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Innovations and Trends in International Logistics with Artificial Intelligence in the Manufacturing Sector: A Literature Review

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***Abstract*— Artificial Intelligence (AI) has become a trend nowadays, being a much-discussed topic in different operations of manufacturing Industries to streamline their logistics processes, being this fundamental to being able to get into the use of new application technologies to improve and boost industries 4.0. In this paper we reviewed the various innovations and trends in AI impact on international logistics in the manufacturing industry. To this end, as part of the method, 271 articles were analyzed and extracted from the most reliable databases such as Scopus, EBSCOhost, WoS and SciencieDirect, using the PRISMA methodology as a source of discarding, resulting in 59 relevant articles after applying the inclusion and exclusion criteria. The results allowed us to identify that the application of AI in manufacturing industry logistics has been studied and carried out by countries developed in technologies and automation, employing different techniques and methods to improve their logistics processes. Finally, it was concluded that the results obtained from this review are a key factor in the growth and research of new application technologies to modernize the industry towards the future and be closer to Industry 5.0 and the metaverse.**

Keywords*— *Artificial Intelligence, Logistics, Trends, Innovation, Manufacturing Industry

I. INTRODUCTION

In the last decade, supply chain management (SCM) has undergone considerable transformation due to globalization and the increasing complexity of logistics operations [1]. Global Supply Chain Management (GSCM) has emerged as a holistic approach aimed at optimizing the flow of goods and services globally, facing the challenges of interconnectedness of multiple markets and regions [2].

The term Artificial Intelligence (AI), proposed by McCarthy at Dartmouth University in 1956, makes it possible to replicate human reasoning in machines, a field that has seen significant progress, particularly in the last decade [3]. This technology combines engineering and mathematics, incorporating different methods that enable machines to replicate behaviour, to obtain better results [4]. In recent times, the volume of data in various formats has grown exponentially, driving the advancement of new technologies, such as increased processing power and the creation of new AI techniques [5].

AI is transforming various industries, such as manufacturing, retail and telecommunications, by being implemented to improve profitability, increase efficiency and strengthen safety. This is achieved using techniques such as Machine Learning (ML), expert systems, computer vision, robotics and optimization, robotics and optimization [6]. It also encompasses various disciplines such as computer science, logic, biology and psychology, with relevant applications in areas such as speech recognition, natural language processing and autonomous robots [7]. Within this domain, subfields such as ML and Deep Learning (DL) allow complex tasks such as classification, regression, clustering and dimensionality reduction to be performed on large datasets [8].

In this context, AI, and in particular advanced techniques such as reinforcement learning (RL), has emerged as a promising solution to optimize efficiency in GSCM [9]. In this regard, according to a report by Markets and Markets, the global market for AI applied to logistics is expected to grow from $10.1bn in 2021 to $37.8bn in 2026, at a compound annual growth rate of 29.2% [10]. One aspect to consider is that, according to recent research, it is proposed that implementing RL in SCM could reduce operational costs by up to 15% by optimizing decision-making and promoting continuous improvement based on feedback [11].

On the other hand, research conducted by the Hamburg University of Applied Sciences has shown that problems related to intermodal transport, involving the combination of different transport modes, represent a growing challenge in global logistics, increasing costs by 20% due to the complexity of coordination and optimization [12]. The focus of this research is crucial as it focuses on the integration of AI in logistics and SCM to address the new challenges arising from globalization and digitalization [13]. AI provides advanced tools that optimize planning, inventory management and route scheduling, essential elements to preserve competitiveness in a dynamic and constantly evolving market [14]. Likewise, digitization in industry has generated a large amount of data detailing the production process, which will be processed and analyzed using ML techniques [15]. In this sense, techniques such as ML and other AI-based solutions provide flexible tools that adjust to changing demands, which supports the conduct of this systematic literature review (SLR) in the field of logistics and SCM. The purpose of this SLR is to examine how various

AI innovations and trends affect international logistics in the manufacturing industry.

