Instituto Superior de Gestão e Administração de Santarém

Mestrado em Gestão de Empresas

Dissertação

A Inteligência Artificial Aplicada à Gestão da Cadeia de Abastecimento e à Logística: Revisão Sistemática da Literatura

Artificial Intelligence Applied to Supply Chain Management and Logistics: Systematic Literature Review

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Muito obrigada,

"If you´re happy doing what you doing then nobody can tell you you're not successful"
HARRY STYLES

Resumo

O impacto crescente da automatização e da inteligência artificial (IA) na gestão da cadeia de abastecimento e logística é notável. Este avanço tecnológico tem o potencial de transformar significativamente a manipulação e o transporte de mercadorias. A implementação destas tecnologias tem impulsionado a eficiência, as capacidades de previsão e a simplificação das operações. No entanto, também levantou questões críticas sobre a tomada de decisões com base na IA. Nesse sentido, foi realizada uma revisão sistemática da literatura, oferecendo uma visão abrangente desse fenómeno, com um enfoque específico na gestão. O objetivo é fornecer perspetivas que possam orientar pesquisas futuras e a tomada de decisões nos setores de logística e gestão da cadeia de abastecimento. Ambos os artigos desta tese e que formam capítulos apresentam metodologias detalhadas e resultados transparentes, reforçando a credibilidade das pesquisas para investigadores e gestores. Isso contribui para um entendimento mais profundo do impacto da tecnologia na logística e na gestão da cadeia de abastecimento. Esta pesquisa oferece informações valiosas tanto para académicos como para profissionais do setor de logística, revelando soluções e estratégias inovadoras viabilizadas pela automatização. No entanto, é crucial reconhecer a constante evolução desse campo e enfatizar a necessidade de uma investigação e adaptação contínuas para garantir o desenvolvimento de um ecossistema logístico seguro, eficiente e sustentável. Os resultados revelam que a integração de tecnologias de automação na logística tem impulsionado a transformação da indústria. No entanto, o desenvolvimento contínuo requer vigilância, adaptação, previsão e uma rápida capacidade de resolução de problemas. Esta pesquisa não apenas esclarece o panorama atual, mas também oferece uma visão do futuro da logística num mundo onde a inteligência artificial deverá prevalecer.

Palavras chave: Inteligência Artificial; Automatização; Gestão da Cadeida de Abasteciemrno; Logistica; Revisão Sistemática da Literatura.

Abstract

The growing impact of automation and artificial intelligence (AI) on supply chain management and logistics is remarkable. This technological advance has the potential to significantly transform the handling and transport of goods. The implementation of these technologies has boosted efficiency, predictive capabilities and the simplification of operations. However, it has also raised critical questions about AI-based decision-making. To this end, a systematic literature review was carried out, offering a comprehensive view of this phenomenon, with a specific focus on management. The aim is to provide insights that can guide future research and decision-making in the logistics and supply chain management sectors. Both the articles in this thesis and that form chapters present detailed methodologies and transparent results, reinforcing the credibility of the research for researchers and managers. This contributes to a deeper understanding of the impact of technology on logistics and supply chain management. This research offers valuable information for both academics and professionals in the logistics sector, revealing innovative solutions and strategies made possible by automation. However, continuous development requires vigilance, adaptation, foresight and a rapid problem-solving capacity. This research not only sheds light on the current panorama, but also offers a glimpse into the future of logistics in a world where artificial intelligence is set to prevail.

Keywords: Artificial Intelligence; Automation; Supply Chain Management; Logistics; Systematic Literature Review

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LIST OF ABBREVIATIONS AND ACRONYMS

3 PL – Third Party Logistics

AI – Artificial Intelligence

ANN – Artificial Neural Networks

AR – Augmented Reality

BDA – Big Data Analytics

CNN – Convolutional Neural Networks

CPS – Cyber Physical System

DL – Deep Learning

FL – Fuzzy Logic

GA – Genetic Algorithms

HAT – Human Acting Technique

HRE – Human-Robot Ecosystem

HRI – Human-Robot Integration

HTT – Human Thinking Technique

IC – Integrated Circuits

ICT – Information and Communication Technology

ML – Machine Learning

MOO – Multi-objective optimizations

PRISMA – Preferred Reporting Items for Systematic Review and Meta-Analysis

RFID – Radio Frequency Identification

RL – Reinforcement Learning

RNN – Recurrent Neural Networks

RTT – Rational Acting Technique

SLR – Systematic Literature Review

SC – Supply Chain

SCM – Supply Chain Management

VR – Virtual Reality

VUCA – Volatility, Uncertainty, Complexity and Ambiguity

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INTRODUCTION

Contextualization

The integration of automation and Artificial Intelligence (AI) into Supply Chain Management (SCM) and Logistics has emerged as a transformative force rather than a mere passing trend (Dubey et al., 2020). This comprehensive analysis explores the impact of automation on the logistics industry, highlighting the pivotal role played by AI, machine learning, deep learning, and robot-driven logistics in reshaping the way goods are transported, processed, and delivered. The influence of these technologies extends across various facets of logistics, from supply chain forecasting and inventory control to delivery processes. While the demonstrable efficiency gains are evident, it is equally imperative to address the persistent concerns surrounding biases in AI decision-making and cybersecurity threats. The observable enhancements in efficiency within the logistics domain, arising from technologies such as AI and automation, are a consequence of improved data processing, heightened predictive capabilities, streamlined warehouse operations, optimized routing and error reduction. These advancements collectively contribute to a more agile, responsive, and cost-effective logistics ecosystem, ultimately culminating in an enhanced customer experience.

In our study, we aim to fill a critical gap in the existing literature concerning the implementation of automation in logistics. The research sheds light on the pivotal role of Machine Learning (ML) in AI by enabling predictive maintenance, demand forecasting, and anomaly detection, further enhancing operational efficiency and cost reduction. Deep learning, a subset of machine learning, excels in image recognition, object detection, and video analysis, with significant applications in logistics and medical diagnostics. Robot-driven logistics, responding to the increasing demand for rapid and efficient deliveries propelled by the e-commerce boom, features autonomous electric vehicles and robots that increasingly automate delivery processes, minimizing errors and boosting delivery volumes. The human-robot interaction element is fundamental, focusing on adapting robotic behavior to human variations, ensuring safety, and enhancing communication between the two.

The examination of automation in logistics is propelled by a desire to harness technological advancements, enhance operational efficiency, cut costs, remain competitive, and align with changing market demands. This analysis seeks to offer insights that can serve as a guide for both academic researchers and professionals in the logistics sector, aiding them in navigating the evolving industry landscape. By exploring current applications and future potentials of automation in logistics, this study establishes a fundamental framework for understanding the intricacies of the field. It emerges as an indispensable resource, providing valuable perspectives for scholars and practitioners alike as they navigate the complexities of the logistics landscape amidst ongoing technological transformations. Nevertheless, it is important to acknowledge the inherent limitations of this research, as systematic reviews may not encompass all the latest developments. Consequently, ongoing research in industrial enterprises remains essential to further explore and refine the application of automation in logistics. As the integration of automation technologies continues to evolve, logistics companies and researchers alike must remain adaptable, embracing emerging technologies while proactively addressing challenges. In doing so, they can ensure the safe, efficient, and sustainable evolution of the logistics ecosystem, shedding light on the current landscape and providing a roadmap for the future of logistics in an automated world.

This extensive literature review explores the impact of automation within the domains of supply chain management and logistics. The increasing role of Artificial Intelligence (AI), Machine Learning, Deep Learning, and Robot-Driven Logistics is revolutionizing the way goods are handled, transported, and delivered. These technologies are driving increased efficiency, improved decision-making, and streamlined operations in the logistics industry. Nevertheless, this transformation is not without its challenges, including concerns about biases in AI decision-making and the need for robust ethical and regulatory frameworks.

In the following sections, we will explore the key insights and contributions of this research, offering a deeper understanding of the current applications and potential of automation in logistics. This analysis serves as a valuable resource for both scholars and logistics professionals, shedding light on innovative solutions and strategies made possible by automation.

However, it is important to recognize that this research, like any systematic review, provides a snapshot of the current state of knowledge. Given the rapid pace of technological advancements, continuous research and adaptation in the field of industrial logistics will be essential to further refine and expand the application of automation. As the logistics landscape evolves, staying abreast of emerging technologies and addressing challenges will be critical to ensure the safe, efficient, and sustainable development of the logistics ecosystem.

Problematic and Research Questions

The problematic can be summarized as the profound impact of automation and AI on logistics and supply chain management. The integration of these technologies is reshaping traditional processes and practices, ushering in a transformative era marked by increased efficiency, enhanced decision-making capabilities, and significant alterations in workforce dynamics. Automation and AI are not merely technological enhancements but catalysts for a paradigm shift, influencing how goods are sourced, transported, and distributed. This work highlights the transformative force that these technologies represent, implying a significant change in the industry. It also alludes to potential concerns, such as biases in AI decision-making and cybersecurity threats. These challenges represent the issues or gaps in knowledge that necessitate further research and exploration. Therefore, the research issues defined for this study are:

- What are the key challenges and opportunities posed by the integration of automation and AI in logistics and supply chain management?
- How do AI techniques enhance supply chain responsiveness in logistics and what are the key implementation factors and challenges?
- How is AI impacting logistics optimization in different academic disciplines, and what key patterns and insights emerge from its adoption?

General and specific goals

AI in supply chain management, share a common thread in their pursuit of shedding light on the transformative impact of advanced technologies in the domain of logistics and supply chain operations.

Two articles were published to address the research inquiries. The two articles under consideration share a common thread in their pursuit of shedding light on the transformative impact of advanced technologies in the domain of logistics and supply chain operations. These articles have both general and specific objectives that collectively aim to explore the implications of cutting-edge technologies in their respective domains.

At a general level, both articles seek to investigate the technological impact on logistics and supply chain management. They explore how automation, artificial intelligence (AI), machine learning, and deep learning are reshaping the logistics landscape and optimizing various facets of logistics operations. The first article focuses on AI techniques in supply chain management and aims to identify the main AI techniques that can enhance the responsiveness of supply chain workflows. Article two, on the other hand, unfolds in two interconnected parts, collectively contributing to a comprehensive understanding of the relationship between Artificial Intelligence (AI) and logistics. The primary focus lies in the systematic analysis of scientific literature related to AI and automation in logistics, with the objective of establishing a foundation for substantial advancements in the field. Complementing this, the second part delves into the examination of how "artificial intelligence" is represented across various academic disciplines pertinent to logistics.

Additionally, both articles aspire to address research gaps within their respective fields. The first article achieves this by conducting a Systematic Literature Review (SLR) review on AI techniques in supply chain management, with the goal of identifying research gaps and assessing the current state of knowledge. The second article mirrors this effort by conducting a systematic literature review to identify areas in automation and logistics that require further investigation. This endeavor to bridge existing research gaps is a fundamental objective that contributes to the advancement of knowledge in the field.

Furthermore, both articles offer a managerial perspective, emphasizing the business and management aspects of technology integration. They aim to provide insights that can guide future research and managerial decision-making in the logistics and supply chain management sectors. By exploring the benefits of combining AI techniques within supply chain management, the first article specifically contributes valuable insights that can inform managerial decisions on technology adoption.

