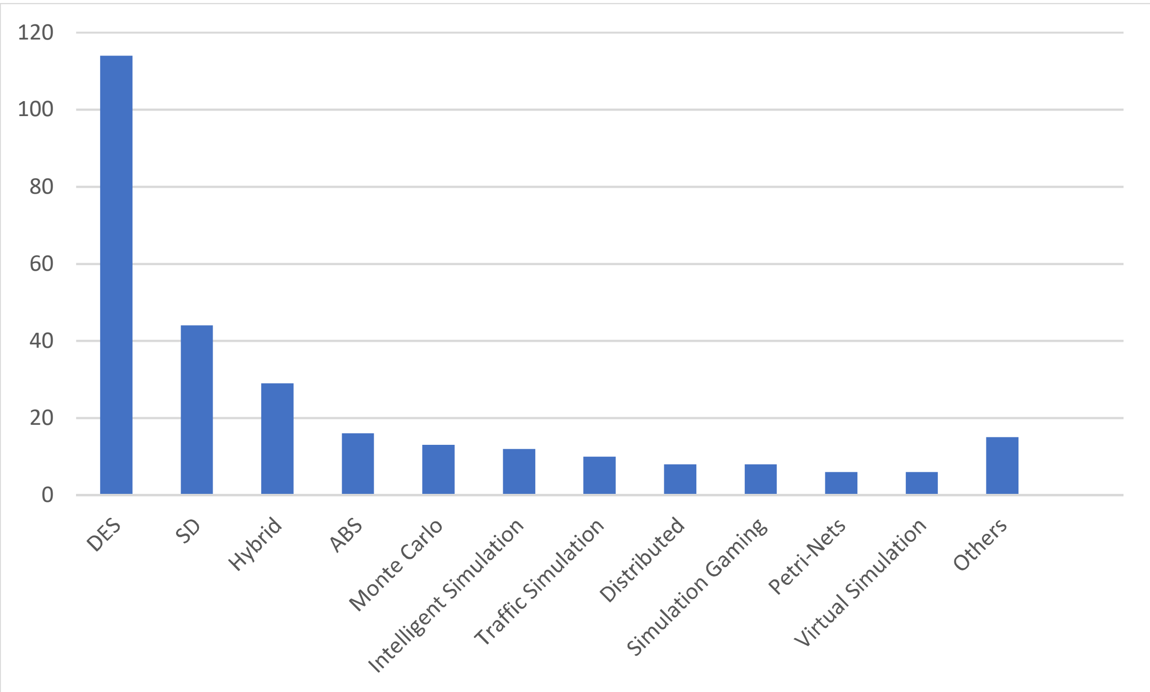


Figure 9*: Number of published papers by simulation technique used in 2010*

Source: (Jahangirian et al., 2010)

In addition to hybrid simulation, agent-based simulation (ABS) emerges as the fourth most favored simulation technique, boasting a usage rate exceeding 5%. ABS finds prevalent application, particularly in the realm of 'strategy.' In this context, each player in an industry is considered as an agent, and the strategic behavior of every agent is modeled in alignment with classic strategy concepts (Silva et al., 2020).

Intelligent simulation is grounded in the fusion of simulation and artificial intelligence (AI) techniques. This concept was initially implemented in a tool named ROSS (McArthur et al., 1984), pioneered by the RAND Corporation.

Simulation gaming (SG) stands out as another technique drawing particular attention from the education and training sectors, having found application in areas like incident management training (Williams-Bell et al., 2015). Notably, simulation gaming has demonstrated its practical utility through pre-developed games tailored for specific industries such as insurance, financial services, or supply chains (Williams-Bell et al., 2015).

Petri-nets, introduced as a graphical and mathematical tool for modeling computer systems, serve to describe and study systems characterized by concurrency, asynchrony, distribution, parallelism, and stochasticity. Petri-nets encompass features essential for modeling processes, yet our review did not reveal any specific usage pattern for this technique. It has been encountered across a diverse array of applications and industries (Reisig, 2016).

Virtual simulation provides companies with the capability to model and simulate a system in a three-dimensional, immersive environment. Typically integrated into broader initiatives to develop virtual environments (e.g., virtual factories), virtual simulation empowers managers and engineers to obtain a clearer and more reliable understanding of the impacts of any changes on the system (Foronda et al., 2020).

- *Augmented Reality*

Augmented reality holds the promise of creating direct, automatic, and actionable links between the physical world and electronic information. It provides a simple and immediate user interface to an electronically enhanced physical world. The immense potential of augmented reality as a paradigm-shifting user interface metaphor becomes apparent when we review the most recent few milestones in human-computer interaction: the emergence of the World Wide Web, the social web, and the mobile device revolution (Schmalstieg &

Hollerer, 2016). Although the term AR has received a lot of attention in recent years, scholars have given it a variety of definitions. AR can be generated by combining novel technologies, such as mobile devices, wearable computers, and immersion technology (H.-K. Wu et al., 2013).

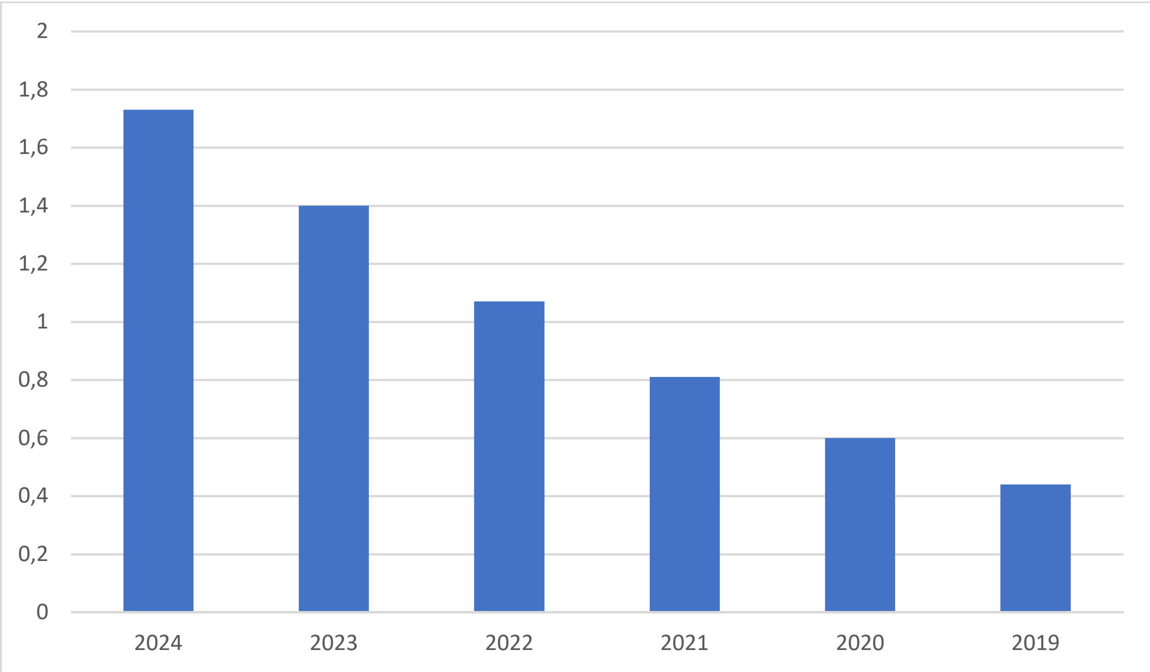


Figure 10: ***Number of active users of Augmented reality Mobile applications (in billions)***

Source: (Statista, 2020)

In the domain of computer sciences and educational technology, augmented reality (AR) has been characterized diversely by researchers. (Milgram et al., 1995) introduced two perspectives in defining AR: a broad approach and a constrained approach. Broadly, AR involves "enhancing the natural feedback to the operator with simulated cues". In contrast, the constrained approach delves into the technological aspect, defining AR as "a version of virtual reality wherein the participant's transparent head-mounted display allows an unobstructed view of the real world". Other scholars have shaped the definition of AR based on its distinctive features. (Azuma, 1997), for example, outlines AR as a system that encompasses three essential features: a fusion of real and virtual worlds, real-time interaction, and precise 3D registration of virtual and real objects.

Arguing against a narrow definition, (Klopfer, 2008) suggests that the term AR can be applicable to any technology seamlessly blending real and virtual information. AR can be

broadly understood as "a scenario where a real-world context is dynamically enriched with coherent location or context-sensitive virtual information. In such situations, AR offers users technology-mediated immersive experiences, seamlessly intertwining real and virtual worlds (Klopfer & Sheldon, 2010), thereby elevating users' interactions and engagement (Dunleavy et al., 2009).
The integration of augmented reality (AR) into the industrial domain holds significance, notably enhancing communication in product design and production development. It proves instrumental in identifying and preventing design errors during the early stages of development, ultimately reducing the need for physical prototypes and saving time and costs for enterprises. AR is recognized as a valuable tool for enhancing and accelerating product and process development across various industrial applications.

Several key areas of application for AR in the industrial domain can be discerned, numbering at least five major domains (Henderson & Feiner, 2010). These encompass Human-Robot Collaboration, Maintenance-Assembly-Repair, Training, Product Inspection, and Building Monitoring. In the Human-Robot Collaboration domain, AR is utilized to craft efficient interfaces for interacting with industrial robots (Nguyen et al., 2018). Within maintenance-assembly-repair tasks, AR enhances effectiveness. For training purposes, users can leverage AR as a potent solution to augment their skills. In the realm of product inspection, controllers can identify discrepancies in items using robust and versatile AR systems. Finally, in building monitoring applications, AR serves to promptly highlight any errors or deviations in facility management in a straightforward and sensitive manner (De Pace et al., 2018). Table 13 shows the major trends in Augmented reality.

Table 13*: trends in Augmented reality*

Topics	**% Papers**	**% Citations**
Tracking	20.1%	32.1%
Interaction	14.7%	12.5
Calibration	14.1%	12.5%
Display	11.8%	5.4%
Evaluations	5.8%	1.8%
Mobile AR	6.1%	7.1%
Authoring	3.8%	8.9%
Visualization	4.8%	5.4%
Multimodal	2.6%	0.0%
Rendering	1.9%	1.8%

Source: (Zhou et al., 2008)

2.2 Environmental sustainability

Sustainability is defined as meeting the needs of the present generation without compromising future generations' ability to fulfil their own needs (Keeble, 1988). Regardless of whether one sees sustainability as a three-legged table consisting of the environment, the economy, and society, or as a dualistic relationship between human beings and the ecosystem they inhabit, there should at least be agreement that ensuring the provision of clean air, clean water, and clean and productive land is the foundation of a responsible socioeconomic system (Morelli, 2011). The environmental pillar focuses on ecosystems and their life-sustaining roles for humanity (Dong & Hauschild, 2017) . Environmental sustainability means ensuring that present and future generations have access to the resources and services they require without compromising the health of the ecosystems that deliver those resources and services (Morelli, 2011). Following the Second Industrial Revolution, concerns about environmental degradation have risen exponentially, as shown in the figure below.

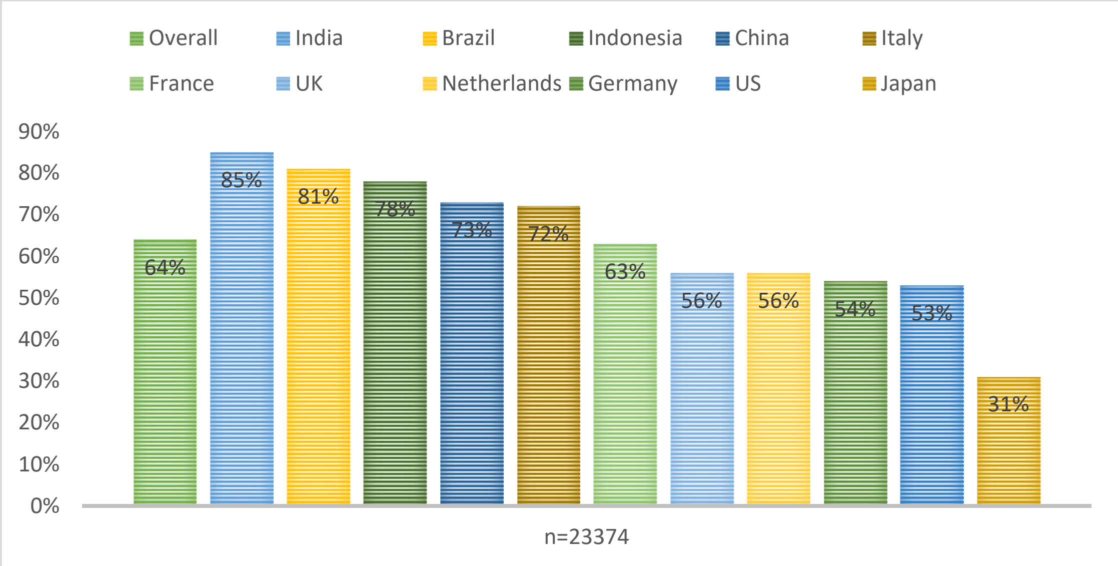


Figure 11: percentage of consumers who are extremely concerned about environmental

Source: (bain consumer lab esg survey, 2023)

Environmental sustainability encompasses a broad variety of challenges, ranging from local to global. Global challenges include GHG reduction, climate change, and renewable energy, whereas local ones include soil erosion, water management, soil quality, waste management, and air and water pollution (Ghosh et al., 2019). Environmental sustainability can be sorted into five main categories: 1-Societal Needs (e.g., examining the environmental characteristics of raw materials and making the environmental sustainability of the raw materials used in the production of new goods and services a primary consideration in the selection process). 2- Preservation of Biodiversity (e.g., utilizing sustainable and ecologically responsible energy sources and investing in energy efficiency improvement). 3- Regenerative Capacity (e.g., maintaining depletion rates of non-renewable resource inputs below the development rate of renewable alternatives). 4 -Reuse and Recycle (e.g., creation for reusability and recycling). 5- Constraints of Non-renewable Resources and Waste Generation (e.g., developing transportation parameters that emphasize low-impact types of transportation) (Goodland, 1995; Moffat & Newton, 2010; Morelli, 2011).

The overall definition of environmental sustainability does not offer a precise explanation of the concept. Employing a similar methodology as described earlier, we utilized the command-line program Astrogrep to analyze 458 articles from Scopus and Web of Science databases. These articles were identified based on the presence of terms such as environmental sustainability, environment, sustainability, ecology, green practices, sustainable practices, and eco-sustainability in either the title or abstract. This process aimed to extract the key aspects of environmental sustainability that will be the focus of our research. The outcomes are presented in Table 14.

Table 14: Most mentioned environmental sustainability aspects

Environmental sustainability aspects	Number of mentioned out of 458 articles
Waste management	112
Resource efficiency	101
Circular economy	98
Energy management	156
Carbon emission	127
Air Quality Control	67
Water Conservation	32
Sustainable Agriculture	9
Biodiversity Preservation	2

Source: Own research

2.2.1 Waste management

Waste management (WM) poses a significant challenge for numerous urban local bodies (ULBs) due to the surge in urbanization, industrial activities, and economic growth, leading to an escalation in waste generation per person, particularly in municipal solid waste (MSW) (Kumar et al., 2017) . Establishing robust waste management infrastructure is paramount for achieving sustainable development (Ambati, 2019). The world's rapid population growth has led to the depletion of natural resources (Sharholy et al., 2008). Viewing waste as potential resources, effective waste management, which incorporates resource extraction, becomes crucial. Extracting value from discarded materials, whether in the form of materials, energy, or nutrients, can not only contribute to effective waste management but also provide livelihood opportunities (Kumar et al., 2017). The transition from waste to resource necessitates investments in waste management, involving a coordinated set of measures to develop markets and optimize the recovery of reusable/recyclable materials (Wilson et al., 2006). Future waste management infrastructure development should prioritize the recovery of materials, energy, and nutrients. Leveraging existing technologies with high potential for resource recovery is essential in achieving these goals (Kumar et al., 2017).
It is anticipated that by 2050, global waste generation will reach approximately 27 billion tons annually, with Asia contributing one-third of the total, led by China and India (Modak et al., 2010). Figure 12 shows the waste generation per region.

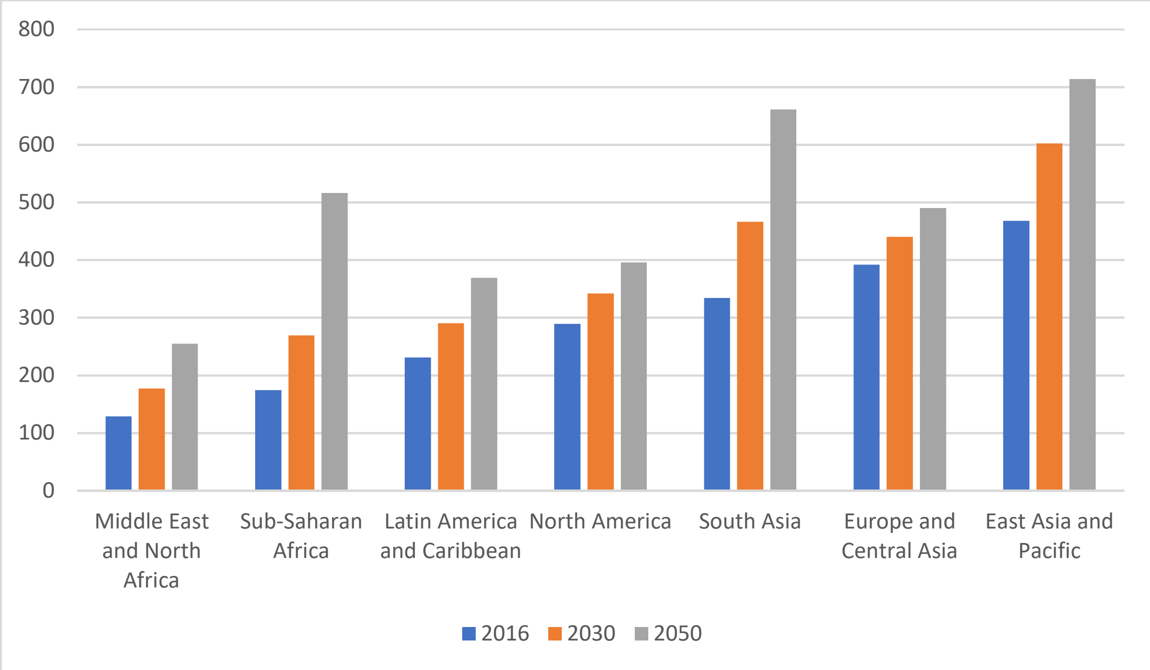


Figure 12: Projected waste generation, by region (millions of tonnes/years)

Source: (The World Bank, 2017)

Projections for 2025 indicate that waste generation in India's metropolitan areas will amount to 0.7 kg per person per day, a four to sixfold increase compared to 1999 (Kumar et al., 2017). As urban communities expand, waste challenges become more pronounced, presenting opportunities for decentralized waste management initiatives led by self-help groups and non-governmental organizations (NGOs) (Al-enezi et al., 2014).

2.2.2 Resource Efficiency

Societal expectations, government regulations, and shareholder demands compel companies to alter their operations. The intensified consumption of energy, water, and raw materials is recognized as a significant contributor to climate change and environmental degradation, necessitating the call for transformative changes (Landrum, 2018). By prioritizing sustainable development objectives in their operations, businesses can contribute to improved energy efficiency, enhanced water resource management, and reduced material consumption. In Brazil for instance, only 39% of the collected wastewater undergoes treatment, while the remaining portion is discharged directly into water sources. This compromised water quality poses significant threats to both the environment and human health (Grejo & Lunkes, 2022).

Innovations in the environmental domain have the potential to enhance the ecological attributes of products and elevate the resource efficiency across both products and processes (Rennings & Rammer, 2009). Figure 13 illustrates seven crucial Material Efficiency Strategies that represent simple yet impactful steps that can significantly contribute to assuring material efficiency.

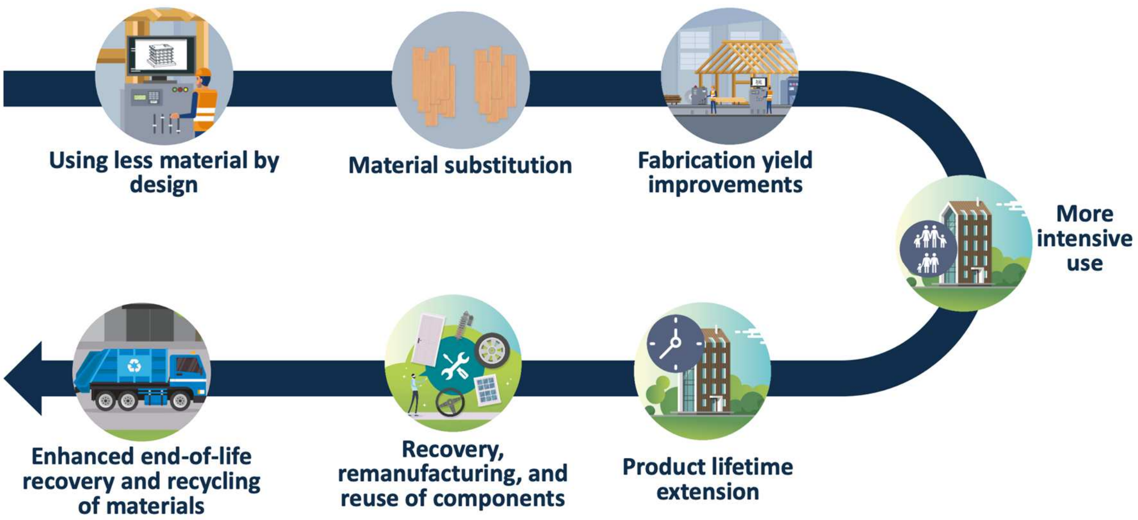


Figure 13: Seven crucial Material Efficiency Strategies

Source: (Hertwich et al., 2020)

Several nations have devised strategies to optimize their resource utilization. For instance, in Germany, the sustainable development strategy aims to double resource efficiency by 2020 compared to the reference year of 1994. During the period from 1994 to 2007, resource productivity experienced a substantial growth of 35% (Diefenbacher, 2009).

2.2.3 Circular economy

The concept of circular economy has been criticized for being overly vague, and hard to define (Peltonen, 2017), many authors suggested that this concept will not survive the years such as (Naudé, 2011) who stated that "CE is a theoretical dream rather than a practical reality", this was not the case as after two decades the concept is still garnering great interest from both practitioners and academics, in 2017 the number of published papers regarding CE and environment have reached 371, that is a 1275% increase compared to the last three years (Ruiz-Real et al., 2018).

Both (Schut et al., 2016) and (Geissdoerfer et al., 2017) stated that the definition that accurately described the Circular economy was provided by (MacArthur, 2013), which is:

"*CE refers to an industrial system deliberately designed to be regenerative or restorative. Instead of the traditional 'end-of-life' approach, the emphasis is on restoration. The system prioritizes the use of renewable energy, avoids harmful chemicals that impede reuse, and eliminates waste through improved design of materials, products, systems, and associated business models*".

The circular economy is also often referred to as the 4R, as (Allwood et al., 2011) stated that CE is based on reuse, recovery, recycling, and reduction. Even though in many cases it was referred to as the 6R (Sihvonen & Ritola, 2015) or 9R in other cases (Van Buren et al., 2016). Figure 14 bellow showcase the 9R.

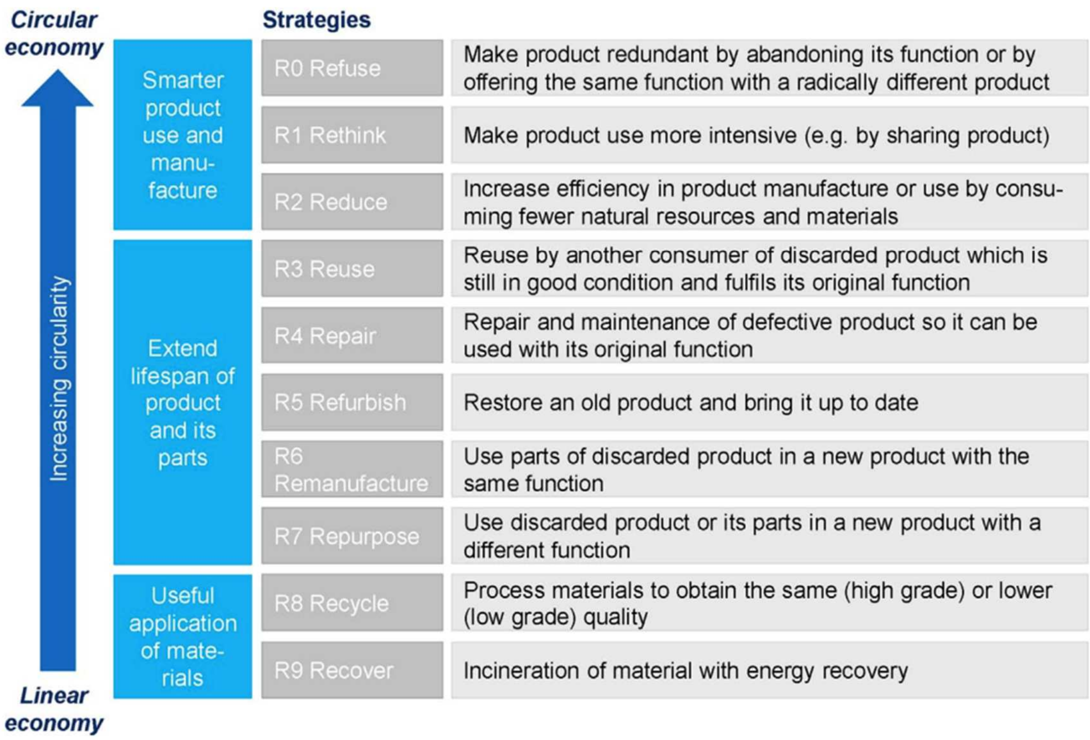


Figure 14: The 9R Framework.

Source: (Potting et al., 2017)

Based on the potential of the Circular Economy, it is considered one of the main pillars contributing to environmental sustainability (Abad-Segura, González-Zamar, et al., 2020). CE, through nearly eradicating waste in various industries and reducing greenhouse gas emissions, has the potential to combat climate change and preserve the environment (Careddu, 2019; Honoré et al., 2019). CE policies offer a framework for initiatives aimed at minimizing waste generation and transforming materials (Bleischwitz et al., 2018). The cornerstone of CE's success lies in optimizing the value of biomass resources, fostering job creation, economic growth, and environmental sustainability (Arora, 2018). EU has particularly focused on in this area and achieved a 12.8 of circularity rate as shown in the figure 15.

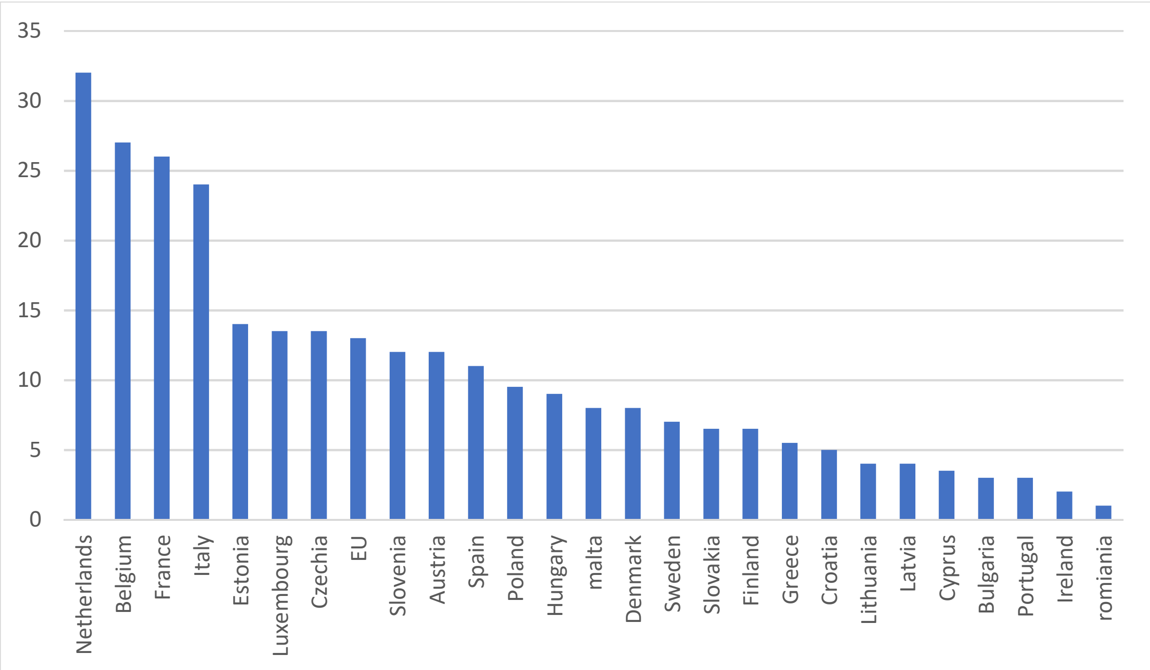


Figure 15: Circular material use rate in the EU, 2020 (%)

Source: (Eurostat, 2021)

According to (Abad-Segura, Fuente, et al., 2020) for CE to contribute to help in achieving the SDGs related to the environment, it is crucial to focus on the following: Decreasing the national consumption of materials relative to GDP; minimizing the generation of waste; reducing food waste across various stages of the food supply chain; enhancing the practice of reuse and preparing items for secondary use; optimizing water efficiency; curbing greenhouse gas emissions within the waste management sector; and fostering specific Circular Economy (CE) training programs, aligning workers' skills with emerging market needs, alongside cultivating a corporate culture that embraces the principles of corporate social responsibility.

Technological advancements play a pivotal role in synergizing with Circular Economy (CE) initiatives. These innovations have significantly impacted various aspects of contemporary life, extending their influence to the domain of Circular Economy. Cutting-edge technologies such as big data, cloud computing, cyber-physical systems, the internet of things, virtual and augmented reality, and blockchain stand out as powerful tools. Their integration can empower governments, organizations, and society at large to not only adopt the Circular Economy concept but also to effectively implement and execute CE strategies (Demestichas & Daskalakis, 2020).

2.2.4 Energy management

Surging energy prices, stricter environmental laws, new supply and demand policies such as the European Union Emissions Trading System (EU ETS), and energy end-use efficiency policy programs have increased demand for reducing energy consumption and associated energy costs in industrial organizations (Schulze et al., 2016).

Over the past two decades, energy management has experienced substantial growth as a pivotal support role in industrial enterprises, figure 16 show the size of the global energy management systems and the projected size for the next decade.

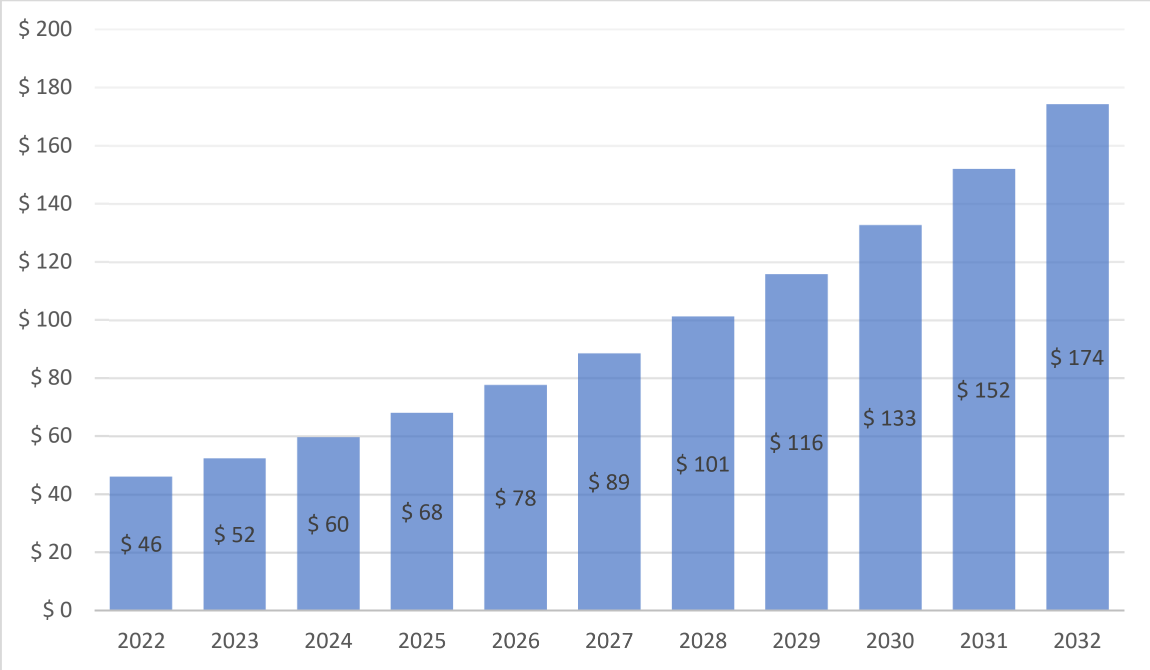


Figure 16: Energy management systems market size, 2022 to 2032 (usd billion)

Source: (precedenceresearch, 2022)

Historically, energy, considered merely as an input factor in the industrial production process, held minimal or negligible priority for corporate management in industrial businesses. This was primarily because energy expenses constituted only a minor portion of total production costs, owing to the low and generally stable energy prices prevalent at the time (Backlund et al., 2012).

