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Exploring AI Adoption for Sustainable Supply Chain Management in the Plastics Industry

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MSc in Management

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BUSINESS SCHOOL

Department of Marketing, Strategy and Operations

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Resumo

O mundo enfrenta uma crise climática e numerosos problemas ambientais, particularmente a má gestão dos plásticos, que resultou num grave problema ambiental. Em resposta a esses impactos ambientais, a indústria de plásticos portuguesa comprometeu-se com práticas sustentáveis, incluindo a adoção dos princípios da Economia Circular. Paralelamente, a transição digital está a ocorrer ao longo da Cadeia de Abastecimento da indústria. Esta pesquisa foca-se nos fatores determinantes e barreiras relacionadas com a adoção de IA para melhorar a circularidade na Gestão da Cadeia de Abastecimento, explora os desafios enfrentados durante a implementação e identifica oportunidades para uma maior adoção de forma aumentar a circularidade. Para obter uma compreensão abrangente, foram realizadas 15 entrevistas com gestores intermédios e de topo da indústria de plásticos portuguesa. Observou-se que essas empresas estão a adotar cada vez mais tecnologias de IA; no entanto, ainda não atingiram a sua plena maturidade. Os benefícios percecionados, particularmente as melhorias operacionais caracterizadas por uma maior eficiência, aumento da produtividade e capacidades analíticas aprimoradas, foram os principais fatores que impulsionaram a adoção da IA. Por outro lado, as empresas não estavam a implementar IA devido à falta de conhecimento e consciência sobre as aplicações mais benéficas. Os principais desafios durante o processo de implementação estavam relacionados com os dados. Os entrevistados identificaram a melhoria da produção e qualidade, particularmente na Manutenção Preditiva, como a oportunidade mais proeminente para uma maior implementação de IA, alinhando-se com os princípios da Economia Circular na Cadeia de Abastecimento. Considerando esses fatores, as organizações podem seguir processos de adoção mais eficazes, resultando numa cadeia de abastecimento mais sustentável.

Palavras-chave: Inteligência Artificial, Economia Circular, Gestão da Cadeia de Abastecimento, Adoção de Tecnologia, Indústria 4.0

JEL Classification:

Q010 - Sustainable Development

O330 - Technological Change: Choices and Consequences; Diffusion Processes

Abstract

The world faces a climate crisis and numerous environmental problems, in particular the mismanagement of plastics, which has become a serious environmental issue. In response to these environmental impacts, the Portuguese plastics industry has committed to sustainable practices, including the adoption of Circular Economy principles. Concurrently, digital transformation is happening across the industry's supply chain. This research focuses on the drivers and barriers related to the adoption of AI for enhancing circularity in Supply Chain Management, explores the challenges faced during implementation, and identifies opportunities for further adoption to increase circularity. To achieve a comprehensive understanding, 15 interviews were conducted with middle and top managers from the Portuguese plastics industry. It was observed that these companies are increasingly adopting AI technologies; however, it has not yet reached its full maturity. The perceived benefits, particularly operational improvements characterized by enhanced efficiency, increased productivity, and improved analytical capabilities, were the main factors driving AI adoption. Conversely, companies were not deploying AI technology due to a lack of knowledge and awareness about the most beneficial applications. Major challenges during the implementation process were related to data. Interviewees identified Production and Quality improvement, particularly in Predictive Maintenance, as the most prominent opportunity for further AI implementation, aligning with Circular Economy principles in the supply chain. Considering these factors, organizations can pursue more effective adoption processes, resulting in a more sustainable supply chain.

Keywords: Artificial Intelligence, Circular Economy, Supply Chain Management, Technology Adoption, Industry 4.0

JEL Classification:

Q010 - Sustainable Development

O330 - Technological Change: Choices and Consequences; Diffusion Processes

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List of Abbreviations

AI – Artificial Intelligence

CE – Circular Economy

EU – European Union

GDP – Gross Domestic Product

GHG – Greenhouse Gas

G-IoT – Green Internet of Things

IT – Information Technology

IoT – Internet of Things

ML – Machine Learning

ROI – Return on Investment

SCM – Supply Chain Management

SMEs – Small and Medium Enterprises

UN – United Nations

Chapter 1

1 Introduction

1.1 Research Context

The world faces a global environmental crisis that transcends geographical borders, impacting ecosystems, climate, and the delicate balance of our planet. There is evidence that unconditional national determined contributions will lead to a global temperature increase of 2.6°C by the year 2100. To limit the global warming to 1,5°C until 2030, it is required to reduce the global carbon emissions by 40%. (UNEP, 2022). The global population is projected to reach the range of 8.9 billion to 12.4 billion by the year 2100. (UNESA, 2022) Meanwhile, global consumption of materials such as biomass, fossil fuels, metals and minerals are expected to double in the next forty years. (OECD, 2019) Therefore, governments globally are urgently taking actions towards more sustainable measures. The Kyoto Protocol, the Paris Agreement, and the EU's circular economy agenda are examples of these actions towards sustainability. (UNFCCC, 1997; UNFCCC, 2015; EC, 2020)

The prevailing economic landscape, marked by the effects of inflationary pressures resulting from severe supply chain disruptions and material shortages, largely attributed to the ongoing conflict in Ukraine and the past covid-19 pandemic, intensifies the urgency for a paradigm shift in our economic system. Overconsumption, driven by the prevailing linear "take, make, dispose" model, is straining our planet's resources and exacerbating environmental problems. (Ellen MacArthur Foundation, 2012) As we confront these pressing environmental challenges, the role of specific industries in exacerbating or alleviating these problems comes into sharp focus. One such industry, central to both the problem and the potential solutions, is the plastics industry.

Plastics have become an integral and indispensable component of our modern lives, primarily attributable to their multifaceted mechanical and chemical properties and cost-effectiveness, rendering them applicable across numerous industries. (Milios et al., 2018) Despite presenting various practical benefits and dominance over conventional materials, the surge in production, along with insufficient waste management practices and impulsive human behavior, has caused a significant negative impact on the environment. The properties of plastics, characterized by its lightweight and non-degradability nature, facilitate its dispersion and enduring presence in the environment. A significant portion of plastic is used only once in products and packaging, with only a limited amount being reused or recycled (Dijkstra et al., 2020) As a consequence this plastic waste ends up in the environment, impacting both terrestrial and aquatic ecosystems. It is estimated that 80% of marine debris found is plastic. (Seyyedi et al., 2023) The degradation of plastic materials has generated minuscule particles, spanning microscale and nanoscale dimensions, intensifying environmental contamination, and subsequently posing potential health risks for humans (Syberg, 2022).

Globally, plastics contribute significantly to the carbon footprint, accounting for 3.4% of total greenhouse gas (GHG) emissions throughout their life cycle. This impact is accentuated by the limited recycling of plastic waste, just 9%, with the remainder undergoing incineration, landfill deposition, or being lost due to mismanagement (OECD, 2022). Amidst the intricate landscape and notwithstanding diligent governmental efforts, projections suggest that global plastic consumption is expected to nearly triple by the year 2060. (OECD, 2022)

In Europe, the scenario reflects these broader trends. The region's annual plastic production amounts to approximately 58 million tonnes, resulting in the generation of 25 million tonnes of plastic waste. Notably, only 30% of this plastic waste is collected for recycling, while 39% is incinerated, and 31% finds its way into landfills. The European plastics industry, which employs over 1.5 million people and generates a turnover exceeding 400 billion euros, constitutes a substantial portion of the global plastic production, contributing to approximately 15%. (Plastics Europe, 2022)

As observed across Europe, Portugal achieved a 33% recycling and reuse rate for its municipal waste in 2022, falling short of the 55% target set by the European directive for 2025. Notably, plastics comprised about 10% of the total municipal waste, with packaging material accounting for 75% of this plastic waste (APA, 2023).This context places Portugal at a crucial juncture, facing the decision to either resist or fully embrace the principles of the circular economy, a pivotal move in the realm of sustainable development (Prata, 2021)

The recyclability of plastics currently presents a crucial opportunity for integrating Circular Economy (CE) principles within their value chain. Nevertheless, the existing recycling process encounters substantial challenges, primarily due to the mixed composition of plastics and the prevalence of contaminants in post-consumer waste, which complicate the recycling process (Uekert, 2018; Zhao, 2022).

For these reasons, Circular Economy emerges as an alternative to the linear economic model. It recognizes and considers the interplay of environment and economic system. It is an economic system that substitutes the traditional 'end-of-life' concept with a focus on reducing, alternatively reusing, recycling, and recovering materials throughout the entire life cycle, encompassing production, distribution, and consumption processes. (Kirchherr, 2017) This paradigm shift holds the promise of reducing the strain on natural resources, curbing pollution, and contributing to the reduction of greenhouse gas emissions (Ellen MacArthur Foundation, 2012; Stahel, 2016). Developing Circular Economy solutions enables companies to enhance resource efficiency and actively contribute to the achievement of the UN Sustainable Development Goals. (Nasr et al., 2018) Although it seems like a new concept, it is result of some establish teachings and refurbished ideas. (Reike et al., 2018) The implementation of a Circular Economy model has the potential to contribute an additional $4.5 trillion to global economic output by the year 2030, with a projected increase to $25 trillion by 2050. (Lacy et al., 2015) Several countries have adopted CE as a key principle for the industrial and environmental policies in recent years. The EU adopted a new circular economy plan in 2020, which constitutes one the main building blocks of European Green Deal. (EC, 2020) In Africa, CE is being promoted through the African Circular Economy Alliance (ACEA). (WEF, 2020) China's inaugural Circular Economy policy was promulgated in 2008 with the implementation of "The Circular Economy Promotion Law of the People's Republic of China." In 2000, Japan incorporated the concept of a Sound Material-Cycle Society (SMCS) into law with its Basic Act on Establishing a Sound Material-Cycle Society, one of the first takes in circular economy. Japan has been one of the pioneering countries regarding CE implementation. (MoE, 2020)

Digitalization is now present in every aspect of our society. At the forefront of innovation emergent technologies like Artificial Intelligence (AI) have ignited interest of scholars, practitioners, policymakers, and corporate entities on a global scale. (Kortelainen et al., 2020) AI is one of the critical technologies of Industry 4.0. While Industry 4.0 is yet to reach its full potential, AI is already shaping the emerging landscape of Industry 5.0. In this new phase, AI extends beyond its traditional role, focusing on harmonizing socio-environmental values with technological advancements. It emphasizes the importance of human-machine collaboration and aims to create value for a broad spectrum of stakeholders (Ghobakhloo et al., 2023). The recent developments in commercial generative artificial intelligence, as exemplified by OpenAI's ChatGPT, have risen public and private interest within the domain of this technology. This technology encompasses a range of systems capable of human-like reasoning and learning (Ellen Macarthur Foundation, 2019). Its accelerated development could generate an increase of 14% on global GDP by 2030. (PWC, 2017) As a result, AI stands out as a leading transformative technology in the digital age, with versatile applications across numerous industries.

(Liengpunsakul, 2021). In 2021, 7% of Portuguese companies adopted AI technologies, including text mining, computer vision, speech recognition, natural language generation, machine learning, and deep learning. (Eurostat, 2023)

In the contemporary landscape of sustainable development and technological evolution, the integration of innovative technologies with sustainable development practices holds the potential to drive transformative change. Implementing the Circular Economy (CE) model, designed to enhance resource efficiency and environmental sustainability, presents numerous challenges. To address these challenges, emerging technologies such as Artificial Intelligence (AI), the Internet of Things (IoT), and big data analytics emerge as vital solutions. AI has been projected to unlock substantial value within the context of a circular economy, with estimates suggesting potential to design out waste up to USD 127 billion in the food sector by 2030 (Ellen Macarthur Foundation, 2019). AI techniques offer crucial support for managers seeking to systematically adapt industrial strategies and practices for successful CE implementation (Agrawal et al., 2021). Remarkably, various companies, including industry leaders like Google, have already embarked on integrating CE practices with AI. (Werner, 2023) This convergence not only demonstrates the innovative potential of AI but also promises resource optimization, waste reduction, and the creation of novel business models (Sivaprakash et al., 2023).

1.2 Research Gap

In the past decade, digitalization and sustainability have ascended to prominence on the corporate agenda, indicating a shift towards more environmentally conscious and technologically advanced practices. This trend aligns with a growing body of empirical research regarding these themes. Reflecting this shift towards more sustainable practices, the integration of Artificial Intelligence in manufacturing has been identified as a key driver for advancing Circular Economy efforts, effectively tackling environmental challenges. (Ronaghi, 2023)

This research aims to broaden the understanding of how emerging technologies, particularly Artificial Intelligence (AI), can enhance Circular Economy (CE) practices in the plastics industry. Recognizing a significant gap in existing literature, this study specifically targets the Portuguese plastics industry, an industry yet to be explored in this context. It aims to derive valuable insights from the implementation strategies and experiences of these companies, insights which could be invaluable for broader application in diverse industrial contexts. The potential of AI in revolutionizing resource optimization and waste reduction aligns with the sustainable development goals related to CE (Vinuesa et al., 2020). However, given the rapid growth of the literature on CE, there remains a significant gap in the literature regarding the practical integration of AI into circular business models, as the field remains in its early stages. (Rosa et al., 2019)

A critical area for AI application in the CE framework is in Supply Chain Management (SCM). The integration of AI in SCM processes can significantly transform material recovery and recycling practices within the broader value chain. This application of AI, aligned with sustainability and efficiency principles, is crucial in transitioning from linear to circular models in the plastics industry. This necessitates a detailed examination, which this research aims to provide, thereby transitioning from a linear to a circular supply chain in the plastics industry (Akanbi et al., 2021; Nascimento et al., 2019).

Moreover, the plastics industry faces considerable environmental challenges. Adopting CE practices to manage plastic materials is vital for reducing environmental impact. Recent studies in the field have explored methods and strategies for implementing CE principles, emphasizing the importance of such practices. (Villanueva & Eder, 2019; Singh & Cooper, 2020)

According to King et al. (2022), research focusing on the manufacturing phase of the plastics supply chain is less abundant compared to the greater emphasis on the end stages, such as recycling. As a result, the upstream stages of the supply chain are less researched, even though they are fundamental for the circularity of the entire supply chain. The success of end-of-life processes depends on the earlier stages (Johansen et al., 2022).

Therefore, this thesis seeks to address the identified gap by exploring the integration of AI in SCM within the plastics industry's CE framework, contributing to both academic knowledge and practical advancements in sustainable supply chain practices.

1.3 Research Proposal, Objectives and Questions

To effectively fill the discussed literature gaps, this research will be guided by a set of focused Objectives (O) and research questions (RQ). The primary objective of this thesis is to examine the transformative impact of Artificial Intelligence (AI) on Circular Economy (CE) practices within the plastics industry's supply chain. This includes examination of drives, barriers, opportunities and challenges inherent to the AI integration, leveraging empirical data from Portuguese companies to develop strategic insights for broader and more effective circular industrial applications. Accordingly, this research is driven by the subsequent objectives:

O1: Assess the current state of AI in the Plastics Industry's Supply Chain

O2: Examine the drivers influencing the adoption of AI in the plastics industry’s supply chain

O3: Identify Barriers and Opportunities for AI Integration in CE Practices

The research questions will serve as a framework to understand and analyze the integration and implications of AI in this specific context, ensuring a comprehensive and targeted approach to the study. Hence, the investigation focusses on the following research questions:

RQ1: What is the current role of technology, particularly AI, in the plastics industry's supply chain?

RQ2: To what extent are AI technologies currently used in supply chain processes in the plastics industry, what are their primary functions, and what are the main challenges faced during their implementation?

RQ3: What are the key drivers influencing the adoption of AI in the plastics industry's supply chain?

RQ4: What barriers and opportunities exist in the implementation of AI for advancing CE practices within the plastics industry's supply chain?

1.4 Thesis Structure

Acknowledging the rapidly evolving domains of Artificial Intelligence and Circular Economy, particularly its role in SCM, this thesis is organized into five chapters. The introductory chapter establishes the framework of the thesis. It commences by setting the context of the problem and highlighting its relevance in the academic discourse. This chapter further delineates the research gap, detailing how this study addresses areas yet to be fully explored in the field. The chapter culminates in delineating the research questions and objectives, thereby charting the scope and direction of the investigation. The subsequent chapter presents a literature review, examining pivotal concepts including the Circular Economy, Artificial Intelligence, Supply Chain Management, the influence of AI on the Circular Economy, as well as the barriers and drivers to AI adoption in SCM. This review is foundational in constructing a theoretical basis vital for the sequential development of the research. The third chapter outlines the methodology of the scientific work, detailing the strategies employed for data collection and analysis. The fourth chapter systematically presents the findings that have emerged from the application of the research methodology. The fifth and final chapter provides a comprehensive discussion and analysis of the findings, culminating in conclusive remarks. It situates the results within the context of extant theoretical frameworks and management paradigms, concurrently addressing the study's limitations and proposing potential pathways for future research.

Chapter 2

2 Literature review

2.1 Artificial Intelligence

The influence of digitalization stands as a major trend shaping the economy and society, where modern technologies, as exemplified by their applications in diverse domains such as socio-economic, environmental, sustainable, and climate research, play a pivotal role in enhancing the productivity and efficiency of various systems (Balogun et al., 2020; Ceipek et al., 2020).

Artificial Intelligence stands out as a leading transformative technology in the digital age, with versatile applications across numerous industries. (Liengpunsakul et al., 2021). The steady growth of its applications has radically penetrated human lives and business organizations. Companies have recognized relevant business opportunities deriving from AI adoption aimed at driving competitiveness, improving products or services, or rethinking business strategies (Campbell et al. 2020) Consequently, AI emerges as one of the major technologies of industry 4.0. The mega trends leading to the rise of AI are the role of big data, cheap storage, faster processors, Internet connectivity and connected devices. Recent developments in Large Language Models and Cloud Computing have allowed the development of many tools from large tech like Google and Amazon. (Burgess, 2018) Currently, AI is yielding various benefits, such as cutting costs, identifying hidden patterns, improving quality, and enhancing responsiveness (Bag et al., 2021).

In the realm of defining AI, a consensus remains elusive, as various definitions have evolved and adapted over the years. Although AI currently stands as a contemporary buzzword, its historical roots trace back to the 1940s when English mathematician Alan Turing devised "The bomb" a groundbreaking code-breaking machine employed by the British Government during World War II to decipher the Enigma code. However, McCarthy pioneered the field in 1956, conceptualizing AI as "the science and engineering of making intelligent machines." (McCarthy et al., 2006) This foundational definition laid the groundwork for subsequent interpretations and explorations.

Since then, several definitions have emerged. According to Russel and Norvig (2016), AI definitions can be clustered into two major approaches: human-centered and rationalist. These approaches are further subdivided into reasoning or behavioral categories: reasoning humanly, behaving humanly, reasoning rationally, and behaving rationally. The human-centered approach focuses on emulating human cognitive processes and behaviors, such as the Turing Test, which measures AI by its ability to mimic human behavior. In contrast, the rationalist approach emphasizes logical reasoning and optimal decision-making, aiming to create rational agents that can surpass human decision-making by adhering to "laws of thought." These agents are designed to maximize outcomes based on information and constraints, focusing on efficiency and specificity rather than mimicking human cognition.

Considering their capacity to execute a variety of tasks, AI systems can be classified into four distinct categories: mechanical, analytical, intuitive, and empathetic. Mechanical AI, focusing on automating simple, repetitive tasks, enhances efficiency and reduces human error in sectors like manufacturing and logistics. (Acemoglu & Restrepo, 2018). Analytical AI, on the other hand, leverages algorithms to solve complex problems and learn from data, finding applications in finance and healthcare to optimize outcomes (Jordan & Mitchell, 2015). Intuitive AI, which simulates human-like cognitive abilities, employs advanced machine learning for tasks requiring creativity and adaptation, pushing AI's problem-solving capabilities further (Lake et al., 2017). Lastly, empathetic AI aims to replicate human emotions, promising transformative impacts on customer service and therapy by making interactions more personalized (Picard, 2000). This framework not only aids in understanding AI’s multifaceted nature but also underscores the progression towards more human-like intelligence in technology.