II. LITERATURE REVIEW

Nowadays, it is unthinkable for companies to lack information [16]. This is why AI is generating a very favorable impact in several sectors due to its speed of response and its remarkable generalizability [17]. On the one hand, micro, small and medium-sized enterprises (MSMEs), with limited resources, see AI as a key tool to boost their growth [18]. According to GOODFELLOW, the main purpose of AI is to address problems that are difficult or impossible to express through code, as they can only be solved through intuition [19].

The emergence of Industry 4.0 has transformed the manufacturing sector by incorporating interconnectivity, decentralization in decision-making, automation and efficient use of resources [20]. These changes are dynamic and evolve rapidly over time [21]. Due to the advancement in digital technologies, along with the accelerated development of cyber-physical systems, the incorporation of 5G, the Internet of Things (IoT), augmented reality (AR) and other smart technologies, there has been a growing need for further development of Industry 4.0 and the metaverse [22].

In the following, some of the most important uses of AI applied to logistics in the manufacturing industry will be presented.

The paper [23] studied the processes linked to the smart economy, focusing on the development of smart manufacturing and the creation of smart markets. For this purpose, a methodology based on graphical visualization methods was used to identify digitization trends and the integration of ICT technologies in global production and logistics processes. The results showed that the adoption of smart manufacturing in the manufacturing industry has enabled a focus on producing higher quality goods, increasing productivity, improving energy efficiency and ensuring safety. Finally, it is concluded that, according to the smart economy data, manufacturing is undergoing a significant transformation thanks to the implementation of technologies such as artificial intelligence, industrial robotics and IoT.

In addition, research [24] examined an Implementation Plan proposed by the Chinese government to promote integration and innovation development in the logistics and manufacturing industries. To this end, a progress evaluation method was used, considering integration as a coupling variable. The results indicated that greater integration in these sectors will favour the growth of digital technologies in local regions. Finally, this approach was implemented in four key areas: asset investment, process optimization, technological modernization and organizational synergy.

On the other hand, the paper [25] investigated the potential of machine learning to predict business failure. In terms of methodology, machine learning-based predictive models were compared with traditional statistical methods and non-automated machine learning models. The results demonstrated high accuracy and ease of implementation in manufacturing industries, allowing them to predict bankruptcies quickly and at low cost. In conclusion, these tools can be valuable in credit scoring, accounts receivable management, accounting records and other applications of machine learning in business.

III. METHODOLOGY

This section is composed as follows: The first point to be touched upon is the research questions, followed by the type of study, then a search strategy and finally inclusion and exclusion criteria will be proposed.

A. *Objective and research questions*

This study, based on a literature review, will examine the impact of AI on logistics in the manufacturing sector, exploring how the implementation of AI contributes to optimizing their logistics processes, in conjunction with current innovations and emerging trends. The research questions are as follows:

- RQ1: How can AI improve logistics processes in the manufacturing industry?
- RQ2: What AI techniques and methods have proven successful in the application of logistics processes in the manufacturing industry?
- RQ3: How can AI reduce the operational costs of logistics processes?

B. *Type of study*

The systematic literature review (SLR) method was chosen because of its usefulness in several key respects, as it provides a synthesis of the current state of knowledge in a specific area. From this approach, concise research is identified that addresses questions that, in some ways, could not be answered by individual studies. The PRISMA method will also be used because it has been adopted by authors and researchers worldwide to plan, prepare and publish systematic reviews and meta-analyses. The wide dissemination and implementation of PRISMA suggests that it has contributed to improving the quality of publication of the methods and results of systematic reviews and meta-analyses [26]. 26] This is key to a more accurate assessment of the impact of AI on logistics in the manufacturing industry.

C. *Inclusion and Exclusion Criteria*

For the systematic review study, the inclusion and exclusion criteria detailed in table 1 were used.

TABLE I. INCLUSION AND EXCLUSION CRITERIA

Inclusion Criteria	
CI1	Articles related to industrial manufacturing
CI2	Articles from 2020 to 2024
CI3	Articles in the English language
CI4	Articles answering the research questions
CI5	Full text articles
CI6	Original articles and conference papers
CI7	Open access articles
Exclusion Criteria	
CE1	Articles related to traditional logistics
CE2	Articles related to service logistics
CE3	Articles published before 2020
CE4	Do not include these, reviews

D. *Search strategy*

The data collection method was supported by a search of reliable sources, which involved a review of articles, highlighting databases such as Scopus, EBSCOhost, WoS and SciencieDirect. A total of 271 articles were found, of which 59 relevant articles were retained by applying the various inclusion and exclusion criteria.