Both articles rigorously detail their methodologies and present their findings transparently. This approach ensures the credibility of their research, making their contributions valuable for researchers and managers alike.

In summary, these articles, with their distinctive yet interconnected goals, contribute to a deeper understanding of the pivotal role of technology in logistics and supply chain management. Their comprehensive investigations promise to advance knowledge, bridge research gaps, and provide valuable insights for both researchers and managers in their respective fields.

The heart of this master's thesis consists of two chapters. Both chapters delve into a systematic literature review. Furthermore, this master's thesis encompasses an introductory section that provides an overview of the topic and a concluding section that encapsulates the key findings and offers recommendations for future research.

CHAPTER I

Artificial intelligence in supply chain management: A systematic literature review and guidelines for future research

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Abstract. Artificial intelligence (AI) has been considered an important enabler of supply chains (SC), as it helps to monitor SC competitiveness and management. Thus, AI has been gaining notability in management. However, no academic manuscript offers a detailed study of specific artificial intelligence techniques. Indeed, several existing reviews in this field provide considerable insight, but are often too general. To address this issue, we conducted a systematic literature review that aims to provide solid and relevant foundation, targeting the artificial intelligence techniques that are most prevalent in supply chain management. This research identified the main artificial intelligence technics in the field of supply chain management, namely, artificial neural networks, fuzzy logic and genetic algorithm, although other topics have emerged as well, such as sustainability, environment, big data, and automatization. We recognize that AI plays an important role in SCM and how beneficial it is to use it while being considered risky at the same time. Additionally, we disclose how beneficial AI techniques are, since when used together they allow using fewer resources to obtain optimal results in SCM. Future research should examine how the application of artificial intelligence techniques may differ across organizations of different sizes.

Keywords: *artificial intelligence; supply chain management; systematic literature review; fuzzy logic; genetic algorithms; artificial neural networks.*

I.1.Introduction

Artificial intelligence has been gaining notoriety in all industries (Dubey et al., 2020) and its impact on supply chain management has become a topic of discussion. AI has the potential to add business capabilities, increase data sharing, reduce costs and increase quality of service in supply chain management (SCM) (Brandon-Jones et al., 2018). It is also predicted that, with the growth of artificial intelligence, many companies will radically change their planning, scheduling, optimization, and transportation (Khalifa et al., 2021). It is common to find similar studies that demonstrate the importance of artificial intelligence in SCM. In this regard, a study carried out by Naz et al. (2021) provides useful information on the most prevalent AI technics in SCM, although it has not analyzed these technics in dept. Another recent study related to this article was developed by Toorajipour et al. (2021), where a systematic literature review on the contributions of AI in SCM was carried out. Although interesting results have been found by the cited authors, such as the most prevalent AI technics applied to the SCM, such as fuzzy logic (FL), genetic algorithms (GA), and artificial neural networks (ANN). However, to our knowledge, no study presents a systematic literature review that can identify research gaps and assess current knowledge in the field of AI from a holistic perspective. In this regard, this article intends to fill the gap in the literature, which is to find the main AI technics that can improve the responsiveness of SCM workflow (Lee et al., 2011). At the same time, we also intend to study the benefits of several combined AI techniques (Madhavaram et al., 2010). Therefore, this article answers the following research question: How did the ANNs, FL, and GA affect the supply chain the most? Although it is known that these three AI techniques are the most prevalent in SCM, we could also recognize that it may be beneficial to use the three together, as they allow the use of fewer resources to obtain optimal results. In this regard, we suggest further investigation into how the application of AI techniques may differ in organizations of different sizes.

The remaining sections of this article are structured as follows: section two presents a description of the methods used to carry out this article, namely the PRISMA statement (Preferred Reporting Items for Systematic Review and Meta-Analysis Protocol) and the content analysis technique. In the third section, the results of the analysis are presented. The fourth section presents a discussion of the results that allow for future guidelines and, finally, the fifth section ends with theoretical and managerial conclusions.

I.2. Materials and Methods

I.2.1 Search Strategy

Elsevier Scopus was the database selected to carry out this review, considering the fact that it is one of the largest databases with a large number of high-quality, peer-reviewed scientific articles (Vinodh et al., 2020), as it is also the database selected by researchers who have articles published in this field (Naz et al., 2022; Toorajipour et al., 2021, Maitre et al., 2022 and Kannan, 2018). This search performed on article title, abstract and keywords, to identify peer-reviewed systematic reviews in English. The search terms used included “artificial intelligence “AND “supply chain management”. Scopus was able to identify a total of 914 manuscripts on August 17th, 2022. A limit was added for the year of publication and the scope ranged from 2018 to mid-2022, as there was an exponential growth of articles in this area during this period of time. Since our objective is not to write a technical article focused on engineering and computer science, but rather an analysis from a managerial point of view, we selected the areas of Business, Management and Accounting. We observed that the main countries that published articles with these search terms were the United Kingdom, the United States and India, as they are considered the most productive and influential in the area of AI research in SCM, however our article does not distinguish in context.

I.2.2 PRISMA Protocol

The objective of this article is to carry out a systematic literature review to obtain an exhaustive search of published manuscripts. In that regard, we used the PRISMA statement tool, which we thought was the most appropriate because it allows a targeted and transparent search (Tranfield et al., 2003). We used only a single database, for several reasons: 1) it is agreed that Scopus is one of the world's largest abstract and citation databases of peer-reviewed research literature; the use of only one database also allows presenting the results in a more transparent way, allowing reliability and reproducibility by other researchers (Cook et al., 1997 and Moher et al., 1999); 3) when compared to other databases (e.g., Web of Science), the use of Scopus is justified by researchers who conducted similar studies (Reis et al., 2021) and who argued that AI research is more representative in this database due to the larger number of documents that can be captured there; and 4) compared to academic search engines (e.g. Google Scholar), Scopus captures fewer documents. However, as we prioritized studies with blind peer review, we had to exclude them from this research.

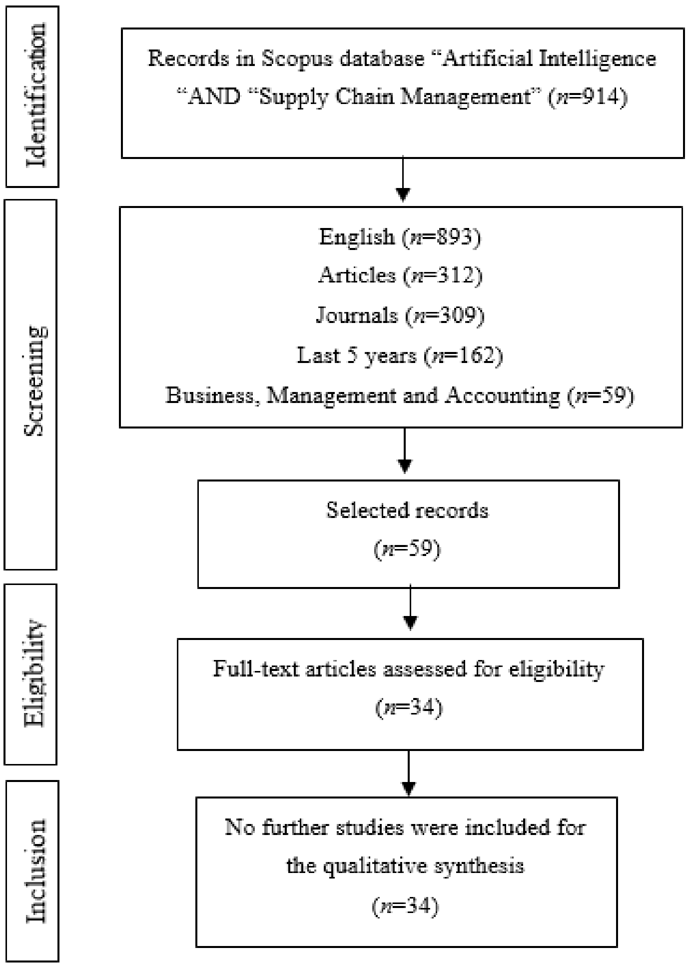

Fig. 1. PRISMA Protocol

Figure 1 shows that a total of 893 manuscripts were identified. The review process was based on filters in order to restrict the search to the best quality articles. We started by excluding journals that were not written in the English language, as English is increasingly becoming a universal language in scientific research. Then we decided to narrow the review to articles and journals in order to select only reliable manuscripts, as journal articles have better quality content than others, such as book chapters and conference proceedings, in a total of 309 manuscripts. This systematic literature review also includes the manuscripts published from 2018 to 2022, as it was possible to perceive an exponential growth in the publication of articles during this period. Finally, a new filter was applied to obtain only articles related to Business, Administration and Accounting, as we intend to obtain an analysis from a managerial point of view, with a total of 59 reviews. During the eligibility phase, after carefully reading all selected manuscripts, it was possible to exclude articles to which we could not have granted access (n=34). Considering that articles other than those obtained through the Scopus search were not included, we ended the search with 34 reviews.

I.3 Results

I.3.1 Sustainability

In supply chain management and artificial intelligence literature, sustainability is a general concern advocated by Ouyang and Li, (2010), Zhang et al., (2017), Thuermer and Karen, (2016), and Dirican, (2015).

In the literature, it is quite evident that the influence of AI on sustainable SCM is still at an early stage (Benzidia et al., 2021). It is argued that to achieve sustainability in supply chain management, it is important to make use of tools such as AI, robotics, big data, digitization and the Internet of things (Sanders et al., 2019). AI has revolutionized the way we do business Schneider et al., (2019) and has made the supply chain management process more transparent, which is an important criterion regarding sustainability (Sanders et al., 2019). For an organization to be more sustainable Elkington, (1998), all three dimensions of sustainability need to be aligned (economic, environmental, and social). In this line of thought, it is stated that the strength of the supply chain mainly depends on an effective articulation between suppliers, customers, and the three aforementioned pillars of sustainability, however, this articulation is more effective in the use of artificial intelligence (Büyüközkan, G and Çifçi, G., 2011). A case of success is the Henkel Ibérica factory, which started to use AI to achieve sustainability in its company, prescribing actions to ensure flawless operations on the production line, using historical data.

Ouyang and Li, (2010) support the idea that AI technologies are not necessary when it comes to achieving sustainability in supply chain management, as existing resources are sufficient. On the other hand, we have Thuermer and Karen, (2016), and Dirican, (2015), who argue that artificial intelligence is crucial to achieving sustainability in supply chain management. It is also emphasized that the role of AI increases an organization's ability to better process information (Benzidia et al., 2021). Thus, when AI is incorporated into supply chain networks, the information circulating in these systems works in pull mode, allowing organizations to improve operations and provide just-in-time deliveries (Olan et al, 2022).

Moreover, Berg et al., (2020) stressed that the goal of supply chain management is to comprehend under what conditions their products or services are designed, produced, and used to maximize sustainability performance and circularity. With this in mind, making informed decisions means that product sustainability and circularity performance need to be evaluated at a case-specific level. In this way, the use of IoT, big data, AI, and blockchain offers great potential to increase sustainability and circularity of products and resources (Moreover, Berg et al., 2020).

In short, it was possible to ascertain that artificial intelligence is an important topic when it comes to achieving sustainability in SCM. Thus, the SCM needs to be aligned with the main pillars of sustainability to get good use of AI. In addition, the literature also mentions that the use of AI increases the sustainability and circularity of products and resources.