Moreover, AI can be classified according to its developmental stages and the manifestation of intelligence. The categorization based on the level of intelligence in comparison to humans comprises three distinct classifications: Narrow Intelligence, General Intelligence, and Superintelligence. Narrow intelligence marks the inaugural stage of AI evolution, embodying systems tailored for specialized tasks or domains. General intelligence encompasses systems demonstrating a more expansive array of cognitive abilities reminiscent of human intelligence. Superintelligence denotes a level of intelligence that exceeds human capacities across all dimensions. (Russel and Norvig, 2016),

From external data inputs, AI derives its functionality, utilizing them to discern rules and patterns essential for executing tasks conventionally necessitating human intervention. The mechanisms underlying AI's learning from data encompass diverse mathematical algorithms and computational methodologies (Kaplan and Haenlein, 2019).

Within the organizational landscape, the integration of AI significantly enhances decision-making for managers. This is achieved through expedited data processing, generating novel information and patterns, and the ability to forecast potential futures based on existing data (Shrestha et al., 2019). Furthermore, it emerges as a pivotal competitive advantage tool, furnishing strategic information that facilitates strategy improvement, innovation exploration and management (Haefner, 2021), and differentiation among competitors (Rosa et al., 2022).

The escalating demand for robust computational infrastructure in AI has catalyzed the emergence of Edge AI, an innovation that facilitates data processing near its source via edge computing, thereby circumventing reliance on centralized locations such as cloud service providers' data centers. (Singh, 2023) Consequently, Edge AI distinguishes itself from cloud-based AI solutions by delivering enhanced data privacy, reduced latency (Lee, 2018), bandwidth efficiency (Shi et al., 2016) and improved operational reliability (Satyanarayanan, 2017) This approach is deemed crucial, offering substantial value and importance not only for the upcoming Industry 5.0 but also in facilitating the transition towards Industry 4.0. (Maddikunta, 2022) The potential and value-laden integration of Edge AI with IoT, Edge-AI G-IoT emerges as a strategic innovation to decrease reliance on cloud-based architectures. By leveraging real-time data from IoT devices, Edge AI enables smart services and the delivery of timely, critical information to various stakeholders, thereby enhancing decision-making processes and operational efficiency. (Fraga-Lamas, 2021)

2.1.1 AI Subfields

Arthur Samuel (1959), a pioneer in the field, coined the term "machine learning" to describe "the field of study that enables computers to learn without being explicitly programmed." This concept underscores how machine learning allows computer programs to improve their performance on a defined set of tasks, as assessed by specific performance metrics, through the accumulation of experience (Mitchell, 1997). The objective is to provide the most accurate predictive outcome based on a efficient algorithm. (Mohri, 2018) It is already a powerful tool for many applications within intelligent manufacturing systems and smart manufacturing. (Wuest, 2016) The supply chain field, by having large amounts of data, is suitable for integrating ML techniques. Moreover, the SC will continuously take advantage of ML's outcomes to automate and streamline processes, forecast future operations, and optimize costs. (Mohamed-Iliasse, 2020)

Machine learning predictions are fundamentally shaped by the insights gleaned from the learning process. The knowledge is acquired through three critical learning paradigms: supervised learning, unsupervised learning, and reinforcement learning. (Kaplan & Haenlein, 2019) Supervised learning uses labeled datasets to train models to map inputs to outputs, requiring external guidance to generalize from training data to real-world applications (Mahesh, 2018). In contrast, unsupervised learning identifies patterns and structures within unlabeled data, making it ideal for exploring intrinsic data properties where labeled data is scarce. Reinforcement learning involves agents making decisions and adapting behavior based on feedback from the environment, learning optimal strategies through interaction. This learning paradigm is a powerful tool for solving problems requiring adaptive behavior and long-term strategic planning. (Goodfellow et al., 2016; Murphy, 2012; Bishop, 2006; Sutton & Barto, 2018; Mitchell, 1997).

Deep Learning algorithms also known as Artificial Neural Networks (ANNs) is a subfield of Machine Learning, a mathematical model or computational model that tries to simulate the structure and functionalities of biological neural networks. (Yegnanarayana, 2009; Krenker et al, 2011) It is one of the most influential techniques in supply chain management, used for a wide range of applications, such as sales forecasting, marketing decision support systems (DSSs), pricing, and customer segmentation. ANNs are favored for their ability to process extensive data to find patterns or models. (Toorajipour et al., 2021)

Natural Language Processing is also an influential AI subfield, it studies and develops algorithms aimed at enabling machines to process, interpret, and generate human language in a manner that reflects both the explicit content and the subtle nuances embedded in texts and speech. (Hirschberg and Manning, 2015) Transitioning from linguistic to visual domains, Computer Vision constitutes a distinct subfield aimed at replicating or enhancing human visual capabilities. It possesses the capacity to process, analyze, and interpret visual data, thereby facilitating the extraction of significant information, identification of patterns, and the formulation of decisions. (Gonzalez and Woods, 2008; Goodfellow, 2016)

Robotics is the study of machines that can replace human beings in the execution of tasks, capable of autonomously decide and perform the consequent physical activity. This field not only aims to replicate human task execution but also to enhance efficiency and adaptability in diverse settings, thereby extending human capabilities and opening new possibilities for innovation and exploration (Siciliano et al., 2009; Murphy 2000) This technology can have a significant and beneficial impact in the SCM. Robots can transform supply chains and create a logistic supply chain that is faster, safer, and more productive (Bonkenburg, 2016)

An expert system is an artificial intelligence system that emulates the decision-making abilities of a human expert in a specific domain. It leverages a comprehensive knowledge base containing domain-specific facts, heuristics, and rules, alongside an inference engine that applies logical reasoning to solve complex problems, akin to a human expert (Feigenbaum, 1988; Russell & Norvig, 2020). In the context of supply chain management, an expert system proves to be suitable for optimizing the supplier selection process. (Yigin, 2007)

2.2 Characterization of the Plastics Industry

Plastics are a broad category of organic polymers that include synthetic, semi-synthetic, and natural materials, known for their mechanical and chemical properties. Their production primarily involves polymerization and polycondensation processes, requiring specific catalysts. Historically, plastics have been derived from natural substances like cellulose and latex, serving various purposes for centuries. The advent of synthetic polymers, created from petrochemicals such as oil, natural gas, or coal, marked a significant milestone in material science. These polymers are divided into two categories: thermoplastics, which can be remolded upon heating, and thermosets, which are permanently set after heating. Various polymers, like polyethylene and polystyrene, have been developed for specific uses, ranging from plastic bags to non-stick surfaces. To enhance their properties for different applications, plastics often contain additives that improve aspects such as flexibility, durability, and resistance to degradation, meeting the needs of diverse industries (Sastri, 2010; Oers et al., 2012; Chen et al., 2019; PlasticsEurope, 2024).

Over the last half-century, global plastic production has experienced an exponential surge, increasing twentyfold, reflecting a dramatic increase in demand and application into various sectors of the economy. (Walker, 2023) In 2022, global plastic production amounted to 400.3 million tonnes, with a significant portion, 90%, being fossil-based. Of this total production, 9,6% was derived from circular practices, including mechanically recylcing, chemically recycling, bio-based and carbon captured. (PlasticsEurope, 2023) Additionally, the plastics' contribution to the carbon footprint is significant, accounting for 3.4% of total GHG emissions throughout their lifecycle, with only 9% of plastic waste being recycled and the remainder undergoing incineration, landfill deposition, or lost due to mismanagement (OECD, 2022). In

2022, the European plastics industry represented 8.9% of global production, achieving a turnover exceeding €400 billion and employing 1.5 million individuals across 53,150 companies. Remarkably, Europe's industry engagement in circular-based production processes reached 19.7%, outpacing the global figure for the same year. However, this effort is juxtaposed against the backdrop that 80.3% of the production still anchors itself in fossil-based sources. Additionally, 39% of the plastics produced in Europe were utilized for packaging. (PlasticsEurope, 2023). Within this European context, only 30% of this plastic waste is collected for recycling, while 39% is incinerated, and 31% finds its way into landfills. Concurrently, Portugal's plastics industry accounted for about 4% of its GDP, realizing a turnover of 8 billion euros and employing 43,000 workers in 1,150 firms (APIP, 2022). As observed across Europe, Portugal achieved a 33% recycling and reuse rate for its municipal waste in 2022, falling short of the 55% target set by the European directive for 2025. Notably, plastics comprised about 10% of the total municipal waste, with packaging material accounting for 75% of this plastic waste (APA, 2023).

While the plastics industry plays a crucial role in modern society, it has paradoxically emerged as a significant environmental threat. This situation is a result of production increase, inadequate waste management practices, impulsive consumer behavior, and the critical mishandling of plastic waste—from consumer misuse to industrial firms' lack of commitment to sustainability—propelling plastics on a damaging post-consumption trajectory. Such mismanagement and misuse has led to substantial environmental plastic pollution, exacerbated by material's inherent low degradation rate. As a result, plastics persistently accumulate in ecosystems, eventually breaking down into smaller fragments. These fragments, existing in micro or nano dimensions, pose a potent threat by being easily absorbed by biological systems across aquatic and terrestrial ecosystems, leading to risks that far exceed the material's inherent harm, affecting organisms, ecosystems, and human health alike. (Moreira et al., 2022; Prata, 2019; Al-Thawadi, 2020; Syberg, 2022). Adopting a circular supply chain offers a viable solution by significantly minimizing the environmental impact, reducing pollution and littering, and enhancing overall resource efficiency. (Karayılan et al., 2021; Barford, 2022)

2.3 Circular Economy

Circular economy emerges as an alternative to the linear economy model. The linear economy model is the traditional economic model. Which is epitomized by its 'take-make-dispose' approach, that has been the prevailing model for economic growth. It has been observed that the relentless extraction of natural resources, rapid production, and disposal of goods associated with the linear model pose severe environmental challenges (Jones, 2017).

It has become evident that our planet's resources are finite and cannot indefinitely support the unsustainable consumption and disposal patterns of the linear economy. In this context, the adoption of the circular economy (CE) stands out as a transformative strategy, meticulously reconfiguring both production and consumption activities. (Kristensen et al., 2021) Circular economy recognizes and considers the interplay of environment and economic system. This paradigm shift holds the promise of reducing the strain on natural resources, curbing pollution, and contributing to the reduction of greenhouse gas emissions (Ellen MacArthur Foundation, 2012; Stahel et al., 2016).

The definition of the Circular Economy (CE) has evolved over time, reflecting its dynamic nature. It comprises various principles and concepts that have evolved over the past decades. Notably, there is a consensus among several scholars that the term "Circular Economy" was first introduced in a pivotal study by Pearce and Turner in 1990. This seminal work explored the intricate connections between environmental concerns and economic activities (Pearce et al., 1990; Geissdoerfer et al., 2017).

While Pearce and Turner (1990) are credited with popularizing the CE concept, the theoretical foundation was laid by several scholars who predated their work, particularly in articulating the loop economy's principles. Kenneth Boulding's seminal work in 1966, introduced the critical distinction between 'cowboy' (open-loop) and 'spaceship' (closed-loop) economies, laying the groundwork for rethinking resource consumption and waste in an interconnected and finite world. Boulding's foresight into the necessity for a sustainable economic system where resources are reused, and waste minimized has been pivotal in shaping subsequent CE theory.

Equally influential, Walter Stahel (1976) research that focused on selling utilization instead of ownership of goods, as the most relevant sustainable business model for a loop economy, allowing industries to profit without externalizing costs and risks associated with waste. Additionally, introduced certain features of the CE, with a focus on industrial economics. They conceptualised a loop economy to describe industrial strategies for waste prevention, regional job creation, resource efficiency, and dematerialisation of the industrial economy. (Boulding, 1966; Stahel and Reday, 1976)

Building upon the foundational insights of previews scholars, McDonough and Braungart (2002) significantly advanced the CE discourse through their pioneering "cradle-to-cradle" concept. This paradigm, distinguished from the conventional linear "cradle-to-grave" model, posits an innovative circular economy predicated on the imperative of closing both "technical" and "biological" loops. Their theoretical construct proposed an advanced model of production and consumption, wherein products and processes are inherently designed for maximum reutilization and recycling. This model not only mitigates waste but also accomplishes an economic system that mirrors the regenerative capacity of natural ecosystems, thereby fostering a sustainable interaction between human activities and the environment. (McDonough and Braungart, 2002)

One of the most widely recognized definitions of the Circular Economy has been articulated by the Ellen MacArthur Foundation (2013b: 14), that defined as *"an industrial economy that is restorative or regenerative by intention and design. It replaces the 'end-of-life' concept with restoration, shifts towards the use of renewable energy, eliminates the use of toxic chemicals, which impair reuse, and aims for the elimination of waste through the superior design of materials, products, systems, and, within this, business models."* (Ellen MacArthur Foundation, 2013).

Recently, Kirchherr et al. (2017) in their seminal work contributed to the conceptual coherence of the CE by delineating a comprehensive definition: "A circular economy describes an economic system that is based on business models which replace the 'end-of-life' concept with reducing, alternatively reusing, recycling and recovering materials in production/distribution and consumption processes, thus operating at the micro level (products, companies, consumers), meso level (eco-industrial parks) and macro level (city, region, nation and beyond), with the aim to accomplish sustainable development, which implies creating environmental quality, economic prosperity and social equity, to the benefit of current and future generations". (Kirchherr et al., 2017, pp. 224 - 225)

In the evolving discourse surrounding the CE, recent scholarly contributions have played a pivotal role in refining and broadening the conceptual framework. Further efforts to enhance the clarity of the CE concept were made by Geissdoerfer (2017), who defined it as *"a regenerative system aimed at minimizing resource inputs as well as waste, emissions, and energy leakages by slowing, closing, and narrowing material and energy loops. Achieving this requires strategies that include durable design, maintenance, repair, reuse, remanufacturing, refurbishing, and recycling."* (Geissdoerfer, 2017)

Building upon this, Korhonen et al. (2018) articulated a perspective of the CE grounded in sustainable development and aiming at maximizing the utility derived from societal production-consumption systems, defining it as "*an economy constructed from societal production-*

consumption systems that maximizes the service produced from the linear nature-society-nature material and energy throughput flow. This is done by using cyclical materials flows, renewable energy sources and cascading -type energy flows. Successful circular economy contributes to all the three dimensions of sustainable development. Circular economy limits the throughput flow to a level that nature tolerates and utilizes ecosystem cycles in economic cycles by respecting their natural reproduction rates." (Korhonen et al., 2018)

In line with these contributions, Alhawari et al. (2021), delved into the strategic dimension of CE, emphasizing the significance of organizational planning. The authors articulated CE as *"the set of organizational planning processes for creating, delivering products, components, and materials at their highest utility for customers and society through effective and efficient utilization of ecosystem, economic and product cycles by closing loops for all the related resource flows."* (Alhawari et al., 2021)

Perfect resource circularity remains an elusive goal according to Figge et al. (2023), which necessitates the inevitable utilization of virgin resources owing to the constraints of the laws of thermodynamics and the potential for human error. Furthermore, it was argued that the definition of the CE provided by Kirchherr et al. (2017) did not satisfy the conditions for a robust definition, since it included criteria that were neither indispensable nor exhaustive, consequently leading to the emergence of counterexamples. Therefore, Figge et al. (2023) provided a different take on defining CE as *"a multi-level resource use system that stipulates the complete closure of all resource loops. Recycling and other means that optimize the scale and direction of resource flows, contribute to the circular economy as supporting practices and activities. In its conceptual perfect form, all resource loops will be fully closed. In its realistic imperfect form, some use of virgin resources is inevitable."* (Figge et al., 2023)

In the broader context, the shift towards a CE is being promoted through diverse approaches by various organizations and entities. In China, this transition is primarily driven by national political strategies, while in Europe, it is more promoted by civil society, environmental organizations, and non-governmental organizations (NGOs). (P. Ghisellini et al, 2016).

2.4 Supply Chain Management

Since its inception in the 1980s, the domain of Supply Chain Management (SCM) has undergone a significant evolution, transitioning from an emerging concept, introduced by Oliver et al. (1982), to describe the integration of logistics with other business functions, into a critical component of strategic business management. This novel term, 'supply chain management,' while capturing the essence of interconnected logistics, was soon recognized by authors such as Ellram (1991) for not fully encapsulating the intricate web of relationships and processes that define the supply chain. As SCM sought to enhance the coordination of traditional business functions and strategies within and across the supply chain network, the early 1990s marked a pivotal moment in its development, gaining substantial attention and leading to a deeper understanding of its multifaceted dynamics. It was during this time that the Supply Chain Council of America offered a comprehensive definition of SCM, characterizing it as an effort that *"encompasses every aspect involved in producing and delivering a final product, from the supplier's supplier to the customer's customer."*. In the turn of the millennium, Mentzer et al. (2001) defined SCM as "*the systemic, strategic coordination of the traditional business functions and the tactics across these business functions within a particular company and across businesses within the supply chain, for the purposes of improving the long-term performance of the individual companies and the supply chain as a whole*.".

Today, according to the Council of Supply Chain Management Professionals, SCM is the coordination and strategic oversight of all activities related to sourcing materials, transforming them into final products, and delivering these to customers. It involves collaboration with suppliers, intermediaries, and customers to ensure a seamless flow of goods. SCM aims to balance supply with demand, linking various business functions—such as manufacturing, logistics, sales, and finance—across companies for a cohesive and high-performing business model. (CSCM, s.d.)

The markets today are vastly different from what they were a few decades ago, largely due to the revolution brought about by digital technologies. Digital innovations have transformed the way people communicate, interact, and access and exchange information, impacting supply chains. In this evolving landscape, having a modern and agile supply chain is the goal of every company. A Modern Supply Chain (MSC) distinguishes itself by being fast, automatic in its processes—from accepting orders to preparing and distributing them to customers—more flexible, and transparent. This evolution is further supported by Industry 4.0, which advocates for digitalization through IT solutions and connections to enhance productivity and reduce costs, thereby optimizing supply chain management.

In this context, a Digital Supply Chain (DSC) is not merely about managing digital goods but rather employing digital methods to the supply chain. At its core, DSC is viewed as a strategically optimized technological system that leverages large data capabilities and promotes superior cooperation and communication through digital platforms. The continuous generation of new and large amounts of data in the modern commercial society's supply chains can be utilized to maximize supply chain value and enhance supply chain management. With the integration of AI, the DSC can transform into a Smart Supply Chain, which enables it to make intelligent decisions that best achieve business objectives. This transformation allows DSC to evolve beyond digital capabilities to become a dynamic, adaptive, and self-optfimizing network. This approach aims to improve organizational interactions, making services more valuable, accessible, and cost-effective, while ensuring outcomes are consistent, agile, and efficient, signaling a significant shift in how supply chains operate (Büyüközkan et al., 2018; Agrawal et al. 2018; Armengaud et al., 2017; Zhang et al., 2022; Sharma et al., 2023).

In the current competitive global landscape, organizations are simultaneously pursuing the digitization and sustainability of their supply chains, moving away from the traditional linear "take-make-dispose" model, which is unsustainable due to its significant waste production, depletion of natural resources, and environmental pollution. (Gouvidan et al., 2017, Nosratabadi et al., 2019) This discourse around sustainability and the circular economy has significantly influenced supply chain management, leading to the emergence of various interconnected concepts. These include sustainable supply chains, green supply chains, environmental supply chains, and closed-loop supply chains, all of which have been introduced and often used interchangeably within both academia and industry. This evolving terminology reflects a broadening understanding and appreciation of sustainability's role within supply chains. (Guide et al., 2003; Srivastava, 2007; Seuring et al., 2008; Chakraborty, 2010; Craig et al., 2011; Seman et al., 2012; Anne et al., 2015; Malviya et al., 2015; Leszczynska et al., 2017).

Since supply chains are recognized as key enablers for CE implementation, the concept of Circular Supply Chain Management (CSCM) has appeared and developed in the literature. Therefore, CSCM, often used as an umbrella term for coordinated forward and reverse supply chains, aligns closely with CE's foundational principles. It offers a sustainable complement to traditional linear supply chains by emphasizing resource efficiency and waste reduction, thereby fostering regenerative supply chain practices and encapsulating a holistic approach to sustainability. (Geissdoerfer et al., 2018; Lahane et al., 2020; Vegter et al., 2020; Amir et al., 2022).