Next, 271 articles were analyzed in the various relevant databases related to the research topic, which discarded duplicate articles that did not meet the inclusion criteria. After reviewing the articles, 212 articles were excluded according to the exclusion criteria and for not answering the research questions. In the end, 59 articles were obtained for the systematic review, as shown in Fig. 1.

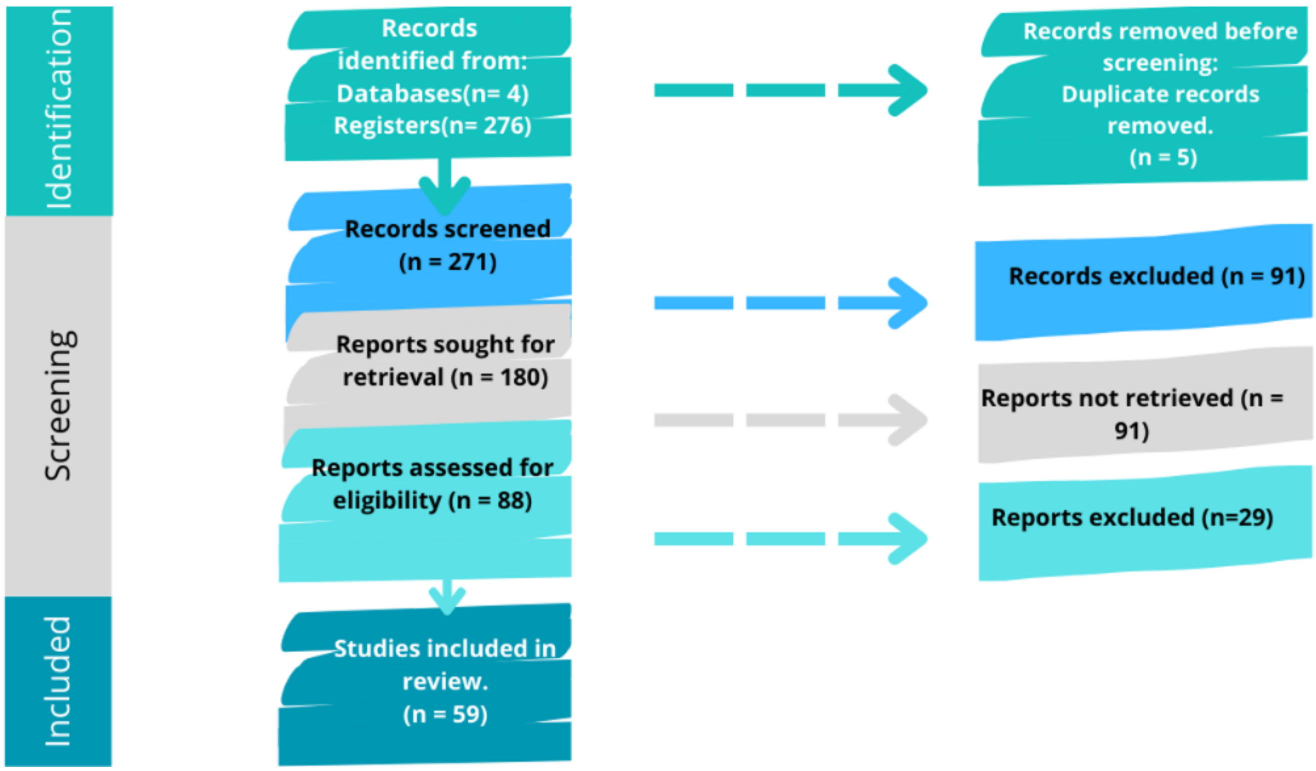

Fig. 1 Application of the PRISMA method

IV. RESULTS

This section will present the results obtained from the different databases used, specifying key criteria such as the types of articles, the approaches used, the number of articles identified per year according to the inclusion and exclusion criteria, and a comparison of the number of articles according to their country of origin. Finally, using the VOSviewer tool, the most relevant keywords in the bibliographic network will be highlighted, establishing connections with other related words that reinforce the central themes of the research.