I.3.1.1 Environment

The environment is another topic associated with artificial intelligence and supply chain management, being discussed mainly by Lee & Choi, (2021) and Zhang et al, (2022). It is also an important pillar of sustainability as it plays a crucial role in implementing sustainable practices in the supply chain (Govindan et al., 2014).

Due to globalization, large distances between two connections have increased, bringing with them unsustainable issues, resulting in the environmental impact on SCM (Elhedhli et al., 2012). The environmental impact represented by the supply chain, such as producing, sourcing, and distributing has been the main concern (Lee & Choi, 2021). Therefore, the need to adopt eco-friendly systems is urgent (Elhedhli et al., 2012). Big data analytics and AI can play a key role in the SCM environment, as with economic development, industrial modernization and better energy structures it is possible to balance the impact (Li et al., 2017). Furthermore, environmental awareness is growing rapidly with the proliferation of information and communication technology (ICT) and social media, another challenge that organizations face in a competitive business environment (Zhang et al., 2022).

Environmental management can also offer financial benefits to organizations in order to increase the competitiveness of their work. In this regard, SC strategies can also be implemented through artificial intelligence Zhang et al., (2022). For instance, a mathematical models using a fuzzy particle swarm optimization were designed to offer a solution for better SCM, considering environmental challenges associated with the manufacturing and industrial sector (Mathivathanan et al., 2018; Che 2010). Accenture leverages this model, providing the flexibility to plan at the city level and the ability to aggregate the data globally. It enables users to make decisions based on data and insights and considers the many factors needed to effectively manage a real estate portfolio of global size. Data is consolidated from multiple systems and provided in near real time.

Suppliers can also play a very important role in enforcing green supply chain practices (Govindan et al., 2014; Kannan et al., 2014). On the other hand, is also considered risky to adopt practices related to the environmental impact of their SC, as they face changes in decision parameters, information uncertainty and changes in decision boundaries (Matos, 2007). However, technological progress can play an important role in economic development, upgrading industrial structure and adjusting energy structure, while decreasing risks (Elhedhli et al., 2012).

That said, it is safe to say that while globalization is a supply chain issue when it comes to environment, AI has the ability to lessen the risks that come with it and create better options.

I.3.2 Artificial Intelligence Techniques

We identified three AI techniques applied to SCM, namely ANN, genetic algorithms and fuzzy logic. Mainly supported by Bottani et al., (2019) Belhadi et al., (2022) and Toorajipour et al., (2021).

Bottani et al., (2019) starts by defining the concept of ANN, stating that is a mathematical tool inspired by biological neural networks that provide, for a given problem, solutions similar to those formulated by the human mind. Similar to the following concept, they also stated that ANNs are typically based on mathematical regression to correlate input and output flows to and from process units. Such models predominantly depend on a large number of experimental data (Yang & Chen, 2015). It is shown that ANN models can provide more accurate predictions taking into consideration other AI techniques (Bottani et al., 2019; Benkachcha et al., 2014; Yeganeh et al., 2012). Therefore, ANN is a technique mainly used in SCM, applied to marketing, sales forecasting and customer segmentation (Kasabov, 2019). As the McKinsey case study illustrates, using ANN in automotive marketing to reach customers at the right moment with a tailored, individual message. Also through programmatic advertising, with AI at its very core, automotive players can allow AI to determine which customers to reach, with which messages, at what time and through which channels. The use of ANNs for demand forecasting problems is not new and has been proposed in different contexts (Eleonora et al., 2019). Thus, if other tools are integrated with artificial neural networks, it is possible to obtain a more effective forecast.

When it comes to genetic algorithms (GA) the most consensual concept is a computational algorithm inspired by Darwinian evolutionary theory, which can be called in short as “survival of the fittest” (Darwin, 1859). GA allows parameter optimization and can also be extended to multi-objective optimizations (MOO) (Streichert, 2002). Fuzzy Logic allows dealing with uncertainty, unpredictability, hard-to-formulate systems and information fuzziness (Solgi & Ganjefar, 2018). Being defined as an approach that perfectly addresses qualitative information and resembles the way humans make inferences and decisions (Keramitsoglou et al., 2006), representing the frontier between AI and non-AI techniques (Bundy, 1997).

Overall, the most prevalent AI techniques in SCM offer the possibility to gain human capabilities such as thinking like humans, acting like humans, reasoning and acting rationally. Based on these characteristics, AI techniques can be grouped into four categories, namely, human thinking (HTT), human acting (HAT), rational thinking (RTT) and rational acting (RAT) techniques (Lee & Choi, 2021; Russell & Norvig, 2010), also giving the possibility to have better forecasting in SCM.

I.3.3 Big Data

Gualandris and Kalchschmidt, (2016) stress that Big Data is a complex and large data set that goes beyond traditional systems that have the ability to process, monitor, and visualize, has been gaining much notability due to the rapid dissemination of information technology (Papadopoulos & Gunasekaran, 2018). Due to the increase size of data, in today's highly competitive market, big data is crucial to help with changes such as the IT revolution, customer awareness and globalization. In this way, supply chain experts seek to find a way to manage a large amount of data in order to achieve an integrated, efficient, effective and agile supply chain system (Benzidia et al., 2021). Keeping this in mind, big data analytics (BDA) in conjunction with artificial intelligence was defined as the best solution, allowing companies to extract useful information from the huge amount of data and use this information to manage supply chain problems (Benzidia et al., 2021; Maheshwari et al., 2021). It was also recently noted that the use of BDA-AI can significantly reduce carbon intensity, making use of two models of hybrid metaheuristic algorithms (Goodarzian et al., 2021; Liu et al., 2021).

Business analytics and big data play an important role while enhancing a company's information processing (Benzidia et al., 2021). In a recent study, a theoretical framework was developed and tested in supply chain finance and studied the effect of big data on analytics capability, reaching the conclusion that big data analytics has a positive effect on the integration of supply chain finance (Yu et al., 2021). As BDA-AI is useful to process unstructured data in order to reveal thoughtful insight. BDA-AI has the ability to analyze dynamic energy consumption and carbon emission data in real time and support the optimization of the manufacturing process with the aim of saving energy and reducing emissions (Singh, et aal., 2019; Ikram & Sroufe, 2021).

Regarding the decision-making procedures of companies, the importance of big data has increased due of technological progress across the industry (Chen et al., 2012). However, research on the influence of big data on the environmental dimension of the SC is still in its early stages (Benzidia et al., 2021). As in such a volatile market, despite the growing popularity of emerging technologies, such as big data analytics and artificial intelligence, there is ambiguity about how the adoption of business analytics affects firm performance (Akter et al., 2016; Wamba eta al., 2022; Ramanathan et al., 2017; Aydiner et al., 2019). It is still considered a risky adoption and leaves stakeholders vulnerable to greater losses.

In this way, the adoption of BDA-AI refers to the use of big data analytics powered by artificial intelligence to extract more meaningful information with which companies can improve their decision-making skills. Enabling better management to fight the market competitiveness. However, scholars still consider the adoption of BDA-AI a risky move.

I.3.4 Automatization

The idea of automatically learning and developing trading strategies on automated supply chain procurement platforms gained interest. Given the inherent suitability of software agents for these tasks, most follow-up work on automation in SCM uses agentbased systems, which began with the proposal of various frameworks detailing agent roles and activities (Glushko et al., 1999; Julka et al., 2002; Xue et al., 2005; Jiao et al., 2006).

Automation in the supply chain took its first steps with the now ubiquitous electronic procurement (e-Procurement) (Neef, 2001; Brandon-Jones & Carey et al., 2011), allowing an increase in accuracy and speed of procurement, and enabling the reduction of costs with bureaucracy and administration. In this regard, some studies reveal that a large percentage of managers may lose their jobs to automation. While opposing arguments claim that it is better to invest in automation as it is becoming an important factor for profit margins as well as allowing for potential expansion in the customer base as more relationships can be easily managed without the need to invest more in capital human, making it an attractive option. With automation, we will start to have a human being whose behavior is imitated by an intelligent agent (Glushko et al., 1999; Julka et al., 2002; Xue et al., 2005; Jiao et al., 2006).

Automation in the supply chain can be divided in three different capabilities, namely “process automation”, “operational automation” and “tactical automation”. Being described that such capabilities are not defined by the “level” of intelligence, but by the “complexity” of the process that the automation activity is being applied (Xu et al., 2021). Process automation is meant for supply chain data entry with robotic process automation and recognition in e-procurement, while operational automation is for coordinating production schedules and co-optimizing inventory levels. Finally, tactical automation concerns the handling of various business-to-business (B2B) processes (Xu et al., 2021).

It is claimed that only three studies made use of multi-agent-based automation approaches (Ying & Dayong, 2005). Proposed by Ying & Dayong, (2005) a framework for 3 PL (Third Party Logistics) for the formation of ad hoc virtual private logistics teams, an automated route planning system was built for cases where transportation and production schedules are closely connected and goods are distributed immediately after production. This system was applied to a German newspaper, resulting in a system that was able to handle fluctuations in production schedules better than the existing centrally planned system. It is argued that automation plays a key role in the supply chain, although it is proclaimed that it can lead to job losses. Within recent research it is stated that human-robot interaction and human-robot collaboration can be of paramount importance in some areas of the SCM (Galin et al., 2020; Reis et al., 2022). To provide a comprehensive overview of the results, we present a summary of this section in Figure 2.

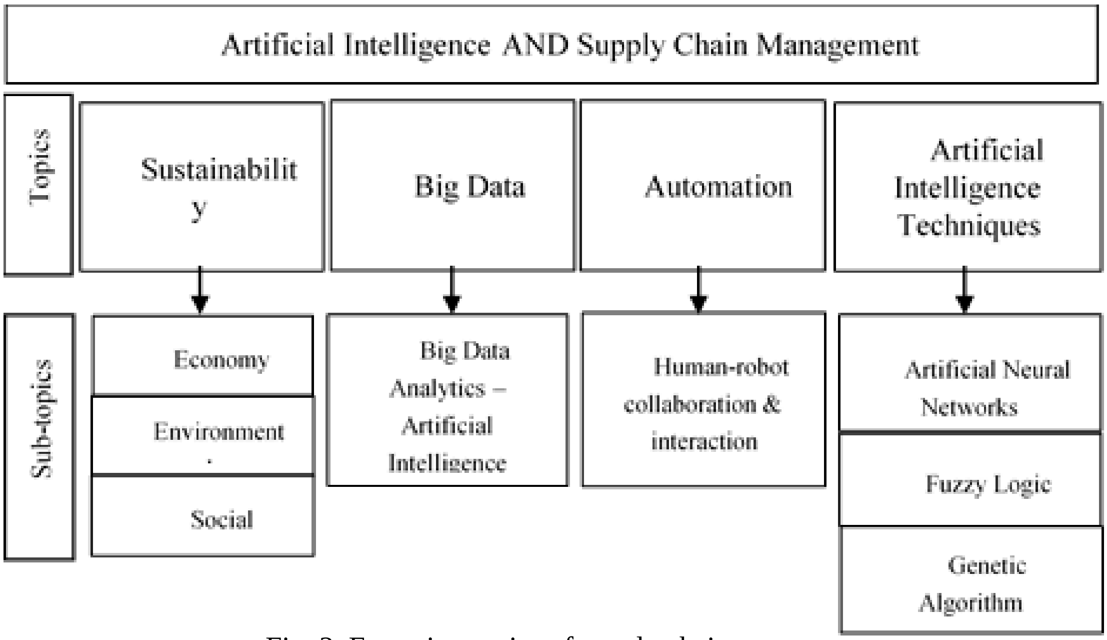

Fig. 2. Emerging topics of supply chain management

The article aimed to provide a solid foundation on the AI techniques that are most prevalent in SCM. However, the results highlighted the existence of other relevant topics and subtopics that are displayed in Figure 2. Based on the results of the systematic review, we, therefore, argue that AI plays an important role in SCM, in particular, within the pillars of sustainability, in the context of big data analytics, and in relation to interactions and collaborations between humans and robots. These results can offer useful paths (topics and subtopics) that allow researchers to justify and carry out research in the field of AI and SCM.