Seeking to enhance the clarity and depth of the CSCM concept, Farooque et al. (2019) contributed to the literature by highlighting the integral roles of restorative and regenerative cycles, as well as the pursuit of a zero-waste economy—both of which are central principles of circular economy philosophy, in the following definition: *"Circular Supply Chain Management encapsulates the fusion of circular economy principles within the framework of supply chain* *management, extending to its interaction with both industrial and natural ecosystems. This approach is characterized by a deliberate effort to systematically recover technical materials and rejuvenate biological materials, all while steering towards a vision of zero waste. Such a transformation is achieved through comprehensive innovation in business models and across all supply chain activities, from the design of products and services to their disposal and beyond into waste management. This strategy necessitates the active participation of an extensive array of stakeholders throughout the entire lifecycle of a product or service, including but not limited to manufacturers, service providers, consumers, and end-users."* (Farooque et al., 2019).

Within this system, the waste generated by one organization becomes valuable for another. Reverse flows that remain within the same sector are part of a closed-loop supply chain, while those extending to different sectors are part of an open-loop supply chain. This approach is vital for recovering value in a Circular Supply Chain, where the emphasis on recirculating resource, aligning with the objective of achieving a zero-waste vision. This not only supports environmental sustainability but social and economic spheres, presenting a multifaceted benefit to businesses that adopt these practices. (Sun, 2017; Farooque et al., 2019; Genovese et al., 2017; Berlin et al., 2022; Kayikci et al., 2022).

2.5 Impact of Artificial Intelligence on Circular Economy

Technological innovations represent an important way to leverage the Circular Economy efforts even further. Integrating these technologies enhances process efficiency, improves process adaptability, improves transparency and ultimately boosts productivity while reducing environmental impact through optimized resource utilization. (Ghoreishi Happonen, 2020a, 2020b; Bag et al., 2021; Sharma et al., 2021; Onyeaka et al., 2023). This convergence culminated in the conceptualization of the Smart Circular Economy (SCE), defined as *"an industrial system that uses digital technologies during the product life-cycle phases to implement circular strategies and practices, aiming at value creation through increased environmental, social, and economic performance."* (Bressanelli et al., 2022)

Artificial Intelligence is an emergent technology, has the potential to increase innovation, creating circular business models that deliver products and services aligned with CE principles. (Nascimento et al., 2019) The consequential role of artificial intelligence in advancing global sustainable development underscores its pivotal utility in addressing challenges associated with the establishment of an intelligent circular economic system. (Khayyam et al., 2021) As one of the most dominant and potential tools to lead the transition of CE from linear to circular (Noman et al., 2022), it has been demonstrated to facilitate the adoption of circular manufacturing approaches, enhance energy efficiency, and prolong the lifespan of products and components by maximizing the value extracted from resources. (Cioffi, 2020)

When exploring the role of AI within the CE, three distinct areas emerge: the design of circular products, components, and materials; the operation of circular business models; and the optimization of infrastructure to facilitate circular flows of products and materials (Ellen MacArthur Foundation, 2019).

Designing circular products helps safely maintain products for longer in the economy, so there is less waste, and less resource extraction needed to allocate to an increasing demand. AI also has the capability to forecast the evolution of materials over time, including factors like their long-term durability and potential environmental impact. (Pregowska, 2022)

Operating circular business models can be enhanced through AI application. These business models are characterized by access over ownership, such as product-as-a-service, leasing, and renting. (Ellen MacArthur Foundation, 2019) Through AI use, sharing economy platforms can increase trust, match assets, and obtain consumer preference knowledge. (Chen, 2021)

Additionally, AI contributes significantly to the optimization of circular infrastructure. (Pathan et al., 2023) Through smart logistics and supply chain management, AI can significantly influence the circularity, facilitating more sustainable and environmentally friendly transportation solutions, improving the efficiency of reverse logistics systems, optimizing freight scheduling, enabling faster and more cost-effective international shipping, and reducing the volume of products discarded. (Lacy et al., 2015)

Major technological companies, such as Google, are actively adopting CE initiatives to blend environmental sustainability with economic and community benefits. Google is recognizes AI potencial to accelerate the transition to CE, this view aligns with the Ellen MacArthur Foundation's (2019) findings. Based on these findings, AI can enhance circular product design, improve circular business models by optimizing supply chains, and optimize circular infrastructure through better waste sorting and recycling (Werner, 2023). In Pakistan, AI-driven CE applications in agriculture and food businesses address industry issues, enhancing sustainability at social, environmental, and economic levels (Ali et al., 2023). In Ireland, enterprises use AI to improve waste management by analyzing waste streams, monitoring food waste, and optimizing resource use, which reduces greenhouse gas emissions and operational costs in buildings. AI also enhances recycling efficiency by improving sorting and reducing contamination (Pathan et al., 2023).

The literature extensively supports the potential advantages of deploying AI to enhance practices within the CE. However, the implementation of such AI-driven enhancements is not without its challenges. Foremost among these challenges is the pronounced scarcity of high-quality training data, which is imperative for the effective application and subsequent optimization of AI technologies in the advancement of CE initiatives. However, the availability of such data in the context of CE, specially at initial stages of business development, can be limited due to various reasons, including privacy concerns, competitive interests, and the variety of materials and processes involved in different industries. Moreover, the accuracy of these models directly impacts the quality of decision-making, where a lack of precision and reliability could lead to inefficient resource use or suboptimal results, further complicating the optimization of CE initiatives. In addition, to run such high-accuracy models, an increase in computational resources needs to be considered, adding another layer of complexity to AI integration. The challenge extends to the 'transparency' of AI decisions and predictions, which is crucial for building trust and accountability. Ensuring models are not only accurate but also transparent and interpretable is a significant challenge. It is also required the latest highly advanced infrastructure. The development of AI models for CE raises important privacy, ethical, and legal concerns. Designing AI models for CE requires data from various sources. Data on user location, behavior, and personal characteristics can lead to privacy issues and the potential misuse of information. The use of such data introduces the risk of algorithmic bias. Furthermore, AI's analysis could infer sensitive details about individuals' lives, raising ethical questions.

Alongside these technical and ethical challenges, there is a presence of the critical challenge of identifying and developing talent with the right mix of managerial, operational, and technical skills. This talent is essential for driving the digital transformation within the CE context. The integration of AI-based human-robot co-working, as propelled by Industry 5.0, introduces a unique dynamic into the CE landscape, where collaborative robots (cobots) work alongside humans to enhance efficiency and innovation. This evolution necessitates not only a redefinition of workforce roles and skills but also careful consideration of the ethical and organizational implications of blending human creativity with robotic precision and autonomy.

The transition to a CE relies on collaboration among stakeholders such as businesses, research centers, and public entities. A collaborative AI ecosystem is needed to support optimized and sustainable processes, nonetheless interconnectedness also increases vulnerability to cyberattacks. To address these challenges, advanced infrastructure is essential for integrating AI technologies, providing the processing capacity and connectivity needed for complex data analysis and real-time decision-making in CE initiatives. (Kozanoglu et al., 2021; Naanani et al., 2021; Maddikunta et al., 2022; Nozari, 2022; Roberts et al., 2022; George et al., 2023; Pathan et al., 2023; Rane, 2024; Schwartz et al., 2023)

2.5.1 Drivers for AI adoption in SCM

In the current landscape of big data, industries are continuously producing, gathering, and storing vast quantities of data. These datasets are critical assets, enhancing process operation, control, and design. The growth in data volumes from various segments of supply chain management (SCM), as result of digitalization process, has opened an opportunity to implement advanced technologies capable of rapidly and intelligently interpreting large datasets. One of these transformative technologies is artificial intelligence (AI), which plays a pivotal role in managing and optimizing the increasing data complexities in SCM. (Tirkolaee et al., 2021)

The implementation of AI technology in SCM is driven by its ability to increase efficiency, productivity, and cost-effectiveness while improving decision-making processes. AI optimizes inventory levels to align stock with demand, reducing holding costs and stockouts. For quality control, AI significantly reduces waste and defects, leading to more streamlined and cost-effective operations. By analyzing vast data, AI identifies inefficiencies and provides insights for strategic decisions in production planning, inventory management, demand forecasting, supplier selection, supplier risk management, logistics, and distribution. These enhancements improve operational performance, giving firms a competitive advantage through faster response times, improved customer satisfaction, and a more agile, resilient, and circular supply chain. The decision-making capability and accuracy of AI solutions are critical factors influencing a firm's AI implementation strategy (Belhadi et al., 2022; Olan et al., 2022; Kar et al., 2021; Shang et al., 2023).

Top management has a crucial role in strategic decision-making, and their support and dedication significantly influence the adoption and implementation of AI technologies within an organization. Consequently, the positive involvement of top management can greatly enhance the successful integration of AI solutions for SCM. (Hangl et al. 2023; Lada et al., 2023) External cooperation, such as partnering with other companies, consultancies, software service providers, and research institutions, can significantly enable the deployment of AI applications, particularly in SME by providing necessary expertise and facilitating interdisciplinary collaboration. (Bauer et al., 2020)

2.5.2 Barriers to AI adoption in SCM

Although artificial intelligence (AI) technologies have been around for several years, their adoption among EU firms remains relatively low. Specifically, in the Portuguese context, the adoption rate for AI technologies was only 7.9% in 2023 (Eurostat, 2024). The EU aims to reach 75% of firms using AI by 2030. The EU average adoption rate in 2023 was 8%, therefore this represents an increase of 837.5% in 7 years (EC, 2024).

In the context of supply chain management, one of the most significant barriers to AI adoption is organizational resistance. This resistance is largely driven by employees' fear that the adoption of digital technologies may eliminate the need for their jobs. Additionally, some AI solutions are perceived as a black box due to a lack of prior AI experience, leading to a perceived lack of transparency and explainability regarding their functionality and benefits. This exacerbates resistance and creates anxiety and lack of trust among employees. Consequently, managing change becomes a crucial part of integrating AI into the supply chain management processes of an organization (Agrawal et al., 2023; Booyse et al., 2023; Polisetty et al., 2023).

Furthermore, data-related obstacles pose substantial challenges to AI adoption in SCM. The integrity and quality of data are paramount, as any discrepancies, inaccuracies, or tampering can compromise AI model efficacy, potentially yielding misleading insights or perpetuating biases. Within this sphere, two primary challenges surface: data quality and collection. Substandard data quality frequently affects organizations, while the process of collecting data from varied sources—including suppliers, customers, and internal systems—remains a formidable undertaking. Additionally, ensuring data security and privacy assumes critical importance considering escalating concerns surrounding data breaches. (Hangl et al., 2023)

Technical barriers are also significant, as many organizations lack the necessary technical proficiency and knowledge to effectively implement and leverage AI technologies within their SCM frameworks. This includes low IT resources, such as a lack of internal IT expertise and skills. Talent shortage and skill gap are significant strategic challenge, particularly for most SMEs, when deploying this technology. As a result, there is a lack of digital strategy to adopt this technology. Infrastructure deficiencies and limitations further hinder technological deployment. Additionally, the incompatibility with the organization's legacy IT systems or processes poses a substantial challenge, making it difficult to integrate new AI solutions seamlessly. (Hansen et al., 2021, Chatterjee et al. 2021)

On the financial barriers, the high initial investment costs of implementing AI solutions, including hardware, software, and skilled personnel, coupled with the uncertainty surrounding return on investment (ROI), dissuade many organizations, particularly small and medium-sized enterprises, from embracing AI technologies in their SCM practices. Additionally, the lack of skilled workers with expertise in AI further complicates these financial challenges, as organizations must invest in training their existing workforce to develop and manage these technologies. Firms that do not have high-quality data readily available, the process of gathering and cleaning data can be particularly costly, adding to the complexity of adopting AI solutions. The absence of governmental support, including monetary incentives, subsidies, and the facilitation of accessible credit, poses a significant barrier to the technological adoption. This is particularly challenging for SMEs that lack the capital requirements to invest in new technologies. (Badghish et al., 2024)

Chapter 3

3 Theoretical Approach

Considering the literature review presented in the previous chapter, which provided insights from several authors on Artificial Intelligence, Circular Economy, Supply Chain Management, Characterization of plastics industry, drivers and barriers related to Artificial Intelligence adoption in Supply Chain Management and the impact of Artificial Intelligence on the Circular Economy, it allowed to develop five pivotal research questions.

Assessing the impact of AI on the circular economy domain, specifically on supply chain management, requires first to have an overall understanding of the current role of technology in the plastics industry supply chain. Hence, it is crucial to examine the scope of AI adoption in Portuguese companies operating in this industry. The review of existing literature unveiled the proliferation of AI applications across diverse industry supply chains, indicating the potencial to enhance circularity. (Pathan et al., 2023) However, this review concurrently demostrated a significant shortfall in scholarly exploration specifically concerning the plastics industry's supply chain. (Echchakoui et al., 2020)This research lacunae was the basis for the following research question, which has the objective of acessing the current state of AI implementation in the Plastics Industry's Supply Chain:

RQ1: What is the current role of technology, particularly AI, in the plastics industry's supply chain?

Studies on AI applications have been predominantly concentrated on plastics mold injection and quality control processes, areas where the existing literature is more abundant (Mok et al., 1999; Petrova et al., 1999; Chen et al., 2005; Ribeiro et al. 2005; Ogorodnyk et al., 2018; Echchakoui et al. 2020; Getor et al. 2020; Gupta et al. 2021; Nara et al. 2021; Oleksy et al. 2021; Aminabadi et al. 2023). Portuguese companies are particularly noteworthy in this regard, as they are already familiar in the concept of Industry 4.0 and its advantages, as indicated by a study conducted by Pereira et al. (2023). This familiarity stems from the fact that the majority of Portuguese companies studied had already initiated efforts in this field. By assessing current AI applications in the industry, it becomes equally relevant to identify the main challenges faced during the implementation phase of these projects.

Therefore, in order to gain a deeper understanding of which AI applications are being pursued within the plastics supply chain management practices, explore its functionalities, and identify the main challenges encountered during the adoption process, the following research question was formulated:

RQ2: To what extent are AI technologies currently used in supply chain processes in the plastics industry, what are their primary functions, and what are the main challenges faced during their implementation?

In the literature review conducted it was possible to identy several studies that focused on the drivers for AI adoption in SCM (Hangl et al., 2023; Mondal et al. , 2023; Oubrahim et al. ,2023; Sassanelli et al., 2023; Taddei et al., 2023). The driving and enabling factors of the implementation of AI in the supply chain are often covered under the umbrela of industry 4.0, where it is frequently analyzed alongside other technologies. These drivers, internal and external, include saving costs, increasing efficiency, improving decision-making capabilities, and enhancing accuracy in prediction and forecasting, all in combination with reducing time and resource wastage through sustainable processes. (Müller et al. 2018; Simões et al. 2019, Cagliano et al., 2021; Kar et al., 2021; Yang et al., 2021; Hangl et al., 2023; Madancian et al., 2024; Oubrahim et al., 2023) As far as it was researched, there was no study that analysed drivers of implementing AI for the plastics supply chain management practices.

Research conducted by Lopes da Costa et al. (2023), revealed that the perception and knowledge about smart systems, as well as the benefits generated by them, positively affect the intention of managers to implement this types of technologies.

According to Ronaghi et al. (2022) the adoption of AI has a positive effect on circular economy practices in manufactering companies. As the AI adoption by the portuguese companies is increasing, makes it appropriate to analyse and identify what are the main factors that drive its incorporation, particularly in enhacing circular practices through supply chain management. Understanding these factors can be important to positively influence and facilitate the adoption process. For this reason the following research question was formulated:

RQ3: What are the key drivers influencing the adoption of AI in the plastics industry's supply chain?

The literature review identified several significant barriers, including those related to data, skills and talent, economic factors, and organizations (Antikainen et al., 2018;

Demestichas et al., 2020; Raj et al., 2020; Costa et al., 2022; Shrivastav et al., 2022; Cannas et al., 2024). While companies that leverage AI are positioned to enhance efficiency, reduce costs, and improve sustainability, it is not without its own set of obstacles. Although AI implementation is being persued by the portuguese industrial companies, there are many companies that aren´t implementing it yet, particularly for managing its supply chain. Simultaneously, it is invaluable to identify AI adoption opportunities that can further enhance circularity in the plastics industry.

Hence, it is essential to identify these implementation barriers, as well as explore opportunities within supply chain management, where AI technologies can enhance circularity. (Richey Jr. et al., 2023) As a result, the following research question was developed:

RQ4: What barriers and opportunities exist in the implementation of AI for advancing CE practices within the plastics industry's supply chain?

Chapter 4

4 Methodology

4.1 Research Model

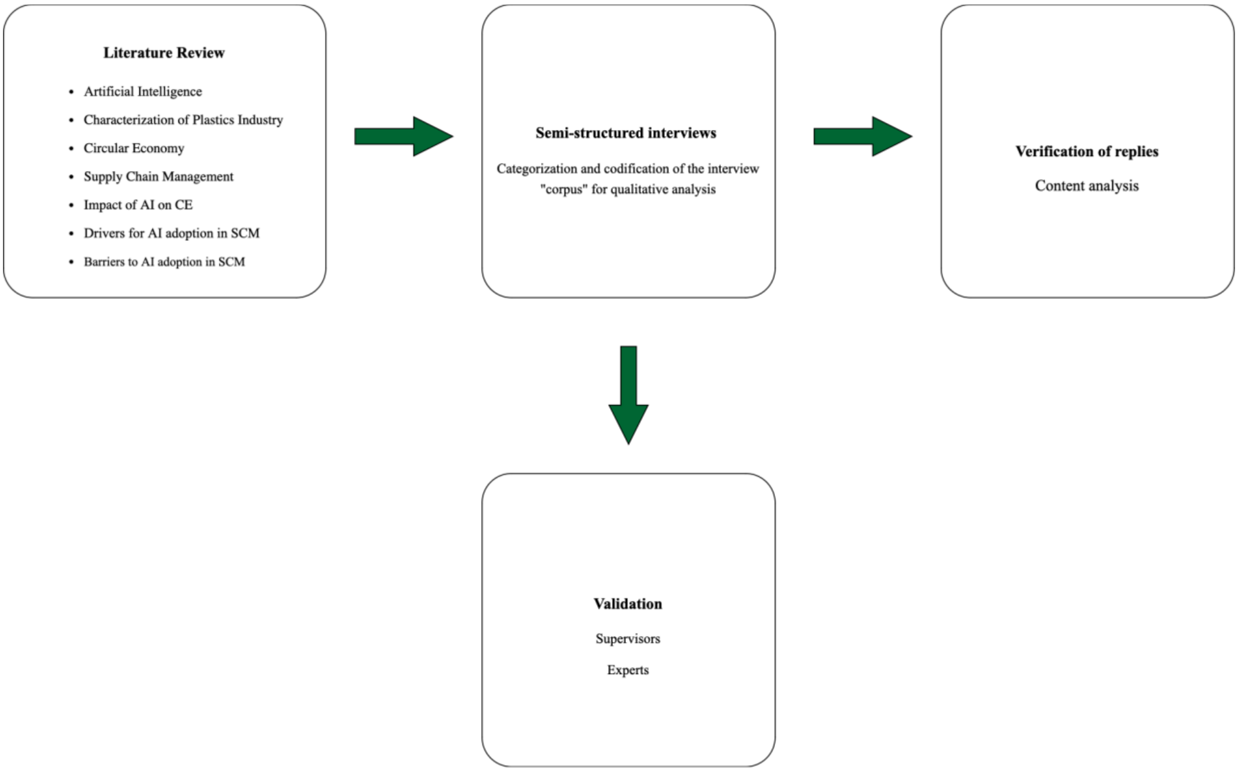
This study aims to uncover previously unidentified drivers, barriers, challenges, opportunities, and to assess the current state of AI implementation in advancing CE practices within the Portuguese plastics industry. Thus, a qualitative approach was selected as the most appropriate methodology to achieve these research objectives. This approach is particularly suitable given the fact that the impact of AI on CE practices remains significantly unexplored, primarily within the supply chain management of companies in the plastics industry. Its exploratory nature, ability to handle the complexity of the research topic, and capacity to provide depth and context-rich understanding of the phenomena under study make it suitable for this investigation. From what I could have access to, this is the first research on impact of AI on CE domain, that specifically focuses on the supply chain mangement practices of portuguese organizations operating on the plastics industry.

The present research was divided into four phases, illustrated in figure 4.1, namely: the first stage, which was based on literature review and processing information on the relevant topics for the research; the second, which consisted of applying the theoretical framework to a practical context, in order to verify theoretical assumptions and improve reliability of findings; the third, concerned fieldwork and the data collection through semi-structured interviews, which included the categorization and coding of the interview corpus; and, finally, the fourth step, which consisted of qualitative analysis of the data collected from the interviews and conclusions.