Fig. 2 shows the final number of articles extracted from the main databases, with a total of 59 articles selected for the final version of this review. Notably, ScienceDirect, with 46 articles, was the most used database and became the main source of information for the study topic. In addition, EBSCOhost contributed 9 articles, enriching the content of the systematic review. On the other hand, Scopus and Web of Science (WoS) registered a lower number of articles, with 2 articles each, although their contribution is still relevant for the development of this review.

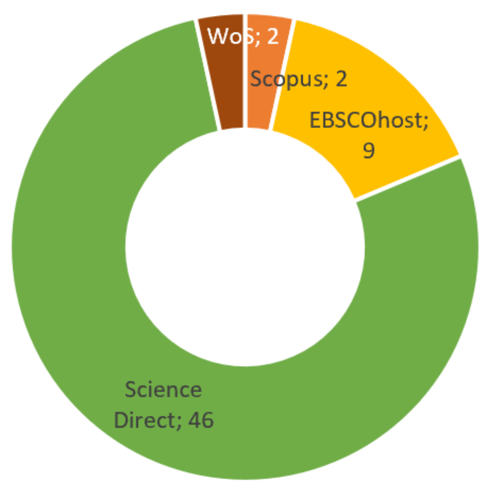

Fig. 2 Article allocation for each database

Fig. 3 below shows the total number of articles found between 2020 and 2024 in different databases, displayed in a 3D graph to facilitate detailed visualization and comparison between them. ScienceDirect stands out above the others, both in terms of the total number of articles and the highest number of publications in 2020, with a total of 12 articles. EBSCOhost records its highest number of articles in 2023, with 4 publications. As for Scopus, 1 article was identified in 2021 and 1 in 2023, while Web of Science (WoS) also has 1 article in 2021 and 1 in 2022, making them the databases with the lowest number of articles.

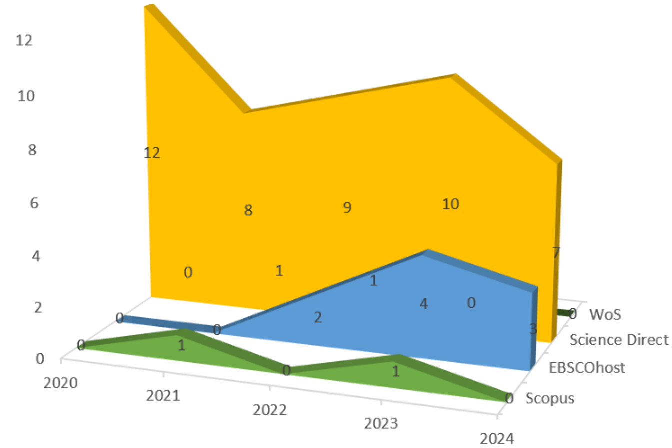

Fig. 3 Contribution of articles by year and database

Table 2 shows the number of articles contributed by each country between 2020 and 2024. The production of information on AI is significant in all the years evaluated, with Germany and China standing out as the countries with the highest frequency of publications, with 9 articles each. India also maintains a relevant presence, with 7 articles. On the other hand, countries such as Greece, Italy, Portugal and the United Kingdom register 3 articles each. Finally, the rest of the countries included in the analysis (such as Austria, Brazil, Canada, Denmark, Finland, Hungary, Iran, Kazakhstan, Korea, Lithuania, Slovakia, Slovenia, South Africa, Spain, Sweden, Thailand, the United Arab Emirates, the United States, the United Kingdom, the United Kingdom, the United States, Hungary, Iran, Kazakhstan, Lithuania, South Africa, Sweden, Thailand and Vietnam) have only 1 article each.

This analysis shows that most of the scientific production on AI comes from highly developed countries in terms of technological progress and innovation, such as Germany, China and the United States. However, there is also a growing participation of emerging countries, such as India, which is establishing itself as a key player in the field of AI. On the other hand, the presence of countries with lower production suggests that, although they are making inroads in this area, they still have some way to go to achieve a greater impact on global AI research.