I.4 Discussion

Four important themes emerged from the literature within artificial intelligence and supply chain management, namely, sustainability allied with the environment, artificial intelligence techniques, big data, and automatization.

Considering the first topic, we can acknowledge that, although the influence of AI in sustainable SCM is still incipient, it already plays a pivotal role in improving the organization's management. In this regard, one should keep in mind that all three dimensions of sustainability are relevant and must should need to be aligned – economic, environmental and social. That said, in order to maximize sustainability and circularity performance, the use of AI can offer options that were previously unavailable in the market, such as route optimization. On the other hand, the environment also strongly contributes to achieving the sustainability goals, in this regard the previous argument, e.g., route optimization through AI, also allows mitigating the effects of globalization. Thus, AI is one of the technologies capable of mitigating risks, as it is able to make use of techniques such as fuzzy particle swarm optimization, helping to optimize a problem by improving an existing solution.

As far as artificial intelligence techniques are concerned, we have identified “ANN”, “genetic algorithms” and “fuzzy logic” as the most relevant techniques when it comes to SCM. Regarding the ANN, they have the ability to predict and provide accurate results, therefore, it is easier to predict the number of sales and solve problems in sales forecasting, which leads to a more sustainable SCM. However, when it comes to solving complicated problems, genetic algorithms have better utility as they work with a larger number and variables and can also be extended to multiple objective optimizations. In addition to the above, fuzzy logic is a great technique when working with qualitative information, as it is able to approach it perfectly. For instance, it is capable of reassembling a human mind, as it works very well under uncertainty and unpredictability. In this way, these techniques together open the possibility of reducing human effort. As when grouped into four categories, namely human thinking (HTT), human acting (HAT), rational thinking (RTT) and rational acting (RAT) techniques, they have great performance forecasting in SCM. Therefore, ANNs, FL, and GA are considered important techniques, since they make available the use of fewer resources to obtain great results in supply chain management.

Due to the increasing size of data in SCM, big data analytics has proven to be crucial in helping with changes such as IT revolution, customer awareness and globalization. The use of big data analytics (BDA) in conjunction with artificial intelligence was defined as the best solution, allowing companies to extract actionable insights from large amounts of data and use that information to SCM issues. Although BDA is still considered a risky adoption, it is taken as the best way to combat market competitiveness. As a last topic, we present automatization, which can be divided into three different capabilities, namely:

"process automation", "operational automation", and "tactical automation". These capabilities are considered very important due to the increase in accuracy and speed of acquisitions, in addition to enabling the reduction of costs with bureaucracy and administration.

I.5 Conclusions

I.5.1 Theoretical and managerial contributions

The main theoretical contributions of this research are the increase of new perspectives on the use of AI in SCM that had not been previously explored. Although other similar studies can be found in the literature, this research is original since it covers an analysis of the most prevalent AI techniques in SCM, providing a more comprehensive knowledge than the existing literature. With the help of the PRISMA statement we were able to refine our search and bring to light the most relevant topics in SCM. In this regard, we have found that sustainability, environment, big data and automation play important roles in how the supply chain is managed and in market competitiveness.

From a managerial perspective, the great challenge that organizations face today are the rapidly changing environments (VUCA) and globalization. We suggest that managers consider the use of big data analytics, which allows them to manage a large amount of data more efficiently, by combining data with AI techniques. In our understanding, it may be relevant that managers are also entrepreneurs so that they can explore new dynamics and obtain competitive advantages. Although it is claimed that automation can lead to operational and tactical level employees (managers) losing their jobs, it is possible to achieve great results by having human capital working alongside automation (Galin et al., 2020; Reis et al., 2022). Thus, organizations can benefit from more accurate results, speed of acquisition and reduction of bureaucracy and administration costs.

I.5.2 Research limitations and suggestions for future research

The limitations of this research are essentially related to the methods. Systematic reviews present a snapshot of a given reality (Reis et al., 2022) at a given point in time. Therefore, while scientific databases are constantly being updated with new peer-reviewed research, they become outdated (Reis, 2021). By restricting the search to certain keywords and applying filters that allowed selecting the most important articles, we may also have run the risk of excluding relevant manuscripts. Although we are aware of the above limitations, we believe in the value of this systematic review, as it presents in a few pages the state of the art of AI in SCM. As for future research, we suggest examining how the application of AI techniques might differ across organizations of different sizes. To this end, empirical studies can be carried out in a real context, in order to explore the application of AI in e.g., sales forecasting and customer experience design. It can also be analyzed how an organization achieves sustainability in SCM via AI, depending on the degree of maturity of these technologies in the organization. Finally, we suggest that an investigation be carried out to explore the risks of using AI technologies in SCM (Akter et al., 2016; Wamba eta al., 2022; Ramanathan et al., 2017; Aydiner et al., 2019).

CHAPTER II

A Systematic Literature Review on the Application of Automation in Logistics

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Abstract. Background: In recent years, automation has emerged as a hot topic, showcasing its capacity to perform tasks independently, without constant supervision. While automation has witnessed substantial growth in various sectors like engineering and medicine, the logistics industry has yet to witness an equivalent surge in research and implementation. Therefore, it becomes imperative to explore the application of automation in logistics. Methods: This article aims to provide a systematic analysis of the scientific literature concerning Artificial Intelligence (AI) and automation in logistics, laying the groundwork for robust and relevant advancements in the field. Results: Automation's foundation lies in cutting-edge technologies such as AI, machine learning, and deep learning, enabling self-problem resolution and autonomous task execution, reducing the reliance on human labor. Consequently, the implementation of smart logistics through automation has the potential to enhance competitiveness and minimize the margin of error. The impact of AI and robot-driven logistics on automation in logistics is profound. Through collaborative efforts in Human-Robot Integration (HRI), there emerges an opportunity to develop social service robots that coexist harmoniously with humans. This integration can lead to a revolutionary transformation in logistics operations. By exploring the scientific literature on AI and automation in logistics, this article seeks to unravel critical insights into the practical application of automation, thus bridging the existing research gap in the logistics industry. Conclusions: The findings underscore the impact of artificial intelligence and robot-driven logistics on improving operational efficiency, reducing errors, and enhancing competitiveness. The research also provided valuable insights into the applications of various automation techniques, including machine learning and deep learning, in the logistics domain. Hence, the study's insights can guide practitioners and decision-makers in implementing effective automation strategies, thereby improving overall performance and adaptability in the dynamic logistics landscape. Understanding these foundations can pave the way for a future where automation and human expertise work hand in hand to drive logistics toward unparalleled efficiency and success

Keywords: *logistic; automation; artificial intelligence, machine learning, deep learning, systematic literature review.*

II.1 Introduction

Intelligent systems have significantly transformed the logistics landscape, primarily through the adoption of automation, which has proven effective in mitigating failure and accidents (Iyer, 2021). Artificial Intelligence (AI) has emerged as a reliable and cost-effective solution, empowering businesses to address uncertainty and efficiently manage complex algorithms (Chowdhury et al., 2012). While automation has been extensively studied in computer science (Sudhakar et al., 2023), engineering (Salehi et al., 2018), mathematics (Jančaří et al., 2023), and medicine (Hamet and Tremblay, 2017), logistics in scientific research still falls short when compared with these domains. To justify our previous argument, we conducted a search on the Scopus database during the final quarter of 2023. Employing the search term "artificial intelligence" in the title, abstract, and keywords, we observed substantial representation in various academic disciplines. Specifically, the field of computer sciences demonstrated the highest prevalence at 37%, followed by engineering at 16.4%, mathematics at 14%, and medicine at 5.4%. When restricting the analysis to the most recent five-year period, a slight shift becomes apparent. During this timeframe, the representation of "artificial intelligence" in the field of computer science amounts to 28.3%, followed by engineering at 16.2%, medicine at 8.9%, and mathematics at 8.7%. In contrast, the occurrence of "artificial intelligence" within disciplines such as materials science and management, was comparatively minimal, accounting for 2.1% and 1.8% respectively. In the last 5 years, materials science presents 3% and management is around 2%. Furthermore, we expanded our investigation by incorporating dual search terms, with no time restriction. The combination of "artificial intelligence" and "engineering" yielded 45,050 manuscripts, while "artificial intelligence" and "computer sciences" resulted in 38,234 manuscripts. Similarly, the search pairing "artificial intelligence" with "medicine" generated 13,394 manuscripts, whereas the intersection of "artificial intelligence" and "logistics" produced a relatively modest 7,333 manuscripts. Some notable studies, such as (Woschank et al. 2020) research on AI in smart logistics and (Iyer, 2021) work on intelligent transportation, have shed light on this issue. "Smart logistics" encompasses the application of advanced technologies (Issaoui et al., 2019) data analysis (Jung and Kim, 2015) and automation (Cimini et al., 2020) in the logistics domain, aiming to optimize supply chain processes (Issaoui et al., 2019). This integration involves interconnected systems and devices enabling real time monitoring, analysis, and decision-making in logistics operations (Feng and Ye, 2021). By utilizing automation and digital technologies, smart logistics strives to enhance supply chain performance, visibility, and responsiveness, resulting in improved productivity, cost efficiency, and heightened customer satisfaction (Shee et al., 2021). Automation facilitates this transformation by enabling intelligent decision-making algorithms, and machine learning models that optimize routing, scheduling, and final delivery, thereby ensuring efficient resource allocation, cost reduction, and timely delivery of goods (Shee et al., 2021). Overall, the incorporation of automation in logistics plays a pivotal role in the evolution of conventional supply chains into intelligent, interconnected, data-driven systems (Nitsche, 2021) that underpin the concept of smart logistics. In this context, several articles delve into the potential applications of cutting-edge technologies, such as the AR/VR (Augmented Reality/Virtual Reality) technologies within Industry 4.0. In that regard, articles such Machała et al., (2022) examine the integration of smart glasses and mobile devices to facilitate augmented reality experiences, thereby expediting work processes and data transfers in developed nations' manufacturing, warehousing, and transportation sectors. It is important to note that this is a single instance illustrating the broader scope of possibilities within this domain.

