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The most commonly used Industry 4.0 technologies in manufacturing: A systematic literature review

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A B S T R A C T

Industry 4.0 presents a modern concept in production management that applies digital technologies and enables more efficient and faster production with minimal waste. This paper presents the concept of Industry 4.0, its development over the years, and related technologies for digitalization and automation of production management. A comprehensive systematic literature review based on the scholarly database Scopus was conducted, using VOSviewer software, along with additional analysis of selected articles by the authors of this paper. The main objective of the paper is to define the technologies most applied in production management and their importance and impact on production. Based on these results, the most important and commonly applied technologies in the manufacturing industry are defined: the Internet of Things (IoT), Artificial Intelligence (AI), and Big Data (BD). This paper highlights the advantages, disadvantages, and potential improvements of each technology in manufacturing companies. The intention of this article is to highlight the importance of applying technologies for digitalization and automation, as well as the concept of Industry 4.0, in manufacturing companies through the presentation of the literature review results. This paper is of high importance for manufacturing companies and managers in supporting decision-making regarding the application of technologies for digitalization, automation, and business improvement.

A R T I C L E I N F O

Keywords:
Industry 4.0;
Smart manufacturing;
Artificial intelligence;
Internet of things (IoT);
Big data;
Digitalization;
Technology adoption;
Systematic literature review

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1. Introduction

Digitalization improves business results and business performance, saves time, reduces the use of human resources and costs, as well as the number of errors, enabling real-time data availability. It increases the level of automation and precedes the optimization of business processes and their reengineering. The aim of this paper is to present the development of digitalization and automation in production, through a literature review. The Fourth Industrial Revolution, i.e. Industry 4.0 (I4.0), connects the physical and virtual world in real time [1] and assumes that the application of modern technologies improves the manufacturing process and focuses on digitalization and automation of the production process, as well as connectivity, highlighting technology as the main focus [2]. It presents "a manufacturing philosophy that includes modern automation systems with a certain level of autonomy, flexible and effective data exchanges ensuring the implementation of next-generation production technologies, innovation in design, and more personalized and agile production, as well as customized products" [3].

I4.0 “enables technological processes and digitalization to ensure the transparency of corporate processes; integrates the corporate value chain and the supply network” [4], while applying “cutting-edge digital technologies to industrial machines and processes” [5]. It creates “smart” factories from manufacturing processes where production is completely digitalized, decentralized, flexible, and intelligent [6]. The application of advanced technologies enables digital production [7]. The main aim of I4.0 is the digitalization of business processes, logistics, and production [8], while the main impacts of I4.0 are cost reductions in production, energy consumption, maintenance, the rational use of resources, and optimization of the value chain [9]. The implementation of I4.0 presents a “new-age solution for industrial operations” [10].

Main results of industrial revolutions are new interaction forms between companies and customers, as well as the transformation of production lines [11]. The most applicable technologies used for digitalization and automation that will be analysed in this paper are [12–17]: Internet of Things (IoT) and Industrial Internet of Things (IIoT), Cyber Security (CS), Cyber-Physical Systems (CPS), Cloud Computing (CC), Big Data (BD), Robots, Machine-to-Machine (M2M), Augmented Reality (AR), Virtual Reality (VR), Business Intelligence (BI), Machine Learning (ML), Artificial Intelligence (AI), and Additive Manufacturing (AM). Digital Twins (DT), as an important result of I4.0, will be mentioned along with other technologies.

Many articles have applied literature review analysis on the topic of the application of I4.0 technologies. Authors Zheng *et al*. [18] conducted a systematic literature review to respond to the question “What are the applications of I4.0 enabling technologies in the business processes of manufacturing companies?”. The results show that the most analysed processes are production scheduling and control, and that IoT, BD analytics, and Cloud are the most used technologies, while Blockchain is the least discussed.

Authors Oztemel and Gursev [3] conducted a literature review on the topic of I4.0 and related technologies, which resulted in six design principles: virtualization, interoperability, real-time capability, modularity, service orientation, and localization. Authors Hernandez Korner *et al.* [19] conducted a systematic literature review on the integration of I4.0 and AM, showing that AM enables the creation of customizable products, reduces costs for low-batch and medium-batch production, and enables material reuse.

As mentioned, these articles applied a systematic literature review, but none of them defined the most applied technologies in manufacturing companies based on their use in practice. Therefore, this paper will fill that literature gap and upgrade previous research and literature reviews. Given that the topic is currently popular and that many articles are still being published on this topic, especially articles including technologies presented in this paper, the authors of this paper considered it very important to select and analyse articles that present actual applications, as well as the results of the application of I4.0 technologies in manufacturing companies, thereby connecting practice and theory. Selecting the most frequently applied technologies indicates the importance of technologies, their application in different countries, as well as good practice.