The content analysis of the information resulting from the interviews, was carried using MAXQDA 2022.

In Table 4.1, the relationship between Objectives, Research Questions, and Supporting Literature is presented, serving as the foundation for this investigation.

Figure 4.1:Research Model



Source: self-elaborated

Table 4.1: Relationship between Objectives, Research Questions and Supporting Literature

Objectives	Related Research Questions	Supporting Literature
Assess the Current State of AI in the Plastics Industry's Supply Chain	RQ1, RQ2	Mok et al. (1999); Petrova et al. (1999); Ribeiro et al. (2005); Echchakoui et al. (2020); Getor (2020); Gupta et al. (2021); Nara et al. (2021); Oleksy et al. (2021); Aminabadi et al. (2023);

Examine the drivers influencing the adoption of AI in the plastics industry's supply chain	RQ3	Simões et al. (2019); Müller et al. (2018); Bag et al. (2021); Cagliano et al. (2021); Yang et al. (2021); Dora et al. (2022); Kar et al. (2021); Hangl et al. (2023); Mondal et al. (2023); Oubrahim et al. (2023); Sassanelli et al. (2023)
Identify Barriers and Opportunities for AI Integration in CE Practices	RQ4	Antikainen et al. (2018); Demestichas (2020); Raj et al. (2020); Fraga-Lamas et al. (2021); Sineviciene et al. (2021); Tirkolaee et al. (2021); Roberts et al. (2022); Onyeaka (2023); Richey Jr. (2023); Taddei et al. (2023)

Source: self-elaborated

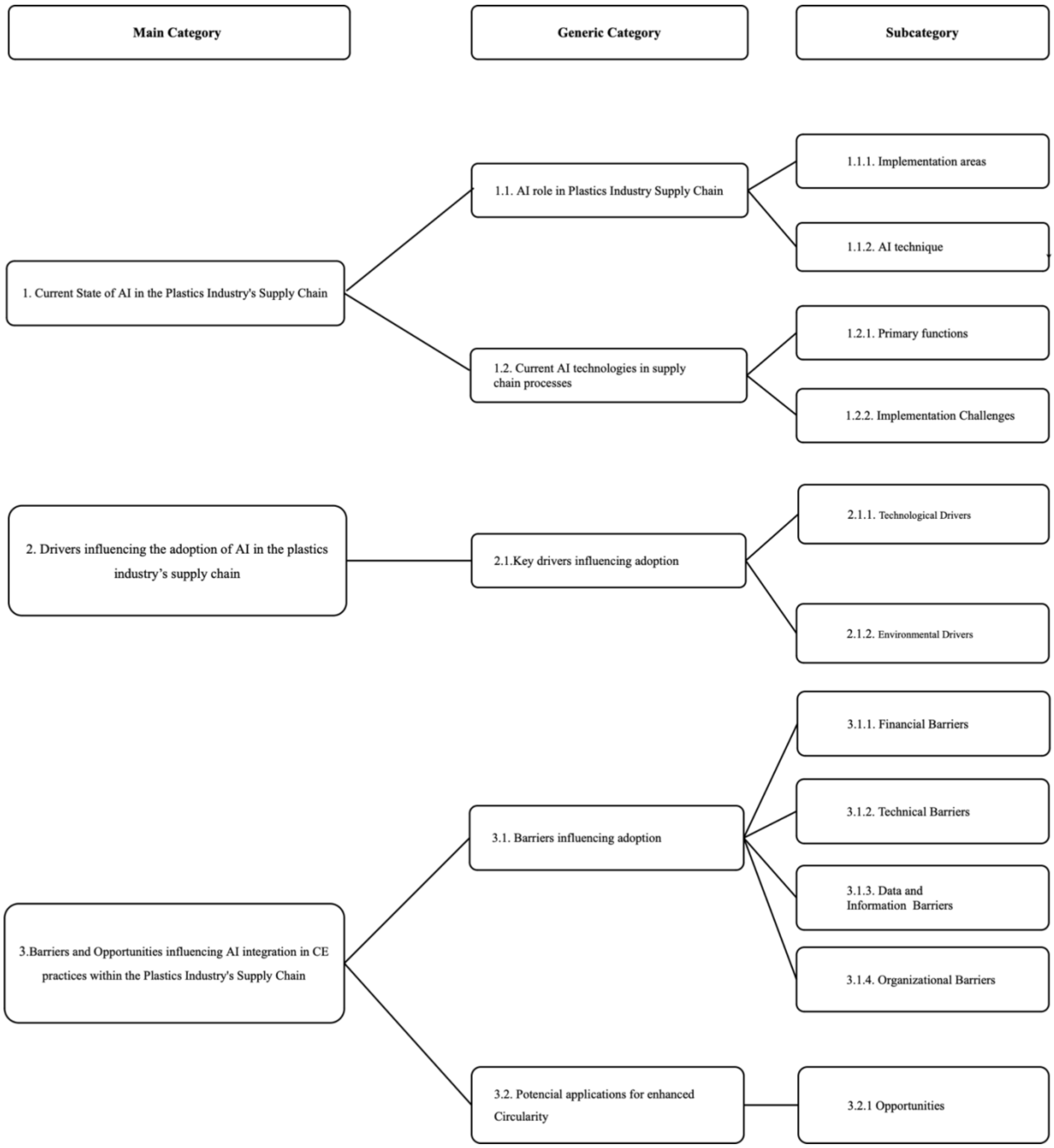
4.1.1 Data Collection Method

Semi-structured interviews were chosen as the data collection method for this study, specifically because they offer the necessary flexibility to capture nuanced and developed responses from participants. By providing this flexibility it ensures that participants are not completely confined to an interview script, thereby enabling the collection of diverse types of information that might not be accessible through more structured methods. Each interview was guided by a set of pre-established questions aligned with the research questions and objectives, which served as a foundation to steer discussions while still allowing the freedom for respondents to explore different perspectives and provide individual insights. Conducted on a one-on-one basis, these interviews allowed individuals with roles in managerial positions in companies operating in the Portuguese plastics industry to explore different prespectives freely and provide individual insights specific to their companies. Participants were selected using a non-probabilistic convenience sampling method, based on their organizational roles and availability, to ensure practical accessibility and relevance to the research objectives.

Although the participants' involvement and responses to the interviews were highly satisfying, the investigation's findings and key lessons should be carefully considered, given the relatively small sample size and the broad range of answers, which does not allow generalization for the overall population. According to Vilelas, et al. (2020), the number of interviews to be carried out for the research to have an acceptable degree of reliability must be between 15 to 20 interviews. Considering this, data collection stopped after 15 interviews as noticeable repetition in the answers began to occur. Although the response rate is considered satisfactory, the findings of this investigation should be carefully taken from a small sample. Thus, given the impossibility of making generalizations, this factor presents itself as the main limitation of this investigation, with the due exception that generalization was not a primary objective either.

Below, in Figure 4.2, it is presented the categorization and codification of the interview corpus for the qualitative analysis.

Figure 4.2: Categorization and codification of the interview corpus



Source: self-elaborated

4.1.2 Interview’s Procedure

The development of the interview script was a critical initial step, which was designed specifically aligned with the research objectives of this investigation. The script aimed to assess the current AI implementation status, explore the factors influencing its adoption, and identify the barriers and opportunities that AI presents for enhancing the Circular Economy at a supply chain management level. To address the diversity in the implementation status of AI within supply chain management, two distinct scripts were crafted, each comprising six questions. These scripts were structured to elicit insights on both scenarios: companies that have implemented AI and those that have not. The inclusion of the second script, specially for the companies that had not yet implemented AI was essential, as it focused on understanding the main reasons that prevent the implmentation of this technology in the supply chain management of their organization.

Following the completion of the scripts, potential interviewees were approached via email and LinkedIn. During this initial contact, they were briefed on the objectives of the study, though no specific questions were disclosed beforehand to ensure spontaneity and unbiased answers.

The interviews were conducted using online platforms such as Zoom and Microsoft Teams. Each session lasted approximately 25 minutes and was audio recorded with the participants' consent. Interviewees were assured that personal data would be handled with the utmost confidentiality. At the beginning of the interviews it was provided a brief overview of the study, which included theme contextualization and the main objectives. For data analysis, all fifteen interviews were meticulously transcribed, with the majority being translated into English to facilitate analysis.

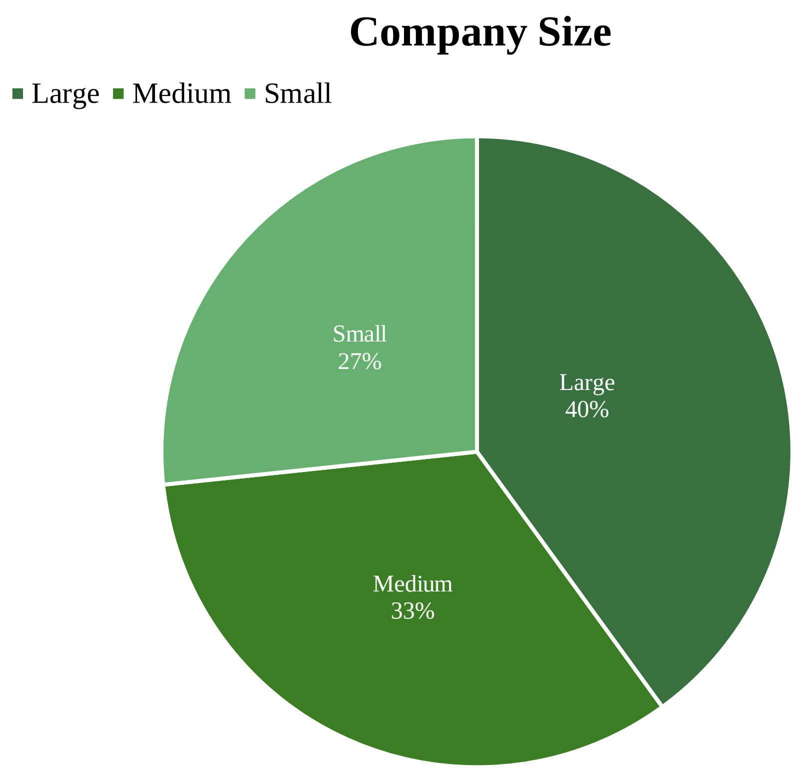
4.1.3 Sample Characterization

The study utilized a probabilistic sampling method, selecting individuals from a defined population to ensure that every member had a measurable chance of being included in the sample. Considering the primary objective of this investigation, the aim was to select companies spanning various segments within the plastics value chain in Portugal, ensuring a comprehensive representation of this industry. As well as obtain responses from those holding management positions in departments with the highest levels of interaction and responsibility with AI technology and supply chain management.

Therefore, 15 interviews were conducted with individuals holding relevant positions in companies operating within the plastics value chain in Portugal. For the sample description and characterization analysis, factors such as company size, sector of activity within the plastics industry, years of operation, and the interviewees' positions were considered.

Regarding company size, out of the 15 companies included in this study, 6 (40%) are classified as Large Enterprises, while 9 (60%) are categorized as SMEs. Among the SMEs, 5 (33%) are medium-sized enterprises and 4 (27%) are small enterprises.

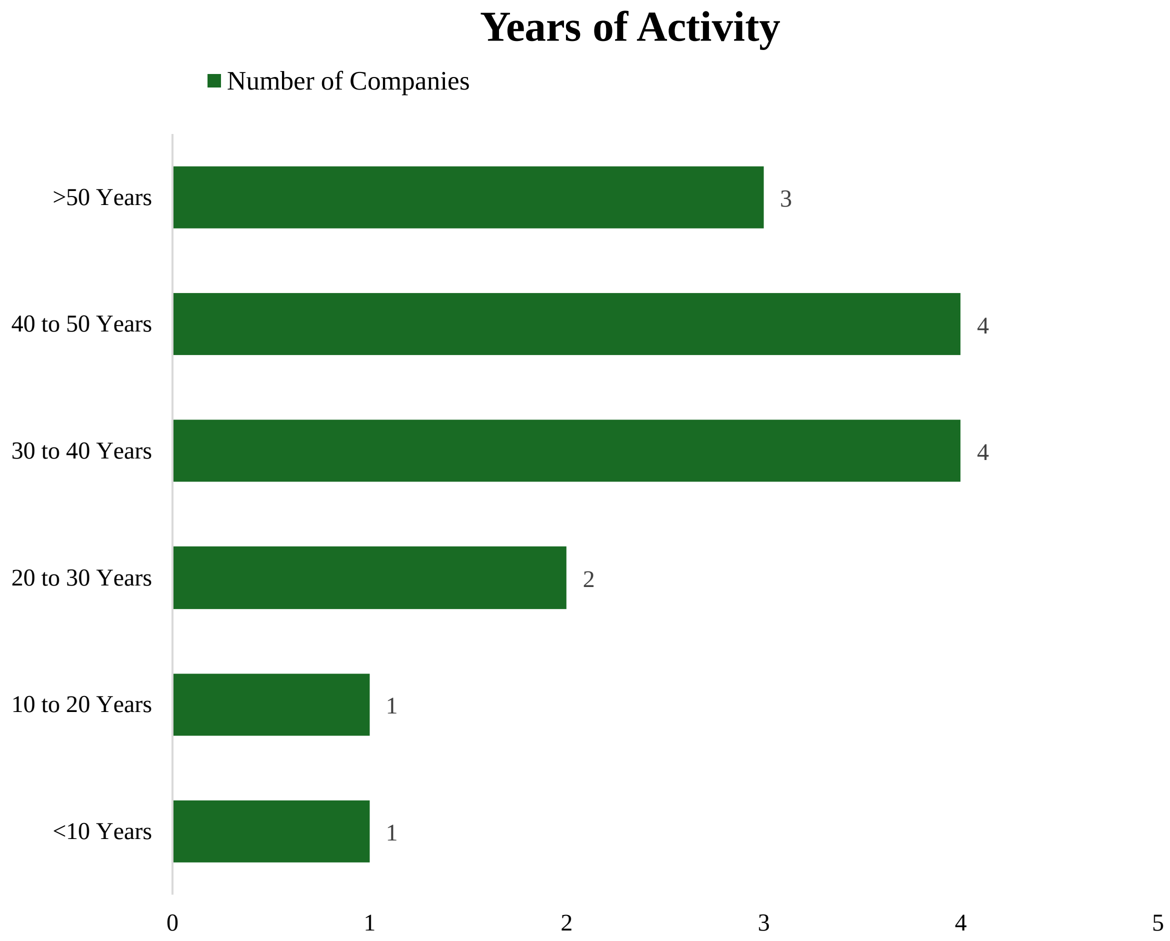
Figure 4.3: Companies' size



Source: Self-Elaborated

Based on the foundation dates of the companies in this investigation, the youngest company has 4 years of activity and the average age of these companies is 43 years of activity. Notably, there are in the sample 3 companies with over 50 years of activity in this industry, with the oldest company having been operating for 68 years

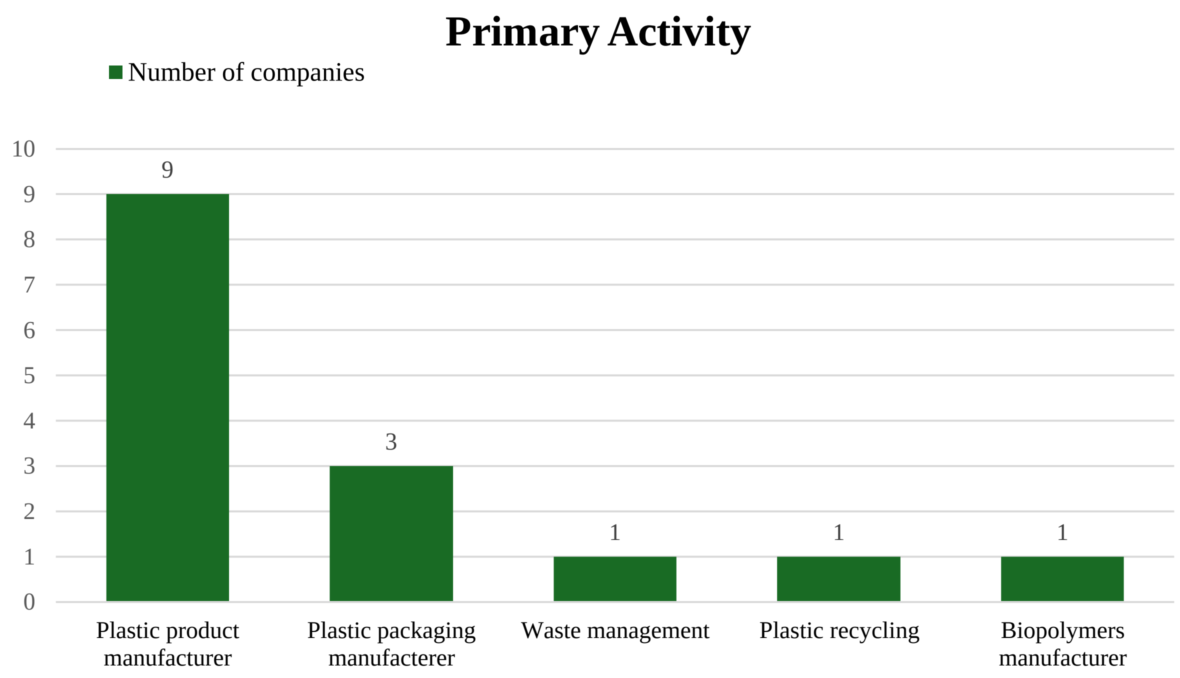
Figure 4.4: Companies' years of activity



Source: Self-Elaborated

Pertaining to the companies' primary activities within the plastics industry, it is observable that the majority, 9 (60%), operate in plastics product manufacturing. This includes the production of automotive parts, household products, mobility products, electronic components, medical products, technical parts, and food storage solutions. Additionally, 3 (20%) of the companies primarily manufacture packaging solutions for a diverse range of sectors, such as dairy, food, personal care, beverage, pharmaceutical, and agrochemical. One company's primary activity is waste management while another company focuses on plastics recycling. Finally, one company specializes in the production of biopolymers.

Figure 4.5: Companies' primary activity



Source: Self-Elaborated

As for the interviewees position in these companies, the majority of the interviewees (54%) occupy top executive positions, including CEO, CTO, and CIO. Meanwhile, the remaining 46% represent a diverse range of roles related to manufacturing and supply chain management, such as Plant Managers, Sustainability Managers, Process Engineer, Production Director, and Quality Director.

Figure 4.6: Interviewees' position

Interviewees Position

Position	Count	Percentage
CEO	4	27%
CTO	3	20%
Plant Manager	2	13%
Sustainability Manager	2	13%
Process Engineering	1	7%
Production Director	1	7%
CIO	1	7%
Quality Director	1	7%

Source: Self-Elaborated

Chapter 5

5 Data Analysis and Discussion

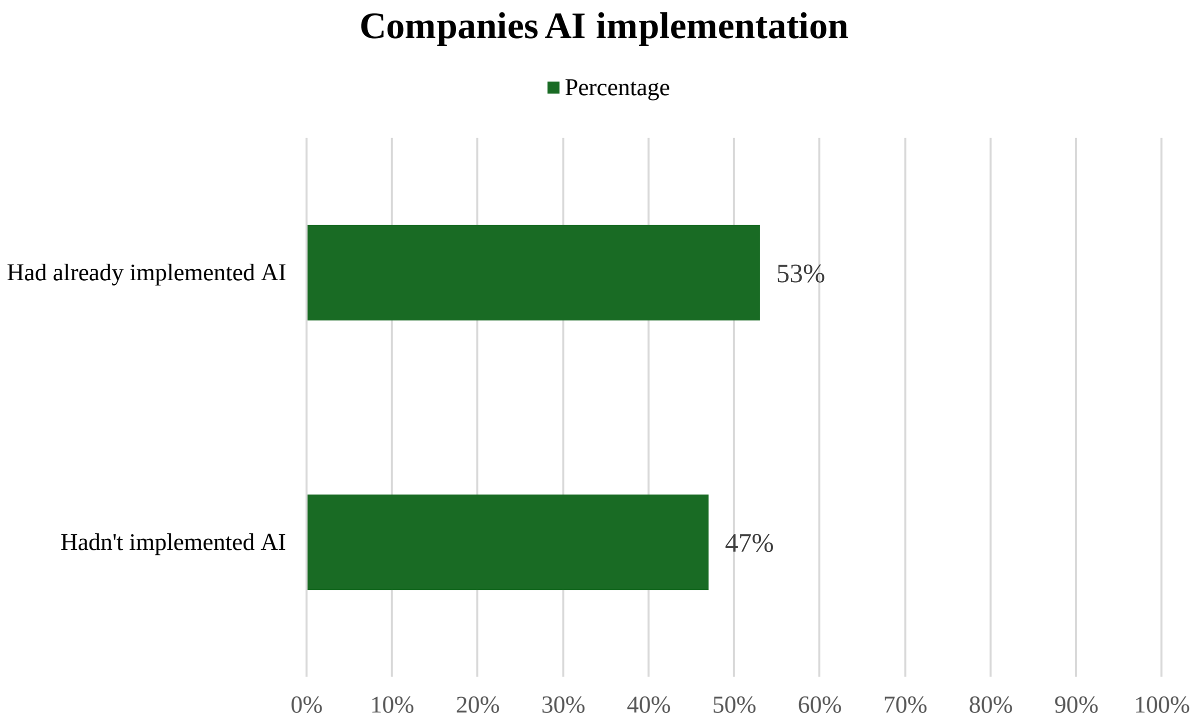
5.1 Current state of AI in the plastics industry

Focusing on the primary objective of first research category of this investigation, where the aim was to explore the current applications of AI adopted by the portuguese companies operating in plastics industry. This involved identifying specific areas where AI had been integrated, evaluating the types of AI techniques used, and understanding the primary functionalities of these applications.