Energy is an intangible concept. It escapes direct observation or precise measurement, yet its value becomes apparent through the work it enables and the considerable expenses associated with energy carriers like electricity and gas. Although we commonly refer to energy consumption, it's crucial to understand that energy isn't consumed; instead, it undergoes transformations from one form to another, inevitably resulting in a loss of value (Vikhorev et al., 2013). Table 15 shows an overview of global consumption of energy between 1980 and 2022.

Table 15: Energy demand by region, 1980 to 2020

	Amounts (TWh)			**Shares (%)**		
	1980	**2000**	**2020**	**1980**	**2000**	**2020**
Africa	2,704	3,298	6,044	2.3	3.0	3.8
Asia	15,844	36,949	84,037	20.6	33.4	53.2
America	27,160	37,460	37,712	35.4	33.9	23.9
Europe	30,958	31,353	28,254	40.3	28.3	17.9
Oceania	997	1,569	1,898	1.3	1.4	1.2
World	**76,753**	**110,630**	**157,944**	**100.0**	**100.0**	**100.0**

Source: (Statista, 2020)

The combustion-based generation of electrical energy negatively impacts our environment by emitting greenhouse gases, and the rising costs of energy carriers further emphasize the need for industries to bolster their energy efficiency. To remain competitive and contribute to global environmental objectives, industries must prioritize strategies that enhance energy efficiency (Vijayaraghavan & Dornfeld, 2010).

Effective industrial energy management often relies on specific contextual considerations, shaped by factors like product design, process selection, national fuel mix, and more. This implies that adopting energy-saving technologies developed in one industry, especially in a different sector or location, can pose challenges (Brown et al., 2010). In contrast to quality management, where ISO standards share common features, energy management requires a more adaptable approach due to its context-dependent nature, even though both follow the 'plan, do, check, act' cycle. Consequently, while energy management demands a flexible strategy, having a framework can prove beneficial for defining and implementing best practices (Vikhorev et al., 2013). The EMS (Energy Management System) have the capability to automatically or semi-automatically manage and control energy usage in diverse settings, including buildings, industries, firms, factories, and equipment. This is achieved through the implementation of various control logics or designed functionalities tailored to the specific needs of each system (D. Lee & Cheng, 2016). The combined heat and power (CHP) in the other hand, has evolved as both one of the oldest and most recent technologies in power generation. Originally, CHP emerged incidentally as a solution to address waste heat generated by conventional combustion-based power generation methods in the past (Erixno et al., 2022). Integrating distributed generation (DG) as an additional energy generation tool is an efficient means of managing energy resources. DG encompasses all power plants interconnected with distribution systems. Specifically, DG refers to facilities that supply (at a minimum) active electricity while connected to the distribution system and possess a rated capacity of less than 50 MW (Calvillo et al., 2016). These facilities have the capability to decrease peak-hour electricity consumption or return excess power to the grid (Cossent et al., 2009).

DG and CHP have attracted much attention as environmentally friendly methods of energy generation; however, renewable energies are the primary sources for efficient and sustainable energy generation. One of the pillars of the European Union's energy policy is the promotion of renewable energy. In 2018, the EU has set a target to attain a 27% proportion of renewable energy by the year 2030 (European Commission, 2018). The updated Renewable Energy Directive, which was enacted in 2023, raises the EU's mandatory renewable energy objective for 2030 to at least 42.5% (European Commission, 2023). Renewable energy, according to the definition provided by the International Energy Agency (IEA), is characterized as "energy obtained from natural processes that renew themselves more rapidly than they are used." Examples encompass sunlight, wind, geothermal, hydro, and biomass (IEA, 2018). The European Union (Euro Stats, 2018) categorizes wind, solar, hydro, tidal power, geothermal energy, biofuels, and the renewable component of waste as constituents of renewable energy. Figure 17 presents global statistics regarding the use of renewable energies in the world.

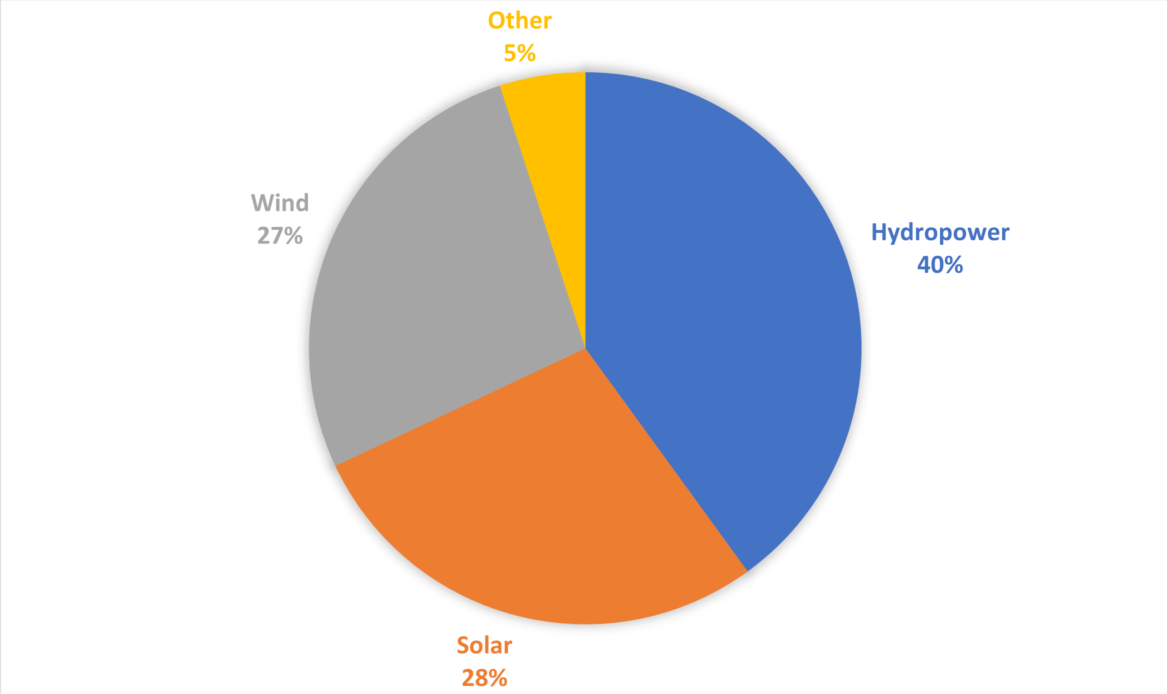


Figure 17: Renewable generation capacity by energy worldwide in 2021

Source: (Renewable Capacity Statistics, 2022)

Renewable energy involves comparisons among the power density, land utilization, capacity, and fluctuation characteristics of different sources, which serve as the primary means of energy harvested. The projected land use intensity is employed to determine power density. The accuracy of this figure heavily relies on the underlying assumptions considered. Nevertheless, the diverse nature of renewables poses challenges for direct comparisons.

Table 16: The varying nature of different renewable energy forms.

Energy Source	Primary Form	Land use intensity	Capacity Factor	Power Fluctuation
Panels of Solar Photovoltaic	Electricity	10	10-30%	Weather is directly dependent. Seasonally dependent in northern latitudes.
Concentrated solar power	Thermal energy	15	25 – 80%	Unless supported by heat storage, directly weather dependant.
Hydropower	Kinetic energy	10	12–62%	Based on seasonal precipitation and silt accumulation.
Wind power	Kinetic energy	1	26–52%	Weather-dependent, with some seasonal variation

Source: (Harjanne & Korhonen, 2019)

Table 16 demonstrates that renewable energy sources differ in almost every aspect. One thing they all have in common is that they all have a fairly low power density per area (Harjanne & Korhonen, 2019). It should be also emphasized that the majority of these renewables cannot directly provide the high temperatures required by many industrial operations (Naegler et al., 2015).

2.2.5 Carbon emission reduction

In order to avert substantial damage from climate change, the global community has reached a consensus that the average Earth's temperature increase should be limited to below 2 degrees Celsius by the end of the century, in comparison to pre-industrial levels (Conte Grand, 2016). According to studies, there is a significant gap between the emissions levels required to attain that objective and the Parties' climate plans; closing it will require emissions reductions of more than 45-70% by 2050 compared to 2010 (Edenhofer et al., 2014). It is widely acknowledged that global warming caused by carbon emissions created damage to the world's ecological environment (Shi et al., 2017). This research centers specifically on carbon and not other greenhouse emissions, due to the heightened significance attributed to its environmental impact. Notably, studies like (Chang et al., 2017) stress the imperative of prioritizing the reduction of carbon dioxide emissions over other greenhouse gases or air pollutants when addressing climate change. Worldwide, as shown in Figure 18, the greatest source of carbon emissions from human activity is the use of fossil fuels for heat, electricity, and transportation (Sawik et al., 2017).

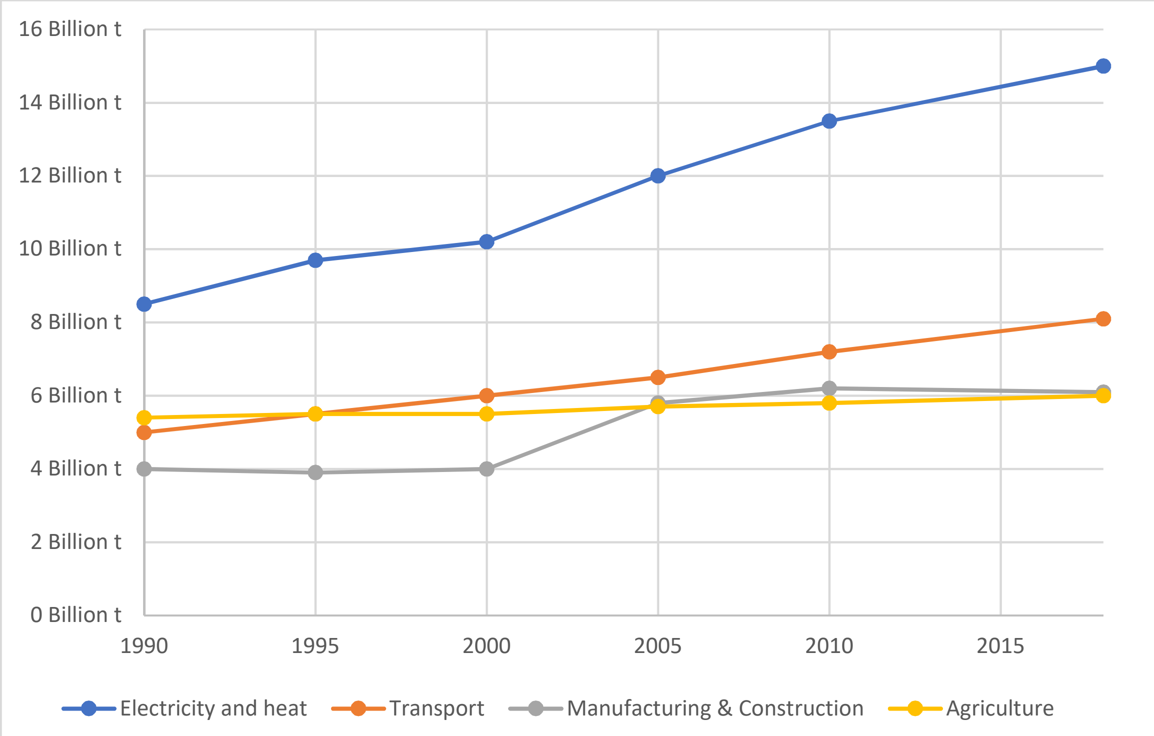


Figure 18: Carbon Dioxide emissions by sector (tonnes)

Source: (Sawik et al., 2017)

The largest responsible of carbon emission is China who jumped from 27.2% as shown in Table 17 to 32.5% of global carbon emissions (World Bank, 2020), and the country is under intense pressure to reduce emissions. EU on the other hand, has officially implemented the Paris Agreement, serving as both a leader and a mediator in problems of climate change and pollution. As a consequence of ongoing efforts, the EU's GHG emissions in 2016 were 22% lower than in 1990 (Radmehr et al., 2021). In its strategy "Clean Energy for All Europeans," the EU also announced that it will be the first continent to accomplish climate neutrality by 2050, calling for a 40% reduction in emissions by 2030 (Gyamfi et al., 2023). The United states on the other hand, is the second largest Carbon dioxide emitter responsible for 14% of the global carbon emission in 2021 (Ian, 2023).

Table 17*: Countries with the highest rates of carbon emission*

Rank	Country	Emission in 2017(MtCO2)	% of Global Emissions
#1	China	9,839	27.2%
#2	United States	5,269	14.6%
#3	India	2,467	6.8%
#4	Russia	1,693	4.7%
#5	Japan	1,205	3.3%
#6	Germany	799	2.2%
#7	Iran	672	1.9%
#8	Saudi Arabia	635	1.8%

Source: (World Economic Forum, 2019)

Following Joe Biden's assumption of office in 2020, his administration committed to prioritizing climate action. In addition to rejoining the Paris Agreement, the Biden administration pledged the United States to achieve net-zero emissions by 2050. At the 26th United Nations Climate Change Conference (COP26) in 2021, the United States also endorsed the Global Methane Pledge, committing to a 30% reduction in methane emissions by 2030 (Bikomeye et al., 2021). Furthermore, in 2021, the United States strengthened its Nationally Determined Contribution (NDC) by setting a new and ambitious climate target: reducing emissions by 50 to 52 percent below 2005 levels by 2030 (Ian, 2023). Countries and regions primarily utilize carbon emission trading and taxing programs to curtail emissions (Du et al., 2015). Both approaches hold the potential to reduce emissions, yet there seems to be no clear superiority of one over the other (He et al., 2015). Notably, developed countries incur higher carbon emission abatement costs compared to major developing nations (A. Li et al., 2015). According to (L. Wu et al., 2015), heightened carbon pricing levels can diminish the economic advantage enjoyed by high carbon emitters. Personal carbon trading (PCT) emerges as a progressive strategy for lowering household carbon emissions, particularly benefiting lower-income consumers (Huisingh et al., 2015). However, strategies to mitigate carbon emission differentiate from a sector to another depend on different set of technical variables, for instance, the construction sector is the largest source of global carbon emissions, contributing significantly to global warming. The construction sector accounts for 40% of global energy consumption and 25% of overall carbon emissions, as reported by the Intergovernmental Panel on Climate Change (Huisingh et al., 2015). In this context, (Kim et al., 2015) devised an integrated CO2, cost, and schedule management (ICCSM) system tailored for building construction projects, grounded in the principles of earned value management theory. This system aims to enhance the monitoring, evaluation, and anticipation of carbon emissions. (X. Wang et al., 2015) introduced an empirical approach for estimating overall carbon emissions arising from highway construction processes, encompassing raw material production, transportation, and onsite construction across diverse project types (e.g., subgrade, pavement, bridge, and tunnels). The research revealed that raw material production constituted over 80% of CO2 emissions, while onsite construction and transportation contributed only 10% and 3%, respectively.

The agriculture sector stands as the third most significant source of CO2 and methane emissions, trailing behind the industrial and construction industries. Enhancing energy efficiency in agriculture is crucial for sustainable development, as it not only lessens carbon emissions but also helps ease climate change risks and safeguards natural resources (Huisingh et al., 2015). (Ebrahimi & Salehi, 2015) Studied the energy use and carbon emissions of button mushroom production in Iran. In button mushroom greenhouses, the average total energy input was 900 MJ m2, and the output was 25 MJ m2. The main energy-consuming inputs were compost, diesel fuel, and electricity, with amounts of 444, 409, and 37 MJ m2, respectively. Efficient units reduced carbon emissions by 27% compared to inefficient units, with total emissions of 23 and 32 kg CO2-eq ha1, respectively. Managing diesel fuel and electricity consumption in mushroom production facilities contributed to these improvements. (Visser et al., 2015) Explored 'farm to ship' cotton production in Australia, finding that producing a bale generates 323 kg CO2-eq. This includes 182 kg CO2-eq from farm production, 73 kg CO2-eq from gin to port supply, and 68 kg CO2-eq from gin trash emissions. If managed at the farm, waste could yield a 48 kg CO2-eq credit per bale, resulting in a 27% farm emissions reduction and a 15% decrease in the overall farm-to-ship carbon footprint.

2.3 Industry 4.0 technologies' effects on environmental sustainability

In the existing literature, Industry 4.0 and its potential impact on different aspects of environmental sustainability have been studied from different perspectives. However, Industry 4.0 is a concept that gathers different technologies that are not necessarily combined. It is clear that the combination of different technologies is the core value of Industry 4.0, but the examination of each technology separately is crucial for determining the right combination of technologies for each specific case. For this reason, in the next section, the literature regarding each Industry 4.0 technology will be presented separately, and its effects on environmental sustainability will be examined. Two sub-sections will be included: the first section will discuss the benefits of each technology on environmental sustainability, while the second one will discuss the challenges of integrating each technology in an environmental sustainability context.

The next section will be based on 107 research paper, Table 18 present an overview of all the articles that based their studies on one of industry 4.0 technology and which environmental sustainability aspect they focus on for an easier navigation of papers by the readers. Figure 19 shows the year where these articles were published.

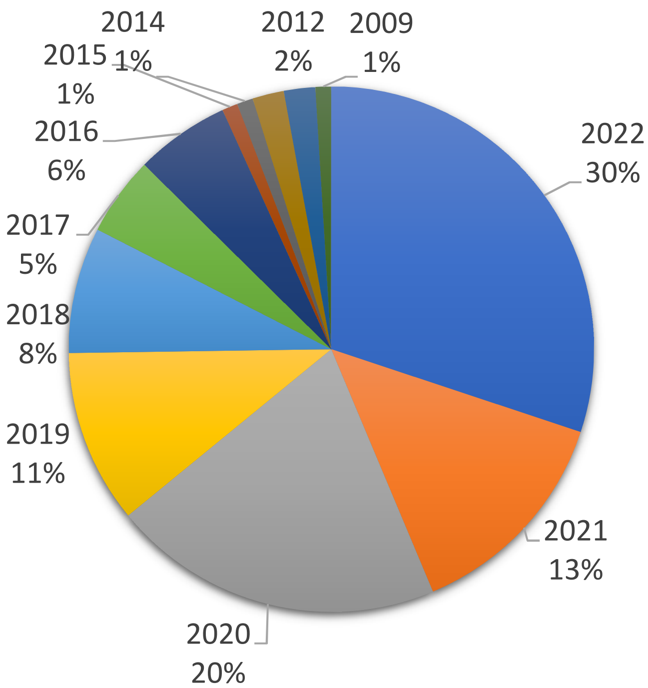


Figure 19: Year of the reviewed papers

Source: Own research

2.3.1 The benefits of Industry 4.0 technologies on environmental sustainability

Industry 4.0 has great potential for environmental sustainability. This combination is expected to improve energy and material efficiency, while also increasing the adoption of renewable energy sources in industrial manufacturing (Ghobakhloo & Fathi, 2021), but it's becoming increasingly clear that sustainability advantages aren't a foregone conclusion, but rather must be deliberately integrated into the digitalization goals of each company (Renn et al., 2021). The global market for the use of advanced technologies to enhance environmental sustainability was valued at USD 13.76 billion in 2022 and is expected to reach around USD 89.18 billion by 2032 as shown in Figure 20. This development is driven by increasing pressure on industries and global awareness of environmental issues, increasing energy expenses, the advancement of smart cities and urban planning, and a heightened focus on effective waste management and recycling.

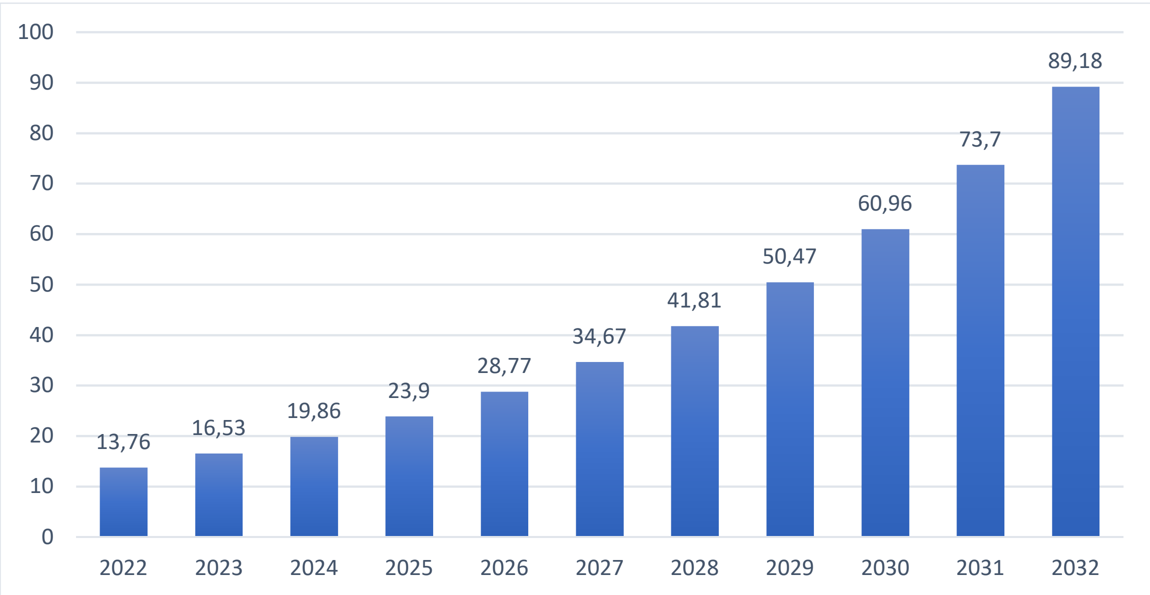


Figure 20: The market size of advanced technologies used for environmental sustainability from 2022 to 2032 (USD BILLION)

Source: (www.precedenceresearch.com, 2023)

In this section, we will present how each technology included in Industry 4.0 can contribute to enhancing environmental sustainability and encouraging green practices.

- *Iot and environmental sustainability*

The Internet of Things (IoT) is the fabric that facilitates the flow of data between people, things, and processes, resulting in a growing data sphere and complex traffic models based on a variety of data sources (Ibrahim et al., 2022). IoT enables citizens to get a variety of services and advantages in an automated way, including logistics product tracking, smart agriculture, smart intelligent transport systems (ITS), smart hospitals, smart grids, smart homes, and smart environments (Y. Li et al., 2017). It is not a surprise that attention has shifted toward the use of IoT to enhance environmental sustainability. As the IoT's main feature is tracking, and waste management has the largest share in the literature in this regard, the internet of things is the most practical way to enhance the effectiveness of municipal hazardous waste management with minimal waste and an efficiency of 95.09% (X. Xu & Yang, 2022). These values might seem exaggerated, but they are supported by several authors in the literature, such as (X. Chen, 2022), who suggested an algorithm based on the Internet of things and machine learning for smart waste management. The IoT-powered devices can be put in waste containers, such as recycling bins, and it gives real-time information about how much garbage people produce. Image processing can be used to figure out how much garbage is at a disposal site. They give a clear picture of trash and recycling trends and give ideas for how to be more productive. The suggested approach led to an accuracy ratio of 96.1 percent, a cost-effectiveness ratio of 92.7 percent, a tracking rate of 89%, and an environmental production/recycle ratio of 91.9 percent, all achieved by the suggested approach in comparison to other ways, according to the trial data. In the same context, based on literature and expert consultation, (Turner et al., 2022) came up with a set of parameters to describe the produced asset to consider its circularity during its whole lifespan, with application to the automotive part relying on the Internet of things. The model is in the form of a central component linked to the Internet of things and sensors that operates as an automated maintenance process generator. This tool would recommend a dynamic method for the technician to follow based on sensor outputs, problem codes, and predictive models available for the vehicle. End users will be able to offer text replies and diagram comments about automobile repair operations, providing another data source for the auto-circular simulator.

The IoT benefits for the environment are not limited to waste management; (Parvathi Sangeetha et al., 2022) implemented a hybrid remote-controlled device based on the Internet of Things and Global Positioning System (GPS) with Radial Function Network (RFN), to manage the pump for storing and transporting groundwater to a farmer's field, as well as monitoring soil humidity, pressure, and temperature in a farm field. The IoT-based system met the goal of monitoring and regulating the agricultural irrigation system. Furthermore, the application provides a dashboard that allows the customer to monitor the irrigation system. In the case of an accident, the program monitors detector values and controls the water pump. Furthermore, a survey conducted by (Hu et al., 2022), based on 355 manufacturing employees in China to measure the impact of eco-sustainability motivational factors on organizations' adoption of the Green Industrial Internet of Things (GIIoT), a tool to achieve green innovation, Eco-sustainable motives have a substantial and beneficial influence on the adoption of GIIoT, according to the findings. Eco-efficiency, eco-effectiveness, eco responsiveness, and eco-legitimacy play major roles in increasing an organization's adoption of GIIoT. By integrating linked assets, real-time data processing, and monitoring, green industrial IoT solutions enable manufacturers to operate more efficiently while being flexible, informed, and in command. Integration of advanced manufacturing technologies with GIIoT can help manufacturers to achieve sustainable development goals while also improving their green innovation.

- *AI and environmental sustainability*

Relying on the machine and deep learning technics, AI has the potential to enhance every aspect of environmental sustainability. In Appendix 3, we have presented many studies that rely on AI in order to enhance different aspects of environmental sustainability. The following paragraph will present some of these cases.

(Vinuesa et al., 2020) studied how AI can impact the advancement of the three sustainability pillars both positively and negatively, as shown in the figure below.

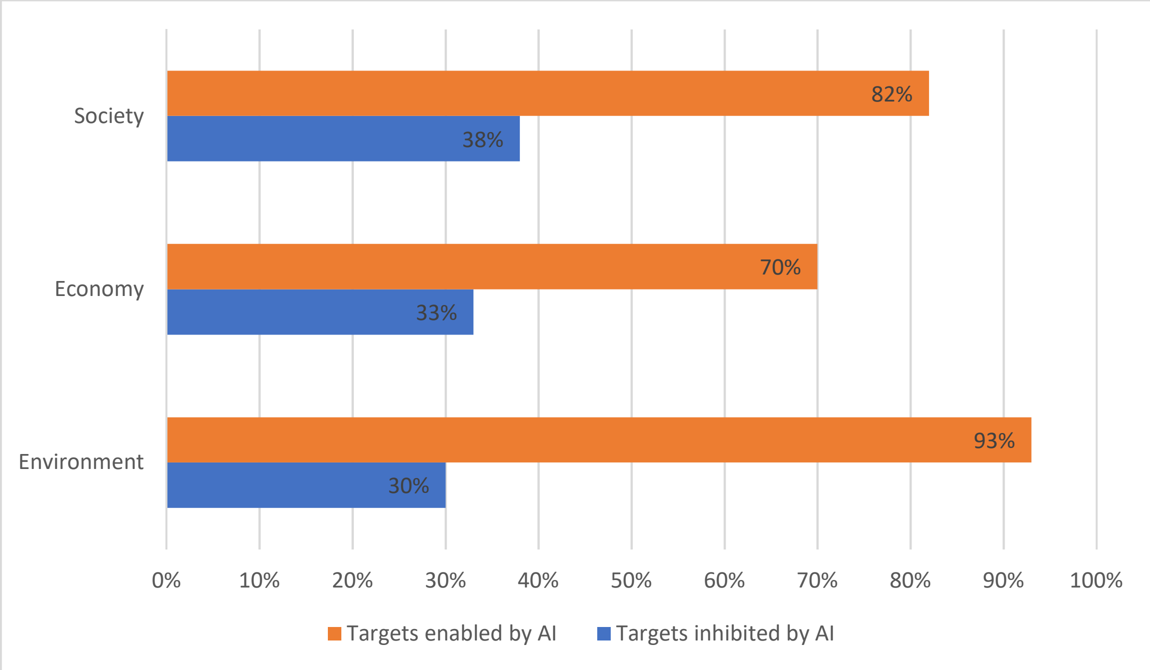


Figure 21: Impact of AI on the achievement of each target from the Sustainable Development Goals.

Source: (Vinuesa et al., 2020)

Starting with waste management, many studies have focused on categorizing waste materials for use in autonomous sorting systems, eliminating the need for manual waste segregation. (Tehrani & Karbasi, 2017) employed Artificial Neural Networks (ANN) and Multispectral Imaging to identify plastic materials within e-waste, achieving an impressive accuracy of 99%. (Vrancken et al., 2019) utilized Deep Convolutional Neural Networks (CNNs), a specific type of ANN, achieving accuracy rates ranging from 61.9% to 77.5% in identifying paper and cardboard among various waste types, despite a limited training dataset of 24 images. Relying on the same technique, (Sudha et al., 2016) automated waste sorting with CNN, significantly improving sorting efficiency compared to manual methods. (Heshmati et al., 2014) employed Quinlan's M5 algorithm, a supervised Machine Learning subfield, to anticipate waste compression ratios crucial for municipal landfill design. The results were impressive during testing, with a coefficient of 0.92. The algorithm, fed with various solid wastes, including biodegradable fractions, dry density, and water content, demonstrated its predictive capabilities.

Resource efficiency is one of the most prominent aspects that can be improved by I4.0. Resource efficiency, viewed as a sub-goal of sustainability and SDG 12, may offer a limited contribution to overall sustainability, yet it remains a crucial aspect (Waltersmann et al., 2021).

Numerous studies highlight that AI enables organizations to automate mid-range monitoring tasks, leading to a flatter organizational structure and contributing to significant economic efficiency (Bloom et al., 2014; Davenport & Ronanki, 2018). (Otabek, 2021) argues that AI applications empower organizations to execute labor-intensive tasks in trade stores, warehouses, and establishments, such as ordering and record-keeping of purchases from various vendors, up to three times faster. These applications support decision-making in production resources by mining firms, gathering information on facility construction, and analyzing data on electricity revenue, resulting in substantial resource reductions.

Artificial Intelligence (AI) technologies have also the potential to support the energy management business in capitalizing on new possibilities brought about by the Internet of Things (IoT) and the integration of renewables (Sodhro et al., 2019). The traditional power grid was not intended to handle the incorporation of renewable energy sources (RES). Changes in the properties of RES (e.g. geothermal, hydrogen, wind, solar) provide issues in complying with the power grid's shifting loads (B. Yang et al., 2019). AI innovations such as machine learning, deep learning, big data, etc, are reshaping the energy industry. Many countries already implemented AI technology to perform various operations related to energy management such as forecasting, controlling, and efficient power system operations (Kow et al., 2016).

Regarding CO2 emissions, the implications of AI is divided, for this reason, there is an intense effort to use AI in a green way. Roel Dobbe and Meredith Whittaker, co-founders of the AI Now Institute, published an article on AI and climate change in October 2019 in which they called for seven policies that might pave the way for "tech-aware environmental policy, and climate-aware tech policy." Two main policies were: reducing the use of AI to extract fossil fuels and investigating the influence of AI on climate change (Dhar, 2020). AI has the capacity to both benefit and negatively impact the environment, and it is critical to prioritize sustainable AI practices throughout the AI lifecycle (Gaur et al., 2023). (Delanoë et al., 2023) demonstrated the dual impact of AI on CO2 emissions. Their study focused on AI applications developed in Brazil, Tunisia, and Sweden, examining both positive and negative effects. Solely considering positive impacts, the models showed a 34%, 73%, and 9% reduction in CO2 emissions, respectively. However, when accounting for negative impacts, the detrimental effects sometimes outweighed the positive ones. However, according to common opinion, AI has overall beneficial effects on carbon reduction (Aghion et al., 2017). Although AI applications themselves contribute to indirect carbon emissions, they are easily tracked and controlled. For instance, (Budennyy et al., 2022) developed an open-source library that measures the carbon emissions of any AI application and it is open to the public. The model uses Python and calculates the RAM, CPU, and energy consumption. According to a report published collaboratively by Microsoft and PwC, "the use of AI technology for environmental preservation is expected to raise global GDP by 3.1 to 4.4 percent by 2030 while cutting global greenhouse gas emissions by 1.5 to 4.0 percent" (C. M. Liu et al., 2019). (P. Chen et al., 2022) employed a two-way fixed effects model using temporal and area-level fixed variables to investigate the relationship between AI development and carbon emissions magnitude. The results showed that the development of AI by 1% can directly contribute to a carbon intensity reduction of 0.0027%, which is a high percentage. (Ding et al., 2023) used a database from 30 provinces in China from 2006 to 2019 to study the relationship between AI and carbon emissions. The study has shown that the development of AI reduces carbon emissions with a spatial spillover effect, this reduction is realized especially by promoting environmentally friendly practices and improving the technological aspect of the industrial sector.