However, a comprehensive understanding of automation's impact on logistics and its development still requires further investigation. To bridge this research gap, we conducted a Systematic Literature Review (SLR) to identify research deficiencies and assess the current state of knowledge regarding automation in logistics from a holistic perspective. This review aims to comprehend how automation is currently enhancing the logistics industry and the ongoing developments in this field. Specifically, we address the research question: How does automation contribute to the improvement of the logistics industry? In this context, AI plays a pivotal role by providing systems with the critical capability of cognition, encompassing modeling, representation, and learning of complex behaviors and interactions within a system's components and data. This ability enables autonomous decision-making by robots, akin to human-like intelligence. By leveraging machine learning, operational efficiency is achieved, costs are reduced, and the work environment is enhanced, empowering the workforce to create and implement process innovations. Additionally, we discovered that a collaborative Human-Robot Integration (HRI) offers the potential to create social service robots that seamlessly coexist with humans in social settings, catering to the genuine demands and expectations of lay experts.

Accordingly, the purview of this article predominantly centers on the examination of the utilization of automation, specifically AI, machine learning, and deep learning, within the sphere of the logistics domain. This article scrutinizes the transformative influence of these technologies on several dimensions of logistics operations, encompassing but not limited to inventory management, supply chain optimization, transportation, and warehouse automation. The primary objective of the article is to furnish a holistic comprehension of the contemporary landscape, challenges, and prospects inherent in the assimilation of automation into the complex web of logistics processes. Particularly, the article deliberately abstains from studying broader subjects detached from the ambit of automation in logistics, such as generic transportation analyses or strategies for logistics management that do not involve automated frameworks.

The following sections of this article are organized as follows: Section 2 outlines the methods employed in this systematic review, including the PRISMA statement (Preferred Reporting Items for Systematic Review and Meta-Analysis Protocol), the SLR process, and content analysis. Section 3 presents the findings from the analyses conducted. Finally, Section 4 discusses the theoretical and managerial contributions derived from this research, illuminating the way forward for automation in the logistics industry.

II.2 Material and Methods

II.2.1 Search Strategy

We opted to use Elsevier Scopus as the primary database for our keyword search due to its well established reputation for systematically mapping and reviewing literature (Fahimnia et al., 2019; Pournader et al., 2020). Notably, Scopus boasts extensive coverage of articles across various scientific domains, including business and management, engineering, and computer science (Martín-Martín et al, 2018). Moreover, many researchers in the fields of automation, AI, and logistics publish their work in this database (Woschank et al., 2020; Tsolakis et al., 2022). Our search, conducted on February 7th, 2023, involved screening the article title, abstract, and keywords using the following search terms: "Logistic*" and "Automation" and "Artificial Intelligence." This led to the identification of a total of 301 manuscripts. To ensure the inclusion of only high-quality studies, we initially considered all types of studies but limited our selection to Journal articles published in the English language. Additionally, we set a timeframe for the research studies from 2019 to 2023, as a growing trend of publications in this field was observed during these years (Tsolakis et al., 2022). This step was vital in capturing the most recent and relevant contributions to the domain of automation in logistics.

II.2.2 PRISMA Protocol

The primary objective of this review is to conduct a thorough and comprehensive search of published manuscripts, making an SLR the appropriate approach. One of the primary benefits of SLRs, as outlined in the literature, is their focused and transparent approach (Tranfield et al., 2003). In adherence to this principle, we adopted the PRISMA statement, enabling us to systematically analyze the research methodology step by step. During our investigation of the Web of Science (WoS) database, we observed that Scopus contained a significant number of highly relevant articles within the specific research areas of interest (Tsolakis et al., 2022). This fact led us to consider Scopus as our initial choice for selecting a single database. Furthermore, Scopus enjoys a widely recognized reputation as one of the most comprehensive repositories of abstracts and citation research literature globally. Scholars have also affirmed that Scopus stands as one of the largest and most pertinent databases, providing a wealth of high-quality documents pertaining to automation and logistics. While academic search engines like Google Scholar may yield a more extensive collection of documents, our primary goal was to focus on studies with blind peer review. In this regard, Scopus proved to be the optimal choice, aligning with our criteria for obtaining rigorously evaluated and reliable research. In summary, based on its comprehensiveness, relevance, and popularity among scholars, Scopus was deemed the most suitable database for our study, ensuring a robust and thorough examination of automation and logistics literature. Thus, Scopus was employed as the primary source, facilitating the collection of information pivotal to the construction of this article's conceptual framework. However, this did not preclude the utilization of supplementary supporting manuscripts from Web of Science (WoS), Google Scholar, and various internet-based platforms as will be seen later by readers.

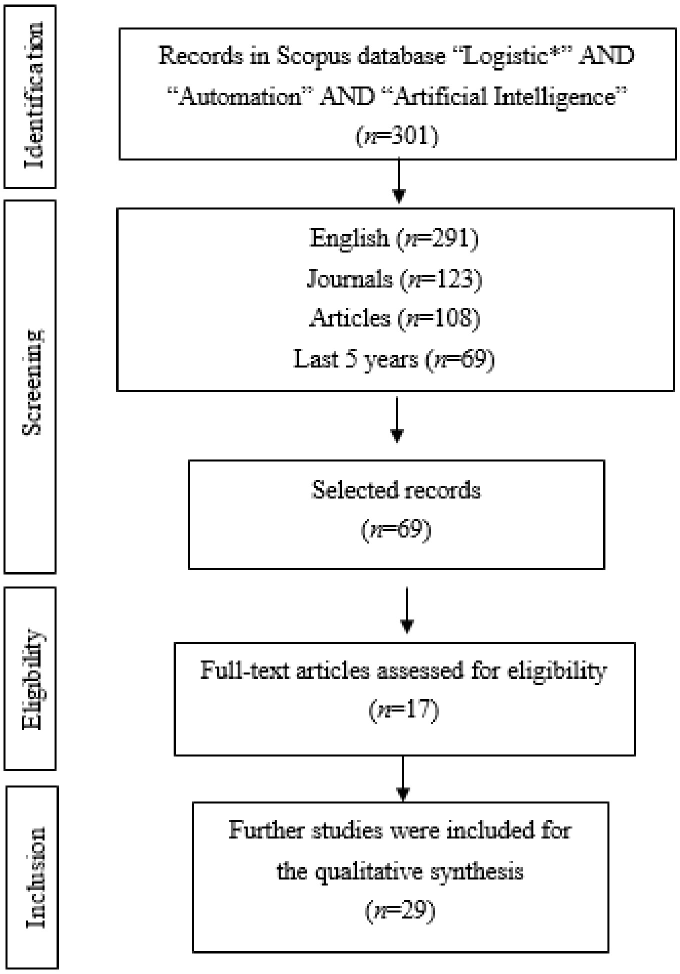

Fig. 3. PRISMA Protocol

Figure 1 presents the initial pool of 301 manuscripts identified during the identification phase. To ensure the inclusion of the highest-quality articles, we applied a series of filters in the review process. Initially, we excluded non-English manuscripts, as English is widely recognized as the universal language of scientific research, resulting in 291 remaining manuscripts. Next, we applied the "Journal" filter, narrowing the results down to 123 manuscripts. Further refining the selection, we applied the "articles" filter, which left us with 108 articles that met our criteria for high-quality studies. To capture the most recent and relevant contributions to the field of logistics and automation, we applied a time filter, considering only articles published between 2019 and 2023. This five-year timeframe was chosen because it coincided with a notable upsurge in published articles in this area. Throughout the eligibility phase, we examined all chosen manuscripts, subsequently excluding 52 articles inaccessible to us, resulting in a final selection of 17 articles. Although the initial search was conducted solely through Scopus, we recognized the importance of including other articles that offered relevant contributions to our study. Consequently, the search was expanded to 12 additional articles, resulting in a final set of 29 reviews that met our stringent criteria for inclusion. The application of these filters and the inclusion of relevant articles allowed us to focus on a select group of high-quality studies, providing a comprehensive foundation for our review on the topic of logistics and automation.

Hence, in our empirical investigation, the primary selection of manuscripts for analysis in the eligibility phase comprised 17 articles. This core set was further augmented by an additional 12 principal articles, expanding the total set to 29 articles during the inclusion phase (n=29). The rationale underlying the incorporation of the supplementary 12 articles (from WoS) was to both validate and introduce diverse perspectives, thereby enhancing the comprehensiveness of our discourse and preempting an overly restrictive view with limited deliberation. Illustratively, within the last paragraph of the results section, the discourse encapsulates the viewpoints of Heinrich et al., (2019) representing a subset of the 17 initial authors. Building upon the insights of Heinrich et al., (2019) we incorporated the contributions of Knight, (2014), which transcended the confines of the former's scope. This approach signifies a comprehensive analysis rooted in the Scopus article corpus, reinforced by the inclusion of authors during the inclusion phase, aiming to bolster or challenge the content derived from the initial selection phase. It is essential to emphasize that the other additional manuscripts (from Google Scholar and various internet-based platforms – e.g., private companies such as DHL) presented in the results maintain a purely supplementary role and do not form part of the core conceptual framework. Their function primarily revolves around providing contextual framing and, in certain instances, presenting illustrative business cases, typified by the inclusion of the DHL case, thus fortifying supplementary practical arguments. This approach serves to enhance the visibility of the presented arguments and establish a trajectory for the future empirical validation of the conceptual framework. Readers of this article seeking comprehensive access to the complete list of articles and their specific role in the analysis process are encouraged to reach out to the corresponding author, who will address any inquiries regarding the article's selection context.

II.2.3 Content Analysis Technique

The data under discussion in this article were synthesized employing the well-established content analysis technique. This specific approach was selected for its capacity to offer a comprehensive view of contemporary phenomena, particularly within qualitative research methodologies (Elo et al., 2014). This technique is recognized for its efficacy in scrutinizing non-statistical data (Hsieh and Shannon, 2005) and exploring the underlying rationales and methodologies elucidating the "how" of the research question (Granheim et al., 2017). The application of this technique encompassed a thorough examination of the textual corpus identified earlier, ensuring an examination of each individual article. Throughout this process, ideas were discerned, and keywords and phrases were systematically coded. Subsequently, this initial coding phase facilitated the identification of overarching categories and their respective subcategories. This procedure enabled us to discern patterns within the codes, ultimately unveiling pertinent themes and facilitating the creation of a comprehensive map that provided an overview of the data, thereby revealing emergent patterns and ideas. Following the completion of the mentioned process, we revisited our methodology, cross-examining the identified keywords in the articles to detect any disparities between the results of the content analysis and the most salient terms attributed by the authors. Once similarities were ascertained, we progressed to discuss the outcomes in the subsequent section, with a high degree of confidence that the topics and sub-topics highlighted within the conceptual framework are indeed robust and reliable.

II.3 Results

In this section, we will conduct an in depth analysis of the descriptive findings related to automation in logistics. Furthermore, we will perform a content analysis of the identified papers to gain a comprehensive understanding of their key insights and contributions.