5.1.1 AI role in plastics Supply Chain

Primarily, to address this research objective, we aimed to ascertain the extent to which the companies in our study had integrated AI into their organizational functions. It is interesting to note that, of the 15 companies examined in the plastics industry, 53% had already implemented AI, while the remaining 47% had not yet adopted these technologies. This finding is slightly below a study by Lopes da Costa et al. (2022), which reported that 76.2% of sampled companies in Portugal engaged in marketing operations had already introduced AI, while the remaining 23.8% had not. Although these studies focus on different industries, the comparison highlights varying levels of AI adoption rate across industries.

Figure 5.1: Companies' AI implementation



Source: Self-Elaborated

The implementation of AI in the Portuguese plastics industry predominantly focuses on Production and Quality Management, highlighted five times in the study. This is consistent with broader trends in the manufacturing industry, where AI applications in production optimization and quality control are commonplace due to their ability to enhance efficiency and product quality. (Piscitelli et al., 2020) Interestingly, product design has emerged as a area of implementation, cited twice. According to Özsoy et al. (2023) and Ghoreishi et al. (2020) interest has been growing in the AI potential as beneficial tool to enhance product design circularity. As stated by Toorajipour et al. (2021), Inventory and procurement, as well as sales, are recognized in the literature as popular AI applications, were implemented once in these organizations.

Further observations from the tables below, indicate that the majority of companies implementing AI technologies predominantly utilized Machine Learning techniques, with six mentions. Machine Learning emerged as the most widely adopted AI method, showcasing its versatility and effectiveness across various applications within these organizations. Supporting

Quayson et al.'s (2024) view on ML being widely adopted AI technique for SCM. Additionally, Computer Vision was employed in two AI applications, while one implementation explored the use of Prescriptive Algorithms.

Table 5.1: Implementation areas

Implementation Areas

Text	Generic Category	Subcategory	Times mentioned	Interviewees
Production and Quality	1.1.	1.1.1.	8	1,4,5,6,7,15 (2x)
Product Design	1.1.	1.1.1.	2	9,11
Inventory and Procurement	1.1.	1.1.1.	1	9
Sales	1.1.	1.1.1.	1	1

Source: Self-elaborated

Table 5.2: AI technique

AI Technique

Text	Generic Category	Subcategory	Times mentioned	Interviewees
Machine Learning	1.1.	1.1.2.	9	1 (2x),4,5,7,9,11, 15
Computer Vision	1.1.	1.1.2.	2	5,15
Prescritive Algorithms	1.1.	1.1.2.	1	9

Source: Self-elaborated

5.1.2 Current AI technologies in Supply Chain processes

As part of the study's objective, the first main research category also endeavored to identify the primary functions of AI applications and the challenges inherent to the process of implementing AI, faced by Portuguese companies in the plastics industry that had already adopted this technology. Considering this, only 53% of the companies in the sample had adopted this technology, which results in a relatively small sample size for this analysis.

5.1.2.1 Primary Functions

Regarding the primary functions of these applications, quality control emerged as the most implemented function. Park et al. (2019) showed how beneficial is AI over other methods for enhanced quality control of injection molding process. AI was adopted twice for circular product design, where AI was used to support the creation of innovative circular designs. As Ghoreishi et al. (2020) and Roberts et al. (2022) mentioned AI will enhance circular design by more efficient utilization of the resources, supporting the creation of durable and sustainable products. In addition, AI was utilized for predictive maintenance once. As stated by Cardoso et al. (2021); Achouch et al. (2022); Ucar et al. (2024), Predictive Maintenance is a proactive strategy that continuously monitors and analyzes machinery or processes using advanced technology. It collects real-time equipment health data to identify potential issues and predict failures, allowing maintenance to be performed precisely when needed. One company has implemented AI for production line scheduling. According to Adenekan et al. (2024) AI-driven SCM optimization integrated with ERP system can enhance production planning capabilities. Noteworthy, material sorting was another implementation mentioned once where AI was deployed, Shukhratov et al. (2024) showed effectiveness of Deep Learning algorithms deployed on embedded systems for plastic sorting. In another application, sales forecasting was leveraged through the implementation of AI. Based on the findings of Mediavilla et al. (2022), AI methods alone or in combination with statistical methods significantly improve the accuracy of demand forecasting methods.

Table 5.3:
Primary functions

Primary functions

Text	Generic Category	Subcategory	Times mentioned	Interviewees
Quality Control	1.1.	1.2.1.	3	4,7,15
Circular Product Design	1.1.	1.2.1.	2	9,11
Predictive Maintenance	1.1.	1.2.1.	1	15
Production Line Scheduling	1.1.	1.2.1.	1	9
Sorting	1.1.	1.2.1.	1	5
Manufacturing Support System	1.1.	1.2.1.	1	6
Sales Forecasting	1.1.	1.2.1.	1	1

Source: Self-elaborated

5.1.2.2 Implementation Challenges

These companies identified Data as the most challenging factor when adopting this technology, mentioned five times. The challenges ranged from difficulties in data collection, lack of quality and consistency in datasets, difficulties choosing the right algorithm for specific datasets, to identifying key variables in the processes. One interviewee emphasized the fundamental challenge*: "To have data, it needs to be correctly and thoroughly collected."* Another expressed concerns about the accuracy of data reflecting actual processes, stating, *"If there is a big gap between what happens on the factory floor and the data we get, we start not trusting the results."* Additionally, the reliance on manual records was noted: *"I wanted to implement an AI tool for predictive maintenance, and the only thing I have are manual records."* Moreover, concerns about data reliability were significant: *"Data is very important, and often it is not reliable...it depends on what is trustworthy or not."* A participant also described the complexity of algorithm selection: *"The difficulty we faced when starting this project was somewhat finding algorithms... it is almost a trial and error process."* Studies by Baez et al. (2021) and Kutz et al. (2022) also highlight data as a significant challenge when integrating AI into company operations.

Infrastructure was mentioned only twice as a significant challenge, specifically referring to the lack of new infrastructure capable of integrating with AI. One interviewee pointed out, *"The second step requires that the equipment... can receive information... and then we face another problem, that our equipment... is not prepared for this,"* emphasizing the difficulty of ensuring equipment is capable of processing AI-related information. Another interviewee highlighted, the issue of having recent technologies coexisting with much older equipment, stating, "*We have recent equipment like collaborative robots coexisting with 20-year-old Cartesian robots and other equipment that is 15 to 20 years old."* Notably, despite the lack of proper infrastructure being among the most significant implementation challenges, according to Nozari et al. (2022), it was identified only twice.

Furthermore, companies identified organizational challenges twice in this study, related to organizational resistance and change management, mostly as a consequence of increased fear of job loss among employees, highlighting the psychological barrier and fear regarding the impact of AI on job security. One participant noted, *"One of the significant challenges is breaking the barrier with people, as they think they will stop creating and may lose their jobs."* Another interviewee emphasized the complexity of managing change, stating, *"The biggest challenges we face are related to change management. When we talk about the human component, it is quite significant. The use of AI here does not aim to replace any employee but rather to accelerate and increase the efficiency of our workforce."* This fear of losing jobs was also found by Demlehner et al. (2024) in the German car manufacturing industry.

Significantly, dependency risks were identified once as a challenge in the implementation process, particularly reliance on technology suppliers. One respondent noted, *"We have our own applications, but we rely heavily on suppliers."* This reliance risks companies losing control over their knowledge, as suppliers absorb and replicate it. The interviewee explained, *"They acquire our know-how, replicate it, and sell it, making us somewhat captive. If we want to develop further, we need to invest more."* Interestingly, considering this context, this specific risk of dependency on suppliers is not comprehensively mentioned in the existing literature.

Table 5.4: Implementation challenges

Implementation challenges				
Text	**Generic Category**	**Subcategory**	**Times mentioned**	**Interviewees**
Data	2.2.	1.2.2.	5	1,9,7,15,15,
Dependency and Technological Risks	2.2.	1.2.2.	2	6,15
Organizational	2.2.	1.2.2.	2	9,11
Infrastructure	2.2.	1.2.2.	1	7

Source: Self-elaborated

5.2 Drivers of AI adoption

The second research category of this investigation aims to understand factors that drive AI adoption in SCM to achieve greater circularity in the plastics supply chain. To facilitate this analysis, the driving factors presented in the two tables below were categorized through TOE framework, namely technological, organizational and environmental context. (Tornatzky et al., 1990) This framework is inherently flexible and has been adapted for various contexts and types of research. (Baker et al., 2011) Therefore, the framework was adapted to focus solely on the technological and environmental context (TE), as there were no organizational factors mentioned by the participants in the interviews.

Technological context refers to the characteristics and aspects of the technology itself that influence its adoption and implementation within an organization. This included factors such as perceived operational benefits associated with the adoption, this technology is perceived as providing greater benefits compared to existing solutions and ease of use. Environmental context encompasses external factors that influence an organization's decision to adopt new technologies. The drivers considered part of the environmental context were associated with partnerships, competitors and client pressures to adopt, available funding towards the investment in this technology and sustainability goals.

As shown in Tables 5.4 and 5.5, technological drivers and environmental drivers were mentioned exactly by an equal amount of interviewees (12 times each), emphasizing the mutual significance of these contexts in the adoption of AI for SCM.

According to Hangl et al. (2023) study, improved decision-making, increased efficiency and cost savings, and competitive advantage were identified as significant driver for AI adoption in SCM processes. Based on the tables below, this view was validated by the participants, which mentioned operational improvement through enhanced efficiency, productivity, and improved analytical capabilities (cited 9 times) as the most significant driver to AI adoption. As described by one of the interviewees *"It is the fact that we aspire to have all our processes digitized in the future, with all information integrated into software that allows for increasingly faster response times, and our operators shifting from physical roles to more management-oriented roles. And, naturally, this leads us to what is efficiency."* Dora et al. (2021) identified the perceived benefits of AI as a critical success factor for the adoption. In contrast to Hangl et al. (2023), the interviewees did not view cost reduction as a primary driver, despite it potentially being a byproduct of operational improvements.

Frequently, SMEs advance their technological capabilities through partnerships, normally due to having limited internal resources and capabilities. Given the absence of in-house AI expertise, SMEs are often compelled to work with technology providers, research institutions, and various organizations to gain the required skills and knowledge for effective AI implementation, as noted by Chen et al. (2020), Kurup et al. (2022). According to Valdez-Juárez et al. (2021), partnerships facilitate open innovation and the co-development of customized solutions. Four participants highlighted these collaborations as key drivers for successfully enabling AI implementation at the organization. One interviewee provided a detailed description of the AI implementation process, highlighting the organization's strategy: *"Our strategy involves seeking the best partners for each project"* which emphasizes a targeted approach to collaboration. This approach allows the organization to leverage the expertise of domain specialists, as noted, *"These partners, being experts in their domains, naturally complement our efforts."* By incorporating existing expertise, the implementation process becomes more efficient: *"This approach saves us time in implementation since they bring existing expertise."* Additionally, the collaboration is mutually beneficial: *"They also gain additional experience from our collaboration,"* creating a win-win situation. The interviewee concluded, *"In the end, everyone benefits,"* underscoring the overall advantage of this collaborative strategy.

External pressures can arise from competitors, consumers, price mechanisms, and regulatory conditions, and several other entities. According to Oliveira et al. (2010), Competitive Pressure refers to the degree of pressure felt by the company from competitors within the industry. Companies experiencing high competitive pressure are driven to pursue innovation capabilities. Kwarteng et al. (2023) and Lai et al. (2018) noted that firms facing intense competition are more likely to adopt advanced technologies to optimize their operations and gain a competitive edge. Chen et al. (2020) and Lada et al. (2023) showed that competitive pressure is not positively correlated with AI adoption, notwithstanding in this study it was identified as driving factor for three participants. From the three, two mentioned that this competitive pressure was related to increased customer demand for services that required this technology. Only one participant highlighted competitive pressure directly from competitors, emphasizing the necessity to maintain competitive advantage through technological implementation and the importance of keeping pace with innovative technologies being deployed in the industry.

Government support through monetary incentives, scientific resources, pilot projects, and training programs is identified as driving new technology adoption in different countries. Particularly, Badghish et al. (2024) showed that Government support significantly impacted AI adoption in Saudi Arabia SMEs. In this study, financial incentives were identified as key drivers of AI adoption. Interestingly, Portuguese companies attributed these incentives not to the national government but to European entities. Notably, European monetary funding programs were highlighted three times.

New technological deployment supports the achievement of sustainability efforts as Sipola et al. (2023) and Badghish et al. (2024) stated. Sustainability goals was outlined twice as direct driver for AI adoption. Aditionally, two participants identified how a specific AI solution was implemented as result of having greater perceived perceived benefits compared to existing technological solutions in the context of a specific problem. However, perceived benefits are frequently cited in the literature as a primary driver for AI adoption, as noted by Pillai et al. (2021); Dora et al. (2021). Although these interviewees did acknowledge the benefits of the technological solution, the adoption was primarly problem driven. It is important to highlight the absence of references to this particular driver in the existing literature.

Hangl et al. (2022) emphasizes that AI tools to be successfully integrated and used, they must be user-friendly and accessible to the workforce. Ease of use was only once refered has a significant enabler for AI implemention.

Table 5.5: Technological drivers

Technological Drivers

Text	**Generic Category**	**Subcategory**	**Times mentioned**	**Interviewees**
Operational Improvement Through Enhanced Efficiency, Productivity, and Improved Analytical Capabilities	2.1.	2.1.1.	9	1,2,3, 4,6,7,8,12,15,
Problem Specific Need	2.1.	2.1.1.	2	9,13
Usability	2.1	2.1.1.	1	9

Source: Self-elaborated

Table 5.6: Environmental drivers

Environmental Drivers

Text	**Generic Category**	**Subcategory**	**Times mentioned**	**Interviewees**
Partnerships	2.1.	2.1.2.	4	7,9,13,15
Competitors and Client Pressures	2.1.	2.1.2.	3	1,10,11
European Funding Programs	2.1.	2.1.2.	3	2,6,14
Sustainability Goals	2.1.	2.1.2.	2	10,15

Source: Self-elaborated

5.3 Barriers and Opportunities in the implementation of AI for advancing CE

For the propose of this research, the third generic category of the research aimed at understand and identify the barriers influencing the adoption of AI in supply chain management of Plastics industry companies. More concretely, interviewees were asked about the main factors that currently prevent their organization from adopting this technology. Moreover, this category aimed at induntively identify opportunities for AI implementation, predomeninately in SCM for enhanced circularity.

5.3.1 Barriers to AI adoption

In an effort to group the main barriers into most appropriate corresponding area, it was clustered into 4 areas, such as financial barriers, technical barriers, data and information barriers and organizational barriers. Financial barriers represent factors that are related to economic aspects of investments in this technology. These include the substantial initial expenditure required for implementation, the perceived insufficient immediate financial benefits, the limited availability of funds to support such investments, and the uncertainty surrounding the return on investment in this technology. Technical barriers represent factors associated with the technological aspects of implementing this technology. These include the low maturity level of currently available solutions, the lack of qualified technical staff to effectively manage and operate the technology, and the absence of specific solutions tailored to the unique needs of the organization. Data and information barriers correspond to the availability, quality, and utilization of data necessary for sucessfully implement AI. These barriers include understanding the specific operational needs that technology must address, the lack of reliable or high-quality data, the general absence of sufficient data, and the lack of digitized data. Organizational barriers represent factors related to the internal capabilities and structures of an organization that affect the adoption and integration of AI technology. These barriers include the lack of knowledge and awareness among staff and management, time constraints that limit thorough planning and implementation, conflicting business priorities that divert resources away from AI projects, and resistance to change within the organization. Additionally, understanding operational needs is crucial to identify where AI can be beneficial.

Based on the tables presented below, organizational barriers were the most mentioned (cited 14 times) by the participants, followed closely by financial barriers (cited 13 times) . Authors, such as Agrawal et al., (2023); Booyse et al., (2023); Polisetty et al., (2023) highlighted the importance and relevance of organizational factors with significant influence in AI adoption. Technical barriers were identified 9 times as significant obstacles to AI adoption, while data and information barriers were mentioned 5 times. According to Hangl et al. (2022), these barriers are among the most frequently cited in systematic literature reviews. Notably, there is a slight divergence regarding data and information barriers. The literature emphasizes security and privacy issues, whereas the participants in this investigation did not mention these concerns when referring to data and information barriers.

The most mentioned barrier by the interviewees was the lack of knowledge and awareness about AI technology (mentioned 6 times). Many individuals within organizations still lack a comprehensive understanding of how AI operates and its potential applications in SCM. One of the interviewees explains that *'The issue is that it is still very new, and we do not yet have a clear idea of where we can use it.'* And this lack of awareness is further exacerbated by outdated knowledge, as another interviewee noted *'What I know about Artificial Intelligence is from 30 years ago, so it's practically the prehistory of Artificial Intelligence.'* This corroborated by the results of the study conducted by Hangl et al., (2023) where the lack of understanding of AI technology was identified as a significant barrier. Although, it is noteworthy the lack of trust in the technology wasn't mentioned as a significant barrier to adoption, as opposed Hangl et al., (2023) study.

Aditionally, the lack of qualified technical staff was also an notable identified barrier (indicated 5 times). One of the interviwee states that *'We don't have enough critical mass within the company. I don't have an engineer here daily to think about artificial intelligence.'* And this interviewee mentioned *'We don't have a team here, a technical staff of many people, to develop these projects.'* This idea is in line with Shrivastav (2022) view that scarcity of AI talent prevents organizations from initiating efforts towards the adoption. In addition, lack of AI talent is considered a significant barrier that will influence other barriers according to Kar et al. (2022).

Two financial barriers where mentioned four times by the participants, these barriers include high initial cost and uncertain ROI. Pandey et al. (2021) states that it can be challenging for companies to reliably measure the ROI of their AI projects. Shrivastav et al. (2022) identified high up front costs of AI initiatives as a significant barrier preventing more widespread adoption.

While the most significant barriers to AI adoption include a lack of knowledge and awareness, insufficient qualified technical staff, high initial costs, and uncertain ROI, it is also important to recognize other less significant barriers identified. These include inadequate cost-benefit analysis, the low maturity level of available solutions, a lack of specific solutions, unreliable data, non-digitized data, organizational resistance, operational needs, and time constraints. These factors can contribute to increased resistance to the integration of AI technologies across the supply chain.