- *Additive manufacturing and environmental sustainability*

Additive manufacturing (AM), also known as three-dimensional (3D) printing, is a revolutionary technology that produces complex-shaped, multi-material parts in a single process (Dvorak et al., 2018). Consequently, additive manufacturing has emerged as a direct digital production technique in the age of industry 4.0 (Bueno et al., 2020). Several studies have highlighted the potential sustainability benefits of additive manufacturing processes in different fields (S. Liu, Lu, et al., 2022), which is supported by the increasing number of studies analyzing the environmental effects of AM (Saade et al., 2020). Additive manufacturing has the potential to reduce energy consumption, and eliminate waste, including waste that affects the environment or threatens long-term sustainability (Ghobadian et al., 2020). When creating lightweight components, the product geometries may be improved, resulting in a reduction in the amount of material required during fabrication and the amount of energy utilized in operation. Due to the simple manufacturing of on-demand parts, transportation and inventory waste are reduced in the supply chain (Mani et al., 2014).

The construction sector has an important share of the literature regarding the impact of 3D printers on environmental sustainability (Khan et al., 2021; Lu et al., 2019). (Adaloudis & Bonnin Roca, 2021) applied grounded theory to analyze the potential effects of 3D printers within the construction business over the three elements of sustainability. Regarding the environmental aspect, the 3D printer can reduce waste and failures resulting from better quality control and reduce the environmental impact of concrete production and transportation. With a holistic design approach, it has the potential to improve energy efficiency and other performance parameters. (Weng et al., 2020) studied the economic cost, environmental effects, and productivity of a concrete bathroom unit. When compared to a precast counterpart, a 3D printed bathroom unit may save 34.1 %, 85.9%, and 87.1 % on overall cost, CO2 emissions, and energy use, respectively.

The additive manufacturing process is constantly improving and can support plastics manufacturers in reducing their carbon footprint (Freitas et al., 2016). To reduce the amount of plastic used in a given product, topology optimization and generative design are used (Javaid et al., 2021). The 3D printer enables the printing of all plastics and eco-friendly materials. In contrast to other engineered materials, the material can be 3D printed and decomposed without the necessity for an industrial composting facility. Because of its lightweight and low cost, the material is suitable for additive manufacturing as a plastic substitute (Jiang & Fu, 2020). 3D printing not only minimizes waste but also enables the reuse of finished goods (Machado et al., 2019).

(Ford & Despeisse, 2016) considered how additive manufacturing (AM) can contribute to the development of more sustainable production and consumption systems. Furthermore, the environmental dimensions of sustainability have emerged as the most prominent in the research. Product and process redesign; material input processing; make-to-order component and product manufacturing; and closing the loop were highlighted as four primary categories in which AM is enabling sustainability. As a result, the benefits of AM for sustainability across the product and material life cycles have been identified, as well as the barriers that must be overcome. From a sustainability point of view, the main areas that AM can represent an advantage are material and energy reduction; minimizing waste; increased durability for longer product life; increased fuel efficiency; reduction of the environmental impact of titanium powder production; and localized material recycling. (D. Chen et al., 2015) provided an overview of Direct Digital Manufacturing along with potential sustainability indicators and related sustainability research. According to this study, direct digital manufacturing has the potential to reduce waste by improving raw material utilization efficiency. Dematerialisation, as well as on-demand potential due to consumer proximity, results in less pollution and energy consumption. DDM reduces the need for inventory due to more decentralized value chains and better user orientation, resulting in energy and material savings for storage and a lower number of degraded products. DDM also requires fewer complex processing tools, which could result in energy and material savings. More concretely, (Mele & Campana, 2022) proposed a 3D liquid crystal display printer with an adaptive slicing strategy. The study aims to investigate the potential long-term benefits of this strategy over traditional slicing. The results show that it causes a significant reduction in environmental impacts, particularly in terms of human health and resource scarcity. In the cases of the dental model and the respirator adapter, this strategy allows for a reduction in total building time of up to 27.8% and 53.6%, respectively. Furthermore, according to the composition of ecosystem quality indices, the resin life cycle contributes between 59 and 86 percent of the total, and significant savings are also made in terms of energy consumption. Energy efficiency is widely discussed in the literature as one of the benefits of AM compared to traditional methodologies, (H. Wu et al., 2022) focus on a bottom-up approach to classify technical elements such as equipment, processes, and interfaces of materials recycling and manufacturing, followed by a benchmark between AM and conventional manufacturing (CM) processes, based on the collection-recycling-manufacturing model as the framework's core area, then it delves into sustainable manufacturing by combining recycling and additive manufacturing. The results show that AM can help to reduce transportation distance, CO2 emissions, and energy consumption, as well as commit to cost savings and shorter lead times. Among all the key factors, design flexibility and localization can be tactical factors that enable AM to fully utilize the collection-recycling-manufacturing (CRM) model and augment AM's advantages.

- *Blockchain and environmental sustainability*

Blockchain is characterized as a tamper-proof decentralized database system that provides consistent transactions across numerous users (Yetis et al., 2022). According to research, blockchain minimizes problems of distrust and suspicion by uniformly presenting confirmed transactions to all parties (Gorkhali et al., 2020). In addition, its scalability, traceability, and sustainability attract interest from several sectors. In contrast to classical systems, it is innovative as it also eliminates central authority (Leung, 2019).

Blockchain technology provides the ability for transparency that allows producers to share the production process step by step in a reliable way. Since green practices are not optional for corporations anymore, the tractability of processes has become more crucial than ever. Based on document analysis, field research, interviews, and focus groups, (Varavallo et al., 2022) designed, developed, and implemented a Blockchain-based traceability platform to ensure traceability in the agricultural and food industries with less environmental impact and lower costs for each transaction sent through the supply chain. The authors could create a Blockchain algorithm that allows the operators in the targeted company to keep a record of all transactions during the packaging stage with a low environmental footprint and overall cost savings. According to (Dey et al., 2022), food waste and loss account for nearly 6% of total greenhouse gas emissions worldwide. To overcome the food waste problem, the authors proposed a multi-layered Blockchain-based framework utilizing machine learning, cloud computing, and QR code in a decentralized Web 3.0 enabled smart city called SmartNoshWaste. The application focuses on the consumption of potatoes in the United Kingdom since it is one of the most common food items that is wasted. At each step of the supply chain, every stakeholder, including the consumer, has access to and can trace the food data. The app includes the ability to track the food items consumed or wasted during the week so that the user can make a more informed decision about what food to buy or not buy the next time they go grocery shopping. The data is processed and managed by a machine learning algorithm that shows that the Blockchain-based platform is capable of reducing food waste by 9.46 percent. (Erol et al., 2022) studied the potential of Blockchain to mitigate the effects of barriers to successfully implementing a circular economy. The results showed that the most important functions of blockchain in overcoming CE adoption barriers are transparent supply chain traceability management, improved collaboration and coordination in supply chain ecosystems; superior trust in supply chain ecosystems; and enhanced business models through cooperation and prosumerism. (Kouhizadeh et al., 2019) studied the environmental and economic effects of the interaction between Blockchain, circular economy, and product deletion. The study showed that multiple levels, including governments, communities, supply chains, companies, and people, are affected by the management and practical consequences of the relationships between the three concepts. The authors discussed how the blockchain can be used to help build the necessary CE infrastructure. If a product gets deleted, the difficulty arises from the inability to monitor the inventory of materials required for suitable development material flows and natural resource policies over a specified planning horizon. In this case, blockchain technology can contribute to identifying which items are accessible and which may be phased out, which might assist in ensuring that materials for certain sectors remain available. The research also discussed how blockchain can contribute to waste management if companies value and strategically exploit choices on product deletions, and then the inter-organizational system will be more proactive and transparent as a result of the blockchain implementation. (Pizzi et al., 2022) investigated the potential effects of blockchain on sustainability reporting based on Banca Mediolanum, one of Italy's most important financial institutions. The company introduced a publicly available blockchain that contains the full report regarding sustainability practices; it has completed the immodificability credential of its sustainability report without relying on a third party that is traditionally responsible for the notarization of these kinds of reports. Due to the immutability feature of the blockchain, the company cannot change or amend its pledges after notarization because blocks have already validated the reliability of the hash. For that reason, the Italian corporation is considered the first mover that notarized its sustainability statement on a public blockchain to address information gaps that harm stakeholder participation.

According to (Strepparava et al., 2022), the production of renewable energy is stochastic, it can only be done if the market is cleared in pseudo-real time, unlike the traditional energy, the use of cutting-edge information and communication technology is required for the application of renewable energy, Blockchain, as a new ICT, opens up new possibilities for decentralized market architectures. For that reason, the authors proposed a market mechanism that is based on dynamic prices and is functionally dependent on the energy produced or consumed in real-time within the local grid. The method is based on a customized Blockchain solution that was developed using the Go programming language. 18 residential buildings in Southern Switzerland were used as part of a test pilot; the results showed the market was able to work without specific issues while avoiding the use of significant amounts of resources. However, the adoption of a blockchain solution is still hampered by the hardware limitations of smart meters.

- *Simulation and environmental sustainability*

Process simulation is a software-based representation of physical, chemical, biological, and other unit operations (Pasha et al., 2021). Simulation models offer considerable potential for adjusting and predicting energy use, material consumption, and reducing rework to improve the performance of sustainable manufacturing (Turan et al., 2022).

Simulation has become an important tool in the construction business to create a more productive, safer, and higher-quality construction process with less negative environmental impact (Teng & Pan, 2019). According to global resource data, the construction industry consumes 32% of resources, generates 40% of greenhouse gas emissions, and creates 40% of construction waste (Han et al., 2020). The construction industry has increased massively and, simultaneously, prefabricated building destruction has also risen, resulting in massive carbon emissions (T. Luo et al., 2021). Building energy performance simulation software such as EnergyPlus, Ecotect, and eQuest is commonly used to simulate existing building energy performance and evaluate retrofit possibilities (Yudelson, 2010). (S. Liu, Li, et al., 2022) simulated different scenarios of the current situation of prefabricated building destruction. Energy consumption simulation for prefabricated building construction indicates that if prefabricated buildings are consistently marketed, the total carbon emissions would reach 32.87 billion tons by 2030. On the other hand, if the construction sector continues to adopt conventional methods, carbon emissions will reach 89.23 million tons. (Jia et al., 2017) carried out dynamic simulations and decision-making analyses to effectively manage construction and demolition waste. The simulation of the business showed that penalties can have a significant impact on the volume of waste that is illegally disposed of and subsidies have the potential to significantly increase the quantity of recycled and reused garbage.

The construction business is not the only sector that can be environmentally friendly relying on simulation; several other cases in different sectors are spotted in the literature. (Naseri-Rad et al., 2022) presented a sustainability assessment by simulating the clean-up of contaminated sites that are associated with health, environmental, economic, and social problems. The model enables site managers to understand the dynamics affecting the sustainability of each remediation scenario throughout the decontamination process's full life cycle. (Abadías Llamas et al., 2019) investigated the performance and environmental impact of the whole primary copper flowsheet by simulating the whole process of circular economy based on numerous metrics, including recovery rates, material, and energy usage, and indicators from life cycle assessment (LCA). (Gbededo & Liyanage, 2020) analyzed the literature to determine the techniques, methods, and methodology used in sustainable manufacturing, which developed into a framework for conceptual modeling of integrated Simulation-based Sustainability Impact Analysis. (Burinskiene et al., 2018) simulated the warehouse's daily operations to make the flow as efficient as possible. The analysis demonstrates tremendous possibilities for reducing waste and achieving economy of distance. (Yeomans & Imanirad, 2012) used simulation-driven optimization (SDO) to produce diverse, maximally different, near-optimal policy solutions for waste treatment and disposal. (Ceschi et al., 2021) explored the impacts of societal norms on recycling behavior by simulating a Taiwanese district based on real data. Although societal norms are a powerful source for enhancing people's willingness to recycle, the findings also support the concept that the quantity of waste existing on the streets is a significant moderator variable that policymakers must consider. (Capellán-Pérez et al., 2019) used a simulation game "Global Sustainability Crossroads" whose primary goal is to increase individuals' understanding of the global sustainability quandary, with a particular emphasis on climate change and the potential alternatives possible in the next decades to reverse present trends. (Ojstersek et al., 2020) assessed the impact of flexibility in manufacturing on sustainability and overcoming the challenges of high-mix, low volume production by simulating the manufacturing schedule. The results showed that, on average, power usage is reduced by 10.6% when compared to other optimization techniques, and scrap rate is reduced by 35% when compared to previous optimization methodologies. (M. Luo et al., 2022) navigated future uncertainties toward sustainability in China by using simulation tools according to 24 different scenarios spanning the years 2020–2100, each with a 10-year time period. (Tinelli & Juran, 2019) used simulation models based on digital twin implementations to reduce water resource pollution through more precise and effective resource management.

- *Augmented Reality and environmental sustainability*

Augmented reality (AR) is a type of reality approximation in which physical items are connected to a virtual equivalent via contextual computer-generated information. AR has progressed from a science-fiction fantasy to a well-established scientific subject (Çakıroğlu et al., 2022). AR simultaneously stimulates several senses, including touch, hearing, and vision. This enables learners to overcome barriers and get access to various inaccessible locations, as well as actively participate in learning and teaching. It provides users with a sensation of presence and immediacy with the subject under investigation (Nincarean et al., 2013). Augmented reality is a technology that is becoming increasingly prevalent in a variety of aspects of our lives. From 2017 to 2019, 1119 articles were published in the SCOPUS database regarding augmented reality (Abad-Segura, González-Zamar, et al., 2020). The technology enables people to develop a more natural interface between humans and the physical environment; hence reducing the amount of hardware devices we must carry (Fraga-Lamas et al., 2018).

As was discussed In the simulation section, the use of building energy performance simulation tools is the most widely used approach for modeling the energy performance of existing structures and evaluating various retrofit alternatives. Based on Energy Performance Augmented Reality (EPAR) modeling,(Ham & Golparvar-Fard, 2013) assessed and illustrated the differences between real and simulation results of the predicted energy performance of buildings. (Bekaroo et al., 2018) developed an Android augmented reality-based application named ARGY to help people better understand the energy use of electronic devices at home and in the workplace. Additionally, the program enables end-users to monitor the amount of energy spent by various devices, measure their energy efficiency, and get relevant suggestions and best practices to educate them about green practices. (Alonso-Rosa et al., 2020) developed an IoT energy device using augmented reality to easily visualize the power quality (PQ) parameters and energy usage of household appliances in real-time. Users simply need to point their smartphones at the appliance they are interested in to learn about the device's overall energy usage. (Mylonas et al., 2019) introduced a prototype that incorporates augmented reality into a classroom exercise to help students learn about school buildings' energy conservation.

As the communication of product sustainability to customers is important, this space is still limited. That results in a lack of transparency, which is seen as one of the primary challenges to environmentally friendly consumption (Trienekens et al., 2012). The augmented reality (AR) technology helps to enhance the actual environment with digital data and supports the decision-making process at the point of sale, as it provides high transparency over products' characteristics, including sustainability aspects (Javornik, 2016). AR-RAs (augmented reality-based recommendation agents) can be effective tools for directing consumers toward more sustainable purchasing decisions not just in the digital world but also in real-world physical shops. Customers choose more environmentally friendly products when they use this technology because it gives them information about the product's sustainability in a simple and contactless way (Joerß et al., 2021).

(Vikiru et al., 2019) developed an application based on AG that allows users to scan the barcode of any kind of waste (e.g., bottles, cans, bags) and it will direct the user to a list of links in which they have several options on how to manage the waste safely. (Somayaji et al., 2020) introduced a drone-based on augmented reality technology to navigate in the E-waste yards and assess the environmental impact of the dump yards. The findings indicated that there are few safety safeguards in place for workers at e-waste dump yards. The paper proposes a technique for remotely monitoring effluent levels in an e-waste disposal yard, minimizing human intervention in determining hazard levels, and also providing staff with the opportunity to take appropriate safeguards.

(Theodorou et al., n.d.) assessed the impact of augmented reality applications to raise awareness of climate change by conducting a survey on 97 tourists on an island in Greece. The results showed that augmented reality technology reinforces tourists' cognitive abilities. Tourists that interacted with the augmented reality technology were responsive and showed an increase in knowledge, attitude, and desire to improve their behavior toward climate change. (K. Wang et al., 2021) evaluated the impact of an augmented reality game called P.E.A.R in raising players' awareness of sustainability and climate change. The game dramatically enhanced players' awareness of sustainability and climate-change-related concerns, as well as numerous associated attitudes. According to a sample of 228 university professors, the use of AR in higher education in Saudi Arabia has the potential to have a significant positive impact on the country's environmental sustainability (Alahmari et al., 2019).

Table 18: List of review papers on each technology and its effect(s) on environmental sustainability

I4.0 technologies / Environmental impact	Internet of things	Additive manufacturing	Blockchain	Simulation	Augmented Reality
Waste management	(X. Xu & Yang, 2022), (X. Chen, 2022)	(Adaloudis & Bonnin Roca, 2021), (Jiang & Fu, 2020), (Ford & Despeisse, 2016), (Chen et al., 2015)	(Dey et al., 2022),	(Jia et al., 2017), (Naseri-Rad et al., 2022), (Burinskiene et al., 2018), . (Yeomans & Imanirad, 2012), (Ceschi et al., 2021), (Ojstersek et al., 2020)	(Vikiru et al., 2019), (Somayaji et al., 2020),
Energy management	X	(Adaloudis & Bonnin Roca, 2021), . (Weng et al., 2020), (Ford & Despeisse, 2016), (Chen et al., 2015), (Mele & Campana, 2022), (H. Wu et al., 2022)	(Strepparava et al., 2022),	(Ojstersek et al., 2020)	(Ham and Golparvar-Fard, 2013), . (Bekaroo et al., 2018), (Alonso-Rosa et al., 2020), (Mylonas et al., 2019
Resource efficiency	(Hu et al., 2022)	(Ford & Despeisse, 2016), (Mele & Campana, 2022)	X	X	X
Gas emission reduction	X	(Weng et al., 2020), (Freitas et al., 2016), (Ford & Despeisse, 2016), (Chen et al., 2015), (H. Wu et al., 2022)	X	(Sha Liu et al., 2022)	X
Spread of awareness on environmental sustainability	X	X	X	(Capellán-Pérez et al., 2019)	(Joerß et al., 2021; Trienekens et al., 2012), (Theodorou et al., n.d.), (Wang et al., 2021), (Alahmari et al., 2019).
Natural resources pollution	X	X	X	(Tinelli & Juran, 2019)	X
Climate change	X	X	X	(Capellán-Pérez et al., 2019)	(Theodorou et al., n.d.) , (Wang et al., 2021)
Circular economy	(Turner et al., 2022)	(Machado et al., 2019	(Erol et al., 2022), (Kouhizadeh et al., 2019)	(Abadías Llamas et al., 2019)	X

Source: Own research

2.3.2 The challenges of the integration of Industry 4.0 and environmental sustainability

It is obvious that Industry 4.0 provides different features and facilities that can be utilized in the transformation of industries to be environmentally sustainable and adopt green practices. Nevertheless, there are many challenges associated with Industry 4.0 adoption, especially within a sustainability context (Verma et al., 2022). These challenges vary from one case to another and cannot be analyzed according to one situation.
In the following section, different challenges and obstacles will be presented for each technology where it has been deployed for one or several aspects of environmental sustainability.

- *IoT and environmental sustainability challenges*

Connecting a large number of devices from any location at any time is made possible by the Internet of Things (IoT). The use of IoT devices such as sensors and actuators allows energy systems to monitor, compute, and regulate the grid, which provides an opportunity to achieve renewable and sustainable energy (Khatua et al., 2020). Yet, IoT in energy systems has its own set of challenges and hurdles. According to the same study, the main obstacles to IoT when it comes to the renewable energy sector are interoperability, efficient bandwidth usage, connection issues, and massive data processing. In smart cities, Internet of Things (IoT) technology has shown advantages in terms of improving our overall quality of life. Although (Almalki et al., 2021) acknowledge that Internet of Things (IoT) development requires significant energy, they also acknowledge that it generates unintentional e-waste and pollution emissions. As a result, the authors presented strategies and techniques to improve the quality of life by making cities smarter, greener, more sustainable, and safer. In particular, they emphasized the green Internet of Things for its efficiency in resource usage, reduction in energy consumption, pollution reduction, and e-waste reduction.
IoT presents an opportunity to develop the green agriculture industry as well, but according to (Ruan et al., 2019) green IoT system deployment raises several new financial, operational, and management (FOM) concerns, such as how to pay for network nodes to be recharged and repaired as well as how to handle IoT data. These FOM concerns need the development of new types of agribusiness firms and creative methods of farm production.

- *AI/ML and environmental sustainability challenges*

It is possible to develop systems of intelligence that will generate the knowledge necessary to preserve life through artificial intelligence (Nishant et al., 2020), but the AI for sustainability is challenged by over-reliance on historical data in machine learning models, the unpredictability of human behavioral reactions to AI-based interventions, increased cybersecurity concerns, negative consequences of AI applications, and difficulty assessing the results of intervention approaches.

(Palomares et al., 2021) conducted a SWOT analysis on the AI effects on environmental sustainability. The most critical challenges of AI in this context are that the wide range of AI approaches makes it difficult to pick the optimal one or ones, especially considering the lack of AI and environmental specialists, Increased consumption as a result of digitization is prone to result in blackouts in emerging countries; cyber-attacks are becoming more common as digital energy systems get automated; and overfitting in AI models might have a severe impact on predicting energy use in unforeseen conditions, such as a lockdown. The energy issue is widely expressed in the literature, data centers consume between 1% and 8% of global energy (Z. Li et al., 2020). While the cost of AI is still beyond the reach of most organizations, sustainability and cost-cutting are often two opposite aims in industrial production. The costs associated with integrating AI or IoT may be regarded as unreasonable by businesses and customers (Kumari et al., 2020).

(Cowls et al., 2021) argue that there are ethical issues that arise from the use of AI for environmental purposes, especially to combat climate change. There is also the computing intensity required for AI development, which poses new concerns related to energy usage and greenhouse gas emissions. However, the use of artificial intelligence in the context of climate change has fewer and less severe ethical issues than the use of artificial intelligence in areas such as health and criminal justice, where personal data and direct human-facing actions are at the heart of all processes (Tsamados et al., 2022).

- *Additive manufacturing and environmental sustainability challenges*

The first uses of AM included rapid prototyping and the development of items by producing original models, which were subsequently subjected to testing for physical validation. This technology has grown significantly in the previous decade and has been used in the automotive, aerospace, and biomedical industries for the direct manufacturing of items

(Prashar & Vasudev, 2021). The usage of AM for sustainability reasons has been noticed since the technology's introduction (Gutowski et al., 2009). With all the great benefits come several challenges. (Ford & Despeisse, 2016) highlighted the benefits of additive manufacturing in a sustainability context, but because AM technologies for direct production are still in their infancy, their widespread acceptance and realization of these benefits are dependent on overcoming considerable difficulties. Due to the presence of mixed materials, products' end-of-life recyclability is limited; also, there is a lack of awareness and comprehension of the environmental impact of additive manufacturing technology, supply chains, and products. These obstacles must be overcome to realize environmental benefits through AM. (H. Wu et al., 2022) explained that additive manufacturing has some bottlenecks as the industry has been hesitant to embrace it due to a lack of reliable standards for transitioning from prototyping to mass production. As a result, scale, speed, and size may be disadvantages that delay the adoption of AM in manufacturing. Relying on a generic case study, (D. Chen et al., 2015) examined the use of energy when the product is made through 3D printers in comparison to mass production (Injection molding). The results show that the 3D printer is significantly more energy-intensive than the injection molding.

(Javaid et al., 2021) pointed out the fact that although the possible benefits of additive manufacturing (AM) are appropriate for complex and small parts, their long-term viability has not been properly investigated. While AM has the potential to improve industrial sustainability, its effects on the industrial system could lead to an alternative scenario in which less eco-efficient localized production, customer demands for customized goods, and a high rate of product obsolescence combine to increase resource expenditure. (Senusi et al., 2021) studied the 3D bone tissue engineering scaffolds as well as their potential environmental impact using the LCA model. The results show that the main factors affecting the environmental impact of fabricating 3D bone tissue engineering scaffolds are the electricity grid mix and ethylene glycol. This is due to the fact that 3D printing technology consumes a lot of electricity compared to other types of manufacturing processes, and the main driver for this fabrication is 3D machine operations. As a result, electrical energy from 3D machine operation provides the most significant sustainability issue in terms of potential environmental impact. Energy utilization issues must be addressed at all stages to achieve high energy efficiency while having a low environmental impact.

As was discussed in the previous section, the use of AM in the construction business is thriving. However, there are still several challenges that have to be addressed to extract the full potential of this technology to enhance the environmental sustainability of this sector. (Adaloudis & Bonnin Roca, 2021) mentioned that within the construction business, material supply for 3D printers is limited, and it may be necessary to transport it over longer distances. Concrete is still large and problematic even when its use is reduced.

- *Blockchain and environmental sustainability challenges*

According to (Dey et al., 2022), one of the most complicated aspects of implementing blockchain in a smart city from an environmental point of view is prioritizing citizen privacy and data security. Examining some of the smart city projects that have implemented blockchain reveals that, regardless of its use as a technology, the implementation to protect citizens' privacy and improve data security varies depending on the project's available infrastructure.

By using the fuzzy Delphi method, (Rejeb et al., 2022) generated a list of the most relevant barriers when adopting the Blockchain to significantly alter aspects of circular economy activities and overcome environmental sustainability problems. To effectively rank these barriers, the best-worst method (BWM) was used. The results showed that lack of knowledge and management support, reluctance to change, and technological immaturity are the most relevant barriers, while investment cost, security risk, and scalability issues are the least impactful barriers to blockchain adoption in the CE.

- *Simulation and environmental sustainability challenges*

Building performance simulation is increasingly being utilized as a tool for building design, operation, and retrofitting to save energy and reduce utility expenses (Clarke & Hensen, 2015). However, using the simulation to decrease the environmental impact still faces several limits. The time and effort needed to gather enough data and produce trustworthy energy models is a major practical concern for the majority of energy modelers. Detailed energy modeling using today's simulation tools involves a large number of inputs, and modelers may be unaware of the relative significance of each input to the simulation output, the amount of uncertainty, and the proper default values to employ (T. Hong et al., 2018). The simulation modeling approach makes it nearly impossible to analyze massive amounts of sustainability data since it contains a lot of variables that have to be taken into consideration (Gbededo et al., 2018).

Aeroengines' role and design are about to undergo dramatic changes to fulfill aggressive emissions requirements and increase efficiency. To model this, a high degree of flexibility and predictive modeling with high accuracy is required (Tyacke et al., 2017) . Turbomachinery simulation is a widely used method in this context, but according to (Tyacke et al., 2019) it is still facing a lot of issues as it requires higher-order schemes, internal and external zonalisation, coupling, hardware exploitation, and pre-and post-processing.

According to (Turinsky & Kothe, 2016), modeling and simulation capabilities help to increase nuclear energy's economic competitiveness and reduce the volume of spent nuclear fuel per unit of energy while maintaining nuclear safety. However, to achieve that, advanced modeling and simulation capabilities in radiation transfer, thermal-hydraulics, fuel performance, and corrosion chemistry are required.

- *Augmented Reality and environmental sustainability challenges*

Augmented reality makes use of sensor technologies to comprehend the real world and enable human interaction within virtual surroundings (Runji et al., 2022). However, the daily usage of AR is still complicated in a way that users' interactions with digital overlays that are placed in front of their vision create the requirement for smooth and lightweight user engagement with such overlays (LaViola Jr et al., 2017). (Garzon et al., 2020) developed and evaluated an AR-based educational application to promote aquaponics-based sustainable agricultural practices. According to the evaluation process, the impact of the AR-based application is similar to what was discussed in the AR benefits section, which is mainly increasing awareness. However, the results also showed that the most critical challenge faced in this context is the accessibility of AR applications. One of the most common devices that supports AR applications is Smartglasses. Still, Smartglasses have limited processing capacity and a short battery life, making them unsuitable for computationally heavy activities. Google Glass (currently available low-end smartglasses) features a 1 GHz ARM Cortex-A9 MPCore SMP processor with a battery life of 1 to 3 hours. This combination is equivalent to 2000 desktop PCs (L.-H. Lee et al., 2022).

Table 19: Most common challenges for each technology in a sustainability context

I4.0 technologies / Common challenges	Internet of things	Artificial intelligence/ Machine learning	Additive manufacturing	Blockchain	Simulation	Augmented Reality
Massive-data processing	(Khatua et al., 2020),	X	X	X	(Gbededo et al., 2018),	(Garzon et al., 2020)
Excessive-energy usage	(Almalki et al., 2021)	(Z. Li et al., 2020)(Li et al., 2020)(Cowls et al., 2021),	(Chen et al., 2015), (Senusi et al., 2021)	X	X	X
Cybersecurity and privacy		(Nishant et al., 2020), (Palomares et al., 2021)	X	to (Dey et al., 2022)	X	X
Complexity	(Ruan et al., 2019)	(Nishant et al., 2020), (Palomares et al., 2021)	(T. Hong et al., 2018)	(Rejeb et al., 2022)	X	(LaViola Jr et al., 2017)
High cost	(Ruan et al., 2019)	(Z. Li et al., 2020), (Kumari et al., 2020)	X	X	X	X

2.4 The literature conclusion

In this literature review, we have clearly defined the two primary topics of the thesis. We began by outlining the historical context of Industry 4.0, tracing its evolution from the first industrial revolution to the current fourth revolution. This section also covered the most prevalent technologies associated with Industry 4.0. Our analysis was based on a comprehensive review of 417 relevant articles from the SCOPUS database, allowing us to highlight the most frequently mentioned technologies. Similarly, we explored the concept of environmental sustainability in detail, focusing on its most pertinent aspects. We then reviewed key studies that examine how Industry 4.0 technologies can enhance environmental sustainability. Despite extensive literature, no existing study offers a practical case study integrating Industry 4.0 technologies specifically to improve environmental sustainability. This identified gap forms the basis of the main objective of

Source: Own research

this thesis: to provide a practical roadmap for decision-makers to navigate the complexities of Industry 4.0 implementation and to showcase possible environmental sustainability outcomes based on this study. This roadmap aims to offer strategic guidance to address challenges identified in the literature and validated through a quantitative study. From this primary objective, eight sub-objectives were derived, each associated with specific questions that need addressing. For the first five sub-objectives, which will be addressed through our quantitative study, four hypotheses were formulated as detailed in Table 1 and illustrated in Figure 22. The methodology employed to achieve these study objectives will be explained in detail in the next section.