The results of this paper can be used to define the best strategy for the implementation of these technologies in practice, to provide recommendations for companies to improve their business, as well as to define the technologies that can be used to achieve that improvement, to point out errors in implementation, and to suggest ways of overcoming them, to discover new approaches to technologies, and others. This paper points out the importance, advantages, but also disadvantages of technologies, the possibilities and obstacles for their application, the multidisciplinary nature of technologies, and the impact of technology on employees.

There are two main contributions of the study. First, the most applied I4.0 technologies for digitalization and automation in manufacturing companies, based on the literature review, are defined. Second, the main advantages and disadvantages of selected technologies, per technology, are presented. This paper is valuable for all decision-makers in manufacturing companies that aim to implement or improve the current level of technology application in their companies, as well as the level of digitalization.

Technologies are developing very fast, and technology development is more than adapting or replicating current technologies [20, 21]. Therefore, this paper will fill the literature gap with an analysis of the latest published articles on this topic, since other literature review articles that dealt with technology applications in manufacturing companies can be outdated, superseded, or not up to date with new, modern technologies that have emerged or improved in the last few years. Additionally, due to the speed at which industry is developing, articles published earlier are losing their relevance.

Furthermore, to the best of the authors' knowledge, there are no other articles that have addressed the same topic, i.e., the selection of the most applied I4.0 technologies for digitalization and automation in manufacturing companies based on literature review analysis. Therefore, this article is of high significance for education and practice. The results presented in this paper will fill a literature gap.

The structure of this paper is as follows. The first chapter presents the introduction and the meaning and application of I4.0 and mentions accompanying technologies for digitalization and automation analysed in this paper. The third chapter presents the research methodology. The fourth chapter presents the characteristics of the sample, using VOSviewer software and the authors' analysis of selected articles. The fifth chapter presents a discussion of the findings from the literature review and responses to research questions defined in this paper. The conclusion is presented in the sixth chapter.

2. Materials and methods

Fig. 1 presents the key steps of the literature review research methodology, adapted from the methodological frameworks proposed in [22, 23].

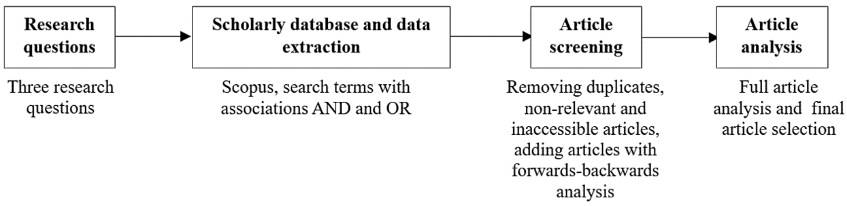


Fig. 1 A research methodology of the literature review

Step 1: Three research questions (RQs) were defined at the beginning of this research:

RQ1: *How do the I4.0 technologies impact production management in manufacturing companies?*
RQ2: *Does the application of I4.0 improve production management?*
RQ3: *What are the most applied, i.e. key I4.0 technologies in manufacturing companies?*

Step 2: In this article, the extraction of articles was done from the scholarly database Scopus, since Scopus has a wider coverage of Journals in all fields [24] and most Journals cover the Technology area [25]. Scopus provides a wider range of journal coverage than WoS [25] with 4 000 publishers, making it "the largest single abstract and indexing database" [26]. These were the main reasons for choosing the Scopus bibliographic database. The database was extracted in February 2024. The data extraction was done in three steps. The inclusion and exclusion criteria are explained below.

Regarding the first data extraction, on the Scopus search webpage researchers have applied additional search limitations, such as the Search option within the Article title, abstract and keywords and searched using terms, with associations, respectively: name of technology (differ per research) AND "production management" OR "manufacturing" AND "industry 4.0", within the range from 2018 to 2024 (which can be considered as a five-year publication window since the database was extracted during February 2024 and in some Journals and Publishers there were breaks in publishing because of the COVID-19 virus (in 2019 and 2020), which affected publications, collaboration and funding, moving them at least for one year later [27, 28].

A five-year publication window is important for the significance of the topic because it shows the growth of publications in the last five years, indicating the relevance and accuracy of the results in a rapidly changing technological environment [29]. Also, it is a commonly used period in bibliometric analyses and presents a balance between short-term and long-term assessments [30].

Selected Subject areas were Engineering; Computer Science; Business, Management and Accounting; Decision Science. As the Document type, Article was seelcted (since articles published in Journals have passed a more rigorous review process that usually guarantees the quality of the article [31]). The Language was selected as English only (as this language is favoured over other languages [24] and authors more frequently decide to write and publish articles in English, according to the number of available articles in this database filter fields), and as Source type was selected as Journal. All articles were selected in one database, and in total there were 3637 articles. After excluding duplicates by title, there were a total of 2020 articles.