Table 5.7: Financial barriers

Financial barriers

Text	Generic Category	Subcategory	Times mentioned	Interviewees
High Initial Cost	2.2.	3.1.1.	4	1,11,14,15
Uncertain ROI	2.2.	3.1.1.	4	1,3,7,13
Lack of Financial Resources	2.2.	3.1.1.	3	2,7,14
Lack of Cost Benefit	2.2.	3.1.1.	2	3,8

Source: Self-elaborated

Table 5.8: Technical barriers

Technical barriers

Text	Generic Category	Subcategory	Times mentioned	Interviewees
Lack of Qualified Technical Staff	2.2.	3.1.2.	5	1,2,5,6,12
Low Maturity Level of Available Solutions	2.2.	3.1.2.	2	8,12
Lack of Specific Solutions	2.2.	3.1.2.	2	8,9

Source: Self-elaborated

Table 5.9: Data and information barriers

Data and Information barriers				
Text	**Generic Category**	**Subcategory**	**Times mentioned**	**Interviewees**
Lack of Data	2.2.	3.1.3.	3	4,5,9,14
Lack of Reliable Data or Data quality	2.2.	3.1.3.	1	9
Lack of Digitized Data	2.2.	3.1.3.	1	14

Source: Self-elaborated

Table 5.10: Organizational barriers

Organizational barriers				
Text	**Generic Category**	**Subcategory**	**Times mentioned**	**Interviewees**
Lack of Knowledge and Awareness	2.2.	3.1.4.	6	2,5,8,10,12,13
Business Priorities	2.2.	3.1.4.	3	5,10,13
Organizational Resistance	2.2.	3.1.4.	3	6,9,11
Understanding Operational Needs	2.2.	3.1.4.	1	6
Time Constraints	2.2.	3.1.4.	1	11

Source: Self-elaborated

5.3.2 Opportunities to implement AI for enhanced circularity

Considering the majority of companies present in this investigation are in the manufacturing context, decisions regarding technology adoption in this context tend to focus on enhancing production processes and capabilities. Consequently, the area where a significant majority of the participants saw greater potential for AI implementation was in Production and Quality improvement. Authors such Getor et al. (2020), Aminabadi et al. (2023) and Willenbacher et al. (2021) highlighted AI implementations in Plastics manufacturing context. In this area, the most cited opportunity was in Predicitive Maintenance, highlighted 4 times. This implementation for Predictive Maintenance will positively influence sustainability and contribute to enhanced circularity, as one of the interviewees describes and explains *"So, if in a production room we monitor all the equipment, we know that under normal conditions, there will be a certain energy consumption. If any equipment has consumption outside of those established limits, something is wrong. Thus, abnormal energy consumption automatically indicates a potential malfunction. A malfunction immediately incurs costs. We're talking about a malfunction that requires fluid replacement, oil waste, cloth waste, which leads to not only financial impacts but also environmental impacts due to waste creation. On the other hand, if these processes run smoothly, working 24/7, and are well controlled, we reduce scrap, waste, and defects. Thus, reducing scrap makes processes more efficient, more profitable, creates less waste, and has lower environmental impacts, contributing to circularity."* This view is in line with Polese et al. (2021), Çinar et al. (2020). Aditionally, the interviews conducted suggest that AI for Predictive Maintenance primarily serves as a decision-support tool rather than directly correcting machine malfunctions. This happens because final adjustments and repairs typically need to be conducted by human operators due to the complexity of the tasks and the need for human oversight in maintenance operations. However, in cases where the equipment is specifically designed and sealed by the original equipment manufacturer (OEM) for autonomous correction, AI can directly handle these tasks without human intervention.

Participants also identified potencial for AI implentation in inventory and supplier management, which was the second most mentioned area of application (cited 5 times). In this area, it was mentioned procurement and replenishment as important application Guida et al. (2023) This application under Procurement was supplier selection and evaluation. It was mentioned using AI to support search for and identification of suppliers that meet specific criteria, particularly those related to sustainability and circularity. By leveraging AI, organizations can evaluate potential suppliers more efficiently, considering factors such as material origin, environmental impact, proximity, and adherence to sustainable practices. This ensures that suppliers not only meet the operational needs but also align with the company's circularity objectives, as one participant remarks *"It is essential to immediately identify potential suppliers who meet a specific set of requirements. For exemple, considering the distance to our supplier, as well as the environmental impact caused by their day-to-day operations."*

There were three participants that identified circular supply chain optimization as interesting potential application. These applications focused on traceability and monitoring of materials throughout the supply chain with the use of AI technology. The main objective of this type of application is to monitor every stage of the material cycle to detect any potential leakages, identify at which step they occur, and provide appropriate solutions. According to Rumetshofer et al. (2023), these types of information based tracking solutions can support the circular economy of plastics.

From the perspective of two participants, AI is viewed as a potential application for big data analysis and as a decision-making support tool for existing organizational information systems. According to one interviewee, organizations are already equiped with digital tools supports productive activities *“Nowadays, any organization must have a robust quality management system that relies heavily on the use of integrated databases and management software, such as ERPs, NRPs, and dimensional control information management software. There is already a whole array of software that supports productive activities.”* However, integrating AI into these systems can bring a significant advantage by *"connecting all this considerable amount data and quickly interpreting them."* AI's capability to analyse information from diverse sources allows decision-makers to access comprehensive insights without manually consulting each data point. By leveraging AI, organizations can *"analyze this data and assist, facilitating the decision-making process."* This means that AI not only automates data analysis but also supports strategic decision-making by providing timely and relevant insights. Consequently, managers can make more informed decisions swiftly, improving overall performance and promote more circular and sustainable business practices. This sustains the views of authors such as Brik et al. (2024), Oppioli et al. (2023); Gašpar et al. (2023).

One participant highlighted an AI opportunity in sales and marketing by utilizing predictive analytics to improve an ad recommendation system. This system would analyze customers' past purchasing behavior and current weather conditions to anticipate their future needs and provide personalized product suggestions. Based on Habil et al. (2023), AI-based recommendation systems deliver informative, relevant, and accurate content to consumers. These systems not only help retailers increase sales, enhance consumer loyalty and satisfaction, while also contributing to circularity by optimizing inventory management, minimizing overproduction, and reducing any excess stock.

Table 5.11: Opportunities for AI adoption for enhanced circularity

Opportunities

Text	**Generic Category**	**Subcategory**	**Times mentioned**	**Interviewees**
Production and Quality Improvement	2.3.	3.2.1.	11	3,4,5,6,9,14,15
Inventory and Supplier Management	2.3.	3.2.1.	5	5,6,7,12,14
Circular Supply Chain Optimization	2.3.	3.2.1.	3	9, 10
Decision Support and Data Analysis	2.3.	3.2.1.	2	8, 12
Sales and Marketing	2.3.	3.2.1.	1	1

Source: Self-elaborated

Chapter 6

6 Conclusion

6.1 Final Considerations

The world faces a climate crisis and numerous environmental problems, prompting organizations to prioritize solutions to address these challenges. Consequently, there has been a growing interest among practicioners, researchers, business stakeholders, policymakers, in concepts such as the circular economy. One significant environmental issue is the mismanagement of plastics. While there is currently no viable substitute for plastic at scale offering the same material properties, versatility, and functionality across numerous industries, a different paradigm is required. The integration of CE principles in the plastics industry can support efforts to mitigate the environmental damage caused by current manufacturing. Despite AI not being a recent development, its applications have become increasingly sophisticated and impactful, specially with the rise of Industry 4.0. This new industrial era's technological advancements and digitalization trends are allowing AI to play a pivotal role at the organizational level, improving circularity in various aspects of supply chain management.

The first and second research question aimed to understand the current state of AI technologies implemented in the plastics industry supply chain and to identify the significant challenges faced by companies during the implementation and integration of this technology.

From the interviews, it was found that 53% of the plastics industry companies in Portugal included in this study had already implemented AI in their operations. Which shows that AI is already a well-assimilated and developed concept among these companies in the plastics industry. From the 53% of companies engaged with AI applications, 56% of applications where in Production and Quality areas of these companies, 67% of these applications employed Machine Learning as main AI technique, 33% was implemented in Quality Control.

Considering these companies that had already implemented AI initiatives in their operations, the most significant challenge faced during the implementation process was related to Data. Specifically, challeges associated with difficulties in data collection, inconsistencies in data quality, challenges in choosing the right algorithms for specific datasets, and identifying key variables in the processes. It should also be emphasized that one participant highlighted the significant challenge of relying on technology suppliers for AI adoption, noting the risk of losing control over knowledge as these suppliers acquire and potentially absorb their know-how.

The third research question aimed at identifying the factors influencing AI adoption and integration in CE practices within the Plastics Industry's Supply Chain Management. From the interviews conducted, it was found that the most significant driver for the adoption of AI technologies, identified by 60% of participants, was operational improvement, characterized by enhanced efficiency, increased productivity, and improved analytical capabilities. Thus, the perception of the specific benefits associated with adopting AI, in particular enhanced efficiency, increased productivity, and improved analytical capabilities, was considered the most significant enabler for the adoption of this technology. This aligns with plastics industry's competitive nature and complex production processes that require operational improvements through precise control and optimization, ensuring high-quality output. Although these factors align with the current literature on the subject, it should be highlighted that cost reduction was not mentioned concurrently with these factors, representing a divergence from previous studies.

Notwithstanding the lesser emphasis, mentioned by 27% of interviewees, partnerships were levaraged to sucessfully drive AI adoption in these companies. By selecting the most appropriate partners, such as technology providers, research institutions, and other organizations, companies had a more efficient and effective implementation process, benefiting from the expertise and resources of their collaborators. At the same time, collaborators benefited by gaining practical insights and additional experience from the implementation process.

The forth research question focused on identifying the primary obstacles to AI implementation within CE practices in the Plastics Industry's Supply Chain Management. To achieve this goal, the study sought to understand the underlying reasons for non-adoption.

Although more companies in this sample have implemented AI than those that have not, some companies still face significant barriers preventing adoption. From the interviews, it can be concluded that the most significant barriers identified were organizational barriers, closely followed by financial barriers. The organizational barriers include the lack of knowledge and awareness among staff and management, time constraints that limit thorough planning and implementation, conflicting business priorities that divert resources away from AI projects, and resistance to change within the organization. The financial barries include the substantial initial expenditure required for implementation, the perceived insufficient immediate financial and operational benefits, the limited availability of funds to support such investments, and the uncertainty surrounding ROI of this technology. Consequently, 66% of the mentions indicated that organizational and financial factors were the primary reasons for not deploying AI in supply chain management.

The most frequently mentioned barrier to AI implementation was the lack of knowledge and awareness about AI technology, mentioned 40% of interviewees. Indicating managers lack a comprehensive understanding on how AI operates and its potential applications in SCM. This knowledge gap, often compounded by outdated information or lack of knowledge regarding the technology, hinders the effective adoption and integration of AI technologies. Notably, the lack of trust in the technology was not mentioned as a significant barrier to adoption, which contrasts with findings from other studies, such as Hangl et al. (2023).

Aditionally, it is important to note that the lack of qualified staff was identified as a significant barrier to AI adoption, mentioned by 33% of the interviewees. Despite the organization's desire to initiate AI projects, they lacked the necessary talent to develop and implement these initiatives. Companies that mentioned this barrier often did not have a dedicated team capable of developing AI projects. This shortfall was frequently associated with resource constraints that limited these companies from acquiring the required talent or provide training and reskilling the current workforce to adopt this technology. Although not as significant, it is worth noting that while the literature emphasizes security and privacy issues as a relevant barriers related to data and information, the participants in this investigation did not address these concerns.

From a distinct viewpoint, fourth research question also endeavored to identify opportunities for AI implementation, particularly in supply chain management (SCM) for enhanced circularity. This was directed to all companies in the sample, which allowed a larger response rate. In the case of insights collected from companies that had already implemented AI areas the aim was on identifying aditional areas with the greatest potential for AI application. As for companies that had not yet implemented AI, the focus was on the areas considered most promising for initial adoption within their SCM. This research focused on opportunities within the supply chain, although not all opportunities mentioned are entirely exclusive to this area.

Based on the interviews, it can be concluded that the majority of participants (73%) identified production and quality improvement as the most significant opportunity for AI adoption to enhance circularity, particularly for Predictive Maintenance. This approach can positively influence sustainability by monitoring equipment for abnormalities, allowing early detection of potential malfunctions. Early detection helps prevent costly downtimes and reduces waste, thereby enhancing both efficiency and environmental sustainability in manufacturing processes. The findings also suggest that AI for Predictive Maintenance primarily acts as a decision-support tool, as final adjustments and repairs typically require human intervention due to task complexity and oversight needs. However, in cases where equipment is specifically designed and sealed by the OEM for autonomous correction, AI can directly handle these tasks without human involvement.

Another significant area identified for potencial AI application is inventory and supplier management, noted by 33% of the participants. The key application identified within this area was deploying AI for supplier selection and evaluation. As referenced by the participants this application can support the search for and evaluation of suppliers that meet specific sustainability and circularity criteria. Allowing organizations to evaluate potential suppliers more efficiently, ensuring suppliers align with both operational needs and the company's circularity objectives, which will consequently result in enhanced circularity in the supply chain.

Overall, it is noteworthy that the companies involved in the study did not view AI as a substitute for current jobs, but rather as a tool for enhancement and for moving employees from repetitive and physical roles into decision-making roles.

In conclusion, the findings of this investigation reveals that the plastics industry in Portugal is experiencing significant technological shift with the advent of Industry 4.0 and the increasing adoption of AI. Additionally, the industry is embracing new sustainability concepts, such as the CE, to enhance sustainability throughout the value chain. While it is evident that companies in this industry are increasingly engaging in AI adoption projects, the full potential of adoption has yet to be achieved. This is corroborated by concentration of the current AI applications presented in this sample on the production and quality domains, which shows its limited exploration into other areas of supply chain. Thus, the findings from this study can be leveraged to foster a more accelarated and efficient integration of AI technologies, ensuring their alignment with CE principles. These findings were made possible due to the exploratory nature of this study, which was based on semi-structured interviews.

6.2 Theoretical Contributions

Artificial Intelligence and Circular Economy are two themes gaining a lot of interest recently from academia, governments and other organizations. Although previous studies focus on specific CE practices such as Recycling, Remanufacturing, Reverse Logistics, to the best of our knowledge, there is less scholarly attention devoted to exploring integration of AI and CE principles with a broader view of entire supply chain management processes, by incorporating research on earlier stages as well.

Adopting this holistic perspective was particularly valuable for this exploratory research, as it allows for a wider scope of investigation, which helped uncover more comprehensive insights. Previous research on the drivers, barriers and challenges often does not explore it through a circular economy framework. Thus, there is lack of industry and country specific studies regarding AI implementation in supply chain management for enhanced circularity. By exploring the intersection of AI and CE within the context of the Portuguese plastics industry supply chain management processes, this research addresses these literature gaps. From a theoretical standpoint, this study offers new prespectives into how managers leverage AI technologies, discussing the drivers and barriers for AI implementation in the plastics supply chain. Additionally, it addresses the significant challenges encountered during implementation and explores opportunities for AI to enhance circularity. These findings contribute to the theory as valuable topics for further exploration.

6.3 Managerial contributions

This study aims to support Portuguese companies in the process of adopting AI for enhanced circularity. It highlights how companies in the plastics industries that have already implemented this technology are utilizing it, detailing the main applications, techniques employed, and challenges faced during implementation process. Additionally, it identifies the primary driving factors that encourage AI adoption, as well as the key inhibitors that prevent companies from pursuing AI adoption projects. The study also uncovers opportunities for AI adoption that can further enhance sustainability. By providing these insights, even though not generalizable, the study offers practical guidance for managers on leveraging AI to achieve sustainability goals, improve operational efficiency, and navigate the challenges associated with technological integration. Managers can use this knowledge to identify areas in their companies where AI could significantly enhance circularity and sustainability. Moreover, the practical insights provided can inspire managers to develop strategic adoption plans, allocate resources effectively, and foster a culture of innovation within their organizations. Understanding the challenges and inhibitors to AI adoption allows managers to anticipate potential obstacles and develop proactive strategies to overcome them, ensuring a smoother transition to AI-enhanced supply chain management operations.

6.4 Limitations

This dissertation employed a qualitative methodology, through analysis of data from 15 semi-structured interviews with middle and senior executives in Portugal's plastics industry, alongside an interpretation of existing literature on the subject. Naturally, this approach is accompanied by inherent limitations. Taking this into account, it is important to note that the conclusions of this study should not be generalized to the entire plastics industry or other industries due to the reduced sample size and the specific context of the country and industry. Given that this study was conducted in Portugal, it is important to recognize that factors such as regulations, market conditions, cultural norms, and available resources can differ significantly across countries, specially those outside the EU. Additionally, it should be noted that conclusions and findings about AI implementation methodologies and challenges were based on an even smaller sample subset, as only 53% of the participants had implemented AI in their organizations. These limitations can serve as valuable starting points for further research and exploration.

6.5 Suggestions for Future Research

Firstly, it is suggested to further investigate this topic by considering a larger sample size, which could address one of the main limitations of the current study. Additionally, a valuable approach for future investigation would be to explore solutions to overcome the identified barriers. Another approach worth pursuing is to examine other areas within the organization, as this study predominantly concentrates on supply chain management. Future research could adopt a quantitative approach, using this study as a starting point to empirically test and measure the relationship between the identified barriers and drivers on AI adoption for enhanced circularity within this industry. This would help determine which factors exert the most significant influence, thereby providing actionable insights for enhancing AI integration. Finally, it would be beneficial to apply this approach in different industries to compare the findings.

7 References

Acemoglu, D., & Restrepo, P. (2018). Artificial Intelligence, Automation and Work. *National Bureau of Economic Research Working Paper Series*, No. 24196. https://doi.org/10.3386/w24196

Achouch, M., Dimitrova, M., Ziane, K., Sattarpanah Karganroudi, S., Dhouib, R., Ibrahim, H., & Adda, M. (2022). On predictive maintenance in Industry 4.0: Overview, models, and challenges. *Applied Sciences, 12*(16), 8081. https://doi.org/10.3390/app12168081

Adenekan, O. A., Simpa, P., Solomon, N. O., & Obasi, S. C. (2024). Enhancing manufacturing productivity: A review of AI-driven supply chain management optimization and ERP systems integration. *International Journal of Management & Entrepreneurship Research, 6*(5), 1607-1624. https://doi.org/10.51594/ijmer.v6i5.1126

Agrawal, P., Narain, R., & Ullah, I. (2018). Analysis of barriers in implementation of sustainable supply chain management in Indian manufacturing industries using interpretive structural modeling approach. *Journal of Modelling in Management, 13*(2), 362-379. https://doi.org/10.1108/JM2-03-2017-0022

Agrawal, R., Wankhede, V. A., Bandrana, A., Luthra, S., Majumdar, A., & Kazançoğlu, Y. (2021). An exploratory state-of-the-art review of artificial intelligence applications in circular economy using structural topic modeling. *Operations Management Research, 15*. https://doi.org/10.1007/s12063-021-00212-0

Al-Thawadi, S. (2020). Impact of plastic waste on marine ecosystems: A review of microplastic contamination and its effects on marine life. *Marine Pollution Bulletin, 150*, 110702. https://doi.org/10.1016/j.marpolbul.2020.110702

Ali, Z. A., Zain, M., Pathan, M. S., & Mooney, P. (2023). Contributions of artificial intelligence for circular economy transition leading toward sustainability: An explorative study in agriculture and food industries of Pakistan. *Environment, Development and Sustainability*. https://doi.org/10.1007/s10668-023-03458-9

Aminabadi, S. S., Tabatabai, P., Steiner, A., Gruber, D. P., Friesenbichler, W., Habersohn, C., & Berger-Weber, G. (2022). Industry 4.0 in-line AI quality control of plastic injection molded parts. *Polymers, 14*(17), 3551. https://doi.org/10.3390/polym14173551

Amir, S., & Maji, K. (2022). A comprehensive review of circular supply chain management. *Resources, Conservation and Recycling, 182*, 105222. https://doi.org/10.1016/j.resconrec.2022.105222

Anne, J., & Daniel, C. (2015). Integrating sustainability into the supply chain management process: A case study approach. *Journal of Cleaner Production, 108*, 86-99. https://doi.org/10.1016/j.jclepro.2015.06.093

Antikainen, M., Uusitalo, T., & Kivikytö-Reponen, P. (2018). Digitalisation as an enabler of circular economy. *Procedia CIRP, 73*, 45-49. https://doi.org/10.1016/j.procir.2018.04.027

APA. (2023). *Municipal waste management report 2023*. Retrieved from https://apambiente.pt/sites/default/files/_Clima/Inventarios/20230404/NIR202315%20April.pdf