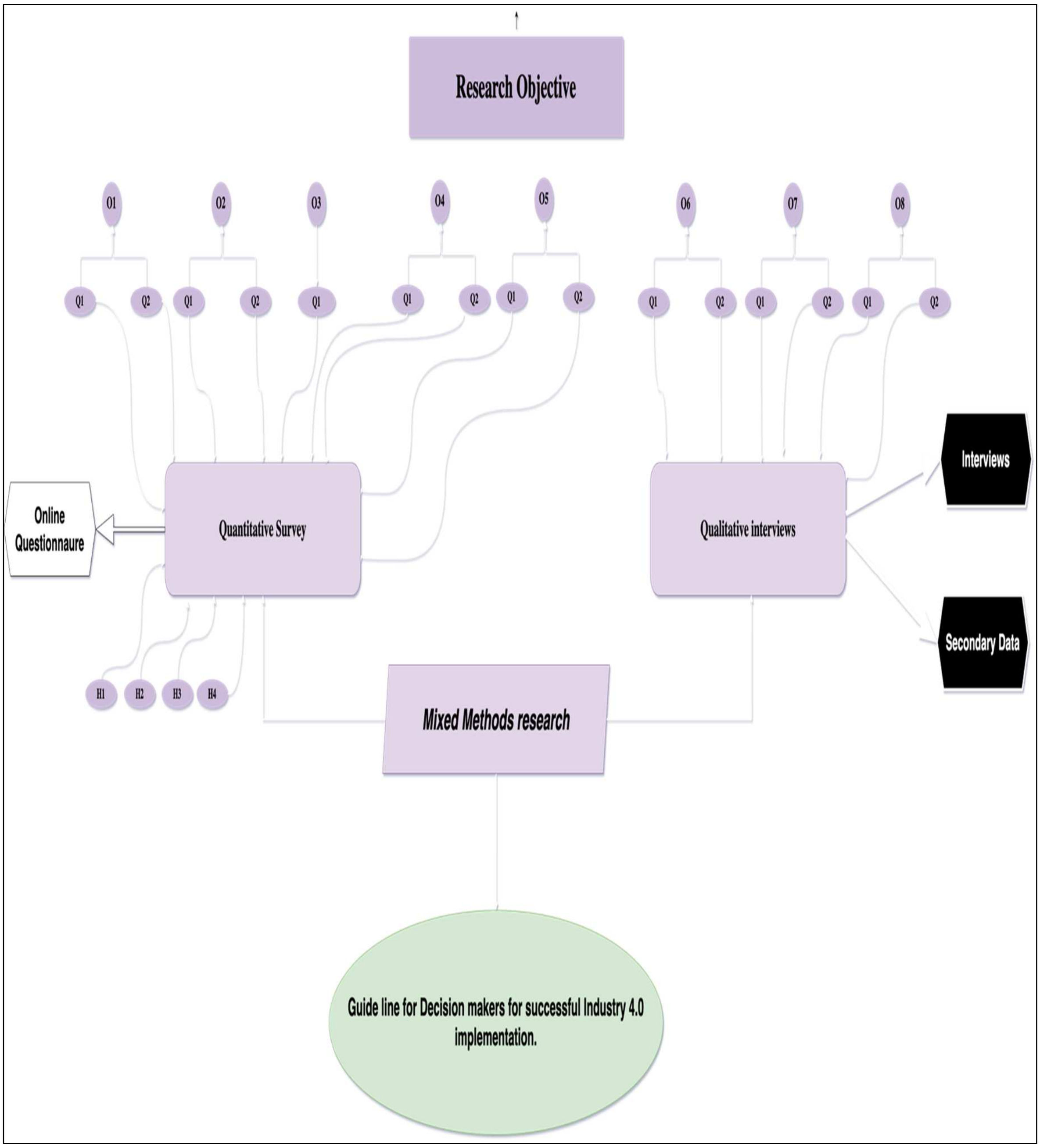
3. METHODOLOGY

3.1 Research structure

This study is organized around eight sub-objectives, each integral to achieving the main goal of providing decision-makers with a well-structured guide for implementing industry 4.0 and utilizing I4.0 technologies to tackle environmental sustainability challenges. Each sub-objective is associated with one or two questions that must be answered. Additionally, four hypotheses were formulated to guide the quantitative aspect of the research. Figure 22 illustrates the research structure, which is built upon the framework presented in Table 1 in the introduction section.

Outlined in the Figure 22 are eight distinct objectives, with five set for resolution through quantitative research, specifically employing an online questionnaire directed at the target group. The quantitative phase will be guided by four hypotheses. Concurrently, three objectives will be addressed qualitatively, involving interviews with industry experts in a big company, supplemented by pertinent secondary data. This mixed-methods approach ensures a comprehensive and nuanced exploration of the research objectives.

Figure 22*: Overview of the research methodology*



Source: Own research

3.2 Hypothesis formulation

As part of the quantitative research, five objectives were formulated to guide this part. The hypotheses were developed to complement these objectives and to gain detailed insights into the differences between SMEs and large companies, differences that could not be discerned without the formulation of specific hypotheses. For instance, as shown in Table 1, Hypotheses H01 and H02 are derived from Objectives 1, 2, and 5. To illustrate, Objective 2 aims to assess the motivations for Industry 4.0 investments and to evaluate the extent to which these investments prioritize environmental sustainability. From this objective, Hypothesis H04 was formulated: "There is no significant difference in the underlying reasons for investment in Industry 4.0 for environmental sustainability between large companies and SMEs at the 0.05 significance level." While the objective seeks to identify the motivators for companies to invest in Industry 4.0, the hypothesis specifically tests whether there is a difference in these motivations between large companies and SMEs. This structured approach ensures that each hypothesis is directly linked to a research objective, providing a clear framework for the analysis. Based on Objectives 1 to 5, the following hypotheses were formulated to guide the detailed analysis of the differences between SMEs and large companies:

H01: There is no association between the intention to invest in Industry 4.0 in the future and the type of company (SMEs and large enterprises) at the 0.05 significance level.

H02: There is no significant difference in the overall distribution of technologies used by companies (both current adopters and future investors) between SMEs and large companies at the 0.05 significance level.

H03: There is no significant difference in the overall distribution of challenges faced by companies that do not currently invest in Industry 4.0, whether they wish to invest in the future or not, between SMEs and large companies at the 0.05 significance level.

H04: There is no significant difference in the underlying reasons for investment in Industry 4.0 for environmental sustainability between large companies and SMEs at the 0.05 significance level.

3.3 Mixed-Methods Research Design

Our study adopts a Mixed Methods Research design to comprehensively investigate the utilization of Industry 4.0, with a particular focus on how it contributes to environmental sustainability. Initially, a quantitative study is employed to explore the general landscape, identifying primary challenges, objectives, and technologies associated with Industry 4.0.

Subsequently, these quantitative findings inform our qualitative research, enabling a deeper examination of specific challenges and technologies aligned with each objective.

This methodological choice aligns with established practices in the literature, as articulated by (Migiro & Magangi, 2011). The mixed methods approach combines quantitative techniques as shown in Figure 23, involving the analysis of numerical data to test correlations and validate hypotheses (Charles, 1998), with qualitative investigation adopting a constructivist approach (Denzin et al., 2006).

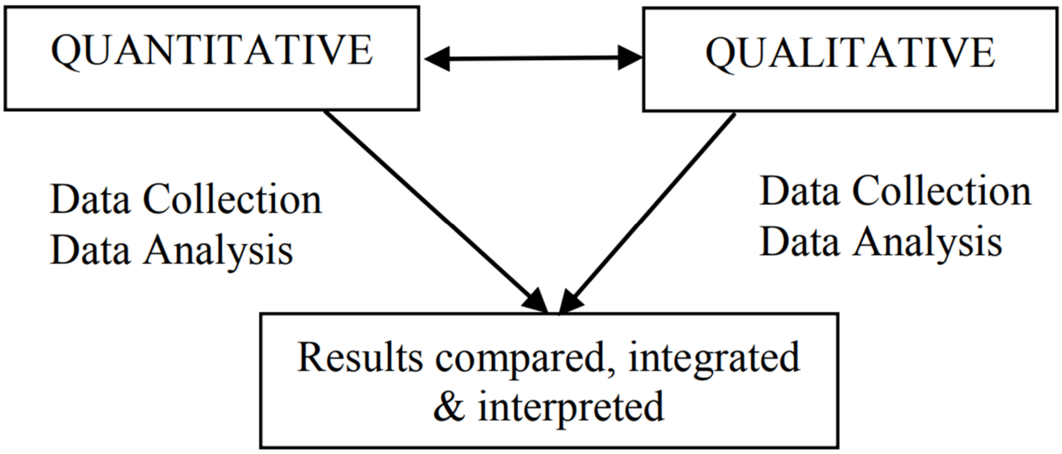


Figure 23: ***Graphic Representation of the Mixed-Methods Approach***

Source: (Atif et al., 2013)

Qualitative research, as a constructivist endeavor, seeks to comprehend significant trends such as the intersection of Industry 4.0 and environmental sustainability, a defining trend of the current era.

The study's overarching questions are designed to explore participants' experiences, necessitating a qualitative lens (Cresswell et al., 2012), and guided by the principle of small sample sizes for in-depth understanding (Patton, 2002). Mixing methods occurs throughout the study, specifically during the development of interview questions to shape research outcomes and during the interpretation phase, aligning challenges identified from quantitative data with qualitative insights obtained through interviews.

According to (Migiro & Magangi, 2011), a mixed-methods approach provides a more comprehensive answer to study questions by avoiding reliance on a single method. It allows researchers to leverage the strengths of each approach, compensating for their respective limitations. The synergy of qualitative and quantitative research, through convergent and corroborated findings, yields valuable insights that inform both theory and practice, contributing to a richer understanding of the complex phenomenon under investigation.

3.3.1 Quantitative phase: Survey-based Exploration

The quantitative methodology employed in this study aims to address five sub-objectives outlined by eight research questions and four hypotheses.

Following the framework proposed by (Aliaga & Gunderson, 1999), quantitative research methods are used to understand and explain issues or phenomena by systematically collecting numerical data and subjecting it to mathematical analysis. At the core of this approach is the goal of comprehensively grasping and clarifying the main issue.

Based on this reasoning, our research primarily focuses on unraveling the details of Industry 4.0 from a business perspective. This involves exploring essential aspects such as the extent of investment in Industry 4.0, prevalent technologies, and the objectives and challenges associated with such investments. The overarching goal is to gain a holistic understanding of the current state of Industry 4.0.

Quantitative research, as defined by (Leedy & Ormrod, 1980), revolves around the systematic collection of data that can be quantified and subjected to statistical analysis, contributing to the validation or refutation of competing knowledge claims. Consequently, every piece of data gathered in our study is meticulously designed to be quantifiable, ensuring that it is amenable to rigorous statistical scrutiny. The procedural steps followed in achieving this are:

- **<u>Step 1: Questionnaire preparation</u>**

At the start of the survey, participants were initially asked whether they use industry 4.0. Subsequent questions depended on their response; for instance, if they answered "NO," the following question inquired about their future interest in investing in industry 4.0. If the response remained negative, the survey concluded. If they expressed interest, they were then prompted to share their views on the challenges and reasons behind their intention to invest.

To explore the objectives associated with this investment, questions focused on underlying reasons were framed using a 6-point Likert scale, ranging from 0 (not interested in this objective) to 5 (considered one of the main reasons for the investment). Personal or company-related inquiries were intentionally avoided, as all pertinent information is already available in the detailed database, which will be further explained in the subsequent step. The only required question pertained to providing their email for correspondence with the relevant person in the database. Appendix 1 presents the questionnaire in details.

- **Step 2: Data Collection and Sampling Methodology**

The database utilized in this thesis was compiled using a Lead Generation methodology, wherein over 1,000 contacts were gathered from LinkedIn and the official websites of companies. This task was performed by a freelancer from the platform Fiverr. The companies included in the survey were located in the UK, Germany, the Netherlands, and France, countries recognized as leaders in Industry 4.0 investments. Limiting the database to Europe ensured coherence and relevance. The contacts were selected based on their positions, specifically targeting Production Managers, Plant Managers, Supply Chain Managers, Logistics Managers, IT Agents, and CEOs (limited to SMEs). These roles were chosen because individuals in these positions are likely to have significant knowledge about their companies' Industry 4.0 strategies.

The raw data was recorded in an Excel sheet, which included details such as company name, location, industry, contact name, position, email address, LinkedIn profile, and the number of employees. Companies were categorized as SMEs or large entities based on their number of employees: those with fewer than 200 employees were classified as SMEs, while those with more were considered large entities. The industries of the companies were not a primary focus, as a broad overview of the situation was needed. However, all the companies fell into one of three categories: manufacturing, logistics, or information technology.

The survey was distributed via Google Forms, initially yielding a low response rate. To improve participation, the survey was repeatedly sent out, ensuring a balance between responses from SMEs and large companies. Ultimately, responses were obtained from 205 companies: 117 from large companies (57%) and 88 from SMEs (43%). In some instances, contacts were also approached through LinkedIn to encourage participation.

- **<u>Step 3: Mails sending</u>**

Due to the substantial volume of data, the email dispatch process was automated using a platform called Integromat. This platform allows the execution of a predefined algorithm or scenario. The variables that underwent changes in each email were the name of the contact and their respective position. The emails were sent out during the period from the 1st to the 25th of July 2021.

- **<u>Step 4: Data collection and analysis</u>**

The information was gathered through a Google form, yielding 205 responses with an 18% response rate. Although this might seem low, it's worth noting that participants were not contacted prior to the survey, making the response rate acceptable in this context. The analysis and interpretation of the collected data were carried out using SPSS.

3.3.2 Qualitative study: in-Depth Case study of a large company

The second phase of our thesis employs a qualitative approach, specifically utilizing a single case study, to address the sub-objectives O6, O7, and O8 These objectives seek to analyze a leading company's successful implementation of Industry 4.0 (O6), investigate the strategies employed to overcome common challenges in Industry 4.0 implementation (O7), and document the objectives successfully achieved by a company through Industry 4.0 investment (O8).

Case study research has gained prominence among qualitative academics, especially when the aim is to comprehend a complex phenomenon within its real-life context (Thomas, 2011; Yin, 2018b). In the context of our research, the complex phenomenon under investigation is the successful implementation of Industry 4.0 and its effects on environmental sustainability within the information technology industry.

Given the scarcity of existing case study research discussing the impacts of Industry 4.0 on environmental sustainability, our study aims to fill this gap by exploring how the selected firm navigated challenges during the digital transformation phase. The focus is on understanding the potential utilization of Industry 4.0 technologies to enhance the efficacy and efficiency of the organization's strategy for environmental sustainability.

This qualitative approach is justified for several reasons. Firstly, a single case study provides an in-depth examination of a particular phenomenon, allowing for a nuanced understanding of the successful implementation of Industry 4.0 (Doz, 2011). Secondly, in addressing our sub-objectives (O6, O7, O8), a single case study design allows us to delve deeply into the specific strategies used by the chosen firm, offering richer insights than a multi-case study design would permit.

Moreover, the single case study approach aligns with the exploratory nature of our research, as it is particularly useful for understanding new and emerging phenomena such as Industry 4.0 and its impact on environmental sustainability (Eisenhardt, 1989). The chosen methodology will enable us to explore and document the details of the challenges encountered, the strategies employed, and the factors that contributed to the firm's success in implementing Industry 4.0.

By adopting a single case study approach, the aim is to provide not only a comprehensive analysis of the firm under study but also to contribute novel insights to the broader literature on Industry 4.0 and environmental sustainability. This methodology ensures a focused, detailed exploration of our research questions, fulfilling the objectives outlined in O6, O7, and O8, and advancing our understanding of the relationship between Industry 4.0 implementation and environmental sustainability. More concretely, Figure 24 illustrates our qualitative approach strategy.

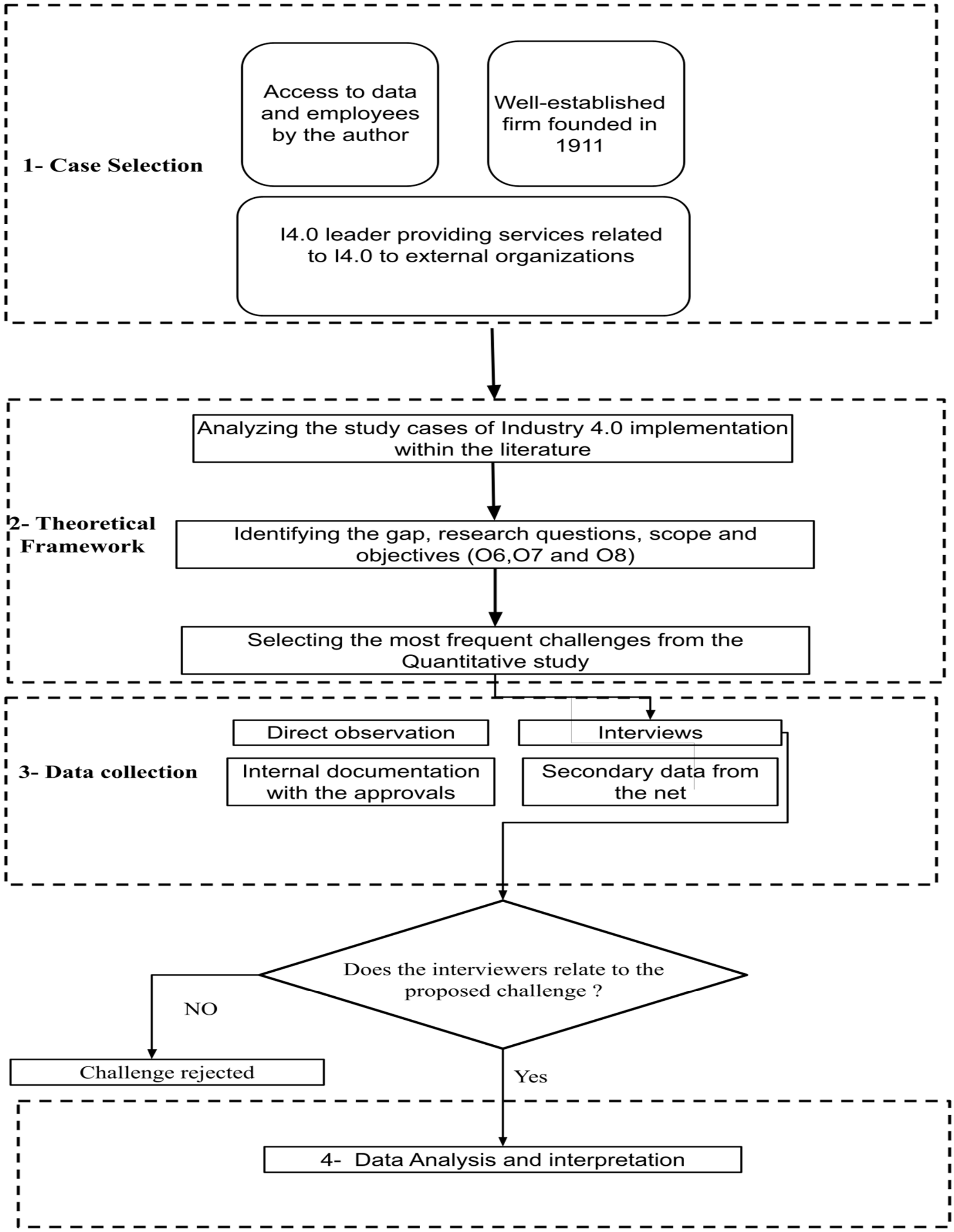


Figure 24*: Qualitative Research Steps*

Source: Own research

- Case selection:

The chosen firm is a well-established firm founded in 1911, operating in the information technology industry, currently employs about 345.000 employees, and is a leader in Industry 4.0 services; this particular firm was chosen for several reasons. Firstly, the author is an employee of the firm, which allowed us to gain access to the firm's data and employees, facilitating online interviews with experts and in-depth analysis of the firm's Industry 4.0 implementation. Additionally, this firm's long history of success and expertise in Industry 4.0 services made it an ideal subject for our study. Finally, given that our study focused on Industry 4.0 implementation from a business perspective and it use to enhance environmental sustainability, valuable insights into the challenges and opportunities of implementing Industry 4.0 and the impact achieved so far, particularly on environmental sustainability, are believed to be provided by this firm's specialization in AI and IoT.

- Theoretical Framework:

For the second step of the methodology, a theoretical framework was developed, combined with the results of the quantitative study, to guide the analysis of Industry 4.0 implementation. This process involved several sub-steps, including the analysis of existing case studies of Industry 4.0 implementation in the literature to identify the state of research in this area and to understand the challenges that other firms have faced, mainly based on the quantitative study. The analysis was utilized to identify research gaps, questions, scope, and the three sub-objectives that would guide the qualitative part of the study. Additionally, the most relevant challenges from the quantitative study were selected as a starting point for the analysis, which was refined through the interview process.

- Data collection:

For the qualitative part data collection, a combination of direct observation, online interviews, internal documentation, and secondary data analysis was employed. The observation component entailed visiting the firm's premises and observing the operations and processes related to Industry 4.0 operations. Regarding the interviews, a semi-structured approach was utilized to gather insights from key stakeholders involved in the implementation process and three of its customers. In Table 20, a comprehensive overview of the expertise of the interviewees who participated in the study is provided. The selection of interviewees was based on a crucial criterion: active involvement in a program within the company dedicated to technological development. This program involves participants who contribute to the company's website by publishing articles on the technologies used by the company. Notably, the chosen participants have authored articles specifically examining the utilization of these technologies for environmental sustainability purposes. The interviews are ranging between 30 minutes to 1 hour and 15 minutes and the interviewees comprise not only internal professionals with various expertises, but also the firm’s customers who have directly benefited from the industry 4.0 solutions provided by the main company. Their diverse perspectives and experiences have been instrumental in shaping our understanding of the transformative impact of these services in the modern business landscape. The internal documentation was obtained with the firm's approval, and included reports, memos, and other materials that provided information on the implementation process and outcomes.

Finally, secondary data analysis was conducted from internal documentation and available documents on the internet to supplement our primary data sources. Our data collection methods were informed by previous research on case study methodology (Yin, 2018a) and mixed-methods research (Creswell & Clark, 2017), and were designed to provide a comprehensive understanding of the challenges, strategies, and outcomes of Industry 4.0 implementation in the context of the selected firm.

Table 20*: Participant Profile Overview*

Position	Number	Firm	Length (min)
Global Research Leader for Industrial products	**2**	**Firm under study**	**48mn & 39mn**
Business Development Executive	**1**	**Firm under study**	**65mn**
Senior Research director	**1**	**Firm under study**	**32mn**
Global Application Modernization and Development Leader	**1**	**Firm under study**	**58mn**
Cloud Solution Architect	**2**	**Firm under study**	**36mn & 41mn**
Transformation Consultant, Cloud Advisory	**2**	**Firm under study**	**55mn & 47mn**
Industry 4.0 Architect	**1**	**Firm under study**	**78mn**
Chief sustainability officer	**1**	**Firm under study**	**45mn**
COO	**1**	**Customer A**	**37mn**
Project Manager	**1**	**Customer B**	**81mn**
Departmental manager	**1**	**Customer C**	**59mn**
SUM	**14**		**721mn**

Source: Own research

3.4 Data analysis

In our research, a comprehensive data analysis approach was embraced, seamlessly applying mixed- methods approach by integrating both quantitative and qualitative methodologies to unveil the complexities of Industry 4.0 adoption and its correlation with environmental sustainability.

The initial quantitative phase, facilitated by statistical analysis using SPSS, provided a broad understanding of Industry 4.0 implementation. Survey responses from 205 companies, including 88 SMEs and 117 large companies, contributed significant quantitative data. Key metrics such as the level of Industry 4.0 usage, adopted technologies, investment objectives, and prevalent challenges were quantified.

Building upon this quantitative foundation, the subsequent qualitative phase strategically shaped interview questions. Drawing inspiration from the challenges identified in the quantitative study, our qualitative approach aimed to dig deeper into specific aspects of Industry 4.0 implementation. This strategy allowed for an in-depth exploration, with a specific focus on understanding the company under study overcome the most common obstacles. The intersection of quantitative and qualitative findings played a pivotal role in our analysis. Challenges identified quantitatively provided a roadmap for the qualitative exploration, offering a deeper understanding of the strategies employed by the company to navigate these challenges. Additionally, technologies of interest highlighted in the quantitative study directed the qualitative inquiry, shedding light on practical applications and successes associated with these technologies.

Synthesizing insights from both approaches, the analysis concluded in the fulfillment of our main research objective. A practical roadmap was precisely crafted, offering decision-makers valuable guidance to navigate the challenges of Industry 4.0 implementation and align their initiatives with the imperatives of environmental sustainability. This integrated approach ensures a comprehensive understanding, contributing to a richer narrative that informs both theory and practice in the dynamic landscape of Industry 4.0.

3.5 Confidentiality and Informed Consent

To ensure the confidentiality and ethical handling of participant data in our study, in the quantitative phase, LinkedIn profiles were checked to verify the alignment with the information in our raw database, specifically for job positions and the country of residence, without disclosing personal details publicly. The questionnaire explicitly stated that responses would be used for academic purposes, maintaining participant anonymity. For the qualitative phase, HR approval was obtained for internal interviews, and organizational guidelines for the use of internal documentation were adhered to. Participants were informed about the academic use of the data, with a commitment to keeping their identities confidential. Nevertheless, this did not compromise the quality of our results, as will be demonstrated in the following discussion.

3.6 Statistical analysis tools

- *Chi-square test:*

The Chi-square test is a statistical method used to determine if there is a significant association between two categorical variables (McHugh, 2013). It evaluates the independence of these variables by comparing the observed frequencies in each category to the frequencies expected if there were no association (Loriaux, 1971). This test is suitable for our study as it assesses the relationship between company type (SMEs and large enterprises) and their intention to invest in Industry 4.0. The first hypothesis will be tested by using SPSS for the Chi-square test.

- *Normality test*:

The normality test is used to determine whether a dataset follows a normal distribution, which is the base for many parametric statistical tests (Razali & Wah, 2011). In our study, we created a composite variable by calculating mean scores for five objectives related to environmental impact. We conducted normality tests on these mean scores using both the Shapiro-Wilk and Kolmogorov-Smirnov tests. These tests assess if our data is normally distributed or no, informing our choice of appropriate statistical methods.

- *Mann-Whitney U Test:*

The Mann-Whitney U test is a non-parametric statistical test used to compare differences between two independent groups when the assumptions of normality are not met (Daniel & Cross, 2018). This test is particularly effective for ordinal data or continuous data that do not follow a normal distribution. The use of Mann-Whitney U test in this study is justified by the non-normal distribution of our composite variable measuring environmental objectives, making the Mann-Whitney U test the appropriate tool for our analysis.

4. RESULTS

In the following section, research findings are shared using a mixed-methods approach. The quantitative results are presented first, addressing the first five sub-objectives and examining four hypotheses. Subsequently, the qualitative phase is delved into to address the remaining three sub-objectives.

4.1 quantitative study

4.1.1 Empirical research result on the use of Industry 4.0 for SMEs and large companies

Out of the 205 survey responses, a majority of 117 (57%) represent large companies, while 88 (43%) are from Small and Medium-sized Enterprises (SMEs).
Generally, to categorize a company as an SME or large company, various criteria are considered. However, in many instances, the upper limit for an SME is typically around 250 employees. It's worth noting that in some countries, the threshold may be set at 200 employees (CFI Team, 2020). In our study, due to the organization of the raw data at our disposal, businesses with 200 or fewer employees will be categorized as Small and Medium-sized Enterprises (SMEs), while those with more than 200 employees will be designated as large companies.
The survey participants hold diverse roles within their organizations, with 47% identifying as Supply Chain Managers (or similar positions), 16% as IT Managers, 12% as Logistics Managers, 11% as CEOs, 10% as Plant Managers, and 4% in other positions. Geographically, the distribution of respondents is 38% from the Netherlands, 29% from Germany, 14% from the UK, and 19% from France.

4.1.2 The landscape of industry 4.0 adoption

This section will be guided by O1: Examine the current extent of Industry 4.0 adoption among companies, and H1: There is no association between the intention to invest in Industry 4.0 in the future and the type of company (SMEs and large enterprises) at the 0.05 significance level.

To address the question of the level of Industry 4.0 adoption, the inquiry posed to participants was straightforward: 'Do you consider yourself an Industry 4.0 user?' The rationale behind this lies in determining whether a company falls under the category of Industry 4.0 adopters, a complex and somewhat ambiguous task (Aromaa et al., 2019). Several authors assert that a company can be deemed an Industry 4.0 user if its main strategy involves a transition from traditional methods to Industry 4.0 (Toni et al., 2021). Following this line of reasoning, the results of the first two questions are as follows:

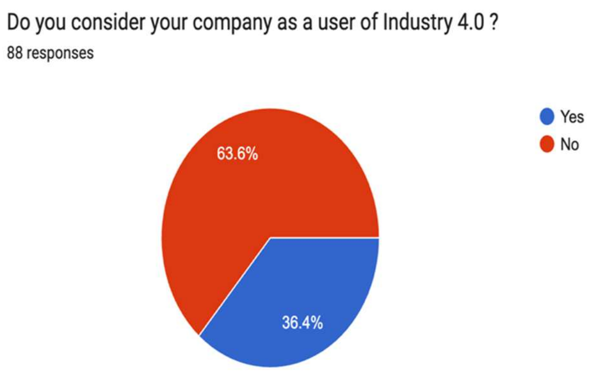


Figure 26*: industry 4.0 users for SMEs*

Source: Own research

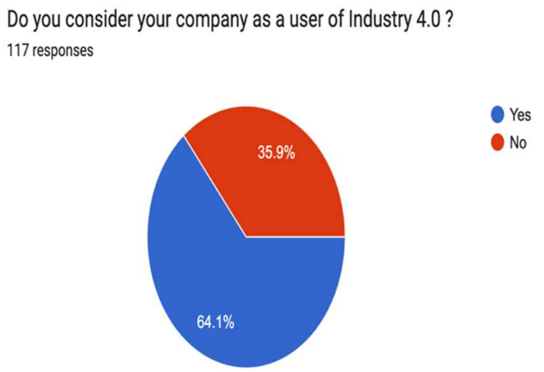


Figure 25*: industry 4.0 users for large companies*

Source: Own research

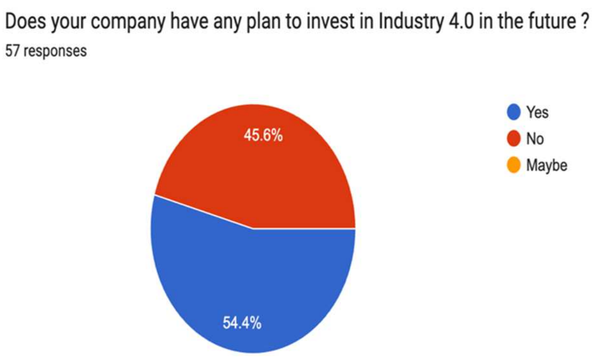


Figure 27*: Industry 4.0 Interest Among Non-User SMEs*

Source: Own research

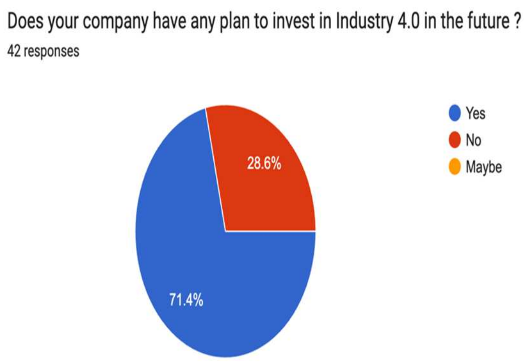


Figure 28*: Industry 4.0 Interest Among Large Non-User Companies*

Source: Own research

It's noteworthy to mention that the second question was exclusively presented to participants responding with a 'No'. If the response was 'Yes,' a subsequent inquiry related to the objectives was administered, and its discussion will follow in the next section. If a participant answered 'No' to both questions, the participant get forwarded directly to the challenges section.

The survey results highlight notable trends in Industry 4.0 adoption among both SMEs and large companies. For SMEs, a substantial percentage (63.6%) currently identifies as non-users of Industry 4.0. Among this group, almost half (45.6%) express hesitancy towards future investments in Industry 4.0, while the remaining 54.5% display an interest in incorporating these technologies in their future strategies. This indicates a nuanced landscape among SMEs, with a sizable proportion considering future Industry 4.0 adoption. On the other hand, large companies exhibit a higher initial adoption rate, with 64.1% identifying as Industry 4.0 users. Interestingly, among those initially reporting non-usage, a considerable majority (71.4%) express intentions to invest in Industry 4.0 in the future. This suggests that, even among large companies not currently utilizing Industry 4.0, there is a significant inclination towards future adoption and investment, emphasizing the evolving nature of Industry 4.0 strategies across different company sizes.

4.1.2.1 Chi-square test

To test our null hypothesis, which posits no association between the intention to invest in Industry 4.0 in the future and the type of company (SMEs and large enterprises) at the 0.05 significance level, the Chi-square test using SPSS was chosen. The analysis involved the creation of a crosstabulation that considered two key variables: the type of the company and future investment plans (coded as 0 for 'no' and 1 for 'yes'). The following summarizes the results:

Table 21*: Chi-square test result to investigate the first hypothesis*

Chi-Square Tests	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	.224[a]	1	.636		
Continuity Correction[b]	.046	1	.830		
Likelihood Ratio	.225	1	.635		
Fisher's Exact Test				.797	.417
Linear-by-Linear Association	.221	1	.638		
N of Valid Cases	83				

Source: Own research

The p-values, obtained from both Fisher's Exact Test and various asymptotic methods, consistently indicate that there is no statistically significant association between the type of company (SMEs or large enterprises) and their intention to invest in Industry 4.0 in the future among those who currently do not use it. The lack of significance suggests that, at the current stage, company size does not seem to influence the likelihood of having future investment plans in Industry 4.0 among non-users. As the obtained p-values exceed the predetermined significance level of 0.05, sufficient evidence to reject the null hypothesis is not found. Therefore, the hypothesis that there is no significant difference in future investment plans between SMEs and large enterprises among those who currently do not use Industry 4.0 is not rejected.