TABLE II. CONTRIBUTION OF ARTICLES BY COUNTRY

Country	quantity	Country	quantity
Germany	9	Portugal	3
China	9	United Kingdom	3
India	7	Denmark	2
Greece	3	Spain	2
Italy	3	other	18

Fig. 4 shows the bibliographic analysis using a map generated by the VOSviewer tool. This map visualizes the most relevant keywords, highlighting Industry 4.0 and Artificial Intelligence as the main foci of study. In the case of Industry 4.0, the ramifications that complement these ideas include topics such as smart manufacturing, sustainability, cyber-physical systems and production control. On the other hand, in relation to AI, there is a strong connection with areas such as machine learning (ML), deep learning (DL), big data, simulation and data technologies. All these branches are associated with systematic review and their applications in the field of logistics within the manufacturing industry.

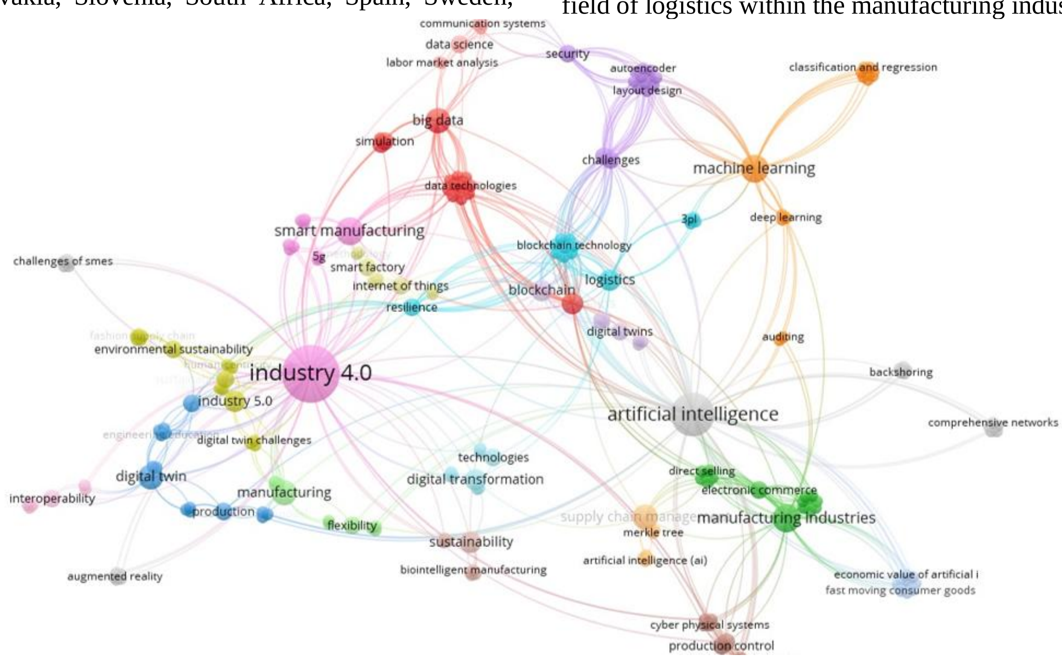

Fig. 4 Bibliometric analysis of the most recurring words

Fig. 5 describes the methodological approach used in the articles collected from the different databases. Fig. 5 shows that ScienceDirect is the database with the highest number of documents, standing out with 9 articles with a quantitative approach and 37 articles with a qualitative approach. It is followed by EBSCOhost, with 2 quantitative articles and 7 qualitative articles. Finally, Scopus and Web of Science (WoS) register 1 article for each methodological approach. In general terms, the qualitative approach is the most recurrent, with a total of 46 articles, while the quantitative approach has 13 articles in total.