APIP. (2022). *Annual report 2022*. Retrieved from https://www.apip.pt

Armengaud, E., Koziolek, H., & Brenner, E. (2017). Quality assurance in smart production environments. *2017 IEEE International Conference on Industrial Technology (ICIT)*, 1325-1330. https://doi.org/10.1109/ICIT.2017.7915570

Badghish, S., & Soomro, Y. (2024). Artificial intelligence adoption by SMEs to achieve sustainable business performance: Application of technology–organization–environment framework. *Sustainability, 16*(5), 1864. https://doi.org/10.3390/su16051864

Bag, S., Gupta, S., & Kumar, S. (2021). Industry 4.0 adoption and 10R advance manufacturing capabilities for sustainable development. *International Journal of Production Economics, 231*, 107844. https://doi.org/10.1016/j.ijpe.2020.107844
Bag, S., Pretorius, J. H. C., Gupta, S., & Dwivedi, Y. K. (2021). Role of institutional pressures and resources in the adoption of big data analytics powered artificial intelligence, sustainable manufacturing practices and circular economy capabilities. *Technological Forecasting and Social Change, 163*, 120420. https://doi.org/10.1016/j.techfore.2020.120420
Baker, J. (2011). The technology–organization–environment framework. In Dwivedi, Y.K., Wade, M.R., & Schneberger, S.L. (Eds.), *Information systems theory: Explaining and predicting our digital society* (Vol. 1, pp. 231-245). Springer. https://doi.org/10.1007/978-1-4419-6108-2_12
Balogun, A. L., Marks, D., Sharma, R., Shekhar, H., Balmes, C., Maheng, D., Arshad, A., & Salehi, P. (2020). Assessing the potentials of digitalization as a tool for climate change adaptation and sustainable development in urban centres. *Sustainable Cities and Society, 53*, Article 101888. https://doi.org/10.1016/j.scs.2019.101888
Barford, A., & Ahmad, S. R. (2023). Levers for a corporate transition to a plastics circular economy. *Business Strategy and the Environment, 32*(4), 1203–1217. https://doi.org/10.1002/bse.3182
Bauer, M., van Dinther, C., & Kiefer, D. (2020). Machine learning in SME: An empirical study on enablers and success factors. *AMCIS 2020 Proceedings, 3*. https://aisel.aisnet.org/amcis2020/adv_info_systems_research/adv_info_systems_research/3
Belhadi, A., Kamble, S., Fosso Wamba, S., & Queiroz, M. M. (2021). Building supply-chain resilience: An artificial intelligence-based technique and decision-making framework. *International Journal of Production Research, 60*(14), 4487–4507. https://doi.org/10.1080/00207543.2021.1950935
Bishop, C. M. (2006). *Pattern recognition and machine learning*. Springer.
Booyse, D., & Scheepers, C. B. (2024). Barriers to adopting automated organisational decision-making through the use of artificial intelligence. *Management Research Review, 47*(1), 64-85. https://doi.org/10.1108/MRR-09-2021-0701
Burgess, A. (2018). *The executive guide to artificial intelligence*. Palgrave.
Büyüközkan, G., Göçer, F., & Vardaloğlu, Z. (2018). A new evaluation model for sustainable supply chain performance: A case of Turkey. *Sustainability, 10*(12), 4136. https://doi.org/10.3390/su10124136
Cagliano, A. C., Mangano, G., & Rafele, C. (2021). Determinants of digital technology adoption in supply chain. An exploratory analysis. *Supply Chain Forum: An International Journal*, *22*(2), 100–114. https://doi.org/10.1080/16258312.2021.1875789
Campbell, C., Sands, S., Ferraro, C., Tsao, H. Y. J., & Mavrommatis, A. (2020). From data to action: How marketers can leverage AI. *Business Horizons, 63*(2), 227-243. https://doi.org/10.1016/j.bushor.2019.11.003
Cannas, V. G., Ciano, M. P., Saltalamacchia, M., & Secchi, R. (2023). Artificial intelligence in supply chain and operations management: A multiple case study research. *International Journal of Production Research, 62*(9), 3333–3360. https://doi.org/10.1080/00207543.2023.2232050
Cardoso, D., & Ferreira, L. (2021). Application of predictive maintenance concepts using artificial intelligence tools. *Applied Sciences, 11*(1), 18. https://doi.org/10.3390/app11010018
Ceipek, R., Hautz, J., Petruzzelli, A. M., De Massis, A., & Matzler, K. (2020). A motivation and ability perspective on engagement in emerging digital technologies: The case of

Internet of Things solutions. *Long Range Planning, 101991*. https://doi.org/10.1016/j.lrp.2020.101991

Cetindamar Kozanoglu, D., & Abedin, B. (2021). Understanding the role of employees in digital transformation: Conceptualization of digital literacy of employees as a multi-dimensional organizational affordance. *Journal of Enterprise Information Management, 34*(6), 1649-1672. https://doi.org/10.1108/JEIM-01-2020-0010

Chakraborty, A. (2010). Managing the reverse supply chain in the circular economy: A systematic review. *Resources, Conservation and Recycling, 54*(10), 711-720. https://doi.org/10.1016/j.resconrec.2010.02.006

Chatterjee, S., Rana, N. P., Dwivedi, Y. K., & Baabdullah, A. M. (2021). Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model. *Technological Forecasting and Social Change, 170*, 120880. https://doi.org/10.1016/j.techfore.2021.120880

Chen, H., Li, L., & Chen, Y. (2020). Explore success factors that impact artificial intelligence adoption on telecom industry in China. *Journal of Management Analytics, 8*(1), 36–68. https://doi.org/10.1080/23270012.2020.1852895

Chen, Y., Prentice, C., Weaven, S., & Hsiao, A. (2021). A systematic literature review of AI in the sharing economy. *Journal of Global Scholars of Marketing Science*. https://doi.org/10.1080/21639159.2020.1808850

Cioffi, R., Travaglioni, M., Piscitelli, G., Petrillo, A., & De Felice, F. (2020). Artificial intelligence and machine learning applications in smart production: Progress, trends, and directions. *Sustainability, 12*(2), 492. https://doi.org/10.3390/su12020492

Çınar, Z. M., Abdussalam Nuhu, A., Zeeshan, Q., Korhan, O., Asmael, M., & Safaei, B. (2020). Machine learning in predictive maintenance towards sustainable smart manufacturing in Industry 4.0. *Sustainability, 12*(19), 8211. https://doi.org/10.3390/su12198211

Council of Supply Chain Management Professionals. (n.d.). What is supply chain management (SCM)? Retrieved from https://cscmp.org/CSCMP/CSCMP/Educate/SCM_Definitions_and_Glossary_of_Terms.aspx

Craig, N., & Pahl, E. (2011). Closed-loop supply chain models with product reuse and remanufacturing. *European Journal of Operational Research, 215*(3), 644-658. https://doi.org/10.1016/j.ejor.2010.06.028

Demestichas, K., & Daskalakis, E. (2020). Information and communication technology solutions for the circular economy. *Sustainability, 12*(18), 7272. https://doi.org/10.3390/su12187272

Demestichas, K., & Daskalakis, E. (2020). Information and communication technology solutions for the circular economy. *Sustainability, 12*(18), 7272. https://doi.org/10.3390/su12187272

Demlehner, Q., & Laumer, S. (2024). How the Terminator might affect the car manufacturing industry: Examining the role of pre-announcement bias for AI-based IS adoptions. *Information & Management, 61*(1), 103881. https://doi.org/10.1016/j.im.2023.103881

Dora, M., Kumar, A., Mangla, S. K., Pant, A., & Kamal, M. M. (2021). Critical success factors influencing artificial intelligence adoption in food supply chains. *International Journal of Production Research, 60*(14), 4621–4640. https://doi.org/10.1080/00207543.2021.1959665

Echchakoui, S., & Barka, N. (2020). Industry 4.0 and its impact in plastics industry: A literature review. *Journal of Industrial Information Integration, 20*, 100172. https://doi.org/10.1016/j.jii.2020.100172

Ellen MacArthur Foundation. (2019). *Artificial intelligence and the circular economy - AI as a tool to accelerate the transition*. Retrieved from http://www.ellenmacarthurfoundation.org/publications
Ellram, L. M. (1991). Supply chain management: The industrial organisation perspective. *International Journal of Physical Distribution & Logistics Management, 21*(1), 13-22. https://doi.org/10.1108/EUM0000000000386
European Commission. (2024). *EU digital strategy*. Retrieved from https://eufordigital.eu/discover-eu/eu-digital-strategy/
Eurostat. (2024). *Use of artificial intelligence in enterprises*. Retrieved from https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Use_of_artificial_intelligence_in_enterprises
Farooque, M., Zhang, A., Thürer, M., Qu, T., & Huisingh, D. (2019). Circular supply chain management: A definition and framework. *Journal of Cleaner Production, 228*, 882-894. https://doi.org/10.1016/j.jclepro.2019.04.303
Feigenbaum, E. A. (1988). *The fifth generation: Artificial intelligence and Japan's computer challenge to the world*. Addison-Wesley.
Gašpar, D., Ćorić, I., & Mabić, M. (2023). Composable ERP – New generation of intelligent ERP. In N. Ademović, J. Kevrić, & Z. Akšamija (Eds.), *Advanced technologies, systems, and applications VIII. IAT 2023. Lecture notes in networks and systems* (Vol. 644). Springer, Cham. https://doi.org/10.1007/978-3-031-43056-5_26
Geissdoerfer, M., Savaget, P., Bocken, N. M. P., & Hultink, E. J. (2018). The Circular Economy – A new sustainability paradigm? *Journal of Cleaner Production, 143*, 757-768. https://doi.org/10.1016/j.jclepro.2016.12.048
Getor, R. Y., Mishra, N., & Ramudhin, A. (2020). The role of technological innovation in plastic production within a circular economy framework. *Resources, Conservation and Recycling, 163*, 105094. https://doi.org/10.1016/j.resconrec.2020.105094
Ghisellini, P., Cialani, C., & Ulgiati, S. (2016). A review on circular economy: The expected transition to a balanced interplay of environmental and economic systems. *Journal of Cleaner Production, 114*, 11-32. https://doi.org/10.1016/j.jclepro.2015.09.007
Ghoreishi, M., & Happonen, A. (2020). New promises AI brings into circular economy accelerated product design: A review on supporting literature. *E3S Web of Conferences, 158*, 06002. https://doi.org/10.1051/e3sconf/202015806002
Gonzalez, R. C., & Woods, R. E. (2008). *Digital image processing* (3rd ed.). Pearson.
Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT Press.
Gouvidan, K., Mesmarian, F., & Mougenot, C. (2017). Circular supply chain management: Theoretical framework and applications. *International Journal of Production Research, 55*(7), 1981-1993. https://doi.org/10.1080/00207543.2016.1193634
Guida, M., Caniato, F., Moretto, A., & Ronchi, S. (2023). The role of artificial intelligence in the procurement process: State of the art and research agenda. *Journal of Purchasing and Supply Management, 29*(2), 100823. https://doi.org/10.1016/j.pursup.2023.100823
Guide, V. D. R., Jayaraman, V., & Linton, J. D. (2003). Building contingency planning for closed-loop supply chains with product recovery. *Journal of Operations Management, 21*(3), 259-279. https://doi.org/10.1016/S0272-6963(03)00049-6
Haefner, N. (2021). The impact of artificial intelligence on strategic management. *Strategic Management Journal, 42*(3), 523-539. https://doi.org/10.1002/smj.3132
Haenlein, M., & Kaplan, A. (2019). A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. *California Management Review, 61*(4), 5-14. https://doi.org/10.1177/0008125619864925

Hala, H., Cherrafi, A., & Benghabrit, Y. (2022). Machine learning for the future integration of the circular economy in waste transportation and treatment supply chain. *IFAC-PapersOnLine*, *55*(10), 49-54. https://doi.org/10.1016/j.ifacol.2022.09.366

Hamid Khayyam, M., Naebe, M., Milani, A. S., Fakhrhoseini, S. M., & Date, A. (2021). Improving energy efficiency of carbon fiber manufacturing through waste heat recovery: A circular economy approach with machine learning. *Energy, 225*, 120113. https://doi.org/10.1016/j.energy.2021.120113

Hangl, J., Krause, S., & Behrens, V. J. (2023). Drivers, barriers and social considerations for AI adoption in SCM. *Technology in Society, 74*, 102299. https://doi.org/10.1016/j.techsoc.2023.102299

Hansen, E. B., & Bøgh, S. (2021). Artificial intelligence and internet of things in small and medium-sized enterprises: A survey. *Journal of Manufacturing Systems, 58*(Part B), 362-372. https://doi.org/10.1016/j.jmsy.2020.08.009

Hirschberg, J., & Manning, C. D. (2015). Advances in natural language processing. *Science, 349*(6245), 261-266. https://doi.org/10.1126/science.aaa8685

Huang, M.-H., Rust, R., & Maksimovic, V. (2019). The feeling economy: Managing in the next generation of artificial intelligence (AI). *California Management Review, 61*(4), 43-65. https://doi.org/10.1177/0008125619863436

Johansen, M. R., Christensen, T. B., Ramos, T. M., & Syberg, K. (2022). A review of the plastic value chain from a circular economy perspective. *Journal of Environmental Management, 302*(Part A), 113975. https://doi.org/10.1016/j.jenvman.2021.113975

Jones, P., & Comfort, D. (2017). Towards the circular economy: A commentary on corporate approaches and challenges. *Journal of Public Affairs*. https://doi.org/10.1002/pa.1680

Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. *Science, 349*(6245), 255-260. https://doi.org/10.1126/science.aaa8415

Kar, S., Kar, A. K., & Gupta, M. P. (2021). Modeling drivers and barriers of artificial intelligence adoption: Insights from a strategic management perspective. *Intelligent Systems in Accounting, Finance and Management, 28*(4), 217-238.

Karayılan, S., Yılmaz, Ö., Uysal, Ç., & Naneci, S. (2021). Prospective evaluation of circular economy practices within plastic packaging value chain through optimization of life cycle impacts and circularity. *Resources, Conservation and Recycling, 173*, 105691. https://doi.org/10.1016/j.resconrec.2021.105691

King, S., & Locock, K. E. S. (2022). A circular economy framework for plastics: A semi-systematic review. *Journal of Cleaner Production, 364*, 132503. https://doi.org/10.1016/j.jclepro.2022.132503

Kortelainen, J., Zeb, A., & Ailisto, H. (2020). Artificial intelligence for the support of regulator decision making. *VTT Technical Research Centre of Finland. VTT Research Report No. VTT-R-01225-20*.

Krenker, A., Bešter, J., & Kos, A. (2011). Introduction to the artificial neural networks. In K. Suzuki (Ed.), *Artificial neural networks - Methodological advances and biomedical applications*. InTech. https://doi.org/10.5772/15751

Kristensen, H. S., Mosgaard, M. A., & Remmen, A. (2021). Integrating circular principles in environmental management systems. *Journal of Cleaner Production, 286*, 125485. https://doi.org/10.1016/j.jclepro.2020.125485

Kurup, S., & Gupta, V. (2022). Factors influencing the AI adoption in organizations. *Metamorphosis, 21*(2), 129-139. https://doi.org/10.1177/09726225221124035

Kwarteng, M. A., Ntsiful, A., Diego, L. F. P., & Novák, P. (2023). Extending UTAUT with competitive pressure for SMEs digitalization adoption in two European nations: A multi-

group analysis. *Aslib Journal of Information Management*. Advance online publication. https://doi.org/10.1108/AJIM-11-2022-0482
Lada, S., Chekima, B., Abdul Karim, M. R., Fabeil, N. F., Ayub, M. S., Amirul, S. M., Ansar, R., Bouteraa, M., Fook, L. M., & Zaki, H. O. (2023). Determining factors related to artificial intelligence (AI) adoption among Malaysia's small and medium-sized businesses. *Journal of Open Innovation: Technology, Market, and Complexity, 9*(4), 100144. https://doi.org/10.1016/j.joitmc.2023.100144
Lahane, S., Kant, R., & Shankar, R. (2020). Circular supply chain management: Concept, literature review and research framework. *Production Planning & Control, 31*(10), 829-846. https://doi.org/10.1080/09537287.2019.1691150
Lai, Y., Sun, H., & Ren, J. (2018). Understanding the determinants of big data analytics (BDA) adoption in logistics and supply chain management: An empirical investigation. *The International Journal of Logistics Management, 29*(2), 676-703. https://doi.org/10.1108/IJLM-06-2017-0153
Lake, B. M., Ullman, T. D., Tenenbaum, J. B., & Gershman, S. J. (2017). Building machines that learn and think like people. *Behavioral and Brain Sciences, 40*, e253. https://doi.org/10.1017/S0140525X16001837
Lee, J. (2018). The future of data privacy and security in edge computing. *International Journal of Computer Science and Information Security, 16*(8), 89-95. https://doi.org/10.1016/j.ijcsis.2018.08.009
Leszczynska, A., & Möller, K. (2017). Sustainable supply chain management: Literature review and research directions. *Journal of Cleaner Production, 154*, 276-287. https://doi.org/10.1016/j.jclepro.2016.12.095
Liengpunsakul, S. (2021). Artificial intelligence and sustainable development in China. *The Chinese Economy, 54*(4), 235-248. https://doi.org/10.1080/10971475.2020.1857062
MacCarthy, J., Minsky, M. L., Rochester, N., & Shannon, C. E. (2006). A proposal for the Dartmouth summer research project on artificial intelligence. *AI Magazine, 27*(4), 12-14. https://doi.org/10.1609/aimag.v27i4.1904
Madancian, M., Taherdoost, H., Javadi, M., Khan, I. U., Kalantari, A., & Kumar, D. (2024). The impact of artificial intelligence on supply chain management in modern business. In Y. Farhaoui, A. Hussain, T. Saba, H. Taherdoost, & A. Verma (Eds.), *Artificial Intelligence, Data Science and Applications. ICAISE 2023. Lecture Notes in Networks and Systems* (Vol. 838). Springer, Cham. https://doi.org/10.1007/978-3-031-48573-2_82
Maddikunta, P. K. R., Pham, Q.-V., Prabadevi, B., Deepa, N., Dev, K., Gadekallu, T. R., Ruby, R., & Liyanage, M. (2022). Industry 5.0: A survey on enabling technologies and potential applications. *Journal of Industrial Information Integration, 26*, 100257. https://doi.org/10.1016/j.jii.2021.100257
Mahesh, P. (2018). Supervised learning algorithms. *Journal of Machine Learning Research, 8*(1), 23-45.
Malviya, R. K., & Kant, R. (2015). Green supply chain management: A structured literature review and research implications. *Benchmarking: An International Journal, 22*(7), 1360-1394. https://doi.org/10.1108/BIJ-01-2014-0001
Mediavilla, M. A., Dietrich, F., & Palm, D. (2022). Review and analysis of artificial intelligence methods for demand forecasting in supply chain management. *Procedia CIRP, 107*, 1126-1131. https://doi.org/10.1016/j.procir.2022.05.119
Mentzer, J. T., DeWitt, W., Keebler, J. S., Min, S., Nix, N. W., Smith, C. D., & Zacharia, Z. G. (2001). Defining supply chain management. *Journal of Business Logistics, 22*(2), 1-25. https://doi.org/10.1002/j.2158-1592.2001.tb00001.x
Mitchell, T. M. (1997). *Machine learning*. McGraw-Hill.

Mohamed-Iliasse, B., Abdulrahman, K. O., & Youssef, R. (2020). Machine learning applications in supply chain management: A comprehensive survey. *Journal of Computational Science, 45*, 101173. https://doi.org/10.1016/j.jocs.2020.101173

Mohri, M., Rostamizadeh, A., & Talwalkar, A. (2018). *Foundations of machine learning* (2nd ed.). MIT Press.

Mok, S. L., Kwong, C. K., & Lau, W. S. (1999). Review of research in the determination of process parameters for plastic injection molding. *Advances in Polymer Technology, 18*(3), 225-236. https://doi.org/10.1002/(SICI)1098-2329(199923)18:3<225::AID-ADV3>3.0.CO;2-3

Mondal, S., Singh, S., & Gupta, H. (2023). Green entrepreneurship and digitalization enabling the circular economy through sustainable waste management - An exploratory study of emerging economy. *Journal of Cleaner Production, 422*, 138433. https://doi.org/10.1016/j.jclepro.2023.138433

Moreira, F. T., et al. (2022). Environmental impacts of plastic waste: A review on microplastic pollution in ecosystems. *Environmental Pollution, 300*, 118983. https://doi.org/10.1016/j.envpol.2022.118983

Müller, J. M., Kiel, D., & Voigt, K.-I. (2018). What drives the implementation of Industry 4.0? The role of opportunities and challenges in the context of sustainability. *Sustainability, 10*(1), 247. https://doi.org/10.3390/su10010247

Murphy, K. P. (2012). *Machine learning: A probabilistic perspective*. MIT Press.