4.1.3 Comprehensive Look at Industry 4.0 Ambitions and Objectives

This paragraph will be guided by two sub-objectives: O2: Assess the motivations for Industry 4.0 investments and evaluate the extent to which these investments prioritize environmental sustainability and O.5: Differentiate desired objectives from Industry 4.0 between large companies and SMEs and assessing the emphasis on achieving environmental sustainability objectives in each category.
Furthermore, the fourth hypothesis will be tested, examining whether a significant difference exists in the underlying reasons for investing in Industry 4.0 for environmental sustainability

between large companies and SMEs at the 0.05 significance level. To evaluate the intended outcomes of Industry 4.0 implementation, 13 objectives were presented to participants engaged in or planning to invest in Industry 4.0. These objectives cover various aspects such as efficiency, effectiveness, and social considerations. Notably, five of these objectives (Waste management, enhance resources efficiency (raw materials and energy), Reverse Logistics improvement, Environment harm reduction and Carbon emission reduction) pertain to the environmental aspect, which is the focal point of our investigation. Participants rated their responses on a 5-point Likert scale, ranging from 'Very High' (indicating one of the main objectives) to 'Very Low' (reflecting low interest in that outcome). If a proposed objective was deemed irrelevant, participants had the option to skip it. The results as follow:

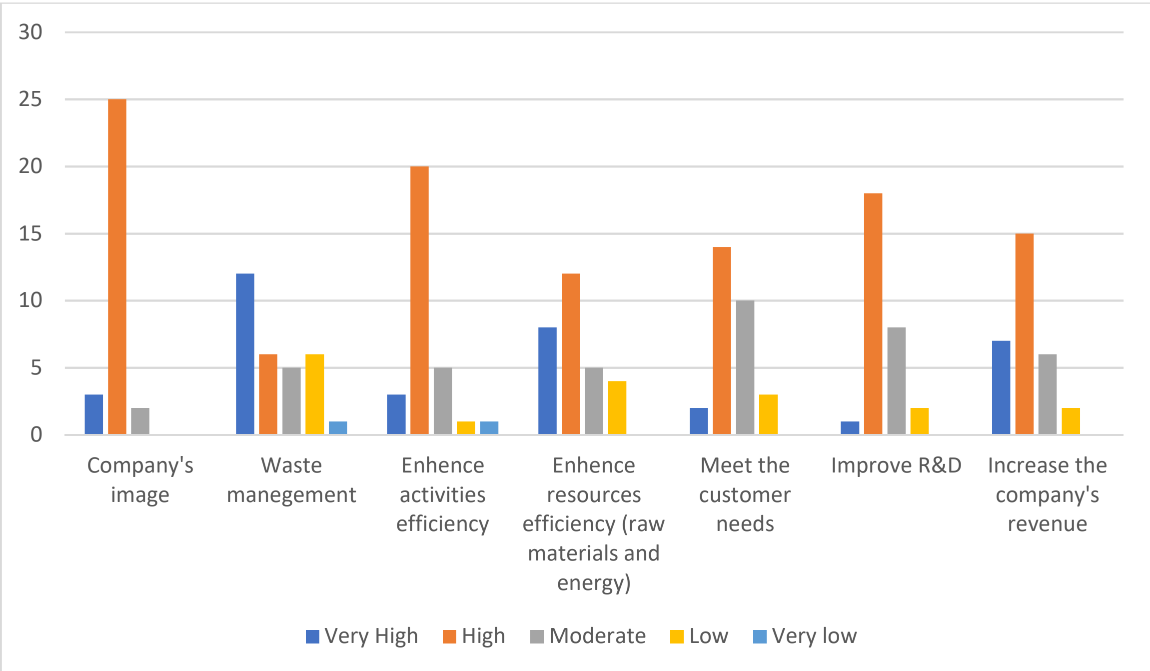


Figure 29*: Desired objectives from Large Companies (first part)*

Source: Own research

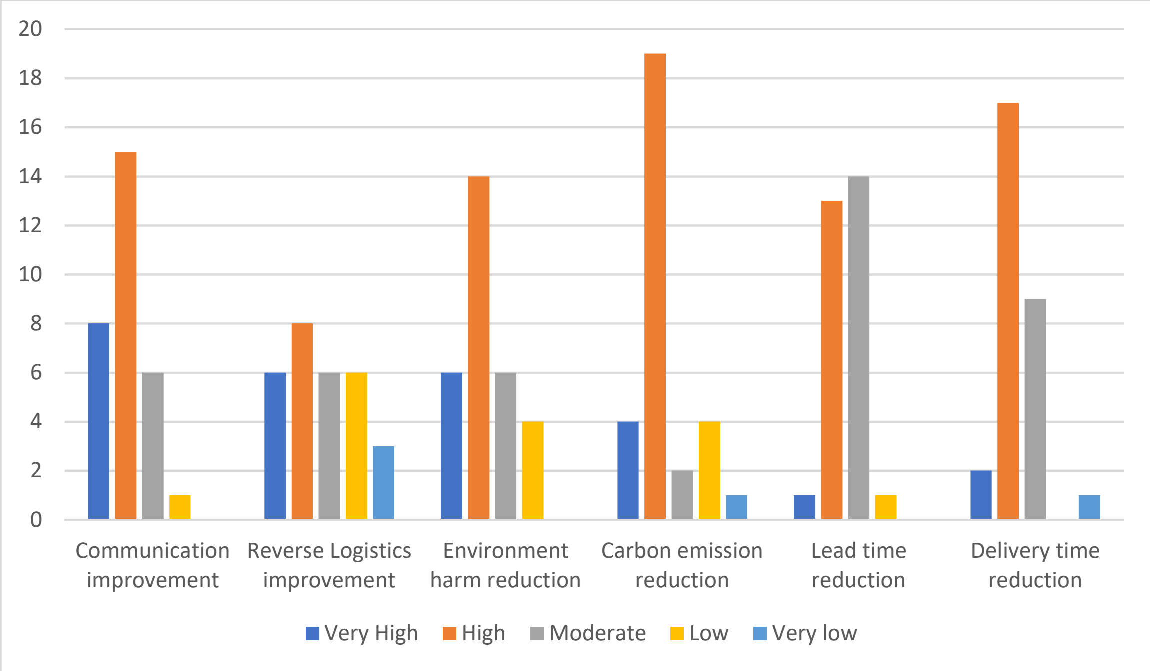


Figure 30*: Desired objectives from Large Companies (second part)*

Source: Own research

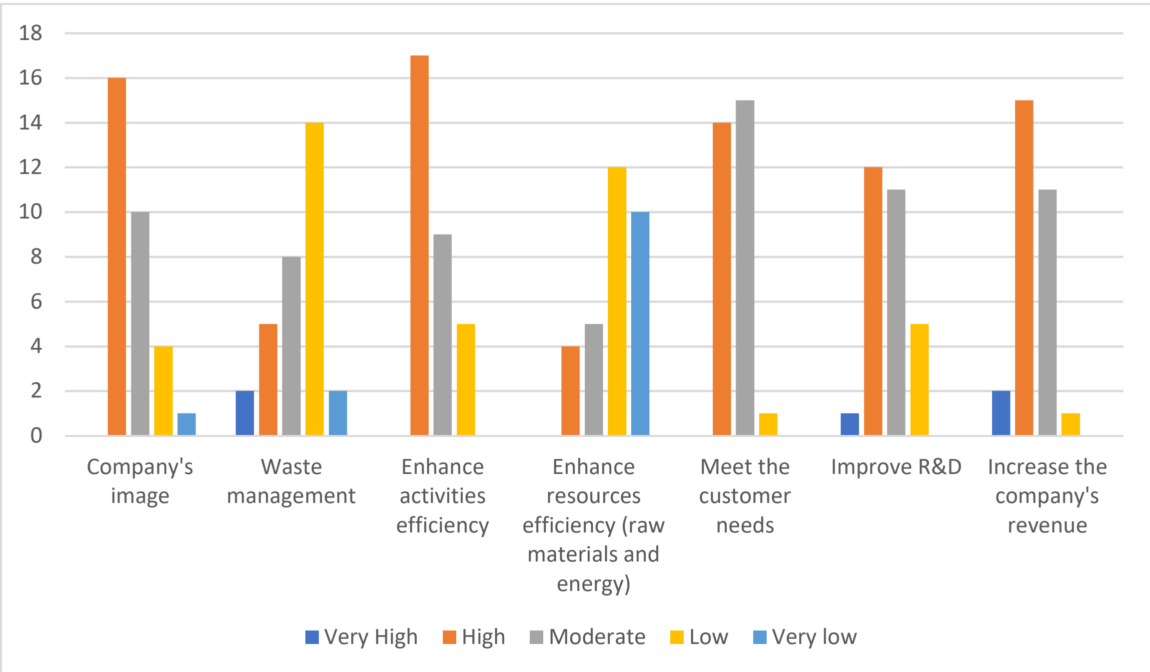


Figure 31*: Desired objectives from SMEs (first part)*

Source: Own research

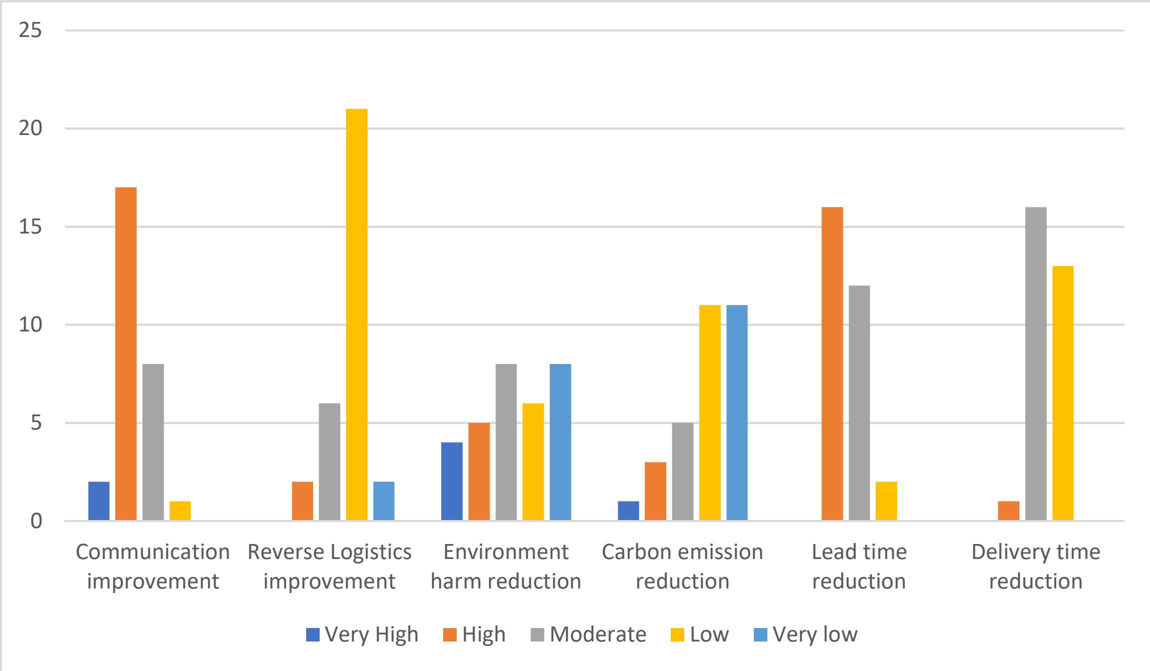


Figure 32***: Desired objectives from SMEs (second part)***

Source: Own research

In our initial analysis of Industry 4.0 adoption among participants from both large enterprises and SMEs, 2D column graphs were employed to visualize how each group rated the relevance of specific objectives. However, it is difficult to capture nuanced differences in importance among the objectives based on the graphs only. To overcome this limitation, a more comprehensive approach was opted for by calculating the mean for each objective. The formula used for the mean calculation is as follows:

$$\text{Mean} = \frac{\sum(Score\ of\ each\ response)}{Total\ number\ of\ participants\ engaged\ in\ the\ specific\ question}$$

Scores were assigned to responses, ranging from 5 for "Very High" to 1 for "Very Low," excluding responses marked as "Not Included at All" (assigned a score of 0). The mean was then calculated by summing these scores and dividing by the total number of participants who engaged in the specific question. The analysis was focused on participants who either confirmed current usage of Industry 4.0 or expressed plans to invest in it in the future. This targeted approach excluded those not considering Industry 4.0 integration in their strategic plans. Our dataset for this question comprises 105 responses from large enterprises and 63 from SMEs, providing a solid foundation for a detailed examination of mean scores. This refined approach helps us better understand and compare the priorities and perceptions of both large enterprises and SMEs regarding their Industry 4.0 investment objectives.

Table 22: Mean Ratings of Objectives by Participant Type (part 1)

Objectives	Company's image	Waste management	Enhance activities efficiency	Enhance resources efficiency (raw materials and energy)	Meet the customer needs	Improve R&D	Increase the company's revenue
Large companies	2.8	0.9	2.4	1.9	2.7	2.6	3.4
SMEs	1.8	0.3	1.7	1.03	4.1	0.9	4.1

Source: Own research

Table 23 Mean Ratings of Objectives by Participant Type (part 2)

Objectives	Communication improvement	Reverse Logistics improvement	Environment harm reduction	Carbon emission reduction	Lead time reduction	Delivery time reduction
Large companies	3.2	0.9	1.06	1.1	5.1	4.2
SMEs	1.7	1.1	1.3	0.2	2.3	1.7

Source: Own research

Table 22/23 reveals distinct priorities between large enterprises and SMEs in Industry 4.0 investments. For large companies, goals like "Reduction of Lead Time" and "Delivery Time Reduction" take precedence, indicated by high mean scores. In contrast, SMEs prioritize revenue growth and customer satisfaction, evident in higher mean scores for "Increasing Revenue" and "Meeting Customer Needs."

Concerning environmental objectives, large companies demonstrate a balanced commitment, with "Raw Materials and Energy Efficiency" leading with a mean score of 1.9. SMEs, however, display a lower priority for environmental sustainability. Notably, "Overall Environmental Impact Reduction" and "Reverse Logistics" receive mean scores of 1.3 and 1.1, respectively, indicating a lower emphasis compared to other objectives.

In summary, for both large and small enterprises, the data underscores that objectives related to efficiency, growth, and customer satisfaction are prioritized over environmental aspects in their Industry 4.0 investment strategies.

4.1.3.1 Normality and Mann-Whitney U tests for H4

Now to test our hypothesis regarding the examination of whether a significant difference exists in the underlying reasons for investing in Industry 4.0 for environmental sustainability between large companies and SMEs at the 0.05 significance level, a composite variable was created by calculating mean scores for five objectives related to environmental impact (Waste management, Enhance resources efficiency (raw materials and energy), Reverse Logistics improvement, Environment harm reduction and Carbon emission reduction). these objectives offer a consolidated measure of the willingness to invest in Industry 4.0 for environmental sustainability. To ensure the validity of subsequent statistical tests, a normality test was conducted on the distribution of mean scores using both the Shapiro-Wilk and Kolmogorov-Smirnov tests.

Table 24: Normality test for the "environmental sustainability" variable

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Sustainability	,240	168	,000	,797	168	,000

Source: Own research

In light of the non-normal distribution observed in the data, the selection of an appropriate statistical test becomes crucial. According to statistical methodologies advocated by (Daniel & Cross, 2018), the Mann-Whitney U test emerges as the preferred choice in situations where the assumptions of normality are not met. This test is specifically designed to compare two independent groups, making it well-suited for our analysis of the willingness to invest in Industry 4.0 for environmental sustainability among large companies and SMEs.

Table 25: Mann-Whitney U Test to test H4

Mann-Whitney U Test	
Sig.	0.115220898865203
Decision	Retain the null hypothesis.
Null Hypothesis	The distribution of Environmental Sustainability is the same across categories of Size.
Test	Independent-Samples Mann-Whitney U Test

Source: Own research

Upon conducting the Mann-Whitney U test, the obtained significance level was found to be 0.115, indicating that the results did not reach statistical significance ($p = 0.115$). The lack of statistical significance suggests that, in terms of the willingness to invest for environmental sustainability, no substantial divergence exists between large companies and SMEs. Consequently, the null hypothesis, which posits no significant difference in the underlying reasons for investing in Industry 4.0 for environmental sustainability between the two groups, is not rejected at the 0.05 significance level.

4.1.4 Industry 4.0 Challenges and the Dominant Technologies

This section will be guide by the third and the fourth sub-objectives which are investigating the prevalent technologies used in Industry 4.0 investments and analyzing the challenges and obstacles faced by Industry 4.0 adopters. This part will also test the two hypotheses that there is no significant difference in the overall distribution of technologies used by companies (both current adopters and future investors) between SMEs and large companies at the 0.05 significance level and there is no significant difference in the overall distribution of challenges faced by companies that do not currently invest in Industry 4.0, whether they wish to invest in the future or not, between SMEs and large companies at the 0.05 significance level. Examining Industry 4.0 technologies, a specific question targeted participants identifying as current users or those with future investment plans. The only distinction lies in the phrasing of the question, as illustrated in Figure 33, while the proposed technologies remained the same.

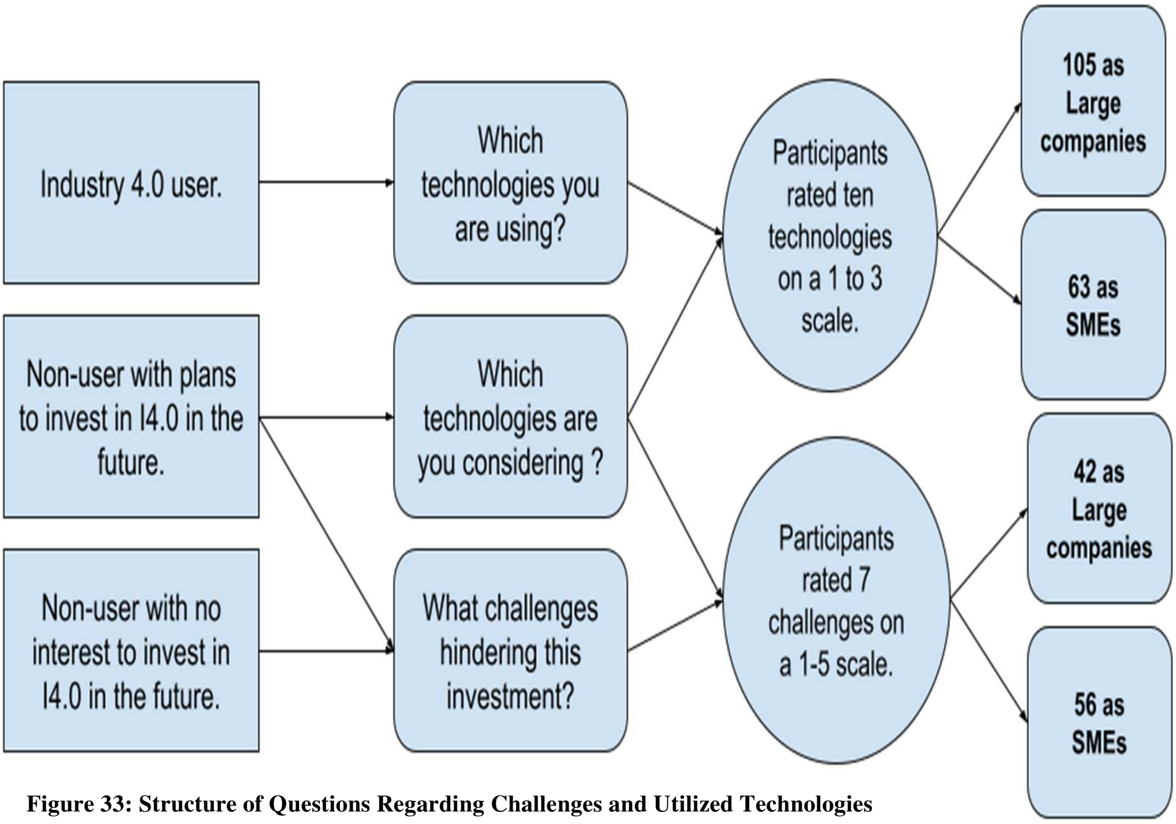


Figure 33: Structure of Questions Regarding Challenges and Utilized Technologies

Source: Own research

For the exploration of challenges and obstacles hindering the adoption of Industry 4.0, the corresponding question was tailored exclusively for participants falling into two categories: those responding negatively to both the current user and future investment questions (indicating no inclination towards Industry 4.0), and those answering negatively to the first question but affirmatively to the second (indicating a potential future interest in Industry 4.0). The category encompassing current users of Industry 4.0 was intentionally excluded from the challenges question. This decision aligns with the primary focus on companies yet to invest in Industry 4.0 and also ensures a smoother questionnaire experience. This approach was adopted to prevent an overwhelming survey structure for the category actively engaged in Industry 4.0.

The results regarding the most common technologies are as follows:

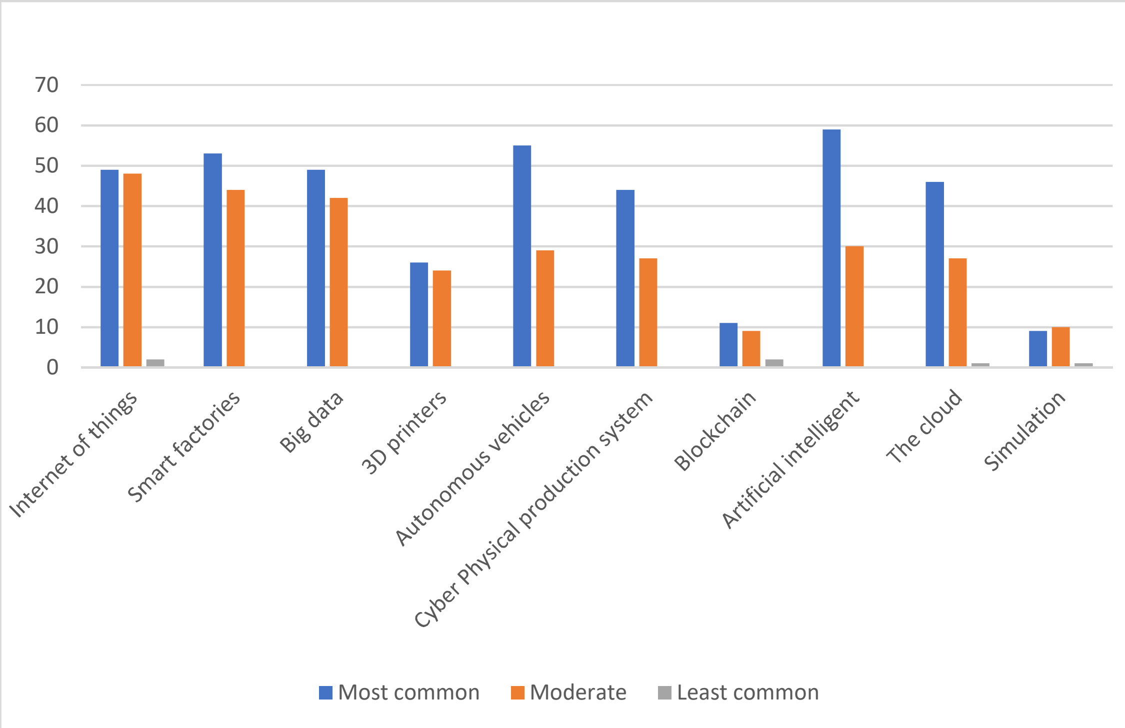


Figure 34: Most common technologies for large companies

Source: Own research

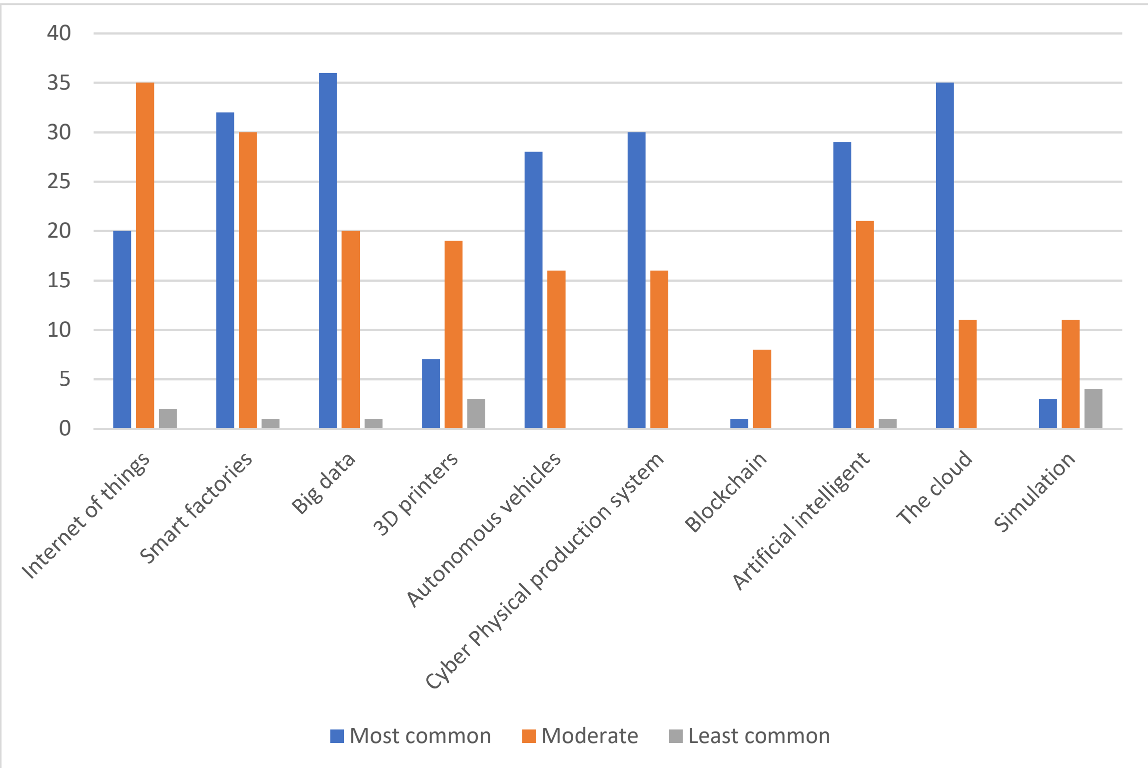


Figure 35: Most common technologies for SMEs

Source: Own research

Considering only the "most common technologies" option, it becomes evident that AI garners the highest interest among large companies, whereas for SMEs, the focus is on Big Data and the cloud. A more in-depth analysis using coefficients will be conducted for enhanced accuracy. The subsequent Figure 36 and Figure 37 illustrate the prevalent challenges among both large companies and SMEs.

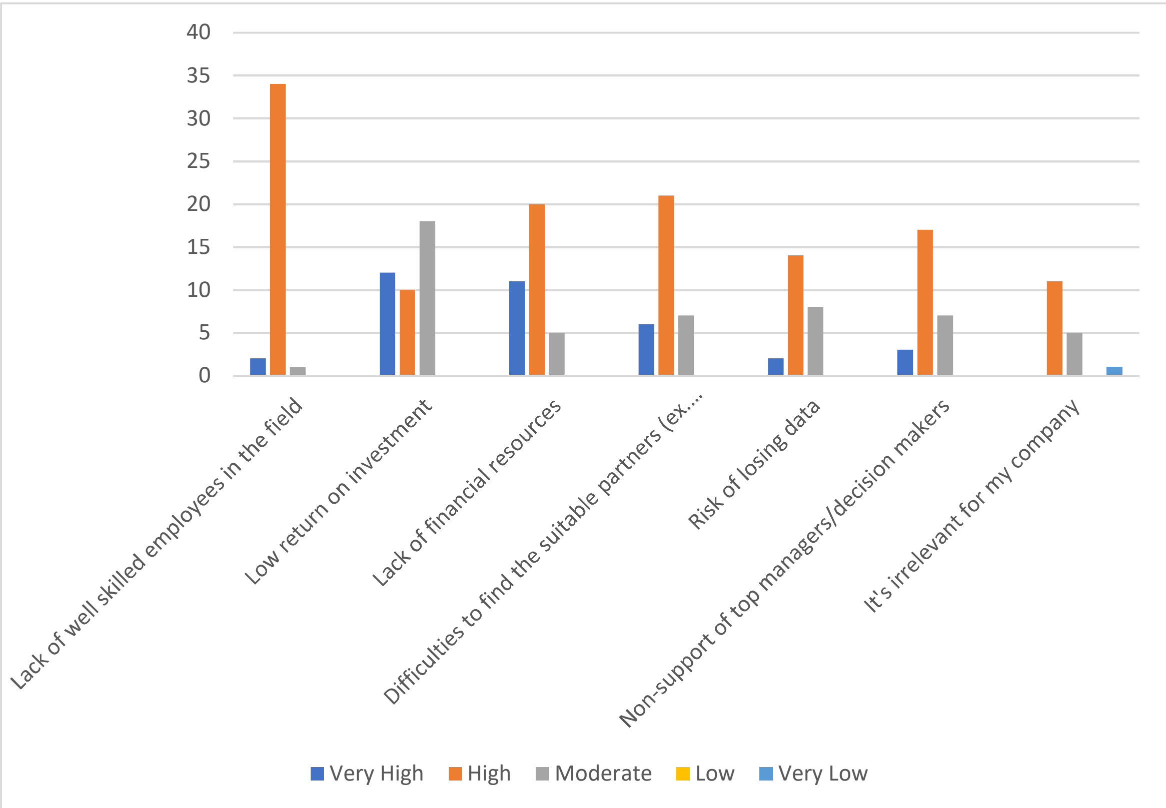


Figure 36: The most common challenges for Large companies

Source: Own research

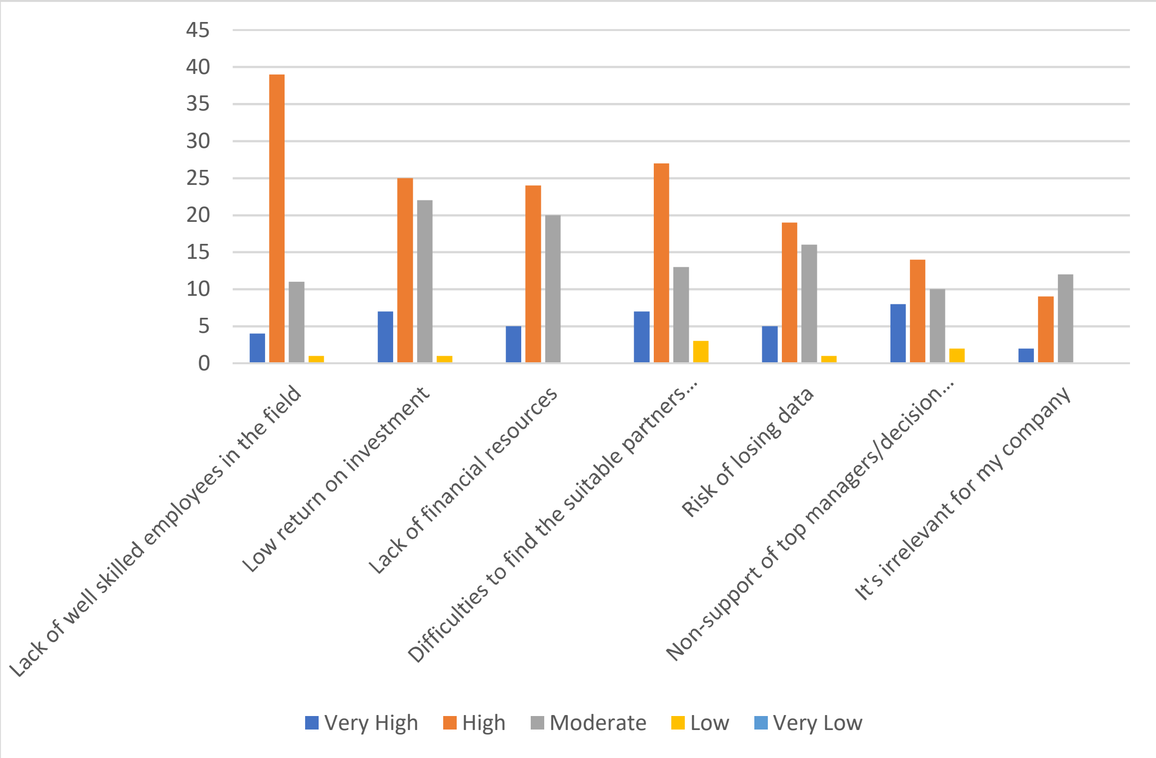


Figure 37: The most common challenges for SMEs

Source: Own research

To analyze our results, the mean will be computed for each technology and challenge, separately for both large companies and SMEs. This involves employing the following formula:

$$\text{Mean} = \frac{\sum(\textit{Score of each response})}{\textit{Total number of participants engaged in the specific question}}$$

For challenges, scores were assigned on a scale of 5 for "Very High" to 1 for "Very Low," and for technologies, the scale ranged from 3 for "Highly Interested" to 1 for "Not That Interested," excluding responses marked as "Not Included at All" (assigned a score of 0). The mean was then computed by summing these scores and dividing by the total number of participants who engaged in the specific question. The results are shown in Table 26:

Table 26: mean score of the technologies used and most common challenges

Technologies	Internet of things	Smart factories	Big data	3D printers	Autonomous vehicles	Cyber Physical production system	Blockchain	Artificial intelligent	The cloud	Simulation
Large companies	2.1	1.9	2	0.9	1.7	1.6	0.4	2.2	1.8	0.5
SMEs	1.9	2.4	2	0.7	1.7	1.8	0.2	1.9	2	0.2
Challenges	**Lack of well skilled employees in the field**		**Low return on investment**	**Lack of financial resources**	**Difficulties to find the suitable partners (ex. Suppliers outsourcers…)**		**Risk of losing data**	**Non-support of top managers/decision makers**	**It's irrelevant for my company**	
Large companies	3.5		3.7	3.6	3.2		2.6	2.4	1.4	
SMEs	3.8		3.5	3.1	2.1		1.3	3.2	2.5	

Source: Own research

In calculating the total number of participants, the structure outlined in Figure 33 was adhered to, considering participants who affirmed their interest or involvement in Industry 4.0 technologies. This encompassed those who responded affirmatively to the first and those who answered negatively to the first but positively to the second. Among large companies, this category comprised 105 participants, while SMEs contributed 63. For the inquiry on the most prevalent challenges, it was directed towards companies not presently investing in Industry 4.0 or having no future investment plans (responding negatively to both first and second questions) and participants responding negatively to the first but affirmatively to the second. This category comprised 42 participants for large companies and 56 for SMEs.