II.3.1 Artificial Intelligence

AI is a rapidly advancing field in science and engineering, focused on creating intelligent machines and computer programs (McCarthy et al., 2006). Moreover, AI possesses the remarkable ability to automate learning and discovery processes by processing information, allowing it to handle repetitive, high-volume tasks tirelessly (Reebadiya et al., 2021). Through successive learning algorithms, AI is gaining knowledge about patterns and structures in its environment, enabling it to adapt and learn from new experiences. However, there are concerns about potential cyberattacks and biased decisions made by AI systems. To address these risks, the European Union (EU) is encouraging companies to adopt regulatory frameworks for innovation, while safeguarding fundamental values and rights (Matt et al., 2020). The transportation and logistics sector, responsible for handling valuable goods worldwide, faces challenges that AI can help overcome. Companies like AI EdgeLabs emphasize the importance of AI in addressing these challenges and improving logistics security. Despite the benefits, AI can also make biased decisions based on historical data. For instance, the male-dominated logistics industry might lead to biased task assignments due to a lack of data related to female work and capacities. AI's potential to enhance the customer journey is significant, aiding product search, lead generation, and customer retention (Ai et al., 2019; Zdravković et al., 2022). In logistics, AI finds applications in inventory control, stock-taking, tracking, forecasting, and back-orders, as well as internal logistics and transport processes. Companies like DHL (Dalsey, Hillblom, and Lynn) and Sky Planner leverage AI to improve task completion time predictions and anticipate future behavior. Among various AI technologies, Artificial Neural Networks (ANN) are extensively used. ANN can significantly reduce inventory levels while maintaining customer demand satisfaction probability (Paul and Azeem, 2011; Bansalk, 1998). Additionally, ANN's precision calculations help anticipate ship-related incidents (Ceyhun, 2020). AI's role in analyzing big data from Cyber-Physical Systems (CPS) is also crucial for automating processes and gaining better visibility into logistics systems (Woschank et al., 2020). CPS is known to be an embedded system that bridges the physical and digital worlds, offering real time data access and processing services (Lu, 2017). AI's cognitive abilities enable it to model and learn complex patterns, making it instrumental in facilitating large-scale CPS and empowering autonomous decision-making (Oliveira et al., 2021). Moreover, the Innovative Cyber-Physical Systems developed by institutions like RMIT University aim to enhance human-machine collaboration and build trustworthy autonomy by leveraging cutting-edge cognitive processing and machine-learning techniques. These advancements have the potential to revolutionize logistics and various other industries, enabling them to tackle complex challenges and optimize operations. By embracing AI, while being mindful of potential biases, the logistics sector can unlock substantial benefits in efficiency, accuracy, and decision-making, paving the way for a more robust and productive future. In the next subsection, we will explore topics such as machine learning and deep learning, followed by a comprehensive analysis of robot-driven logistics.

II.3.1.1 Machine Learning

To enhance efficiency in logistics, utilizing machine learning is a suitable and powerful approach for analyzing various prediction and decision problems (Amiri et al., 2023). Machine learning excels in solving classes of predictions and decisions where traditional analytical or programmatic methods may not efficiently handle domains with data-driven experiences, thus automatically improving the overall efficiency of solutions (Pereira et al., 2009). Moreover, machine learning can be employed to extract valuable insights (Heidari et al., 2022), such as identifying rare but significant customer needs Seo et al., 2020).

Data-driven AI combines machine learning techniques like supervised, unsupervised, and reinforcement learning with large scale data analysis to identify risks, market trends, and ease traffic congestion (Iyer, 2021). In that regard, supervised learning involves learning from labeled input-output data and has been extensively used in logistics, utilizing methods like multilayer perceptron artificial neural networks, Gradient Boosting Trees, Random Forest, Naive Bayes, and Logistic Regression (Singh et al., 2021; Russell and Norvig, 2020). On the other hand, unsupervised learning uses non labeled data for training, employing dimensionality reduction and clustering to organize datasets and detect structure in the data (Singh et al., 2021; Russell and Norvig, 2020). For example, in logistics, unsupervised learning (clusters) can be used to address challenges in intermodal transportation, where no straightforward routes to the destination exist. Lastly, reinforcement learning is another valuable approach, allowing an algorithm to learn how to act in an unfamiliar environment to maximize rewards. In logistics, reinforcement learning can be utilized to address issues like demand uncertainty, where fluctuations caused by external factors can lead to unexpected increases or decreases in demand (Singh et al., 2021; Yoon and Chow, 2020).

Machine Learning (ML) is providing relevant contributions in known domains, such as the medical field. In this case, ML using Recurrent Neural Networks (RNN) can be applied for stroke diagnosis and tracking, leveraging their ability to recognize patterns and sequences to predict likely scenarios (Ong et al., 2020). In logistics, machine learning is similarly providing relevant contributions by testing for anomaly detection, successfully producing accurate discriminative models integrated into smart logistics management systems with high accuracy levels (Kerdprasop et al., 2019). For instance, predictive maintenance software utilizing machine learning and deep learning algorithms, such as Presenso, are significantly benefiting logistics companies by optimizing maintenance processes and operational efficiencies (Woschank et al., 2020). Undersampling machine learning models can amplify the anticipated profit of back-order decisions (Hajek and Abedin, 2020). Therefore, machine learning enables predicting future events, like traffic, leading to increased operational efficiency, cost reduction, and fostering a work environment that encourages innovation and process improvements (Li et al., 2014; Woschank et al., 2020). It also paves the way for autonomous acting, decision-making processes, and the achievement of autonomous configuration (Sanchez et al., 2020).

Overall, embracing machine learning in logistics is presenting a transformative opportunity, empowering businesses to make more informed decisions, improve overall performance, and adapt swiftly to evolving challenges and opportunities in the dynamic logistics landscape.

II.3.1.2 Deep Learning

Deep learning is a specialized subset of AI techniques and falls under the umbrella of machine learning. Its primary goal is to explore into the intricate layers of non-linear information processing, enabling the analysis and classification of supervised and unsupervised features and patterns. Both machine learning and deep learning algorithms heavily rely on the quantity of data used for training. As machine learning algorithms approach consistency with an adequate amount of training data, deep learning algorithms exhibit enhanced performance as the volume of data increases. In the present scenario, deep learning finds widespread applications, exemplified by Google's voice and image recognition capabilities, HBO and Amazon's recommendation engines, Apple's Siri, automated email, and text reply processing, as well as chatbots (Diez-Olivan et al., 2019). Moreover, deep learning facilitates image detection, empowering machines to identify various objects and transmit their findings to a cloud-based server (Subakti and Jiang, 2018). Notably, deep learning also plays a significant role in predictive maintenance, as highlighted by Wang and Wang, (2018). They discuss an array of cutting-edge algorithms in this field, such as convolutional neural networks, deep belief networks, and long short-term memory models. These sophisticated algorithms are considered pivotal to the future success of companies (Wang and Wang, 2018).

Considering the above, the literature also discusses Convolutional Neural Networks (CNN), an effective classification algorithm that assigns weights and biases to distinct objects in an image, thereby distinguishing them from one another. One of the key advantages of CNN is its reduced reliance on extensive preprocessing compared to other classification algorithms. By utilizing relevant filters, CNN can effectively capture spatial and temporal dependencies within an image when integrated with deep learning. Consequently, it becomes adept at identifying intricate patterns in images and recognizing objects, classes, and categories, such as lung nodules in the medical field. This application enhances sensitivity in detection and reduces reading times (Liu et al., 2019), improving predictions (Causey et al., 2018), and proving invaluable in medical diagnostics (Ciompi et al., 2017). Convolutional Neural Networks (CNN) contribute to logistics in various ways, leveraging their strengths in image recognition and classification. Some of the keyway's CNN enhances logistics operations including object detection, package sorting, etc., as we will see further on.

Computer vision stands out in the literature and employs CNNs and deep learning techniques to achieve high-speed, high-volume unsupervised learning of visual information. This approach enables machine learning systems to interpret data much like the human eye does, extracting valuable insights from images and videos. Thus, computer vision aims to achieve comprehensive understanding, effectively substituting human eyes with the capabilities of computers and cameras. This technology enables the extraction of reliable measurements, precise tracking, and accurate recognition of visual elements. Given the broad scope of computer vision, it can be categorized into six well known directions that fall under this domain: image segmentation, face recognition, object detection, image semantic segmentation, video object segmentation, and background/foreground separation (Dong et al., 2021). The assimilation of these technical issues of computer vision within the domain of logistics enables the facilitation of tasks encompassing automated inventory management, quality control, and heightened security. Through the utilization of autonomous systems impelled by computer vision, logistical operations can attain heightened precision, augmented efficiency, and substantial cost savings over an extended duration. Each of these directions plays a significant role in extracting meaningful information from visual data, thereby contributing to the multifaceted applications of computer vision to logistics.

Image segmentation is a vital topic in the dominion of AI, which normally involves CNN and computer vision. It serves to segment or partition unidentified objects, especially those that are new or unfamiliar. Beyond this, image segmentation finds practical applications in enhancing existing methods, such as duplicate photo detection and human-computer interaction. In certain scenarios, adopting a segmentation approach brings the problem closer to semantic understanding. For instance, in content-based image retrieval, breaking down each image into smaller components when uploading them to a database allows for more refined search queries by clients. Similarly, in human-computer interaction, segmenting all elements within each video frame enables more effective interactions between the user and various persons or objects in the environment (Mallik and Chaushury, 2012; Coleman and Andrews, 1979). In logistics systems, image segmentation plays a crucial role in precisely identifying and isolating specific objects or items within an image. This capability offers benefits that enhance logistics operations. Firstly, image segmentation enables logistics companies to automate their inventory management processes. By identifying and delineating each item in stock, the system can track the quantity, location, and condition of various products. This automation streamlines inventory tracking, reduces human errors inherent in manual inventory counts, and ensures a more accurate and up-to-date view of stock levels. Additionally, image segmentation empowers logistics systems to recognize product attributes, such as shapes, colors, and sizes. This enables warehouse personnel to handle a diverse range of products. By understanding the unique characteristics of each item, the system can effectively categorize products, making it easier to organize and retrieve them. This optimization of storage and retrieval processes leads to improved warehouse efficiency and quicker order fulfillment. Overall, image segmentation is a vital component in logistics, enabling accurate identification and isolation of specific objects or items within images. Its automation capabilities contribute to more efficient inventory management, better recognition of product attributes, and optimized utilization of storage space in warehouses. By leveraging image segmentation, logistics companies can achieve higher operational efficiency, reduce costs, and deliver improved services to their customers.

Another key aspect addressed in this context is face recognition, which leverages biometric identification techniques based on human facial characteristics. In this process, video or image data containing faces are captured by a camera, and then deep learning is employed to extract facial recognition features. The model may also include display constraints or post-processing to enhance accuracy. Deep learning, particularly convolutional neural networks, is widely utilized in the field of face recognition due to its effectiveness. Additional advancements in this area include robustness modeling of deep learning for face pose, deep non-linear face recognition technology, and face recognition in various environmental contexts (Huang et al., 2012). These sophisticated deep learning-based face recognition technologies have significantly advanced the capabilities of this biometric identification method. The contribution to facial recognition logistics lies in its potential applications to improve security measures, which will be referred to later in the context of video object segmentation.

Another topic addressed in the literature was object detection, a fundamental task in image understanding and computer vision, which involves identifying specific item categories, such as human faces, eyes, or animals, within images or videos. It serves as the cornerstone for resolving numerous complex issues, including scene understanding, picture captioning, event detection, and activity recognition, among others. Industries spanning consumer electronics, robotic vision, security, autonomous vehicles, and human-computer interfaces heavily rely on object detection (Fischler and Elschlager, 1973; Dai et al., 2016). We identified two main types of object detection challenges. The first type involves locating a particular object, like the face of a famous actor or a renowned monument. The second type aims to identify generic objects belonging to a certain category, such as birds, dogs, and vehicles, even if they have not been seen before (Fischler and Elschlager, 1973; Dai et al., 2016). Object detection plays a crucial role in revolutionizing inventory management within logistics warehouses and distribution centers. By leveraging advanced object detection algorithms, these systems can seamlessly and automatically identify and locate various items throughout the warehouse. This capability empowers logistics teams to efficiently track inventory levels, closely monitor item movements, and effectively manage their inventory in real time. As a result, logistics operations become more streamlined, accurate, and responsive to changing demands (Alnahas, 2023).