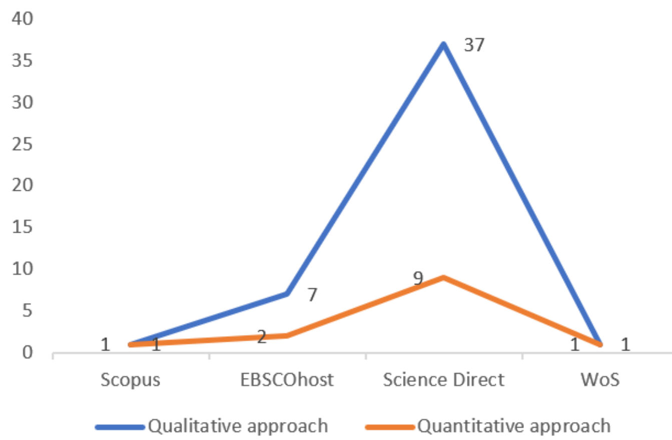

Fig. 5 Article contribution by approach

V. Discussion

This section will compare previous work with the subject of the literature review, highlighting key aspects of its most common and effective applications, as well as assessing the results obtained by implementing these methods. Following this analysis, the research questions posed will be answered and substantiated.

A. How can AI improve logistics processes in the manufacturing industry?

There are several ways in which AI can optimize and improve logistics processes within the manufacturing industry. For example, the paper [23] highlights that, through the application of information and communication technologies (ICT), intelligent robots and the Internet of Things (IoT), productivity, efficiency, quality and safety in the processes were increased. This study is mainly associated with the aspects of Productivity and Control in Production, as well as Quality and Safety in Products and Processes. Also, the work [22] used digital twins and augmented reality (AR) to optimize and transform logistics processes, focusing on improving visibility, efficiency and real-time decision making within the manufacturing industry. This study is related to Intelligent Decision Making and Risk Management.

On the other hand, the work [20] demonstrates that AI is revolutionizing manufacturing by improving efficiency, optimizing resources and reducing waste. This approach aligns with principles of sustainability and demand resilience, contributing to minimizing environmental impact and improving Supply Chain Management (SCM). This study is linked to Resource Optimization and Operational Sustainability. As shown in table 3

TABLE III. Impact of AI on logistics

Impact of AI on logistics	***Quantity***	***References***
Supply Chain Optimization and Automation	7	[27], [28], [29], [30], [31], [32], [33]
Production, Productivity and Control	6	[34], [35], [36], [37], [38], [39]
Efficiency and Flexibility in Operational Processes	7	[36], [40], [41], [42], [43], [44], [45]
Sustainability and Energy Efficiency	4	[46], [47], [48], [49]
Intelligent Decision Making and Risk Management	5	[50], [51], [52], [53], [54]
Quality and Safety in Products and Processes	4	[55], [56], [57], [58]
Intelligent Automation in Production	13	[59], [60], [61], [62], [63], [64], [65], [66], [67], [68], [69], [70], [71]
Resource Optimization and Operational Sustainability	3	[72], [73], [74]
E-Commerce Innovation and Traceability	5	[52], [75], [76], [77], [78]

B. What AI techniques and methods have proven successful in the implementation of logistics processes in the manufacturing industry?

There are several AI approaches and implementation methods that have proven to be highly effective in the manufacturing industry, offering viable solutions to optimize and improve logistics processes. These advances are key to transforming the industry, while ensuring that high quality standards are maintained. In this context, the study [25] highlights that the application of ML and DL techniques, especially automated ones such as H2O, CatBoost and XGBoost, has proven to be effective in forecasting demand, optimizing routes and reducing operational failures. This evidences a connection with successful methods such as queuing theory, ML, DL and automation.

The paper [21] reaffirms these findings, pointing out that both ML and reinforcement learning (RL) contribute to optimizing demand management and logistics routing, improving efficiency and reducing costs in the manufacturing industry. This study also highlights that DL is one of the most widely applied methods, along with RL and queuing theory, consolidating its relevance in transforming logistics processes. Table 4 presents the most used methods.