Analyzing the results in Table 26, it can be observed that Internet of Things (IoT) and Artificial Intelligence (AI) emerge as the predominant technologies among large companies,

closely followed by Smart Factories, Big Data, and the Cloud. SMEs, on the other hand, exhibit a similar trend with Smart Factories leading, followed by IoT, AI, and the Cloud.
In examining the most prevalent challenges, Large Companies highlight Lack of Well-Skilled Employees, Low Return on Investment, and Limited Financial Resources, ranking closely in mean. Conversely, the perceived insignificance of Industry 4.0 ranked lowest. For SMEs, Lack of Well-Skilled Employees and Low Return on Investment are predominant, followed by Non-support from Top Managers/Decision Makers and Limited Financial Resources. The least encountered challenge for SMEs is the Risk of Data Loss.

4.1.4.1 Mann-Whitney U Test to examine H2

In this section, our second Hypothesis will be tested, implying that there is no significant difference in the overall distribution of technologies used by companies (both current adopters and future investors) between SMEs and large companies at the 0.05 significance level. Our analysis focuses on examining potential disparities in the overall distribution of technologies among companies, comprising both existing adopters and future investors. Attention is directed towards comparing Small and Medium-sized Enterprises (SMEs) and large companies, exploring whether their preferences for specific technologies exhibit significant divergence. For this investigation, the Mann-Whitney U test, a non-parametric method suitable for scenarios where assumptions of normality are violated or when dealing with ordinal data, was opted for. Our decision to employ the Mann-Whitney U test motivated by the nature of our dataset, which involved the ranking of 10 technologies on a scale from 1 to 3. This non-parametric test was appropriate due to its ability of handling ordinal data and its applicability when parametric test assumptions are not met.
The initial steps involved the preparation of data, with participants ranking each technology on a unique scale. After calculating the mean of participants' rankings for the 10 proposed technologies, the Mann-Whitney U test was then applied to assess the statistical significance of observed differences in mean rankings between the two groups as shown in Table 27.

Table 27: Mann-Whitney U Test to test H2

column	row	V3
Sig.	1	0.0138578483876921
Decision	1	Reject the null hypothesis.
Null Hypothesis	1	The distribution of Technologies Mean is the same across categories of Size.
Test	1	Independent-Samples Mann-Whitney U Test

Source: Own research

The results of the Mann-Whitney U test yielded a statistically significant p-value of 0.014. This outcome led to the rejection of the null hypothesis, indicating a meaningful distinction in the overall distribution of technologies between SMEs and large companies. The observed difference in distribution implies that SMEs and large companies exhibit varying preferences and levels of interest when ranking the proposed technologies, highlighting distinct patterns in their technological priorities. Considering the low p-value, the robust evidence against the null hypothesis is acknowledged.

4.1.4.2 Mann-Whitney U Test to examine H3

The same approach was followed to test H3 as was done for H4 and H2, employing the Mann-Whitney U test. This statistical analysis method was chosen to compare the overall distribution of challenges faced by Small and Medium-sized Enterprises (SMEs) and large companies during Industry 4.0 implementation. The decision to use the Mann-Whitney U test was based on the same reasons as for H3 and H4; the nature of the data, which involved Likert scale ratings for seven challenges. Given the ordinal nature of the data and potential non-normality, the Mann-Whitney U test, a non-parametric test, was deemed more appropriate for comparing distributions between SMEs and large companies. This test provides a robust analysis without assuming normality and is well-suited for ordinal data. To assess the challenges, the mean of Likert scale ratings across the seven distinct challenges was calculated for each participant. This test comprises participants who answered "no" to the first question, indicating that they are not current users of Industry 4.0. For the subsequent question about future investment plans in Industry 4.0, participants in this category provided

responses encompassing both "yes" and "no." There are 42 participants from large companies and 56 from Small and Medium-sized Enterprises (SMEs) in this category.
The Mann-Whitney U test results revealed a statistically significant difference between SMEs and large companies with a p value of 0.001.

Table 28: Mann-Whitney U Test to test H3

column	row	V3
Sig.	1	0.00130324647714186
Decision	1	Reject the null hypothesis.
Null Hypothesis	1	The distribution of ChallengesMean is the same across categories of Size.
Test	1	Independent-Samples Mann-Whitney U Test

Source: Own research

This significance indicates a substantial distinction in the challenges faced by SMEs and large companies, which allow us to reject the null hypothesis H03, emphasizing the need for tailored approaches in implementing Industry 4.0 strategies based on organizational type.

4.1.5 Analysis

Valuable insights into the adoption of Industry 4.0 from a business perspective, particularly examining distinctions between large companies and SMEs, have been garnered.
Initiating our discussion with the accomplishment of the first sub-objective on the extent of Industry 4.0 adoption, it became evident that larger enterprises exhibit a greater inclination towards investing in Industry 4.0, a predictable trend. Nonetheless, it is noteworthy that a substantial 54.4% of SMEs have plans to integrate Industry 4.0 in the future.
Subsequently, our exploration delved into addressing the second and fifth sub-objectives. For large companies, factors such as lead time reduction, revenue enhancement, and communication improvement emerged as significant motivators for investing in Industry 4.0. Conversely, SMEs placed a high priority on revenue increase and meeting customer needs. The Mann-Whitney U test revealed a noteworthy similarity in the environmental investment objectives between SMEs and large companies, leading to the retention of our null hypothesis H04 as shown in table 29. However, a closer examination of our data in

Table 22/23 disclosed that mean values related to environmental objectives were comparatively lower than those for economic and social objectives, emphasizing that Industry 4.0 investments are predominantly driven by economic considerations.
Addressing the prevalence of industry 4.0 technologies and thus meeting the third sub-objective, our findings from Table 26 indicated that technologies such as AI, IoT, and smart factories dominated the landscape for both types of organizations. Surprisingly, Blockchain, despite its success in the realms of cryptocurrencies and smart contracts over the past decade, did not command significant attention from the participants. Furthermore, based on our man U test illustrated in Table 27, there is a substantial difference between SMEs and large companies regarding the technological choices in the context of industry 4.0, which allowed us to reject the null hypothesis H02.

Table: 29 Hypothesis overview

Hypothesis	Test type	Decision
H01: There is no association between the intention to invest in Industry 4.0 in the future and the type of company (SMEs and large enterprises) at the 0.05 significance level.	Chi-square test	Accepted
H02: There is no significant difference in the overall distribution of technologies used by companies (both current adopters and future investors) between SMEs and large companies at the 0.05 significance level.	Mann-Whitney U Test	Rejected
H03: There is no significant difference in the overall distribution of challenges faced by companies that do not currently invest in Industry 4.0, whether they wish to invest in the future or not, between SMEs and large companies at the 0.05 significance level.		Rejected
H04: There is no significant difference in the underlying reasons for investment in Industry 4.0 for environmental sustainability between large companies and SMEs at the 0.05 significance level.		Accepted

Source: Own research

Turning our attention to the challenges hindering companies from embracing Industry 4.0 (Sub objective 4 and H03), a notable distinction in distribution between SMEs and large companies emerged. Consequently, our subsequent section, offering guidance to overcome these challenges, proves more relevant to large companies. However, our examination of challenges (Table 28) reveals common obstacles for both large companies and SMEs, such as the lack of skilled employees and low return on investment.

As outlined in the introduction, our quantitative study serves as a foundation for shaping the challenges addressed in our qualitative study. The results indicate that all seven challenges identified in the quantitative study exert some level of influence on the decision to invest in Industry 4.0. Consequently, these challenges will form the basis for our qualitative study. Importantly, Figure 25 illustrates that interviewees will have the flexibility to omit discussion on specific challenges if they deem them irrelevant to their case study, and they also have the opportunity to introduce additional challenges.

4.2 Qualitative study

As previously outlined, this section will focus on O6, O7, and O8, representing the following sub-objectives: analyzing a leading company's successful implementation of Industry 4.0, investigating strategies employed to overcome common challenges in Industry 4.0 implementation, and documenting the environmental objectives successfully achieved by a company through Industry 4.0 investment, using qualitative methodology. Our study will leverage online interviews, internal documentation, and secondary data. Since the company under investigation operates as an Industry 4.0 solutions provider, online interviews were conducted with three of its customers to enhance our research. The upcoming section will delve into the details of the research steps and outcomes.

4.2.1 Case description

The firm under study, a pioneer in the information technology industry, is at the leading edge of digital transformation. This forward-thinking organization not only demonstrates a substantial adoption of Industry 4.0 technologies for its internal operations but also holds a distinguished position as a leader in providing automation and technological-specific services. The firm under study lays the path for digital transformation in the industry by focusing on artificial intelligence solutions, cloud and data management and Internet of Things (IoT) solutions. Through its extensive utilization of these advanced technologies, it empowers businesses to optimize their operations and seize new opportunities in the evolving digital landscape. As the subject of this case study thesis, the company under study serves as a compelling example of the successful implementation and utilization of Industry 4.0, illustrating the profound impact it has on enhancing environmental sustainability, efficiency, innovation, and overall business performance.

This section focuses on the challenges of industry 4.0 adoption and the environmental sustainability outcome of digital transformation. To achieve the related sub-objectives, as shown in Table 20 and figure 38, three customers of the company under study that have purchased technological solutions from the company were also invited. Customer A, a long-standing telecommunications client of the company under study, recently expanded their technological capabilities by purchasing an AI solution. Customer B, also in the telecommunications sector, has been a loyal client who initially adopted cloud solutions and later integrated AI solutions into their operations. In contrast, Customer C, operating in the energy sector, is a new client that recognized the value of cloud technology and swiftly engaged the company's services.

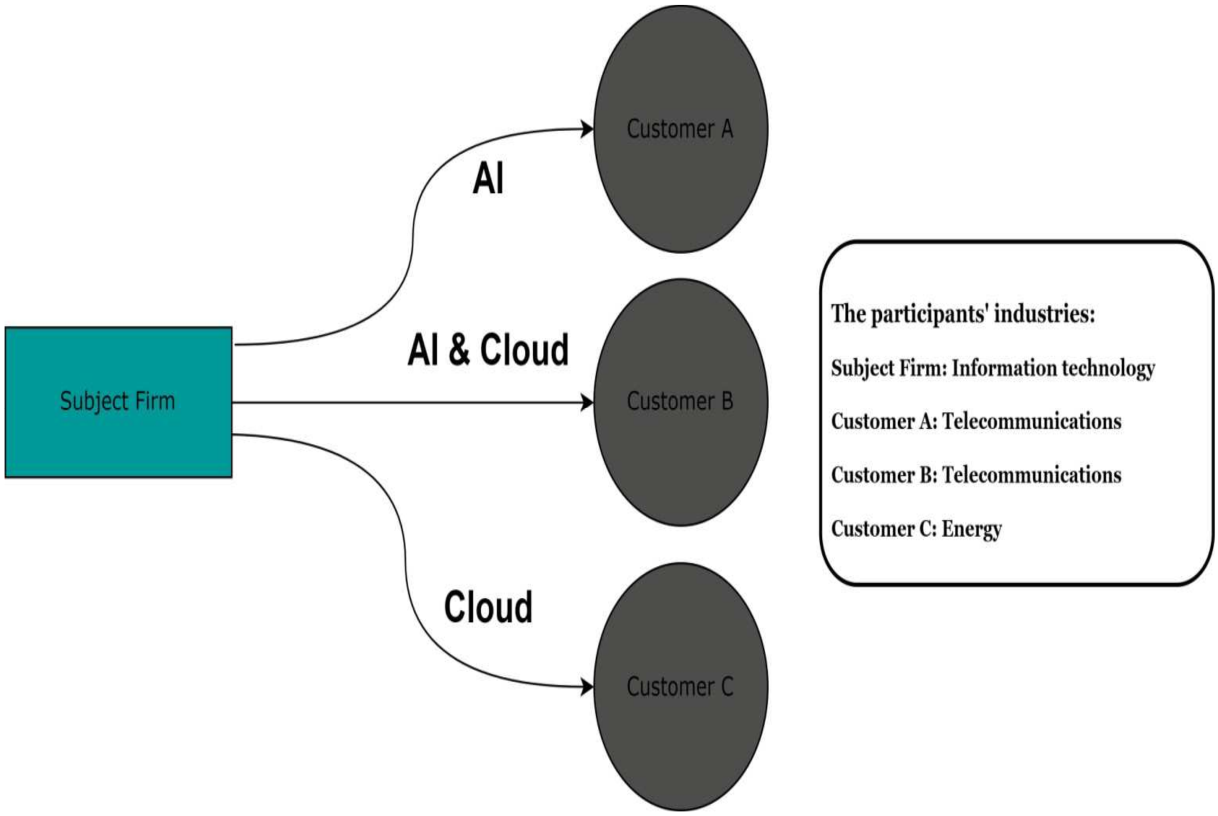


Figure 38: The Customers Contributions and Technology Adoptions

Source: Own research

The data collected from the interviews with the three customers was not included in the challenges verification process, as the customers invested in specific technologies and not entirely on industry 4.0, additionally, the aim of this section is providing high-quality research for practitioners that describes the best practices to overcome the most common challenges, which is not the case for the customers. For this reason, the data will be dedicated solely to discuss the impact of industry 4.0 on environmental sustainability.

4.2.2 Data Sources and Collection Methods

To ensure a robust exploration of the qualitative dimensions, a multi-faceted approach encompassing direct observation, online interviews, scrutiny of internal documentation, and secondary data analysis was adopted. The qualitative data collection period spanned from April 2023 to July 2023.

- *Direct Observation*

Our observational component involved an on-site presence at the company's premises, facilitating a first-hand understanding of Industry 4.0 operations. This approach allowed us to observe and document the details of the processes and operations.

- *Online Interviews*

Online interviews were conducted with key stakeholders pivotal to the implementation process, including three customers of the company, employing a semi-structured approach. The interviews, conducted between April and July 2023, lasted between 30 minutes to 1 hour and 15 minutes as shown in Table 20. The selection of interviewees was based on a crucial criterion: active participation in a program dedicated to technological development within the company. This program, involving individuals contributing to the company's website with articles on utilized technologies, ensured that participants possessed valuable insights. Notably, some of the chosen participants had authored articles focusing on Industry 4.0 or ideally, the environmental sustainability aspects of these technologies.

- *Internal Documentation*

With the firm's approval, internal documentation including reports, memos, and other materials were obtained. These documents provided invaluable information on the aspects of the implementation process and its outcomes.

- *Secondary Data Analysis*

Supplementing our primary data sources, a comprehensive secondary data analysis was conducted. This involved analysing publicly available materials, ensuring a holistic perspective on the challenges, and environmental related outcomes of Industry 4.0 implementation.
Our qualitative data collection methods were guided by established research methodologies, drawing from case study methodology (Yin, 2018b).

4.2.3 Navigating Industry 4.0 Challenges Selection process

The starting point for identifying challenges was a thorough review of various academic papers. By carefully examining these papers, common themes were found that helped identify seven main challenges. These challenges include a lack of skilled employees, low return on investment, limited financial resources, difficulty in finding suitable partners (like suppliers and outsourcers), the risk of losing data, a lack of support from top managers and decision-makers, and the perception of Industry 4.0 as irrelevant for some companies.

In our quantitative analysis, it was observed that all these challenges posed significant obstacles for participants. Therefore, all seven challenges were presented to our interviewees during the qualitative phase. Through detailed interviews, further refinement of understanding of these challenges was achieved. The challenge of 'Difficulties in finding suitable partners' was described by interviewees as 'Constraints in Decision-Making,' using the language they employed during the interviews.

The challenge of 'Risk of losing data' received partial agreement, leading to the addition of related challenges within the context of Industry 4.0, eventually characterizing it as 'Data Abundance, Untapped Value.'

The challenge of 'Lack of qualified skills' was relatable and remained unchanged. Both 'Low return on investment' and 'Lack of financial resources' were partially accepted, with a nuanced perspective that emphasized the intense financial requirements of Industry 4.0. Consequently, these challenges were reframed as 'Industry 4.0 Investment Intensity.' The perception of Industry 4.0 as irrelevant was acknowledged, attributed to a lack of awareness, and subsequently presented as 'Lack of Awareness about I4.0.'

Importantly, our interviewees introduced a new challenge not initially proposed — 'Integrating Information Technology (IT) with Operational Technology (OT).' This addition reflects the dynamic nature of challenges in the industry 4.0 landscape and underscores the valuable insights gained from our qualitative research process.

4.2.4 Results and Discussion on Industry 4.0 Challenges and Strategies

In this section, a detailed exploration is embarked upon regarding how the company successfully implemented Industry 4.0, unraveling the intricate strategies employed to overcome the common challenges encountered in the process. Our analysis shed light on the overall success of the implementation by delving into each identified challenge, unveiling the specific strategies that were instrumental in navigating and overcoming these hurdles, and thus answering the sub-objectives O6 and O7. By dissecting the company's journey, the aim is to provide a comprehensive understanding of the synergistic relationship between successful Industry 4.0 implementation and the strategic measures employed to tackle challenges head-on.

4.2.4.1 Constraints in Decision-Making

Despite being one of the first digital transformers within the industry, the firm under study has faced tremendous pushback from decision-makers during the first phases. In 2015, the firm was going through a rough transition from a hardware-based company to a company where 95% of its income comes from software and services. That period was described as ideal to implement industry 4.0 technologies. As the company was going through a radical change in its business model and operations, implementing Industry 4.0 will not be as turbulent as if the company were stable. Additionally, it can contribute to a successful transition. However, decision-making processes were impeded, and important decisions were continuously deferred, neglecting the critical aspect of implementing digital solutions. It was only when the situation became untenable that the company realized the urgency of embracing Industry 4.0 technologies as the sole viable solution.
“As we were the first to consider industry 4.0 within the information technology industry, the decision-makers exhibited uncertainty regarding the digital transformation, especially with the ongoing internal switch from hardware to software. Finally, an IOT department was implemented in the Switzerland site, and only after the success that this department has achieved; the company demonstrated significant commitment and financial dedication to the adoption of Industry 4.0” (Senior Research Director)

The decision-makers will naturally aim for the sustainability of their company; in this case, both the pressure of the company’s transformation and the success of IOT have led them to take the risk of diving into the realm of Industry 4.0. One of the aspects that the decision makers had to consider during that period was the organizational culture. Since the company was already operating in the IT sector, the cultural change did not face as much pushback as the other aspects, the firm’s culture has always supported innovation, agility, collaboration, and continuous learning.

For the firm under study to assist its customers in overcoming this barrier, a collection of endorsements and experiences from other companies is available, illustrating the diverse impacts of Industry 4.0 on various aspects of their operations, both in the medium and long term. Given that investment in Industry 4.0 necessitates substantial financial commitment and entails high risk and uncertainty, access to transparent information about the experiences of other companies often empowers decision-makers to proceed confidently with the digital transformation process

4.2.4.2 Data abundant, untapped value

Manufacturing data is often affected by biases, inaccuracies, and outdated information due to the challenging conditions during data gathering, the presence of incompatible proprietary systems, and the dispersion of walled operational data across multiple databases in various formats. A well-structured data that can be transformed to information is the core of industry 4.0. According to a report made by the firm; manufacturers are currently underutilizing their data resources. For instance, a typical contemporary manufacturing firm operating a single production line with 2,000 separate pieces of equipment, each equipped with 100 to 200 sensors capturing data every second, may generate an astounding 2,200 terabytes of data each month. Companies often employ alarm systems to collect data and identify production anomalies for quality control, but, on average, 90% of the manufacturing data collected is utilized.
The firm under study has built a solid data-driven structure that focuses on five main areas:

- *Unlock the latent power of data*

To optimize digital technologies for a successful manufacturing process, advanced data management capabilities play a crucial role. Standardized data architecture, an enterprise database-governance framework, centralized data storage facilities, and smart data loading are all used to improve data structures. The firm under study has progressed beyond centralized data models by implementing a semantic model—a system of organizing data that reflects its fundamental meaning.

- *Attain cyber resilience*

In contemporary manufacturing cyber security, encompassing both IT and OT, adopting a "zero trust" methodology becomes imperative. This approach entails treating all sources behind the firewall as untrusted, requiring cybersecurity teams to assume the presence of potential attackers both internally and externally. Consequently, all network traffic should be viewed with suspicion. For this reason, thorough authentication and authorization of each party (users and their devices) are mandatory before allowing any communication. Furthermore, to give or retain access to apps and data, continual security validation of their setup and posture is required.

- *Establishing an Integrated Enterprise Architecture*

To fully embrace Industry 4.0, manufacturers must implement a hybrid multicloud IT infrastructure. This configuration allows for smooth connection and workload optimization across several cloud environments. Real-time data acquired from factory floor sensors, devices, and equipment becomes important for other manufacturing assets and may be shared across several parts of the company's software system, including ERP and other business management programs.

At the shop floor, standardized hybrid cloud architecture effectively manages required IT workloads such as OT-IT integration, edge analytics, OT safety, and both new and standard applications. Data acquired from different plants may be consolidated, cleaned, and regulated, enabling for cross-factory insights, KPI illustration, and optimization while preserving full control and data integrity across factories, organizations, clients, and suppliers.

- *Elevating Manufacturing Excellence through Technological Advancements*

The company under consideration has upgraded its raw material management structures, management of warehouses, and maintenance management applications. In addition, AI is being integrated into expenditure evaluation, contract negotiations, strategic procurement and more services that can generate a tremendous amount of data, so that the AI can learn from the patterns within the data, so it can provide the most efficient strategy for each case.

The firm under study overpass it competitors because of one main reason, which is the high value extracted from the technological facilities. The integration of Industry 4.0 was a core reason in increasing efficiency, productivity and safety.

- *Synergizing Digital Innovations with Manufacturing Operations and Management*

To a significant extent, the firm under study has integrated its digital strategy with its manufacturing plan. It recognizes the untapped opportunity that digital transformation presents, and they use the power of data and digital technology to fuel innovations and transformation in production.
As a result of this alignment, the firm find itself in a favourable position to update it plant applications and network, establish seamless connections between data, applications, and processes for operational efficiency, build a robust platform to manage plant data and facilitate analytics, and expand it utilization of edge analytics and technological facilities.

4.2.4.3 Lack of qualified skills

When a company's employees lack the ability to properly utilize the technology they are purchasing, it paralyses their capacity to first take advantage of the technology and then invest in other technologies (Breunig et al. 2017). As most Industry 4.0 technologies are new, successful implementation requires a substantial change in the workforce. According to (Gehrke et al. 2015), the employees' qualifications and talents in a future factory must meet two basic aspects: technical and personal. IT skills and knowledge of expertise in information processing and analytics, statistical skills, organizational and process understanding, and the capacity to deal with current interfaces (human-machine/human-robot), Regarding personal skills, they include self-control, time management, flexibility, capacity to work in a team, social skills, and communication skills. When one of our interviewees was asked about this challenge, his answer was:
"We were aware of this when our business began its journey toward digital transformation since the market lacked the resources necessary to satisfy the needs of Industry 4.0, a brand-new industry. As a result, we created a unique educational facility as a testament to our dedication. This institution has since blossomed across our five main plants. It serves as a

model for free, online education, encouraging the growth of critical competencies for our workforce. The institute is dedicated to offering a wide range of courses related to IoT, cloud computing, coding, AI, Big data, and all the technological expertise necessary to navigate the years to come with five different languages." (Business Development Executive).

As the company is investing heavily in training its employees to be adequate for new technologies and to be able to adapt to any change, it simultaneously created a strategy to maintain a healthy environment for its employees. As an illustration, the three fundamental principles of the company are diversity, inclusion, and equity, and it regards these values with great seriousness. The company offers an extensive array of additional activities and allocates a budget for recreational purposes, ensuring a harmonious balance between work and personal life for its employees. Finally, the firm puts forth a significant effort to analyze in real-time the resignations, why they happened, and how they can fix it.

4.2.4.4 Integrating Information Technology (IT) with Operational Technology (OT)

The evolution of Industry 4.0 poses the challenge of the integration of IT and OT, the opening of OT networks to the Internet, and the network of an IT organization. As a result, the manufacturing environment faces a variety of structural problems and emerging cyber-security threats. The typical manufacturing firm can be divided into five main levels; the physical processes, the intelligent devices that are the actuators, the process sensors and analyzers, the control systems, the manufacturing operations systems that manage the production workflow, and finally the business logistics system. The first two levels are usually referred to as the OT, and from level 3 to level 5, the IT. In order for contemporary businesses to operate effectively, essential components are OT and IT—two distinct yet interlinked technologies. While IT assumes responsibility for managing and processing data, OT takes on the role of overseeing and automating physical processes.

Addressing contemporary challenges in the business landscape involves a strategic integration layer that merges IT and OT at the plant level. This integration fosters seamless connectivity between a wide array of protocols, facilitating the deliberate deployment of applications. The shift towards "OT Infrastructure as Code" is fortified by contemporary cloud deployment models. Enhanced manufacturing Key Performance Indicators (KPIs), including overall equipment effectiveness (OEE), gain substantial advantages through direct oversight of OT elements, enabling advanced applications for more intelligent operations. This makes it possible for businesses to maximize OEE. This might be accomplished by minimizing unexpected downtime by predicting asset breakdowns, prescribing repair approaches, and optimizing maintenance schedules utilizing telemetry from shop-floor sensors and machine learning (ML).

4.2.4.5 Industry 4.0 Investment Intensity

One of the most common challenges is the high investment in industry 4.0's implementation and the high barrier to exit. Companies who want to embrace Industry 4.0 projects will need to increase their anticipated annual capital investments by 50% over the following five years (Geissbauer, Schrauf, and Koch 2014) .

"When we made the decision to invest in Industry 4.0, we were fully aware of the substantial financial commitment ahead of us. Our goal was simple: achieve a rapid and substantial return on investment to ensure our company's ongoing financial strength for sustained operations. With the help of our IT background, we could gain a high expertise and knowledge regarding Industry 4.0 technologies, and we became one of the leaders of industry 4.0. This approach not only helped us to succeed within the market, but also to become leaders in industry 4.0 implementation. Our successful journey in mastering these technologies played a pivotal role in attracting clients to seek our services. We don't just talk about what we can do; our achievements speak for themselves." (Senior Research director)

Taking the step from being an Industry 4.0 consumer to an Industry 4.0 provider insured a high ROI for the company, which allowed further investment and research and development within the field. Now the firm is operating with a strategy that allows any new successful innovation to be not only used internally but also generate a high return from selling it to external entities. Furthermore, the company had created multiple partnerships in which they collectively invested in a certain technology in order to share both the expertise and the financial burden.

4.2.4.6 Lack of awareness about I4.0

The company under study doesn't see a lack of awareness about Industry 4.0 as a major hurdle. Instead, they're pointing out that many of their customers, before diving into digital transformation, simply didn't have a clear grasp of what Industry 4.0 really meant.

"One of our foremost priorities is to raise awareness about the advantages of Industry 4.0 among our potential clients. It never fails to astonish us how limited the knowledge is among other businesses when it comes to Industry 4.0. Our marketing campaigns play an essential role in sustaining our ability to offer Industry 4.0-related services. This is crucial because a large number of companies truly lack a clear understanding of what Industry 4.0 entails" (Project Manager)

The firm under study has consistently placed a strong emphasis on promoting its new projects and sharing its accomplishments with the public. They have gone so far as to establish a dedicated institution that regularly publishes articles on various trending subjects. Presently, numerous companies have already integrated certain Industry 4.0 technologies into their operations. However, the prevailing lack of awareness often prevents them from fully comprehending the extensive capabilities and possibilities offered by these technologies.

4.2.5 Environmental Sustainability effect Through Industry 4.0 Case Study

Sustainability stands as a central focal point within each corporate strategy, a guiding principle that shapes most of firms' operational structure. This concept encompasses three main elements: social, economic, and environmental factors. Regrettably, the environmental dimension often finds itself in the shadows due to the absence of instant and direct benefits. However, because of the escalating intensity of regulations and penalties surrounding environmental considerations, businesses have taken proactive strides to conscientiously mitigate their impact on the ecosystem. In order to answer our 8^{th} and last sub-objective;

To document the environmental objectives successfully achieved by a company through Industry 4.0 investment, focus was placed on the use of Industry 4.0 for environmental sustainability objectives during the qualitative phase of our thesis.

In 2020, the firm under study held a roundtable discussion with experts and stakeholders about the potential of data and digital technology to enhance environmental sustainability. The event drew over 25 people worldwide from government, the commercial sector, academia, and non-profit groups. The discussion led to multiple conclusions, one of the main topics that were discussed is that the environment is full of data, the rivers flow alongside, storms encircle, and the earth teems with life. In numerous ways, the advent of what is generally referred to as "big data" large data sets defined by their speed of generation, frequently in real-time, as well as their diversity and granularity should be viewed as just an extension of how humans interact with the environment around us. Earth is a big data source. Since the nature provides this large amount of data, there are two opportunities that can be seized to enhance environmental sustainability, first step is to gather and compile environmental data across industrial sectors, government agencies and Nonprofits in a transparent and accessible manner. Second, that data must be transformed into quality information.

Drawing on the company's strong technological expertise, a strategic move was made. By utilizing different Industry 4.0 technologies such as; software on the cloud and AI applications powered by advanced machine learning and deep learning, the company initiated a significant effort at five of its main sites. As a first step, prioritizing the gathering of useful data concerning the company's environmental impact was crucial.

Over a span of more than six months, meticulous work was undertaken to collect data. Three primary aspects became prominent and demanded attention: waste management, CO2 emissions reduction, and energy management. Different technological tools were employed to address these environmental challenges. In the next section, each issue is discussed, and the application of Industry 4.0 technologies to overcome them is explored.

4.2.5.1 Waste management

Although more than 90% of the firm's activities are software-related, waste remains a significant concern with regard to environmental sustainability. Notably, over 70% of the waste generated by the company originates from electrical and electronic equipment (WEEE). Such wastes are among the most hazardous for both workers' well-being and the environment (Burns, Sayler, and Neitzel 2019)

In its previous approach, the company predominantly outsourced waste management activities to third-party providers. These providers undertook treatment and recycling in separate workshops. Unfortunately, the unregulated recycling and disposal of WEEE, involving manual dismantling, open burning, and acid treatment, led to severe environmental contamination. This contamination not only jeopardized the health of local inhabitants in areas where third-party providers operated, but also highlighted a lack of ecological awareness and surveillance measures.