Murphy, R. R. (2000). *Introduction to AI robotics*. MIT Press.

Noman, A. A., Akter, U. H., Pranto, T. H., & Haque, A. B. H. (2022). Machine learning and artificial intelligence in circular economy: A bibliometric analysis and systematic literature review. *Annals of Emerging Technologies in Computing (AETiC), 6*(2), 13-40. https://doi.org/10.33166/AETiC.2022.02.002

Nosratabadi, S., Mosavi, A., & Semih, Y. (2019). The role of digital transformation in enhancing supply chain performance: An empirical investigation. *Technological Forecasting and Social Change, 148*, 119719. https://doi.org/10.1016/j.techfore.2019.119719

Nozari, H., Szmelter-Jarosz, A., & Ghahremani-Nahr, J. (2022). Analysis of the challenges of Artificial Intelligence of Things (AIoT) for the smart supply chain (Case study: FMCG industries). *Sensors, 22*(8), 2931. https://doi.org/10.3390/s22082931

OECD. (2019). *Global material resources outlook to 2060: Economic drivers and environmental consequences*. OECD Publishing. https://doi.org/10.1787/9789264307452-en

Ogorodnyk, O., Lyngstad, O., Larsen, M., & Martinsen, K. (2020). Prediction of width and thickness of injection molded parts using machine learning methods. In K. Gupta, R. Malhan, R. Srivastava, & K. Kumar (Eds.), *Advanced Manufacturing Technologies: Proceedings of ICAMT 2019* (pp. 309-318). Springer. https://doi.org/10.1007/978-981-15-6779-7_32

Olan, F., Arakpogun, E. O., Suklan, J., Nakpodia, F., Damij, N., & Jayawickrama, U. (2022). Artificial intelligence and knowledge sharing: Contributing factors to organizational performance. *Journal of Business Research, 145*, 605-615. https://doi.org/10.1016/j.jbusres.2022.03.008

Oliveira, T., & Martins, M. R. (2010). Understanding e-business adoption across industries in European countries. *Industrial Management & Data Systems, 110*(9), 1337-1354. https://doi.org/10.1108/02635571011087428

Oliver, R. K., & Webber, M. D. (1982). Supply-chain management: Logistics catches up with strategy. *Outlook*, Booz Allen & Hamilton Inc. Reprinted in: Christopher, M. (1992), *Logistics: The Strategic Issues*. London: Chapman & Hall.

Onyeaka, H., Tamasiga, P., Nwauzoma, U. M., Miri, T., Juliet, U. C., Nwaiwu, O., & Akinsemolu, A. A. (2023). Using artificial intelligence to tackle food waste and enhance the circular economy: Maximising resource efficiency and minimising environmental impact: A review. *Sustainability, 15*(13), 10482. https://doi.org/10.3390/su151310482

Oppioli, M., Sousa, M., Sousa, M., & de Nuccio, E. (2023). The role of artificial intelligence for management decision: A structured literature review. *Management Decision*. https://doi.org/10.1108/MD-08-2023-1331

Oubrahim, I., & Sefiani, N. (2023). Exploring the drivers and barriers to digital transformation adoption for sustainable supply chains: A comprehensive overview. *Acta Logistica - International Scientific Journal about Logistics, 10*(2), 305-317. https://doi.org/10.22306/al.v10i2.396

Pandey, S., Gupta, S., & Chhajed, S. (2021). ROI of AI: Effectiveness and measurement. *International Journal of Engineering Research & Technology (IJERT), 10*(5). http://dx.doi.org/10.2139/ssrn.3858398

Park, H. S., Phuong, D. X., & Kumar, S. (2019). AI based injection molding process for consistent product quality. *Procedia Manufacturing, 28,* 102-106. https://doi.org/10.1016/j.promfg.2018.12.017

Pereira, A., Renato, D., Costa, A., Gonçalves, R., Pereira, L., & Dias, Á. (2023). Industry 4.0 in Portugal - The state of the art. *International Journal of Internet Manufacturing and Services, 9*(1), 44-59. https://doi.org/10.1504/IJIMS.2023.129286

Petrova, T., & Kazmer, D. (1999). Incorporation of phenomenological models in a hybrid neural network for quality control of injection molding. *Polymer-Plastics Technology and Engineering, 38*(1), 1-18.

Picard, R. W. (2000). *Affective computing*. MIT Press.

Pillai, R., Sivathanu, B., Mariani, M., Rana, N. P., Yang, B., & Dwivedi, Y. K. (2021). Adoption of AI-empowered industrial robots in auto component manufacturing companies. *Production Planning & Control, 33*(16), 1517–1533. https://doi.org/10.1080/09537287.2021.1882689

PlasticsEurope. (2023). *Plastics - the facts 2023: An analysis of European plastics production, demand, and waste data*. Retrieved from https://plasticseurope.org/knowledge-hub/plastics-the-fast-facts-2023/

PlasticsEurope. (2024). *Plastics - the facts 2024: An analysis of European plastics production, demand, and waste data*. Retrieved from https://www.plasticseurope.org/en/resources/publications/4312-plastics-facts-2024

Polisetty, A., Chakraborty, D., G, S., Kar, A. K., & Pahari, S. (2023). What determines AI adoption in companies? Mixed-method evidence. *Journal of Computer Information Systems, 64*(3), 370-387. https://doi.org/10.1080/08874417.2023.2219668

Prata, J. C. (2019). Microplastics in wastewater: Fate and removal. *Environmental Science and Pollution Research, 26*(4), 1-16. https://doi.org/10.1007/s11356-018-1829-0

Pregowska, A., Osial, M., & Urbańska, W. (2022). The application of artificial intelligence in the effective battery life cycle in the closed circular economy model—a perspective. *Recycling, 7*, 81. https://doi.org/10.3390/recycling7040081

PwC. (2017). *Sizing the prize: What's the real value of AI for your business and how can you capitalise?* PwC. https://www.pwc.com/gx/en/issues/analytics/assets/pwc-ai-analysis-sizing-the-prize-report.pdf

Raj, A., Dwivedi, G., Sharma, A., Jabbour, A. B. L. de S., & Rajak, S. (2020). Barriers to the adoption of industry 4.0 technologies in the manufacturing sector: An inter-country comparative perspective. *International Journal of Production Economics, 224,* 107546. https://doi.org/10.1016/j.ijpe.2019.107546

Rane, N., Paramesha, M., Choudhary, S., & Rane, J. (2024). Business intelligence and artificial intelligence for sustainable development: Integrating internet of things, machine learning, and big data analytics for enhanced sustainability. *SSRN*. https://doi.org/10.2139/ssrn.4833996

Ribeiro, B. (2005). Support vector machines for quality monitoring in a plastic injection molding process. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), 35*(3), 401-410. https://doi.org/10.1109/TSMCC.2004.843228

Richey, R. G., Jr., Chowdhury, S., Davis-Sramek, B., Giannakis, M., & Dwivedi, Y. K. (2023). Artificial intelligence in logistics and supply chain management: A primer and roadmap for research. *Journal of Business Logistics*, *44*(4), 532-549. https://doi.org/10.1111/jbl.12364

Richey, R. G., Jr., Chowdhury, S., Davis-Sramek, B., Giannakis, M., & Dwivedi, Y. K. (2023). Artificial intelligence in logistics and supply chain management: A primer and roadmap for research. *Journal of Business Logistics*, *44*(4), 532-549. https://doi.org/10.1111/jbl.12364

Roberts, H., Zhang, J., & Bariach, B. (2024). Artificial intelligence in support of the circular economy: Ethical considerations and a path forward. *AI & Society, 39*(4), 1451–1464. https://doi.org/10.1007/s00146-022-01596-8

Ronaghi, M. H. (2022). The influence of artificial intelligence adoption on circular economy practices in manufacturing industries. *Environment, Development and Sustainability, 25*(12), 1-26. https://doi.org/10.1007/s10668-022-02670-3

Rosa, Á., Bento, T., Pereira, F. L., Lopes da Costa, R., Dias, Á., & Gonçalves, R. (2022). Gaining competitive advantage through artificial intelligence adoption. *International Journal of Electronic Business*. https://doi.org/10.1504/IJEB.2022.10044363

Rosa, P., Sassanelli, C., Urbinati, A., Chiaroni, D., & Terzi, S. (2020). Assessing relations between circular economy and industry 4.0: A systematic literature review. *International Journal of Production Research, 58*(6), 1662-1687. https://doi.org/10.1080/00207543.2019.1680896

Rumetshofer, T., & Fischer, J. (2023). Information-based plastic material tracking for circular economy—A review. *Polymers*, *15*(7), 1623. https://doi.org/10.3390/polym15071623

Russell, S. J., & Norvig, P. (2016). *Artificial intelligence: A modern approach* (3rd ed.). Pearson.

Samuel, A. L. (1959). Some studies in machine learning using the game of checkers. *IBM Journal of Research and Development*, *3*(3), 210-229. https://doi.org/10.1147/rd.441.0206

Sassanelli, C., Garza-Reyes, J. A., Liu, Y., Pacheco, D. A. de J., & Luthra, S. (2023). The disruptive action of Industry 4.0 technologies cross-fertilizing Circular Economy throughout society. *Computers & Industrial Engineering, 183*, 109548. https://doi.org/10.1016/j.cie.2023.109548

Seman, N. A. A., Zakuan, N., Jusoh, A., Arif, M., & Saman, M. Z. M. (2012). Green supply chain management: A review and research direction. *International Journal of Managing Value and Supply Chains, 3*(3), 1-18. https://doi.org/10.5121/ijmvsc.2012.3301

Seuring, S., & Müller, M. (2008). From a literature review to a conceptual framework for sustainable supply chain management. *Journal of Cleaner Production, 16*(15), 1699-1710. https://doi.org/10.1016/j.jclepro.2008.04.020

Shang, G., Low, S. P., & Lim, X. Y. V. (2023). Prospects, drivers of and barriers to artificial intelligence adoption in project management. *Built Environment Project and Asset Management, 13*(5), 629-645. https://doi.org/10.1108/BEPAM-12-2022-0195

Sharma, R., Jha, R., & Kumar, A. (2023). The role of artificial intelligence in the digital transformation of supply chain management. *Journal of Business Research, 145*, 606-617. https://doi.org/10.1016/j.jbusres.2023.02.008

Shi, W., Cao, J., Zhang, Q., Li, Y., & Xu, L. (2016). Edge computing: Vision and challenges. *IEEE Internet of Things Journal*, *3*(5), 637-646. https://doi.org/10.1109/JIOT.2016.2579198

Shrestha, Y. R., Ben-Menahem, S. M., & von Krogh, G. (2019). Organizational decision-making structures in the age of artificial intelligence. *California Management Review*, *61*(4), 66-83. https://doi.org/10.1177/0008125619862257

Shrestha, Y. R., Krishna, V., & von Krogh, G. (2021). Augmenting organizational decision-making with deep learning algorithms: Principles, promises, and challenges. *Journal of Business Research*, *123*, 588-603. https://doi.org/10.1016/j.jbusres.2020.09.068

Shrivastav, M. (2022). Barriers related to AI implementation in supply chain management. *Journal of Global Information Management (JGIM)*, *30*(8), 1-19. https://doi.org/10.4018/JGIM.296725

Shukhratov, I., Pimenov, A., Stepanov, A., Mikhailova, N., Baldycheva, A., & Somov, A. (2024). Optical detection of plastic waste through computer vision. *Intelligent Systems with Applications*, *22*, 200341. https://doi.org/10.1016/j.iswa.2024.200341

Siciliano, B., Sciavicco, L., Villani, L., & Oriolo, G. (2009). *Robotics: Modelling, planning and control*. Springer.

Simões, A., Oliveira, L., Rodrigues, J. C., Simas, O., Dalmarco, G., & Barros, A. C. (2019). Environmental factors influencing the adoption of digitalization technologies in automotive supply chains. In *2019 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC)* (pp. 1-7). Valbonne Sophia-Antipolis, France. https://doi.org/10.1109/ICE.2019.8792639

Singh, A. (2023). Edge AI: Harnessing the power of edge computing for AI applications. *Journal of Computing and Artificial Intelligence*, *5*(2), 34-46. https://doi.org/10.1016/j.jcai.2023.02.003

Sipola, J., Saunila, M., & Ukko, J. (2023). Adopting artificial intelligence in sustainable business. *Journal of Cleaner Production*, *426*, 139197. https://doi.org/10.1016/j.jclepro.2023.139197

Sivaprakash, J. S., & Mahesh, G. N. (2023). Leveraging circular economy using AI. *International Research Journal of Modernization in Engineering Technology and Science*, *5*. https://doi.org/10.56726/IRJMETS35784

Srivastava, S. K. (2007). Green supply-chain management: A state-of-the-art literature review. *International Journal of Management Reviews*, *9*(1), 53-80. https://doi.org/10.1111/j.1468-2370.2007.00202.x

Stahel, W. (2016). The circular economy. *Nature*, *531*(7595), 435–438. https://doi.org/10.1038/531435a

Sutton, R. S., & Barto, A. G. (2018). *Reinforcement learning: An introduction* (2nd ed.). MIT Press.

Syberg, K., et al. (2022). Plastic pollution in the environment: A review. *Current Opinion in Environmental Science & Health*, *28*, 100347. https://doi.org/10.1016/j.coesh.2022.100347

Taddei, E., Sassanelli, C., Rosa, P., & Terzi, S. (2022). Circular supply chains in the era of industry 4.0: A systematic literature review. *Computers & Industrial Engineering*, *170*, 108268. https://doi.org/10.1016/j.cie.2022.108268

Tirkolaee, E. B., Sadeghi, S., Mooseloo, F. M., Vandchali, H. R., & Aeini, S. (2021). Application of machine learning in supply chain management: A comprehensive overview of the main areas. *Mathematical Problems in Engineering*, *2021*, 1476043. https://doi.org/10.1155/2021/1476043

Toorajipour, R., Sohrabpour, V., Nazarpour, A., Oghazi, P., & Fischl, M. (2021). Artificial intelligence in supply chain management: A systematic literature review. *Journal of Business Research*, *122*, 502-517. https://doi.org/10.1016/j.jbusres.2020.09.009

Tornatzky, L. G., Fleischer, M., & Chakrabarti, A. K. (1990). *The processes of technological innovation*. Lexington Books.

Ucar, A., Karakose, M., & Kırımça, N. (2024). Artificial intelligence for predictive maintenance applications: Key components, trustworthiness, and future trends. *Applied Sciences*, *14*(2), 898. https://doi.org/10.3390/app14020898

United Nations Environment Programme. (2022). *Emissions gap report 2022: The closing window — Climate crisis calls for rapid transformation of societies*. Nairobi. https://www.unep.org/emissions-gap-report-2022

Valdez-Juárez, L. E., & Castillo-Vergara, M. (2021). Technological capabilities, open innovation, and eco-innovation: Dynamic capabilities to increase corporate performance of SMEs. *Journal of Open Innovation: Technology, Market, and Complexity*, *7*(1), 8. https://doi.org/10.3390/joitmc7010008

Vegter, D., & de Koster, R. B. M. (2020). Managing circular supply chains: Strategies and tools for the logistics professional. *International Journal of Logistics Research and Applications*, *23*(5), 1-20. https://doi.org/10.1080/13675567.2020.1729192

Vilelas, J. (2020). *Investigação o processo de construção do conhecimento* (3rd ed.). Sílabo.

Walker, T. R., & Fequet, L. (2023). Current trends of unsustainable plastic production and micro(nano)plastic pollution. *TrAC Trends in Analytical Chemistry*, *160*, 116984. https://doi.org/10.1016/j.trac.2023.116984

Werner, M., & Jaffe, E. (2023). How Google is supporting the circular economy. *Scientific American*, *328*(1). https://www.scientificamerican.com/article/how-google-is-supporting-the-circular-economy

Willenbacher, M., Scholten, J., & Wohlgemuth, V. (2021). Machine learning for optimization of energy and plastic consumption in the production of thermoplastic parts in SMEs. *Sustainability*, *13*(12), 6800. https://doi.org/10.3390/su13126800

Wuest, T., Weimer, D., Irgens, C., & Thoben, K. D. (2016). Machine learning in manufacturing: Advantages, challenges, and applications. *Production & Manufacturing Research*, *4*(1), 23-45. https://doi.org/10.1080/21693277.2016.1192517

Yang, M., Fu, M., & Zhang, Z. (2021). The adoption of digital technologies in supply chains: Drivers, process and impact. *Technological Forecasting and Social Change*, *169*, 120795. https://doi.org/10.1016/j.techfore.2021.120795

Yegnanarayana, B. (2009). *Artificial Neural Network*. PHI Learning Pvt. Ltd.

Yigin, S. (2007). Expert systems applications in supply chain management: Supplier selection problem. *Expert Systems with Applications*, *34*(3), 1371-1379. https://doi.org/10.1016/j.eswa.2006.01.022

Zhang, X., Liu, Z., & Li, X. (2022). The impact of digitalization on green supply chain management: A bibliometric and systematic review. *Environmental Science and Pollution Research*, *29*(18), 26995-27008. https://doi.org/10.1007/s11356-022-18757-w

8 Annex

8.1 Annex A- Interview script

Research Theme Framework

Before we begin, I'd like to provide you with a brief overview of the theme of my dissertation. The focus of my research is to examine the impact of Artificial Intelligence on Circular Economy practices within Portuguese plastics industry’s supply chain, with particular focus on reverse logistics. This dissertation aims to understand the current state of AI adoption and identify the factors influencing companies' management implementing this technology to leverage circular economy practices that promote environmental sustainability. At the same time, identifying opportunities and barriers associated with this implementation within the context of the plastics industry's supply chain.

Research Questions

Now, let's dive into the questions related to my research:

If the organization has implemented AI:

RQ1: What is the current role of technology, particularly AI, in the plastics industry's supply chain?

- Has your organization started integrating AI technologies into your supply chain operations?
- Could you provide specific examples?

RQ2: To what extent are AI technologies currently used in supply chain processes in the plastics industry, and what are their primary functions?

- What specific AI techniques are implemented within your supply chain, and what are their primary functions? How do they facilitate circular economy practices?

RQ3: What are the key drivers influencing the adoption of AI in the plastics industry's supply chain?

- What factors have primarily motivated your company to adopt AI within the supply chain, particularly in the context of enhancing sustainability/CE? Was it mostly internal or external factors?

RQ4: What barriers and opportunities exist in the implementation of AI for advancing CE practices within the plastics industry's supply chain?

- What have been the most significant challenges to implementing AI in your supply chain, specifically in relation to CE practices? How are you addressing these challenges?
- Looking forward, what do you see as the most promising opportunities for AI to further enhance CE practices in your organization's supply chain?

If the organization hasn't implemented AI:

RQ1: What is the current role of technology, particularly AI, in the plastics industry's supply chain?

- In your organization, are you aware of any AI implementation? If so, could these technologies be applied to your supply chain management, specifically within reverse logistics, to improve circular economy practices?

RQ2: To what extent are AI technologies currently used in supply chain processes in the plastics industry, and what are their primary functions?

- Considering the broader industry context, are you aware of how AI technologies are being utilized in supply chain and reverse logistics processes of other organizations?

RQ3: What are the key drivers influencing the adoption of AI in the plastics industry's supply chain?

- What is the most significant effort related to sustainability, specially circular economy, in your organization? In your view, do you see AI having a role in enhacing this effort? How?

RQ4: What barriers and opportunities exist in the implementation of AI for advancing CE practices within the plastics industry's supply chain?

- Could you share the primary barriers preventing the implementation of this technology in your organization's supply chain? Are these challenges related to technical, financial, organizational, or regulatory factors?
- Looking forward, what do you see as the most promising opportunities for AI to further enhance CE practices in your organization's supply chain?

Closing

Thank you for sharing your insights and expertise on this topic, "Name". Your input will be crucial to my research. The information will be treated with due confidentiality. If you have any additional thoughts or comments, please feel free to share them.