TABLE IV. presents the most used methods

Methods and techniques	***Quantity***	***References***
Hierarchical clustering	1	[43]
Machine learning (ML)	6	[37], [51], [55], [79], [80], [81]

Federated learning-artificial intelligence (FAI)	1	[72]
Deep learning (DL)	1	[81]
Autodesk Inventor Nastran	1	[71]
Autodesk Inventor Nesting	1	[71]
Automation	1	[36]
Big data	6	[27], [36], [45], [54], [69], [82]
Blockchain	1	[78]
Blockchain	1	[66]
E-commerce	2	[52], [75]
Cloud computing	3	[30], [45], [69]
Smart contracts (SC)	1	[72]
Computer numerical control (CNC)	1	[73]
Robotic sensing	1	[59]
Smart manufacturing (SM)	2	[34], [46]
Digital Twin (TD)	3	[38], [44], [76]
Internet of Things (IoT)	11	[28], [30], [31], [34], [36], [37], [58], [60], [66], [67], [69]
Internet of Touch (IT)	1	[83]
k-means	1	[43]
Non fungible tokens (NFT)	1	[77]
Delphi method	1	[64]
Decision tree model	1	[51]
Gaussian Mixture Model	1	[43]
Business models (BM)	1	[80]
MUL 4.0	1	[63]
Intelligent Image Processing (IIP)	1	[79]
Datafication Process (PD)	1	[31]
Augmented Reality (AR)	2	[42], [61]
Virtual Reality (VR)	1	[56]
Human Robot Collaborative (HRC) systems	1	[61]
Flexible Manufacturing Systems (FMS)	1	[45]
Intelligent product and service systems	1	[53]
Digital transformation technology (DTT)	2	[47], [65], [84], [85]
Queuing theory	1	[50]
Evidence theory	1	[50]
Computer vision	1	[41]

C. *How can AI reduce the operational costs of logistics processes?*

The integration of AI tools has multiple benefits for manufacturing companies, with a key factor for any industry being economics.

Contributing to this research question the paper [17] adds through the results that through zero-defect manufacturing (ZDM) can help to reduce defects in logistics processes, being able to optimize costs and improving efficiency in operational processes, reaching high levels of quality in manufacturing, linking this paper to the reduction of human error through computer vision. For a better understanding, see table 4 for references addressing the impact of AI on operational costs.

TABLE V. IMPACT OF AI ON OPERATIONAL COSTS

Impact of AI on operational costs	***References***
Reduces costs to monitor shelves	[79]
Reduces risks of uncertainty in economic crisis	[72]
Automates complex logistics processes	[81]
Reduces human error through computer vision	[41]
Reduces parts recovery through disposable materials	[37]

VI. CONCLUSIONS

After conducting a RSL of 59 articles that are related to the research topic, it is concluded that the application of AI has a beneficial impact on the logistics processes of manufacturing industries. Being able to adapt to Industry 4.0 systems and streamline their operations, allowing the work to be more practical and manageable based on production and demand uncertainty. It also provides security for the databases of manufacturing companies through software, preventing them from being obtained and/or manipulated by other companies or hackers, protecting the privacy of the company itself as well as that of its workers, suppliers and customers.

The implementation of AI in logistics processes involves innovating or adapting the use of new technologies that support the processes that are carried out, such as simulation, ML or DL. Based on table 3 and fig. 5, it can be concluded that many of the AI methods and techniques were implemented by highly developed countries in terms of technology, being able by using these techniques to face problems such as costs, quality, uncertainty of demand and discarding of products due to defects, so that by eliminating these obstacles in their processes they could be more efficient and able to adapt to current market changes.

In summary, the new trends of AI application is an important factor within logistics, having a better development of new technologies in the manufacturing industry, generating greater adaptability in the process of product transformation, volume capacity and historical demand.

On the other hand, it is fundamental to understand that the results acquired from this systematic review are useful for future research in the development of advanced AI-based technologies that help to improve logistics processes, thus enabling the growth of current industries, opting for continuous improvement and digitization.

In this review, the eligibility criteria were used to focus more directly on work related to the contribution of AI to manufacturing industry processes. This tactic is also a way to be more precise, but it is possible that several papers have been excluded by not considering theses or other reviews that may contain valuable and complementary information for this article.

Finally, the prioritization of articles in English probably excluded research in other languages that would contribute to the research. If the limitations that were placed on data collection had not occurred, it is possible that we would have had a larger number of articles. These limitations prioritize the need for the future, more complex and comprehensive studies to continue to address this issue effectively.

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