In order to solve this issue, the firm has implemented an in house system that based on IoT and cloud services, which allowed the company to achieve circular economy (CE). The system contains four main layers that are interconnected through internet of things; the physical layer, the communication, services and application. The physical layer is the level of the floor, which contains the disassembly segment, which has been installed with several robots and sensors. The application layer plays the perception role; it takes real-time data throughout the production history and transfers it to the communication layer via field connectors. Meanwhile, the physical layer's control section will receive information from the communication layer and carry out the physical action accordingly. The objective of the communication layer is to send information from the physical layer to the internet. The service layer collects and manages the information received from the communication layer. The top application layer makes use of the features of the previous layer, allowing users to conduct activities like prediction, monitoring, logistics, and. Control.

The Cyber realm acquires operational data starting from the foundational physical layer, encompassing parameters like robotics. Simultaneously, it issues directives to the Physical layer, facilitating the establishment of the Cyber-Physical System (CPS). Within the sphere of services, data undergoes analysis utilizing intelligent algorithms and cloud computing, profoundly influencing decision-making processes. The realization of a comprehensive, cloud-centric remanufacturing approach for the sustainable management of Waste Electrical and Electronic Equipment (WEEE) is the ultimate objective. In this context, real-time data is gathered and seamlessly conveyed via an Internet of Things (IoT) infrastructure.

Within this intelligent disassembly framework, the employment of cloud computing permits the exchange of disassembly plans and the reciprocal transfer of data. By invoking the existing WEEE model from the cloud, the local robotic systems can directly execute disassembly tasks, obviating the need for repetitive self-learning cycles with human intervention. Moreover, in instances where the model is unavailable in the cloud's knowledge base, the local robots possess the capability to construct an independent disassembly model. This technology also extends services such as predictive maintenance and early error detection for physical devices. Subsequently, the finalized model is uploaded to the cloud, fostering collaborative sharing among other users engaged in disassembly activities.

4.2.5.2 CO2 emissions reduction

Following the tremendous acceleration that happened in recent decades, carbon dioxide (CO2) emissions have climbed to catastrophic levels in the last century. Since manufacturing isn't the primary focus of the company, its CO2 emissions were not as significant as those of its peers. Nonetheless, the company has embarked on a journey to minimize its impact on environmental sustainability. Furthermore, customer B has also stated that AI-related applications were used to reduce CO2 emissions. The basics of the system for both the firm under study and customer B are based on AI and cloud-based solutions. The companies used AI and cloud technology to establish a predictive system for monitoring CO2 emissions. Through this innovative system, the companies gained valuable insights into certain areas that require attention and offer room for enhancement. By analyzing a set of big data, the system identifies patterns and trends, enabling the identification of emission hotspots. The system not only highlights potential issues but also provides the company with actionable solutions. Furthermore, the system goes beyond detection, offering possible solutions for high-emission zones. The use of both AI and cloud technologies brought a powerful system for prediction and CO2 emission mitigation. The results from both companies are promising and the AI learning capability makes the system more effective over time.

4.2.5.3 Energy management

The firm under study and the three customers have all used industry 4.0 In one way or another to achieve energy efficiency. The customer C stands as a leader in this regard, as they are operating in the energy sector, the use of technological solution to manage the energy consumption was inevitable.

"As our company is operating in the energy sector, our primary focus is to reduce the internal energy consumption as low as possible and to provide to our customers the most energy efficient solutions. Through the strategic implementation of additive manufacturing for specific product lines, we've effectively curtailed energy usage during manufacturing processes. AI applications are also part of our strategy to reduce energy usage. These applications are used to detect in real-time areas where the energy usage is unusual or super high, and also provide possible solutions. In tandem with this, we've harnessed simulation methodologies. We cautiously present new tactics to simulations before applying them, allowing us to anticipate their influence on energy usage." (Customer C representative) .

The company under examination, alongside its three prominent clients, is firmly committed to effective energy management. While each entity employs distinct strategies, a common thread unites them: a reliance on advanced technological solutions. For instance, the subject company has adeptly interconnected a substantial portion of its operations through the Internet of Things (IoT), which resulted in a reduction of the daily operations that contributed directly to energy efficiency.

While the above presentation of results effectively addresses our eight sub-objectives, it does not fully outline the guidelines for decision-makers, which is the primary aim of this research. Therefore, the following section presents these guidelines in a clear and detailed manner.

5. GUIDELINE FOR DECISION MAKERS TO IMPLEMENT INDUSTRY 4.0

To effectively address our study's primary objective and provide comprehensive insights into objectives 7 and 8, we have crafted a roadmap tailored for decision-makers ready to embrace Industry 4.0. This roadmap encompasses a thorough examination of key challenges, strategic mitigation measures for these challenges, and the promising environmental sustainability outcomes derived from a diligent synthesis of literature, quantitative analysis, and qualitative insights. Through this approach, we aim to equip decision-makers with the necessary tools and knowledge to navigate the transition to Industry 4.0 with insight and efficacy.

5.1 Key Challenges and Mitigation Strategies

Any company planning to invest in Industry 4.0, or currently undergoing its transformation, will inevitably encounter one or more of the following challenges. Based on our research, we have identified several key strategies to mitigate these obstacles:

First Challenge: The shortage of skilled workers capable of managing and operating Industry 4.0 technologies.

Mitigation:

1) Training Programs: Invest in extensive training programs tailored to Industry 4.0 skills.
2) Educational Partnerships: Collaborate with educational institutions to develop curricula that align with industry needs.
3) Continuous Learning: Foster a culture of continuous professional development to keep the workforce updated on new technologies.

Second Challenge: Uncertainty about the financial returns from investing in new technologies.

Mitigation:

1) Pilot Projects: Start with small-scale pilot projects to demonstrate the value and feasibility of Industry 4.0 technologies.
2) In case of a successful implementation, provide your knowledge as a service for your client that are interested in the technologies you have mastered.
3) ROI Analysis: Conduct detailed ROI analyses and use case studies from similar industries to build a compelling business case.
4) Gradual Scaling: Scale the implementation gradually based on initial success and learnings.

Third Challenge: High initial costs associated with implementing Industry 4.0 technologies.

Mitigation:

1) Phased Investments: Implement Industry 4.0 technologies in phases, prioritizing high-impact areas first.
2) Financial Planning: Develop robust financial plans that include potential cost savings and efficiency gains.
3) Government Grants and Subsidies: Explore government funding opportunities aimed at promoting digital transformation.

Fourth Challenge: Identifying reliable suppliers and partners for technology and service provision.

Mitigation:

1) Network Building: Participate in industry forums and digital transformation alliances to build a network of trusted partners.
2) Due Diligence: Conduct thorough due diligence to assess the reliability and capability of potential partners.

3) Pilot Partnerships: Engage in pilot projects with new partners to evaluate their performance before full-scale implementation.

Fifth Challenge: Concerns about data security and privacy breaches.

Mitigation:

1) Cybersecurity Measures: Implement robust cybersecurity protocols, including encryption, secure access controls, and regular security audits.
2) Data Governance Framework: Develop and enforce a comprehensive data governance framework to ensure data integrity and compliance with regulations.

- Challenge: Resistance or lack of commitment from senior management.

Mitigation:

1) Communication: Communicate the strategic benefits and long-term value of Industry 4.0 to senior management.
2) Involvement: Involve top managers in pilot projects and training sessions to build their commitment and understanding.
3) Success Stories: Share success stories and case studies from other companies to demonstrate the potential benefits.

Sixth Challenge: Misconception that Industry 4.0 is not applicable to certain sectors or business models.

Mitigation:

1) Awareness Programs: Conduct workshops and seminars to educate stakeholders about the relevance and benefits of Industry 4.0.
2) Real-World Examples: Use real-world examples and case studies to illustrate the applicability of Industry 4.0 across various sectors.

3) Customization: Highlight how Industry 4.0 solutions can be customized to fit different business models and industries.

Seventh Challenge: Difficulty in integrating new IT systems with existing operational technologies.

Mitigation:

- Integration Strategy: Develop a clear integration strategy that includes phased implementation and interoperability standards.
- Collaborative Planning: Involve both IT and OT teams in the planning process to ensure seamless integration.
- Interoperability Standards: Adopt industry-wide interoperability standards to facilitate smooth integration.

5.1 Environmental Sustainability Outcomes

In the following section, we will explore how environmental sustainability can be enhanced through Industry 4.0 technologies. Our findings will be supported with examples drawn from both the literature and our case study.

- Waste Management Improvement

Outcome: Enhanced processes for managing and reducing industrial waste through smart technologies and predictive maintenance, leading to significant waste reduction and cost savings.

Case Study Example: The company under study with over 90% software-related activities implemented an IoT and cloud-based system to manage Waste Electrical and Electronic Equipment (WEEE). This system includes robotics and sensors at the physical layer, which facilitate real-time data transfer and predictive maintenance. By leveraging cloud computing and intelligent algorithms, the company achieved a circular economy, significantly reducing hazardous waste and improving ecological awareness.

- Resource Efficiency

Outcome: Increased efficiency in the use of raw materials and energy, resulting in lower operational costs and a reduced environmental footprint.

Literature Example: AI technologies can significantly enhance resource utilization efficiency. For instance, (K. Wang, 2023) demonstrated that AI technologies improve natural resource utilization efficiency across 30 provinces in China. Additionally, (C. Li et al., 2023) found that AI applications directly boost firms' innovation efficiency, leading to more efficient resource use.

- Carbon Emission Reduction

Outcome: Lower carbon emissions resulting from more efficient energy use and the adoption of renewable energy sources, helping to combat climate change.

Case Study Example: The company utilized AI and cloud-based solutions to create a predictive system for monitoring and reducing CO2 emissions. By analyzing big data, the system identified emission hotspots and provided actionable solutions, leading to significant reductions in CO2 emissions over time.

- Energy Efficiency

Outcome: Increased energy efficiency in manufacturing processes, reducing overall energy consumption and lowering the environmental footprint.

Case Study Example: Additive manufacturing (AM) has shown significant potential in reducing energy consumption and minimizing waste. By optimizing product designs to be more lightweight, AM reduces the material and energy required both in the production process and during the product’s operational life. For instance, (Weng et al., 2020) found that using 3D printed bathroom units instead of precast counterparts can save 85.9% on CO2 emissions and 87.1% on energy use. Furthermore AI applications in photovoltaic systems lead to better energy management and efficiency (Mohammad & Mahjabeen, 2023).

- Circular Economy

Outcome: Enhanced recycling and reuse processes, reducing the environmental impact of production and consumption.

Case Study Example: I4.0 can play a crucial role in advancing the circular economy by improving sorting and recycling processes. (Onyeaka et al., 2023) illustrated that AI-powered sorting systems in recycling facilities can identify and separate different types of materials with high precision, ensuring more materials are recycled efficiently. This leads to higher recycling rates and reduces the need for virgin raw materials

- Air Quality Control

Outcome: Reduced air pollution through better monitoring and control systems.

Case Study Example: IoT-based air quality monitoring systems can track pollutants in real-time and trigger automatic responses to mitigate emissions. (Almalki et al., 2021) described how IoT sensors deployed in industrial areas continuously monitor air quality and activate ventilation or filtration systems when pollutant levels rise, thereby maintaining air quality within safe limits.

- Water Conservation & Sustainable Agriculture

Outcome: Improved water management in agriculture and industrial processes, leading to reduced water usage and wastage.

Case Study Example: (Parvathi Sangeetha et al., 2022) implemented a hybrid remote-controlled device based on IoT and GPS to manage groundwater storage and transportation. This system also monitors soil humidity, pressure, and temperature, optimizing water usage in agricultural field, it also monitors and regulates agricultural conditions, promoting sustainable farming practices.

5.2 Best Practices for Implementing Industry 4.0

Drawing from the literature, as well as both quantitative and qualitative research, the following practices are essential for a successful Industry 4.0 implementation. These practices can be tailored to specific cases with minor adjustments:

1. Develop a Comprehensive Vision and Strategy:

Articulate a detailed Industry 4.0 strategy that is closely aligned with both short-term and long-term business objectives. Include a roadmap that specifies phases of implementation, resource allocation, and anticipated milestones.

2. Foster an Inclusive Culture of Innovation:

Cultivate a culture that encourages innovation across all levels of the organization. This involves setting up cross-functional teams to brainstorm and experiment with new ideas, as well as providing platforms for employees to propose and test their innovations.

3. Implement Agile Project Management:

Adopt agile methodologies to manage Industry 4.0 projects. This includes constant development, continuous feedback cycles, and adaptive planning. Agile practices help in responding swiftly to challenges and changes during the implementation process as shown in the case study.

4. Prioritize Workforce Transformation:

Go beyond basic training to offer comprehensive workforce transformation programs. This includes reskilling and upskilling employees through advanced training modules, workshops, and real-time simulations. Emphasize the development of both technical and soft skills necessary for operating in a digitized environment. Focus on the needs of employees and adopt techniques such as diversity and inclusivity. This approach creates a friendly environment for your employees and an attractive workspace for a well-skilled workforce.

5. Utilize Advanced Data Analytics:
Leverage advanced data analytics and artificial intelligence to gain deeper insights and drive decision-making. Implement predictive analytics for maintenance and process optimization.

6. Strengthen Cyber-Physical Security:
Implement integrated security measures that cover both cyber and physical aspects. This includes advanced threat detection systems, regular security audits, and employee training on security protocols.

7. Establish Strong Governance and Compliance Frameworks:
Develop robust governance structures to oversee Industry 4.0 initiatives. This includes setting up dedicated oversight committees, establishing clear compliance guidelines, and ensuring adherence to regulatory standards.

8. Enhance Supplier and Partner Integration:
Work closely with suppliers and technology partners to ensure seamless integration of Industry 4.0 technologies. Develop collaborative frameworks and joint ventures to leverage external expertise and resources.

9. Drive Sustainability and Efficiency:
Incorporate sustainability goals into your Industry 4.0 strategy. Utilize smart technologies to reduce energy consumption, minimize waste, and enhance overall environmental performance.

10. Monitor and Evaluate Continuously:

Implement continuous monitoring and evaluation mechanisms to assess the effectiveness of Industry 4.0 implementations. Use KPIs and performance metrics to track progress and identify areas for improvement. Regular reviews and adjustments based on real-time data ensure that the implementation remains aligned with business objectives.

6. DISCUSSION OF FINDINGS, NOVEL SCIENTIFIC OUTCOMES, AND STUDY LIMITATIONS

6.1 Discussion

Our research focused on exploring Industry 4.0 and its applications for environmental sustainability, with the goal of providing practitioners and academics a comprehensive understanding of industry trends, technologies, challenges, and potential environmental benefits. To accomplish this, our study pursued eight distinct sub-objectives, employing mixed methods approach.

Our quantitative research delved into the current landscape of Industry 4.0, addressing the five objectives outlined in our study. Firstly, the extent of Industry 4.0 adoption among companies (O.1) was examined. Subsequently, desired outcomes from Industry 4.0 investments were identified and the proportion dedicated to environmental sustainability (O.2) was assessed. Additionally, prevalent technologies used in Industry 4.0 investments (O.3) were investigated, challenges preventing companies from investing in Industry 4.0 (O.4) were explored, and objectives between large companies and SMEs were differentiated, emphasizing the achievement of environmental sustainability objectives in each category (O.5).

These findings collectively offer comprehensive insights into the current trends surrounding Industry 4.0. The most frequently used technologies were highlighted, the desired objectives were outlined, emphasis was placed on the types of objectives that attract the most attention, challenges hindering investments in Industry 4.0 were identified, and results were compared between SMEs and large companies. The results notably indicated that environmental sustainability is not a primary objective for both SMEs and large companies when investing in Industry 4.0. This insight underscores the significance of our study, as it reveals the potential for these technological advancements to assist companies in meeting their environmental sustainability goals without negatively impacting their core business objectives.

Refining the challenges identified in the quantitative section took place during qualitative interviews with the internal employees of the company under study. The challenges included constraints in decision-making, untapped value in abundant data, lack of qualified skills, integrating Information Technology (IT) with Operational Technology (OT), Industry 4.0 investment intensity, and lack of awareness about I4.0.

Drawing on the experiences of the company, acknowledged as a leader in Industry 4.0 technologies globally, a guideline on overcoming these challenges was presented. Utilizing a single case and employing various qualitative tools such as interviews, internal documentation, and secondary documents enabled a deep dive into the strategies employed during the implementation phase. Additionally, the impact of Industry 4.0 technologies on environmental sustainability was investigated. To gain a broader perspective on this topic, three of the company's clients who have adopted one or multiple technological solutions were invited. Our results indicated that Industry 4.0 holds significant potential for mitigating environmental effects, particularly in waste management, CO2 emission reduction, and energy management – areas where our interviewees demonstrated notable achievements through Industry 4.0 adoption.

6.2 Novel Scientific Insights

In the literature, (Margherita & Braccini, 2023) delved into the value generation of Industry 4.0 technologies within flexible manufacturing, examining multiple cases from a sustainability perspective. (Sishi & Telukdarie, 2020) explored the application of Industry 4.0 in a contemporary mine, employing a single case study to analyze its real-time impact on information flow between enterprise-level and shop floor systems. (Ramanathan & Samaranayake, 2022) presented a readiness assessment framework for Industry 4.0, demonstrating its applicability through a single case study involving a large manufacturing firm in an emerging economy.

However, our research marks a significant contribution to the field of Industry 4.0 and case study integration. To the best of our knowledge, there exists no precedent for a study that comprehensively examines the strategies employed in implementing Industry 4.0, with a singular focus on environmental sustainability outcomes, using a mixed methods approach. Our scientific contributions, thus, not only augment the existing body of knowledge but also serve as a ground-breaking exploration in this intersection of Industry 4.0 and case study research. The scientific contributions of our work are multifaceted and substantiate significant advancements in the literature. More concretely, key scientific results include:

- Scientific outcome 1: Adoption of Industry 4.0 by Large Enterprises vs. SMEs

Our study highlights a significant disparity in the adoption of Industry 4.0 between large enterprises and SMEs, with 63% of large enterprises identifying as adopters compared to 35% of SMEs. This indicates a stronger inclination towards digital transformation among larger companies. Furthermore, both SMEs and large enterprises display similar intentions regarding future investments in Industry 4.0, driven by motivations such as enhancing revenue and fulfilling customer demands.

- Scientific outcome 2: Future Investment Intentions:

Statistical analyses, including Chi-square and Mann-Whitney U tests, underscored similarities between SMEs and large companies in their future investment intentions. Furthermore, both groups exhibit similar investment intentions, the primary drivers are economic (e.g., revenue increase and operational improvements) rather than environmental sustainability. This reinforces the need for policies that emphasize the environmental benefits of Industry 4.0 alongside economic advantages.

- Scientific outcome 3: Divergent Patterns of Investment:

Our research identified distinct differences between SMEs and large companies in their Industry 4.0 technology investments and the challenges they face. The Mann-Whitney U tests revealed that large enterprises are more likely to invest in advanced technologies like AI and IoT, while SMEs focus on more accessible solutions like cloud computing. Additionally, large companies face challenges such as integration complexity and data security, whereas SMEs are more concerned with financial constraints and a lack of skilled personnel.

- Scientific outcome 4: Implementation Strategies

By examining the company's journey, six critical challenges that often impede Industry 4.0 adoption were addressed and surmounted: navigating constraints in decision-making, leveraging the abundance of data for untapped value, addressing the lack of qualified skills, seamlessly integrating Information Technology (IT) with Operational Technology (OT), managing the intensity of Industry 4.0 investments, and tackling the pervasive lack of awareness about Industry 4.0. By providing a comprehensive guide, our research contributes significantly to the scientific community's understanding of actionable strategies for overcoming these common obstacles.

- Environmental Sustainability Outcomes: Through collaborative efforts with the company's customers, our study highlights tangible environmental sustainability outcomes resulting from Industry 4.0 investments. Specifically, the positive impact on waste management, the reduction of CO2 emissions, and improved energy management were highlighted. This aspect of our research is pivotal in reshaping the discourse around Industry 4.0, emphasizing the need to redirect attention towards its environmental implications.

In summary, our research fills a void in the existing literature, offering nuanced insights into Industry 4.0 implementation, investment patterns, and environmental sustainability outcomes. These findings contribute substantively to both academic discourse and practical applications in the field.

6.3 Study Limitations

Our study bears several limitations that warrant acknowledgment. Firstly, the quantitative research conducted in 2020, while still relatively recent, faces the challenge of Industry 4.0's rapid evolution. Given the dynamic nature of this field, even a one-year gap can introduce significant changes to various variables. Similarly, the qualitative research occurred in 2023, creating a three-year interval between the two phases. Despite this temporal gap, the intersection between the quantitative and qualitative studies was diligently refined, which is the challenges of industry 4.0 adoption in our case, ensuring their relevance by refining them during the interviews phase.

A second limitation arises from our use of a single case study. While such an approach facilitates a profound understanding of the subject (Smith, 2015), it inherently possesses limitations outlined in the literature. Single case studies may present a restricted perspective, emphasizing the need for caution when generalizing findings to broader contexts (Hodkinson

& Hodkinson, 2001). It is essential to acknowledge these constraints and interpret our results within the context of this specific case.

Lastly, the broad and complex nature of the topic itself presents a challenge. While our study aimed to comprehensively cover various aspects of Industry 4.0 and environmental sustainability, the extensive scope of the subject implies that a single research undertaking cannot encapsulate all aspects. This limitation underscores the necessity for further research efforts in this domain, emphasizing the need for a collective body of work to provide decision-makers with a holistic understanding of the immense potential that Industry 4.0 holds for environmental sustainability.

7. SUMMARY

In summary, our research represents a comprehensive exploration of Industry 4.0 implementation, addressing various dimensions such as challenges, technologies, adoption trends, investment inclinations, implementation hurdles, perceived obstacles, and desired outcomes, with a crucial emphasis on environmental sustainability.

Employing a mixed-methodology approach, our quantitative study provides a broad overview of Industry 4.0 trends across SMEs and large companies, offering a numerical perspective on the current state of adoption. Simultaneously, our qualitative investigation delves deeply into a singular case study, extracting detailed perspectives into successful implementation strategies and the achievement of environmental objectives.

The overarching goal of this extensive exploration is to extract valuable insights for decision-makers, offering a comprehensive comprehension of Industry 4.0 adoption. As a primary objective, our study aims to provide a practical roadmap, guiding decision-makers through the complexities of Industry 4.0 implementation. This roadmap serves as a strategic guide, assisting decision-makers in overcoming existing challenges and aligning their efforts with the necessities of environmental sustainability.

With eight sub-objectives outlined, our study has fulfilled the overarching objective, offering decision-makers a coherent and well-structured reference for Industry 4.0 implementation. This research not only contributes to academic discourse but also holds practical significance, empowering decision-makers to navigate the complex landscape of Industry 4.0 while addressing crucial environmental sustainability concerns. As this thesis concludes, the lasting need for ongoing research and strategic approaches to ensure the continued success and positive impact of Industry 4.0 in the realm of environmental sustainability is emphasized.

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Appendices

Appendix 1: Questionnaire

For your information:

The Industry 4.0 is a name for the current trend of automation and data exchange in manufacturing technologies, including cyber-physical systems, the Internet of things, cloud computing, and cognitive computing and creating the smart factory.

Please provide your email:

____

Question 1: Do you consider your company as a user of Industry 4.0?
Yes
No

If "Yes":

Question 2: Which technologies is your company investing in?

(Please rate the following options: Highly invested, Basic usage, Thinking to invest. If no answer is provided, it means they do not use it at all. You can also add a technology that is not listed.)

1. Smart factories
2. Internet of things
3. Big data
4. 3D prints
5. Autonomous vehicles
6. Cyber Physical production system
7. Blockchain
8. Artificial intelligence
9. The cloud
10. Simulation
11. [Other (please specify): ________________]

Question 3: The Industry 4.0 helps us to: (Please ignore the irrelevant options)

(Please rate the following options based on a 5-point Likert scale: Strongly Disagree, Disagree, Neutral, Agree, Strongly Agree. You can also add a new objective.)

1. Strengthen the company's image
2. Manage the waste
3. Make activities more efficient (less time, less cost, fewer employees)
4. Make activities more efficient (less energy, fewer raw materials)
5. Make processes more effective (respond to customer requirements)
6. Improve the research and development department

7. Improve the financial benefits of our operations (e.g., revenues)
8. Improve communication within the company
9. Improve reverse logistics (reproduction of used goods, return of packaging)
10. Reduce the fingerprints on the environment
11. Reduce gas emissions
12. Reduce lead time
13. Reduce delivery time
14. [Other (please specify): _______________]

End of Questionnaire Part 1

If "No":

Question 4: Does your company have any plan to invest in Industry 4.0 in the future?

- Yes
- No
- Maybe

If "Yes" or "Maybe":

Question 5: Please select the technologies your company might invest in. (You can ignore the technologies that are not an option.)

1. Smart factories
2. Internet of things
3. Big data
4. 3D prints
5. Autonomous vehicles
6. Cyber Physical production system
7. Blockchain
8. Artificial intelligence
9. The cloud
10. Simulation
11. [Other (please specify): _______________]

Question 6: The Industry 4.0 will help you to: (Please ignore the irrelevant options)

(Please rate the following options based on a 5-point Likert scale: Strongly Disagree, Disagree, Neutral, Agree, Strongly Agree. You can also add a new objective.)

1. Strengthen the company's image
2. Manage the waste
3. Make activities more efficient (less time, less cost, fewer employees)
4. Make activities more efficient (less energy, fewer raw materials)
5. Make processes more effective (respond to customer requirements)
6. Improve the research and development department
7. Improve the financial benefits of our operations (e.g., revenues)
8. Improve communication within the company
9. Improve reverse logistics (reproduction of used goods, return of packaging)

10. Reduce the fingerprints on the environment
11. Reduce gas emissions
12. Reduce lead time
13. Reduce delivery time
14. [Other (please specify): ________________]

Question 7: What are the main challenges/reasons that discourage your company to invest in Industry 4.0?

(Please rate the following challenges up to 5.)

1. Lack of well-skilled employees in the field
2. Low return on investment
3. Lack of financial resources
4. Difficulties to find suitable partners (e.g., suppliers, outsourcers)
5. Risk of losing data
6. Non-support of top managers/decision makers
7. It's irrelevant for my company

If "No" to both:

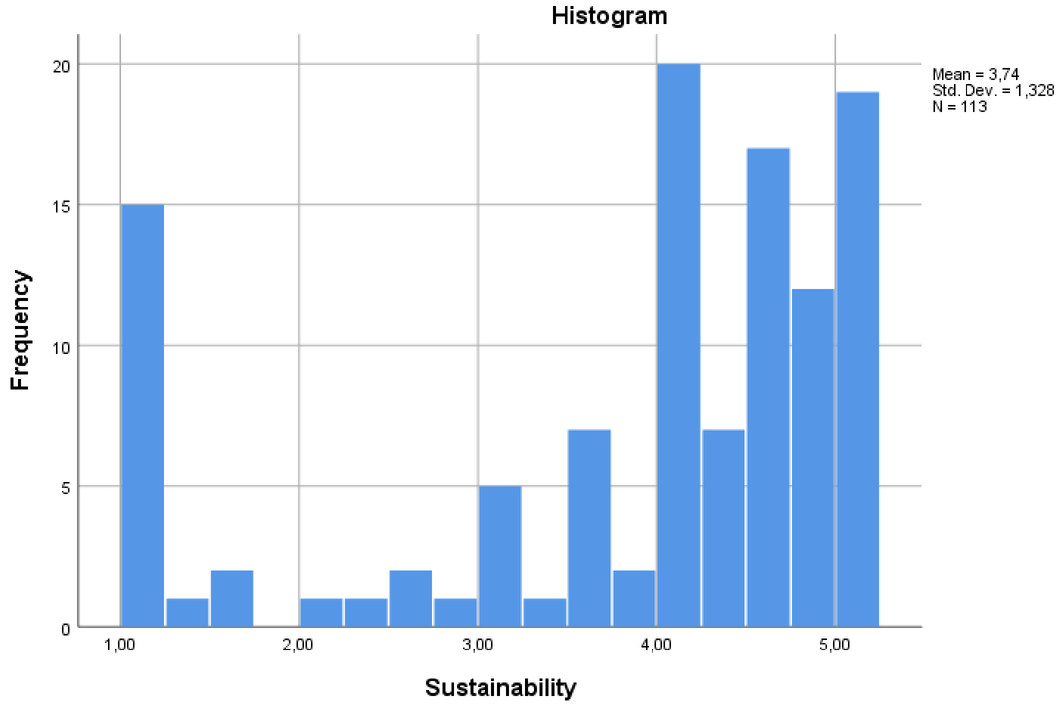
Question 8: What are the main challenges/reasons that discourage your company to invest in Industry 4.0?

(Please rate the following challenges up to 5.)