Image semantic segmentation, on the other hand, refers to the technique of dividing an image into specific regions and extracting relevant targets. This process is vital for image processing and analysis. Instead of individually classifying each pixel, image semantic segmentation groups pixels based on their semantic relevance. For instance, a self-driving vehicle must recognize other vehicles, pedestrians, traffic signs, pavements, and various road elements for safe navigation (Höft et al., 2014). Semantic segmentation of images finds valuable applications in quality control processes within the logistics industry. This powerful technique enables the identification and categorization of defects or anomalies in products, packaging, or shipments with remarkable precision. By employing semantic segmentation, logistics companies can ensure that only high-quality products are dispatched to customers, significantly reducing the occurrence of returns and customer complaints. This not only enhances customer satisfaction but also streamlines operations and minimizes associated costs.

In video object segmentation, the foreground target and background region are segmented into two groups of pixels, creating an object segmentation mask. This is a crucial step in behavior identification and video retrieval. Additionally, object tracking is employed to determine an object's location within a video, proving highly valuable in intelligent surveillance. Video object segmentation is a powerful tool that enhances surveillance and security within logistics facilities. Accurately isolating moving objects or people in video streams, significantly improves the ability to detect potential unauthorized access or security breaches. This heightened vigilance ensures a safer work environment and effectively safeguards valuable assets. By leveraging video object segmentation, logistics companies can proactively respond to security threats and maintain a high level of protection throughout their operations. On the contrary, the discourse concerning security in the context of logistics also encompasses the contemplation of potential cybersecurity threats that accompany the heightened integration of automation. These concerns primarily revolve around the susceptibility of data and operational systems to malicious cyber intrusions. Therefore, it is imperative to underscore the criticality of instituting resilient security protocols to safeguard sensitive information and mitigate the likelihood of security breaches.

Object tracking and segmentation techniques complement each other, as accurate object segmentation enhances object tracking, and vice versa. Instance-level object segmentation is popular in video processing for tasks like object recognition, video editing, and video compression. Video segmentation further categorizes video content into multiple subcategories based on specific elements, such as object demarcation, movement, color, texture, or other visual attributes (Shin Yoon et al., 2017; Goel et al., 2018). These advancements significantly contribute to the sophisticated handling of video content and facilitate a wide range of applications in various fields.

Background/foreground separation is also a powerful image segmentation technique performed by advanced algorithms. Its applications span various fields, including intelligent surveillance in public spaces, traffic monitoring, and industrial machine vision. In recent times, neural network-based models have been increasingly employed for background separation tasks, revolutionizing the accuracy and efficiency of this process. In logistics, this technique can be applied to various scenarios, including object recognition, tracking, and inventory management. By accurately distinguishing between foreground (objects of interest) and background, logistics systems can better understand and process the visual information captured from cameras or sensors. This can improve object identification, reduce errors, and optimize logistics operations, such as automated package sorting and warehouse management. One notable application of foreground and background separation is in enhancing the detection of non-authorized objects within facilities using X-ray images (Javed et al., 2015). By effectively isolating the foreground (the objects of interest) from the background, this technique helps security personnel identify potential threats or unauthorized items in X-ray scans more accurately and swiftly. Consequently, it contributes significantly to bolstering security measures in sensitive environments and critical infrastructures. In logistics, this has significant implications for security measures in sensitive environments such as airports, seaports, and critical infrastructure. By precisely isolating objects in the foreground from the X-ray background, security personnel can more effectively identify potential threats or unauthorized items such as contraband, weapons, or dangerous goods hidden in cargo or luggage. This feature enhances security checks and helps prevent security breaches, smuggling, and illegal transport within logistics facilities.

All in all, deep learning plays a crucial role in revolutionizing logistics, whether in the logistics warehouse or in the outdoor context of using autonomous vehicles for making deliveries Ong et al., 2020). While the potential of deep learning to facilitate automated actions is evident, it is essential to acknowledge the associated risks. The level of automation achieved does not guarantee a flawless outcome, and there are inherent challenges that demand careful consideration (Baryannis et al., 2019). Safety, reliability, and adaptability are paramount concerns that require addressing to ensure the successful integration of autonomous vehicles into logistics operations. It is worth noting that deep learning, despite its immense promise, remains an evolving field that requires further in-depth exploration of its applications. Continued research and development efforts are needed to enhance its capabilities, overcome limitations, and maximize its positive impact on logistics. In conclusion, deep learning's integration into logistics, especially in the domain of warehoused and autonomous deliveries, holds enormous potential. However, a cautious approach must be taken, considering the challenges and risks associated with automation. By dedicating efforts to advancing the field through continuous investigation, the logistics industry can harness the true transformative power of deep learning.

II.3.2 Robot- Driven Logistics

The growth of autonomous vehicles, as discussed in the previous section, has been spurred by the exponential rise of electronic commerce (E-Commerce), leading to a significant increase in the daily volume of goods being transported. Consequently, consumers have developed higher expectations for deliveries, demanding speed, and convenience (Pernestål et al., 2020). To meet these demands, autonomous electric distribution and delivery vehicles are revolutionizing the industry by reducing human labor and enabling quicker deliveries, resulting in a 25% to 35% increase in the number of successful deliveries. As automation becomes more prevalent in logistics, the challenge lies in enhancing decision-making capabilities for autonomous robot navigation, which requires complex self-optimization and self-configuration processes (Tsolakis et al., 2022; Minovski et al., 2020). Autonomous robots have the potential to forecast delivery schedules for electric vehicles, leading to a significant reduction in faults and errors during the delivery process (Pernestål et al., 2020). As this technology continues to advance, it will pave the way for even more efficient and reliable delivery systems in the future.

Therefore, AI is playing a vital role in enhancing safety and building trust in robots (Sado et al., 2023). Traditionally, robots were perceived as products of mechanical or electrical engineering, adopting a bottom-up approach that prioritizes embodiment and sensorimotor functions. However, the integration of AI with robotics has led to remarkable innovations (Tussyadiah, 2020). One area where AI and technology have improved internal logistics is by reducing errors during product picks in warehouse stations. Utilizing Radio Frequency Identification (RFID) technology has proven effective in mitigating these errors (Geigl et al. 2017). RFID chips, also known as integrated circuits (ICs), store unique identifiers transmitted via radio waves to nearby readers, making it possible to locate and track autonomous robots with ease (Pavlović et al., 2019). Companies like Confidex have specialized in developing RFID tags designed to withstand chemicals, washing, and high temperatures during the manufacturing process, further automating logistics. Despite RFID's advantages, challenges remain, including malfunctioning tags and the time-consuming creation and maintenance of look-up tables with geopositions (Senta et al., 2007). Here, computer vision offers a valuable solution as it serves as the primary sensory system for both navigation and load detection (Garibotto et al., 1998). Companies like DHL leverage computer vision by employing cameras to capture images or videos, and AI algorithms to analyze the data from the digital imagery. These AI systems can distinguish between items and even learn to follow objects across various views autonomously. By combining the strengths of AI and robotics, we can continue to enhance the efficiency, reliability, and safety of robotic systems, ensuring a bright future for autonomous technologies.

However, not everything is perfect in relation to humans and technologies such as AI and robots, as risks exist. For instance, in this regard, Oliff et al., (2020) emphasize that Reinforcement Learning (RL) plays a crucial role in enhancing human-robot interaction, especially in autonomous robotics operations within internal logistics, but security risks remain a significant concern. Kiangala et al., (2022) support this perspective by highlighting RL as a valuable tool that enables robots to learn new paths and navigate complex and unpredictable environments without prior knowledge, thus reducing potential dangers. A collaborative approach between Human-Robot Integration (HRI) opens possibilities for developing social service robots that coexist harmoniously with humans in their social environments, effectively meeting the needs and expectations of lay experts. However, designing service robots that are relevant to human social contexts while aligning with popular media portrayals and preparing for the future of technology poses more challenges (Weiss and Spiel, 2022).

As the number of humans in smart factories remains high, unpredictability and disturbances, such as data misplacement, miscommunication, and process skipping, persist. To address this, robotic operations must adapt their behavior to accommodate variations in human task performance (Oliff et al., 2020). Currently, robots primarily react to pure sensor information regarding safety requirements, resulting in inadequate responses when encountering unexpected obstacles (Heinrich et al., 2019). A significant drawback is that robots fail to halt their activities in the presence of unforeseen events or when humans approach the safety perimeter, as laser scanners lack the necessary information, such as 3D size, distance, or direction of objects. Implementing sensor elements like Time of Flight or Radar sensors provides an effective solution by enabling the detection of 3D environmental information (Heinrich et al., 2019). Knight, (2014) argues that human-robot interaction entails a balanced combination of profound comprehension of information, mechanical capabilities, sophisticated systems thinking, and the ability to handle novel or unexpected phenomena while considering human interests. He also notes that current robotic companies tend to prioritize the perception of perfection over promoting open communication and collaboration within their ecosystems. Additionally, the lack of information regarding types of robot failures and potential solutions poses a challenge. Existing robotic fail-handling paradigms struggle to address foreseeable failures, let alone unforeseen ones that can disrupt the Human-Robot Ecosystem (HRE) (Honig and Oron-Gilad, 2014). The graceful extensibility theory offers a framework to model, assess, and enhance the HRE's capacity to respond to unforeseen failures. By extending the human-robotic interaction (HRI) to the HRE, adaptive fail-handling strategies and the social and technical enablers to support these strategies can be identified (Honig and Oron-Gilad, 2014). For a summary of this section, refer to Figure 2 below.

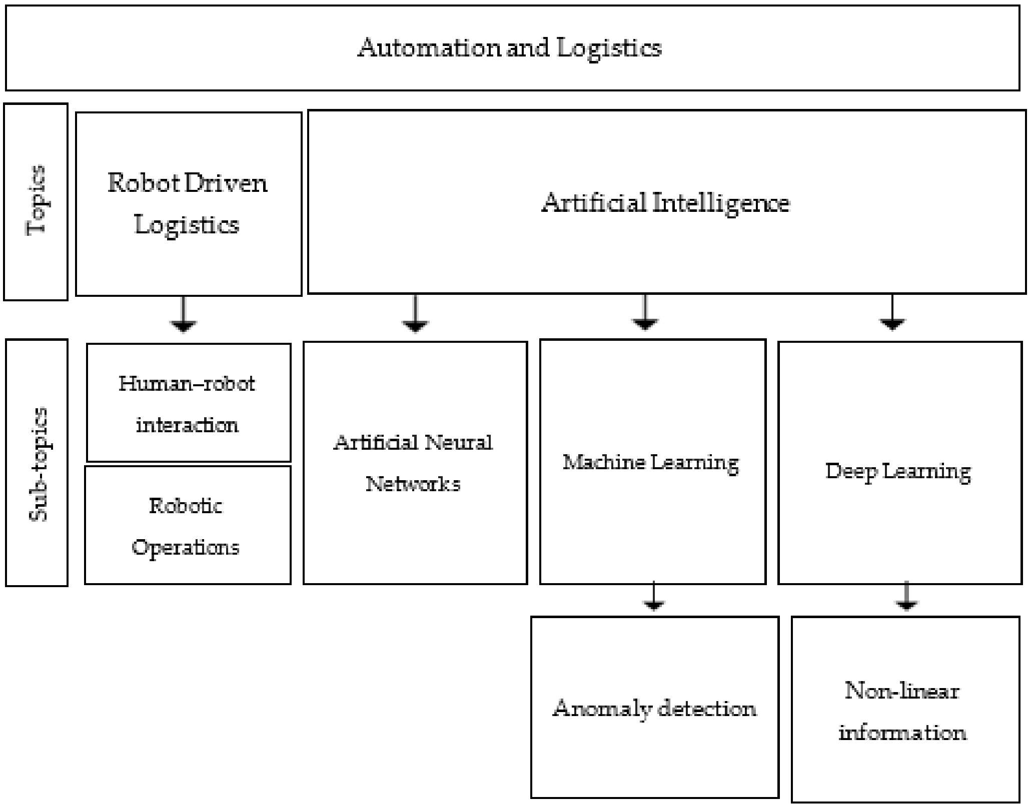

Figure 4. Emerging topics of automation in logistics

II.4 Conclusions

II 4.1 Theoretical and managerial contributions

This research makes significant theoretical contributions by providing novel perspectives on the application of automation in logistics. While there are existing studies on the topic, this research stands out for its unique analysis of how automation is currently enhancing the logistics industry, offering a more comprehensive understanding compared to the existing literature. Employing the PRISMA statement allowed us to focus our search and highlight the most crucial themes.

Our research revealed that artificial intelligence and robot-driven logistics have a profound impact on how automation supports logistics operations, resulting in improved competitiveness and reduced margin of error. The potential of automation-based solutions in logistics has captured the attention of managers and practitioners across various logis-tics businesses and sectors. However, due to their complexity, practitioners often struggle to assess their practical use or gain a holistic understanding of the current landscape. Therefore, our aim was to bridge this gap by presenting real world examples from management literature, which can serve as instructive references for both academics and practitioners. By offering a summary of available approaches and fresh ideas for planning and implementing automation initiatives in logistical processes, this research equips practitioners with valuable insights to navigate the challenges and leverage the benefits of automation effectively.

Hence, it is the contention of this research that the implications of the findings hold wide-ranging significance and bear substantial potential for various stakeholders. Through an extensive exposition of the underlying phenomenon, this study delineates its primary implications and prospective benefits. In essence, our aim is to target four key cohorts. Firstly, among those mentioned in the previous paragraph, professionals and businesses can gain from the acquisition of valuable insights concerning the diverse applications of automation technologies within their operations. By leveraging these insights, enterprises can make well informed decisions about the assimilation of automation into their logistics frameworks, thereby fostering enhanced performance and adaptability within the swiftly evolving logistics landscape.

Simultaneously, scholars and researchers can embark on a trajectory akin to our own, exploring the convergence of automation and logistics. By employing the findings, researchers can delve deeper into the dynamics of human-robot interaction and explore the scope for the fusion of artificial intelligence with robotic systems in the purview of logistics processes. Alternatively, they may pursue our recommendations for prospective research, such as the empirical validation of the conceptual framework or the adoption of quantitative methodologies. Thus, this study lays the groundwork for more profound analyses, whether quantitative or empirical, and sets the stage for pioneering research endeavors that can catalyze transformative changes within the field.

Thirdly, policymakers can glean meaningful insights from this research, which can serve as a compass for the formulation of guidelines governing the integration of automation in the logistics sector. By comprehending the potential benefits, challenges, and best practices associated with the adoption of automation, policymakers can devise strategies that advocate for the responsible and ethical implementation of automation technologies in logistics operations. Addressing the ethical ramifications of automation within the logistics sector, particularly concerning job displacement and the ethical application of AI in decision-making procedures, holds significant importance. Consequently, advocating for the conscientious deployment of AI and acknowledging the social repercussions of automation on the labor force and the broader society emerges as a pivotal consideration for policymakers.

Lastly, the general populace and consumers stand to benefit from the integration of automation in logistics, which can engender improved service provision, expedited deliveries, and enhanced consumer experiences. By enabling more efficient and reliable logistics operations, automation can contribute to the punctual and accurate conveyance of goods and services to consumers, thereby fostering greater satisfaction and cultivating stronger customer relations. Furthermore, the study underscores the criticality of upholding a balance between automation and human engagement, accentuating the potential for automation to augment, rather than supplant, human labor within the logistics industry. By underscoring the benefits, challenges, and best practices associated with the integration of automation into logistics, this study sets the stage for future advancements and innovations within the domain.

II 4.2 Research limitations and suggestions for future research

The methodologies employed in this study bear responsibility for its limitations. Systematic reviews, while valuable, offer a moment-in-time snapshot of a specific reality (Reis et al., 2022). Consequently, despite updating scientific databases with fresh, peer-reviewed research, the information eventually becomes outdated (Reis et al., 2021). Our approach of limiting the search to specific terms and using filters to select significant articles carried the risk of omitting relevant manuscripts. Despite these acknowledged limitations, we believe that this systematic review holds value as it provides a concise overview of the current state of automation in logistics. It is important to acknowledge that the rapidly evolving nature of technology and logistics means that new advancements and innovations are continually emerging. Therefore, our study, although comprehensive within its scope, may not capture the very latest developments in the field. To address this limitation, we encourage researchers and practitioners to continually update and expand on our findings, incorporating new data and insights as they emerge. The results of this study should serve as a catalyst for further research on the application of automation in the field of logistics within industrial enterprises. We believe that this research can lay the groundwork for more in depth investigations into specific aspects of automation, such as its impact on supply chain efficiency, costeffectiveness, and environmental sustainability. Furthermore, exploring the humanrobot interaction dynamics and the potential for integrating artificial intelligence with robotic systems can open new avenues for optimization and innovation in logistics processes. Moreover, the results offer industrial company practitioners a valuable framework for effectively implementing cutting-edge technologies. As automation continues to revolutionize the logistics industry, organizations can utilize our findings to be more informed and shape their automation strategies. By understanding the potential benefits, challenges, and best practices associated with automation adoption, businesses can proactively adapt to the changing landscape and gain a competitive advantage. In conclusion, while this study has its limitations, we believe it helps to provide a deeper understanding of automation in logistics. As the field continues to evolve, we encourage fellow researchers and industry practitioners to build upon this work, pushing the boundaries of knowledge and innovation to unlock the full potential of automation in revolutionizing industrial logistics. To illustrate, scholars can fortify these findings through a quantitative/bibliometric analysis of the literature, elucidating the essential components of logistics automation, such as the significance of each technology, frequency of citation for individual techniques, keyword tracking, and so on. On the other hand, practitioners can contribute by identifying recent practical cases that facilitate the empirical validation of the conceptual framework proposed in this article. By collaboratively advancing research in this domain, we can drive transformative changes that lead to more efficient, sustainable, and resilient logistics operations in the modern era.

CONCLUSION

In summary, the incorporation of automation and artificial intelligence (AI) within the field of Supply Chain Management (SCM) and logistics represents not only a transient phenomenon but a profound transformative influence that is significantly shaping these industries. It is paramount for both organizations and researchers to remain well-informed, adapt to these changes, and confront the challenges and opportunities that arise, in order to ensure the secure, efficient, and sustainable advancement of the supply chain and logistics ecosystem. The reviews presented herein serve as a robust foundational basis for further exploration and research in these dynamically evolving fields.

This comprehensive analysis comprehensively examines the transformative influence of automation on the logistics sector. The investigation underscores the pivotal role of Artificial Intelligence (AI), Machine Learning, Deep Learning, and Robot-Driven Logistics in reconfiguring the methods of goods transportation, processing, and delivery.

AI, with its exceptional capacity to automate routine tasks, analyze extensive datasets, and forecast outcomes, has ushered in a new era of operational efficiency in logistics. Its applications in supply chain forecasting, inventory management, and internal logistics processes have yielded more precise predictions and streamlined operations. Nevertheless, concerns persist regarding biases in AI decision-making and cybersecurity vulnerabilities, highlighting the critical importance of ethical and regulatory frameworks in the field of technological innovation.

Machine Learning complements AI by facilitating predictive maintenance, demand forecasting, and anomaly detection, thereby enhancing operational efficiency and cost reduction. Deep Learning, a subset of Machine Learning, excels in image recognition, object detection, and video analysis, with far-reaching applications in logistics and medical diagnostics.

Robot-Driven Logistics is a response to the escalating demand for rapid and efficient deliveries driven by the e-commerce boom. Autonomous electric vehicles and robots are increasingly automating delivery processes, thereby reducing error margins and amplifying delivery capacities. The interaction between humans and robots assumes a pivotal role in this automation, with a primary focus on adapting robotic behavior to human variations, ensuring safety, and enhancing communication between the two entities.

Theoretical contributions of this research delve deep into the subject of automation in logistics, furnishing a nuanced understanding of its current applications and potential. It serves as an invaluable resource for both academics and logistics practitioners, offering insights into innovative solutions and strategies propelled by automation.

However, it is imperative to acknowledge the limitations inherent in this research. Systematic reviews provide a snapshot of the prevailing state of knowledge but may not encompass all the latest advancements. Therefore, ongoing research in industrial enterprises remains imperative to further explore and refine the application of automation within the logistics domain.

In the context of future research endeavors, we propose an examination of how the application of artificial intelligence (AI) techniques varies across organizations of differing sizes. To facilitate this investigation, we advocate for the implementation of empirical studies within real organizational contexts. These studies can delve into the practical applications of AI in areas such as sales forecasting and the enhancement of customer experience design.

Moreover, it is imperative to explore the attainment of sustainability within the domain of supply chain management (SCM) through AI interventions, while considering the varying degrees of technological maturity within distinct organizational settings. This exploration can yield valuable insights into the strategic deployment of AI to enhance sustainability efforts in SCM.

Additionally, we recommend the undertaking of a comprehensive inquiry into the potential risks associated with the adoption and utilization of AI technologies in the domain of SCM. It is crucial to assess the challenges, vulnerabilities, and potential drawbacks that may arise when AI systems are integrated into supply chain operations.

These proposed research directions are rooted in the works of esteemed scholars such as Akter et al. (2016), Wamba et al. (2022), Ramanathan et al. (2017), and Aydiner et al. (2019), and they provide a robust foundation for advancing our understanding of the intricate interplay between AI, organizational dimensions, sustainability, and associated risks within the context of supply chain management.

In conclusion, the integration of automation technologies into logistics is not a passing trend but an enduring transformative force that is profoundly reshaping the entire industry. This research not only sheds light on the current landscape but also provides a roadmap for the future of logistics in an automated world. This innovative integration brings something new and original when compared to other existing works. As this transformation continues to evolve, logistics companies and researchers must maintain vigilance, adapt to emerging technologies, and address challenges in order to ensure the secure, efficient, and sustainable evolution of the logistics ecosystem.

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