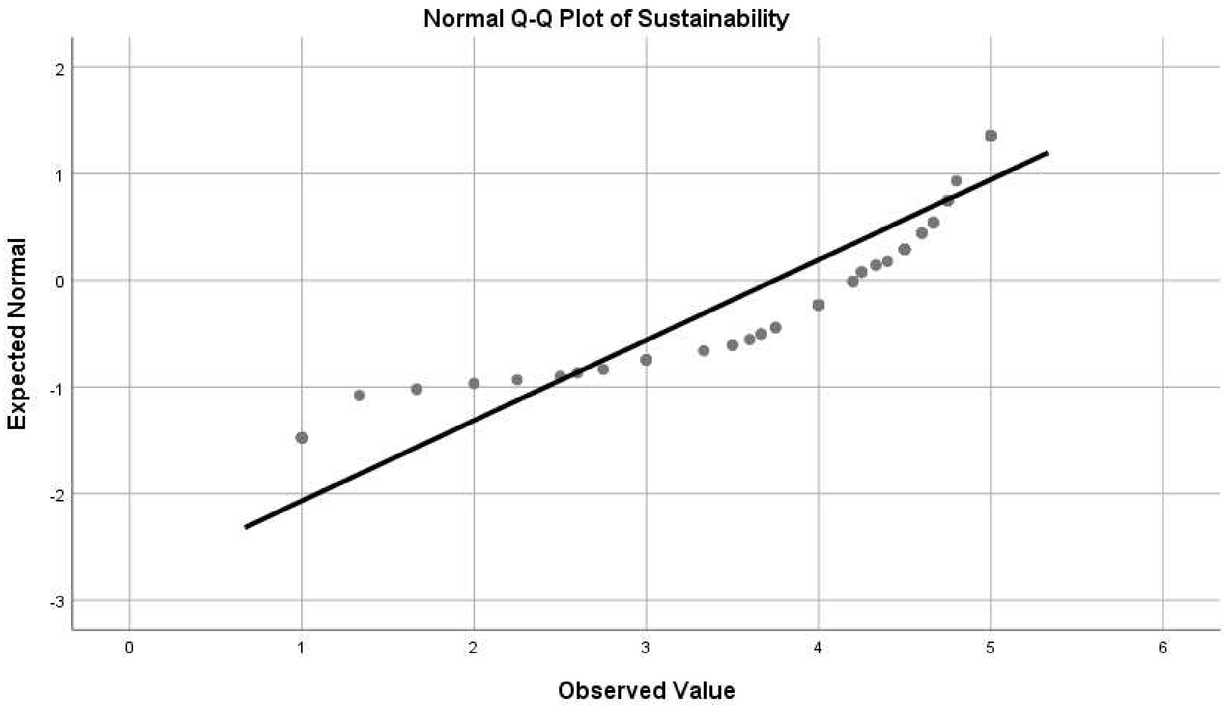
1. Lack of well-skilled employees in the field
2. Low return on investment
3. Lack of financial resources
4. Difficulties to find suitable partners (e.g., suppliers, outsourcers)
5. Risk of losing data
6. Non-support of top managers/decision makers
7. It's irrelevant for my company

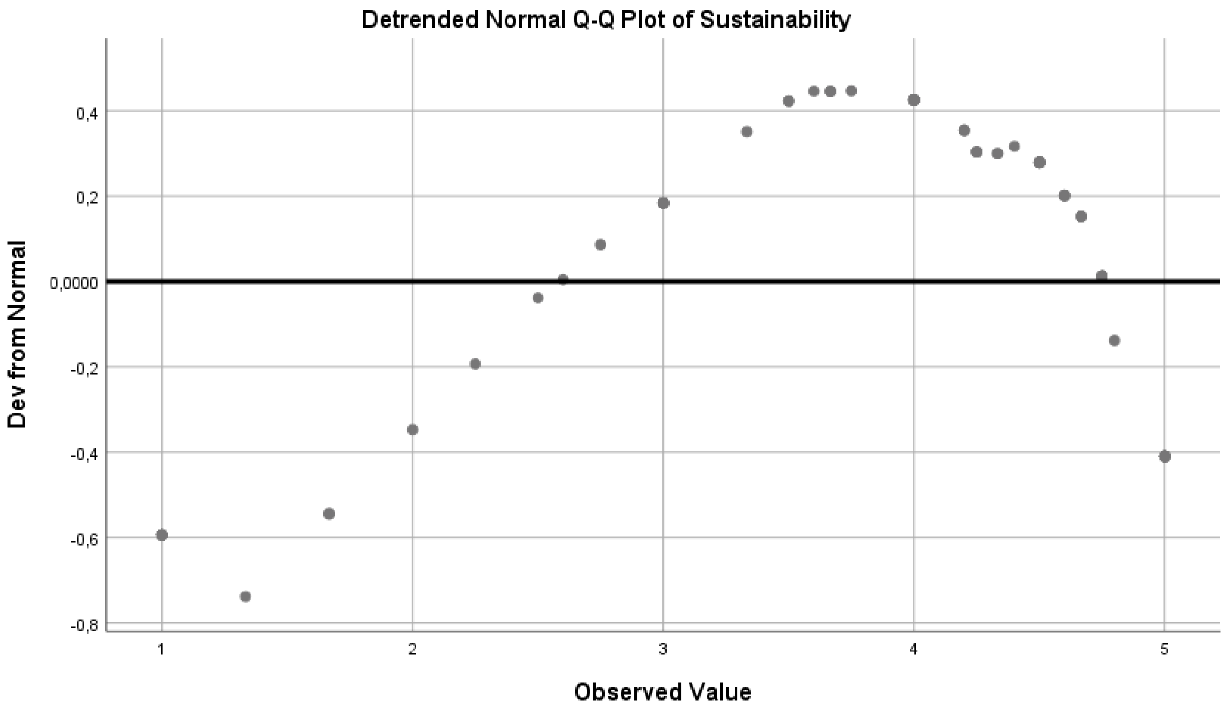
Appendix 2: Raw data from SPSS

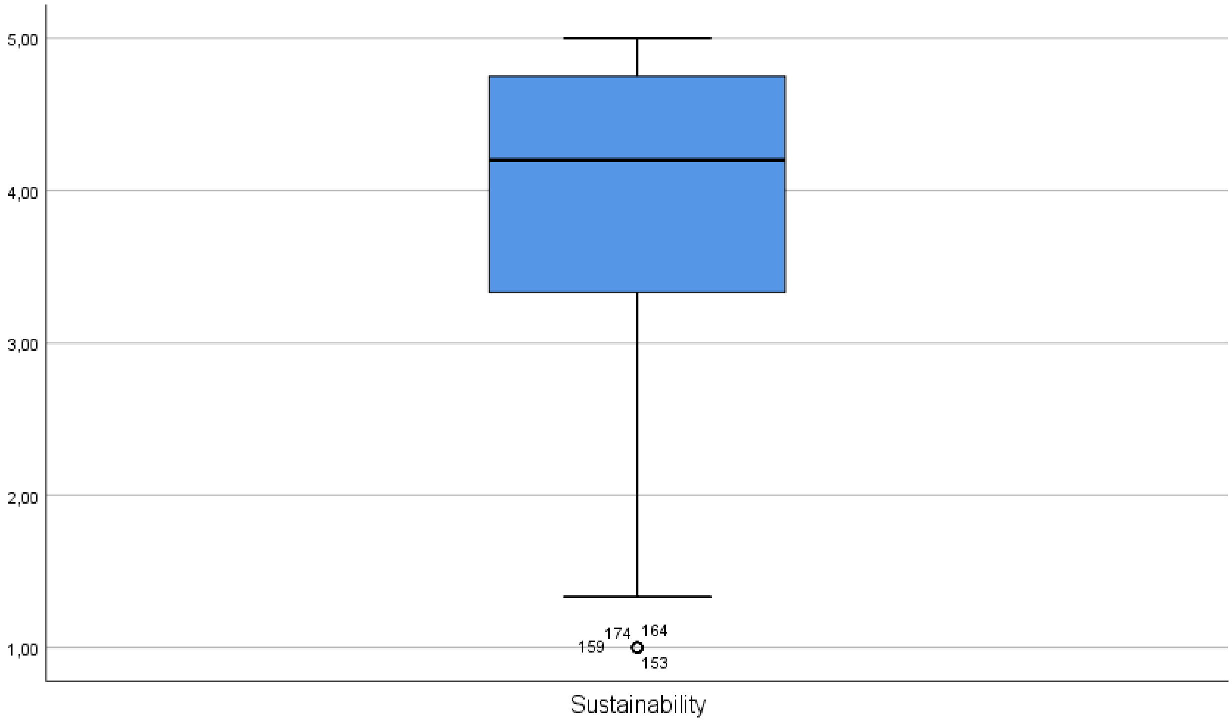
Raw data for the T test regarding the environmental sustainability as an objective:




```
Sustainability Stem-and-Leaf Plot

 Frequency    Stem &  Leaf

    15,00 Extremes    (=<1,0)
     1,00        1 .  3
     2,00        1 .  66
     2,00        2 .  02
     3,00        2 .  567
     6,00        3 .  000003
     9,00        3 .  555666677
    27,00        4 .  000000000000000022222222334
    29,00        4 .  55555555566666666777777777778
    19,00        5 .  0000000000000000000

 Stem width:      1,00
 Each leaf:        1 case(s)
```


Normal Q-Q Plot of Sustainability
Expected Normal
Observed Value
2
1
0
-1
-2
-3
0
1
2
3
4
5
6


Detrended Normal Q-Q Plot of Sustainability
Dev from Normal
Observed Value
0,4
0,2
0,0000
-0,2
-0,4
-0,6
-0,8
1
2
3
4
5




```
*Nonparametric Tests: Independent Samples.
NPTESTS
  /INDEPENDENT TEST (Sustainability) GROUP (Size)
  /MISSING SCOPE=ANALYSIS USERMISSING=EXCLUDE
  /CRITERIA ALPHA=0.05  CILEVEL=95.
```

Nonparametric Tests

null : null

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.	Decision
1	The distribution of Sustainability is the same across categories of Size.	Independent-Samples Mann-Whitney U Test	,115	Retain the null hypothesis.

Asymptotic significances are displayed. The significance level is ,05.

```
T-TEST GROUPS=Size(1 2)
  /MISSING=ANALYSIS
  /VARIABLES=Sustainability
  /CRITERIA=CI(.95).
```

T-Test

Group Statistics

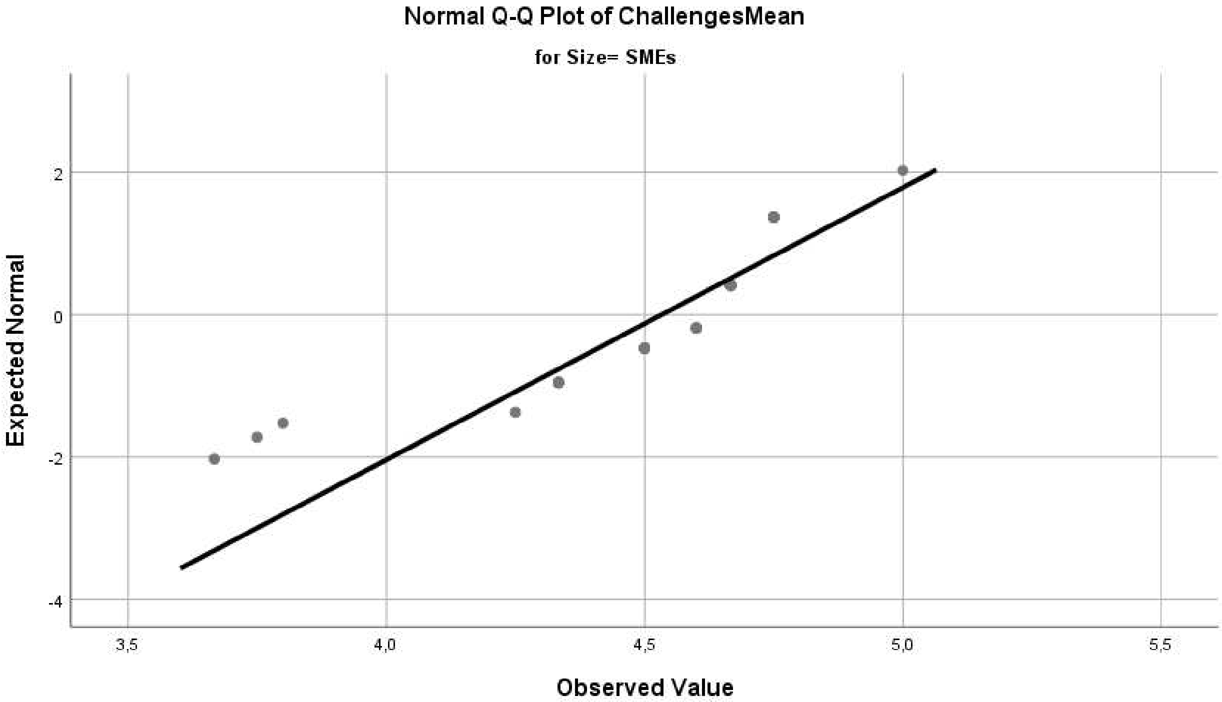
	Size	N	Mean	Std. Deviation	Std. Error Mean
Sustainability	SMEs	33	4,2207	,78524	,13669
	Large companies	80	3,5488	1,45440	,16261

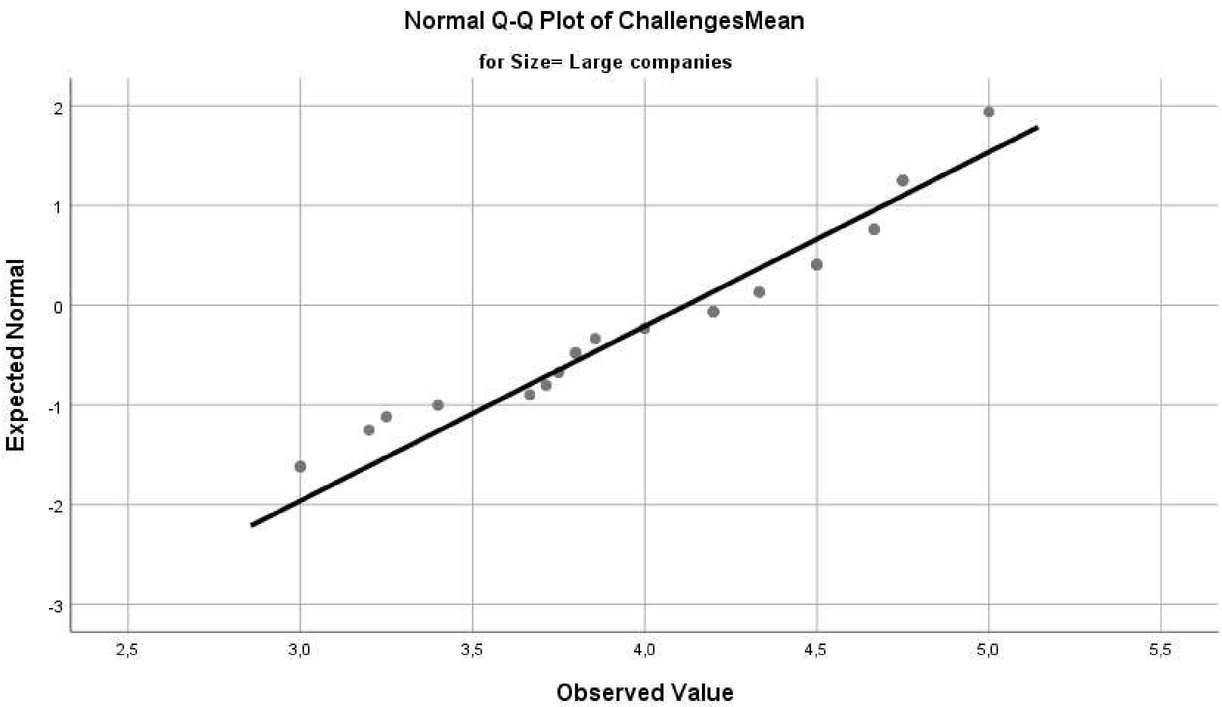
Independent Samples Test

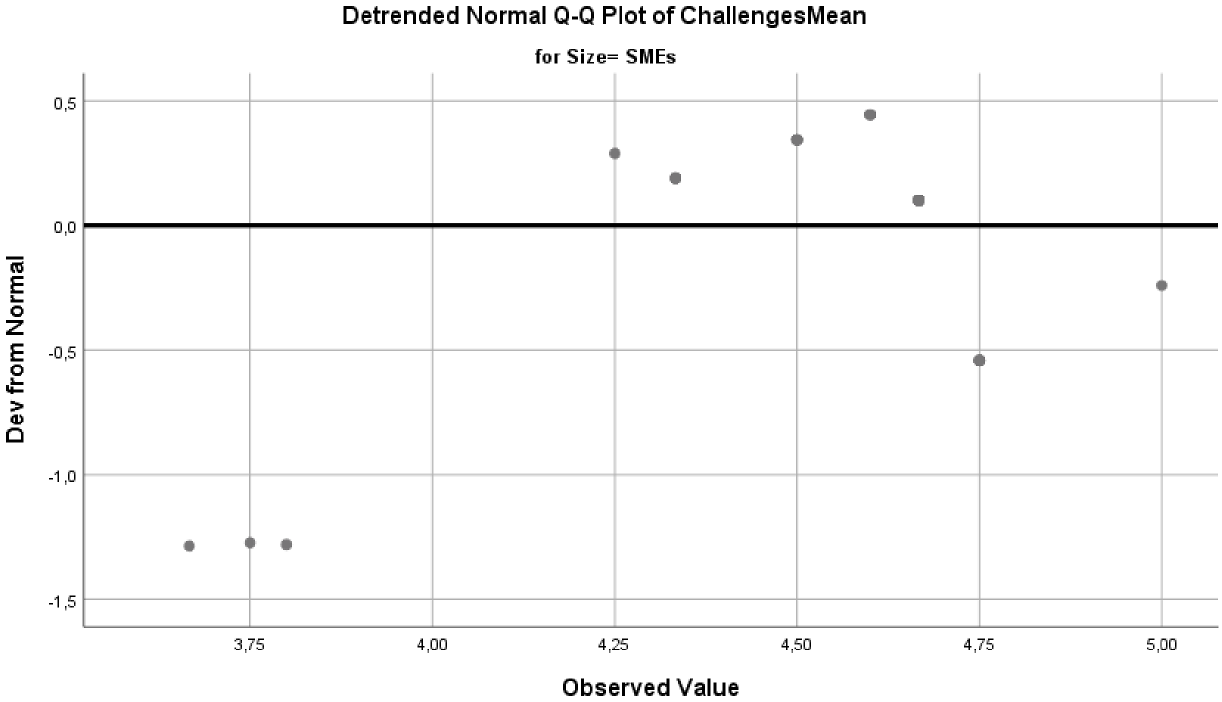
		t-test for Equality of Means						
							95% Confidence Interval of the Difference	
		t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Sustainability	Equal variances assumed	2,503	111	,014	,67196	,26842	,14007	1,20384
	Equal variances not assumed	3,163	103,055	,002	,67196	,21243	,25066	1,09326

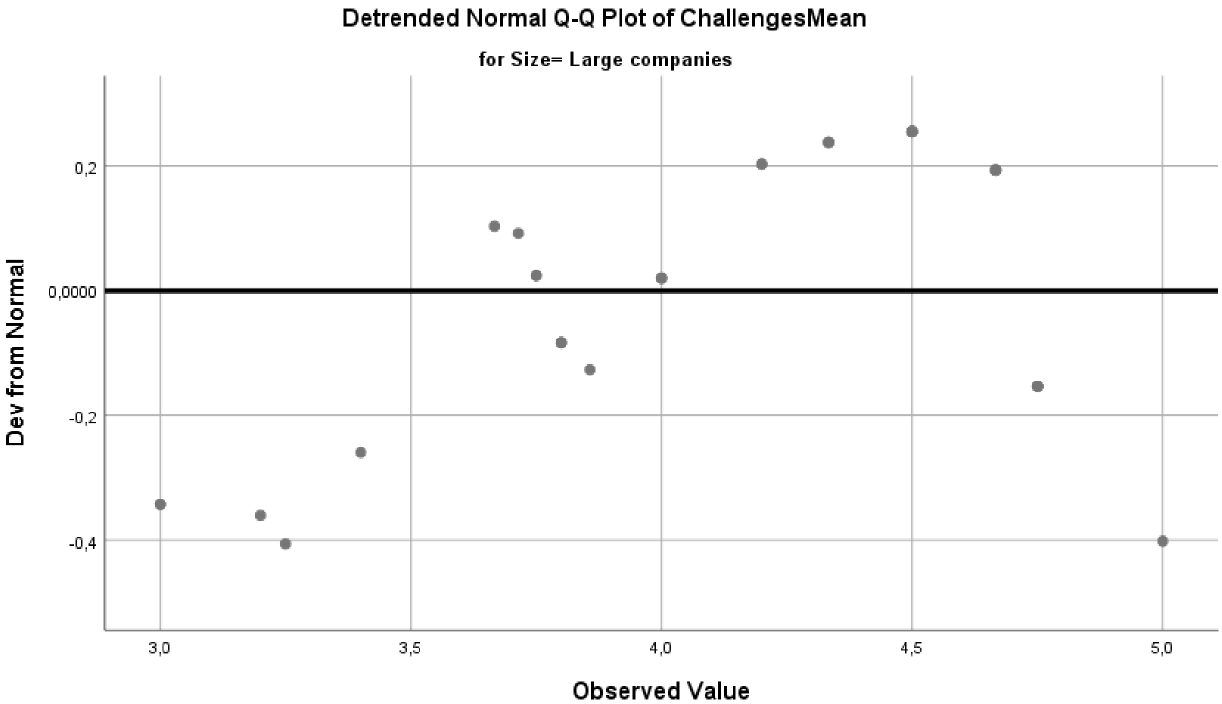
Raw Data for T test related to challenges:

Normal Q-Q Plots


Normal Q-Q Plot of ChallengesMean
for Size= SMEs
Expected Normal
2
0
-2
-4
3,5
4,0
4,5
5,0
5,5
Observed Value


Normal Q-Q Plot of ChallengesMean
for Size= Large companies
Expected Normal
2
1
0
-1
-2
-3
2,5
3,0
3,5
4,0
4,5
5,0
5,5
Observed Value


Detrended Normal Q-Q Plot of ChallengesMean
for Size= SMEs
Dev from Normal
0,5
0,0
-0,5
-1,0
-1,5
3,75
4,00
4,25
4,50
4,75
5,00
Observed Value


Detrended Normal Q-Q Plot of ChallengesMean
for Size= Large companies
Dev from Normal
0,2
0,0000
-0,2
-0,4
3,0
3,5
4,0
4,5
5,0
Observed Value

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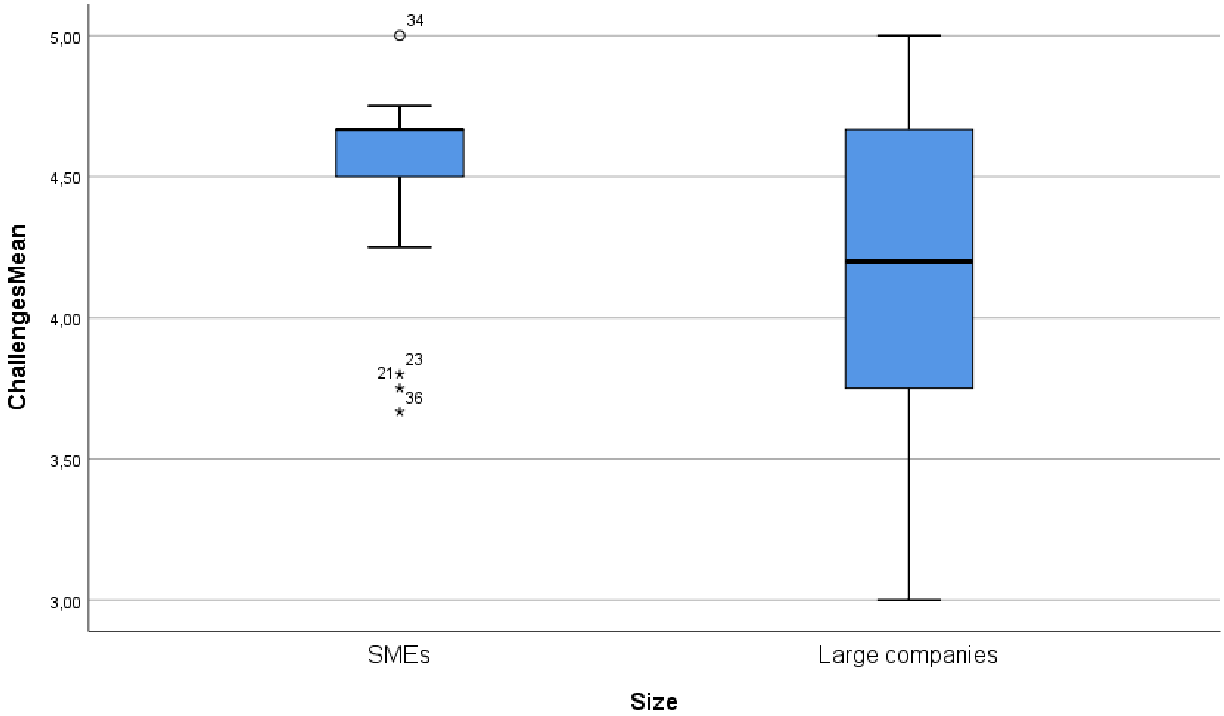


```
*Nonparametric Tests: Independent Samples.
NPTESTS
  /INDEPENDENT TEST (ChallengesMean) GROUP (Size)
  /MISSING SCOPE=ANALYSIS USERMISSING=EXCLUDE
  /CRITERIA ALPHA=0.05  CILEVEL=95.
```

Nonparametric Tests

null : null

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Hypothesis Test Summary

	Null Hypothesis	Test	Sig.	Decision
1	The distribution of ChallengesMea is the same across categories of Size.	Independent-Samples Mann-Whitney U Test	,001	Reject the null hypothesis.

Asymptotic significances are displayed. The significance level is ,05.

T test for the challenegs used:

Mann-Whitney Test

Ranks

	Size	N	Mean Rank	Sum of Ranks
TechnologiesAv	SMEs	53	82,41	4367,50
	Large companies	89	65,01	5785,50
	Total	142		

Test Statistics[a]

	TechnologiesAv
Mann-Whitney U	1780,500
Wilcoxon W	5785,500
Z	-2,461
Asymp. Sig. (2-tailed)	,014

a. Grouping Variable: Size

```
*Nonparametric Tests: Independent Samples.
NPTESTS
  /INDEPENDENT TEST (TechnologiesAv) GROUP (Size)
  /MISSING SCOPE=ANALYSIS USERMISSING=EXCLUDE
  /CRITERIA ALPHA=0.05  CILEVEL=95.
```

Nonparametric Tests

null : null

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.	Decision
1	The distribution of Technologies is the same across categories of Size.	Independent-Samples Mann-Whitney U Test	,014	Reject the null hypothesis.

Asymptotic significances are displayed. The significance level is ,05.

Appendix 3: Summary of the papers focusing on the practical use of AI on environmental sustainability.

Publication Date	Title	Environmental Aspect	AI-model used	Key results	Citation Count	Reference
2023	Towards intelligent building energy management: AI-based framework for power consumption and generation forecasting	Energy management	Convolutional long short-term memory & Percepton	AI model was used to accurately predict the energy generation and consumption	23	(S. U. Khan et al., 2023)
2023	Prediction of Carbon Emission of the Transportation Sector in Jiangsu Province-Regression Prediction Model Based on GA-SVM	Carbon emission	Genetic Algorithm	Development of an AI model that can accurately estimate CO2 emission and the peak time for CO2 emissions.	3	(Huo et al., 2023)
2023	AI-guided design of low-carbon high-packing-density self-compacting concrete.	Carbon emission	Machine Learning	Development of an AI based model for the self-compacting design that showed a 57,2% reduction in carbon emission compared to the traditional way	0	(Cheng et al., 2023)
2023	Development of hybrid surrogate model structures for design and optimization of CO2 capture processes: Part I. Vacuum pressure swing adsorption in a confined space.	Carbon emission	Hybrid model	Development of an AI model that demonstrated a reduction on CO2 concertation going from 1000 ppm to 399 ppm in a confined space.	1	(J. Du et al., 2024)
2022	eco2AI: Carbon Emissions Tracking of	Carbon emission	Python	Development of an open-source library to measure the	41	(Budennyy et al., 2022)

	Machine Learning Models as the First Step Towards Sustainable AI			carbon emissions of any AI-based application		
2022	Design and simulation of global model for carbon emission reduction using IoT and artificial intelligence	Carbon emission	Decision Tree Algorithm	Presentation of an AI based model that could achieve a 21% reduction in carbon emissions in residences	5	(Alpan et al., 2022)
2022	Artificial intelligence enabled efficient power generation and emissions reduction underpinning net-zero goal from the coal-based power plants.	Carbon emission	Vector Machine & Extreme Learning Machine	AI model development that can reduce the carbon emission in a coal plant by 210KG tons annually.	17	(Muhammad Ashraf et al., 2022)
2021	Digitalization, Circular Economy and Environmental Sustainability: The Application of Artificial Intelligence in the Efficient Self-Management of Waste	Circular economy	Convolutional Neural Networks and image identification	AI can assist in distinguishing between glass and plastic based on 1000 images, a crucial process to achieve CE in relevant sectors. The results showed that the application provide a 90% reliability.	29	(Nañez Alonso et al., 2021)
2021	AI-Assisted approach for building energy and carbon footprint modeling	Energy management	Deep learning technique of long short-term memory	The study relied on AI to estimate energy consumption in office building. The model showed a high estimation ability.	14	(C.-Y. Chen et al., 2021)
2020	Edge computing enabled production anomalies detection and energy-efficient production decision	Resource efficiency	Recurrent Neural Network	The creation of a Long Short-Term Memory (LSTM) in order to detect manufacturing errors. The experiment showed a 21%	17	(C. Zhang & Ji, 2020)

	approach for discrete manufacturing workshops			increase in product quality.		
2020	From Trash to Cash: How Blockchain and Multi-Sensor-Driven Artificial Intelligence Can Transform Circular Economy of Plastic Waste?	Circular economy	Multi-sensor data-fusion algorithms	Presentation of ongoing attempts to sort plastics by type and to increase the accuracy of information about recycled plastics using blockchain supported by multi-sensor data-fusion algorithms powered by artificial intelligence. The result showed a precise separation of commingled plastic waste.	148	(Chidepatil et al., 2020)
2020	Artificial Intelligence-Based Emission Reduction Strategy for Limestone Forced Oxidation Flue Gas Desulfurizatio n System.	Carbon emission	Neural Network	Reduction of 35% of Sulphur Dioxide (SO_2) AND a 42% reduction of Mercury (Hg) is possible by integrating AI in a 2*660 MW supercritical coal-fired power plant.	20	(Uddin et al., 2020)
2019	Deep learning in material recovery: Development of method to create training database	Waste management	Deep Convolutiona l Neural Networks	The identification of paper and cardboard with an accuracy of 61.9% to 77.5%	30	(Vrancken et al., 2019)
2019	Content-based image retrieval system for solid waste bin level detection and performance evaluation	Waste management	Gray-level aura matrix	Detection of the bin overloading level with an accuracy of 95% and the differentiation between different type of wastes.	32	(Hannan et al., 2016; Rajamanika m & Solihin, 2019)
2019	Assessment of waste characteristics and their impact on GIS	Waste management	Artificial Neural Network	An optimization within the waste collection	90	(Vu et al., 2019)

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	vehicle collection route optimization using ANN waste forecasts			route by 19.9% compared to the non-modified composition		
2017	A novel integration of hyper-spectral imaging and neural networks to process waste electrical and electronic plastics	Waste Management	Artificial Neural Network	The identification of Plastic material within e-waste with a 99% accuracy	30	(Tehrani & Karbasi, 2017)
2017	Smart Technologies in Reducing Carbon Emission: Artificial Intelligence and Smart Water Meter	Carbon emission	Artificial Neural Network & Hidden Markov Model & Dynamic Time Warping	Presentation of an AI model that can manage water cycle to reduce carbon emission	12	(K. A. Nguyen et al., 2017)
2017	New artificial intelligence technology improving fuel efficiency and reducing CO2 emissions of ships through use of operational big data	Carbon emission	Human-centric AI Zinrai	Calculation of vessel performance in actual sea conditions with a margin of error of no more than 5%.	28	(Anan et al., 2017)
2016	An automatic classification method for environment: Friendly waste segregation using deep learning	Waste management	Deep Convolutional Neural Networks	The improvement of the timing of the waste sorting, enhance the workers safety and improve efficiency.	73	(Sudha et al., 2016)
2016	How to improve WEEE management? Novel approach in mobile collection with application of artificial intelligence	Waste management	Fuzzy Logic and Genetic Algorithm	Mobile phone-based application to collect waste in the easiest and most efficient way.	73	(Król et al., 2016)
2015	A Multi-Criteria Decision Support System for a Routing Problem in Waste Collection	Waste management	Genetic Algorithm	Maximizing the volume of the collected waste while optimizing the journey distance	28	(Ferreira et al., 2015)

2014	Prediction of the compression ratio for municipal solid waste using decision tree	Waste management	Quinlan's M5 algorithm	The anticipation of waste compression with a coefficient of 0.92	20	(Heshmati R et al., 2014)
2014	Comfort-based fuzzy control optimization for energy conservation in HVAC systems	Energy management	Fuzzy Logic	Comparison of the traditional control system with an AI-based system showed that AI model achieved a reduction of 16.1% in the energy consumption	84	(Hussain et al., 2014)
2010	Estimation of static formation temperatures in geothermal wells by using an artificial neural network approach	Energy management	Artificial neural network	Introduction of an Artificial neural network that can be used to predict the static formation temperature	83	(Bassam et al., 2010)
2010	ANN and ANFIS models for performance evaluation of a vertical ground source heat pump system	Energy management	Adaptive Neuro-Fuzzy Inference System	The AI model was used to evaluate the Vertical Ground Source Heat Pumps (VGSHP)	82	(Esen & Inalli, 2010)
2010	Fuzzy Control for an Oceanic Structure: A Case Study in Time-delay TLP System	Energy management	Fuzzy Logic Control	The AI model showed promising results regarding reducing the impact of ocean waves.	152	(C.-Y. Chen et al., 2010)
2010	Genetic Programming for Sea Level Predictions in an Island Environment	Energy management	Artificial neural networks	AI models were used to forecast the sea level variation.	20	(Ghorbani et al., 2010)
2008	Evaluation of genetic algorithm based solar tracking system for photovoltaic panels	Energy management	Genetic Algorithm	The use of AI in the solar system can optimize solar tracking for improved photovoltaic and improve the design of a Solar Water Heating System	36	(Mashohor et al., 2008)
2005	Using decision tree-based data mining to	Resource efficiency	Decision Tree	Development of an AI model to	108	(Hsu & Wang, 2005)

	establish a sizing system for the manufacture of garments			identify human body size patterns for clothes and determined the amount of fabric needed for clothing patterns		
2004	Nonlinear regression fits for simulated cycle time vs. throughput curves for semiconductor manufacturing	Resource efficiency	metamodeling approach	Streamline simulation work for semiconductor manufacturing systems to and improve numerous parameters such as semiconductor production efficiency	26	(Johnson et al., 2004)

Source: Own research

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Declaration

I, **Mohamed El Merroun**, hereby declare that my Ph.D. thesis titled "**Industry 4.0 Implementation Strategies to Enhance Environmental Sustainability in Modern Enterprises**." was conducted independently and in compliance with the regulations outlined in LXXVI and the rules of the Doctoral School, particularly with regard to citations and references[1].

Furthermore, I affirm that I did not provide any misleading information to my supervisor(s) or program leader during the dissertation process. By signing this declaration, I acknowledge that if it is proven that my dissertation was not self-made or if any copyright infringement is discovered, the University of Sopron has the right to reject the acceptance of my dissertation. In addition, I confirm that the thesis presented here was not previously submitted to any other academic institution, including universities, universities of applied sciences, universities of education, or any other comparable institution, for the purpose of obtaining an academic degree.

Sopron, 2024 June 8th.

PhD candidate

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