In the second data extraction, the research was done with a combined search for all technologies, using the "OR" association. This resulted in 2020 articles, which were the same as the results from the first search. The results from the second data extraction resulted in too wide a range of articles, usually written in general about technologies, rather than applications in production.

Since the main idea of this article is to define a set of technologies used in I4.0 and for production management, and to decrease the number of articles by search terms, in the third data extraction the researchers added additional search criteria: AND "production company" OR "manufacturing company". The research resulted in a total of 123 articles. The export option "All documents" in CSV format were used, with the options "Citation information", "Bibliographical information", and "Abstract & Keywords". This extracted database was used for further analysis.

Step 3: Fig. 2 presents the steps of article screening and selection of relevant articles.

Step 4: Selected articles were thoroughly analysed and additional analysis was done, as presented in the following chapters.

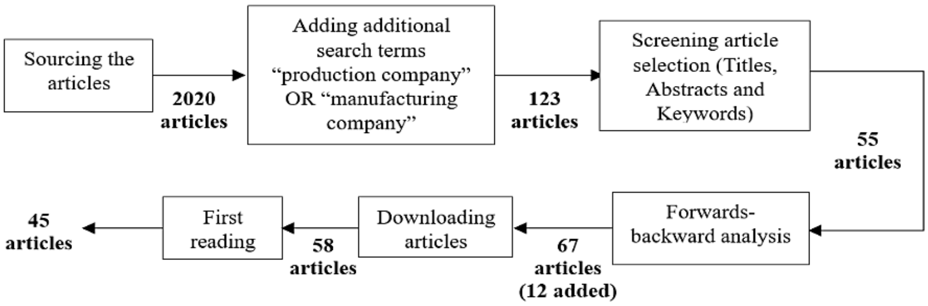


Fig. 2 Selection steps of the articles for the literature review

3. Research results

This chapter presents the literature review results of articles extracted from the Scopus database to present whether I4.0 is a modern concept implemented in manufacturing companies and which technologies are most used, individually and in combination.

3.1 Sample characteristics

The following subchapters present results from the analysis using VOSviewer software and the authors' analysis. VOSviewer software is a freely available program for viewing and constructing bibliometric maps that enable easy interpretation and can be presented graphically [32]. The analysis in VOSviewer was done using keywords, because "keyword search provides an intuitive, convenient, and effective way for users to interact with and explore the structured data stored in databases" [33]. Authors' Keywords were selected, not Index Keywords, because they were not listed for all articles from the database and could lead to inadequate analysis.

Clusters present a grouping of keywords into sets that are similar within the cluster, where the thickness of the line presents the strength of their correlation [34]. The more frequent keyword is presented with a larger circle and text font [35]. According to the results, keywords are grouped into four clusters (Fig. 3). After identifying and confirming the relationships between keywords in clusters, the clusters are explained.

In cluster 1 (green), "Industry 4.0" enables the "digitalization" of processes [36], while "additive manufacturing" and "cyber security" are technologies used under the concept of "Industry 4.0", mostly in production, and are also connected to "digitalization" [16, 37, 38]. "Additive manufacturing" enables companies to adapt processes to changes made by "Industry 4.0" [38], while "cyber security" prevents cyberattacks, protects intellectual property, and data in the digital environment [37]. “Management” enables the coordination of activities, while “Industry 4.0” enables management to introduce more flexible processes that can replace conventional ones [39].

In cluster 2 (red), “internet of things”, “machine learning”, “simulation”, “automation”, “digital twin”, “robots” and “virtual reality” are technologies and concepts commonly used in “manufacturing” [15, 40, 41]. “Internet of things” through “automation” empowers manufacturing companies to implement more advanced processes digitalization [36]. Application of some of these technologies implies “automation” of processes, while many improvements and tests in manufacturing are done with “simulation”. “Automation” and “robots” are usually used together because the application of robots enables the automation of processes, i.e. “robots” are a component of an “automation” system [42]. “Simulation” is combined with “machine learning” [43] and “digital twin”, as “digital twin” enables the virtual “simulation” of the physical world [44]. Creation of “digital twin” can be done with computer “simulation” [12] and “simulation” with “digital twin” can be conducted together with physical tests [45]. Moreover, the collaboration of “digital twin” and “virtual reality” makes digital twin-based virtual factory concept [46].

In cluster 3 (blue), “big data” and “data analysis” are usually used together and applied with “artificial intelligence”[47], as presented in [48] as big data analytics-powered AI, where access to the data could not be possible without “cloud computing” as a new form of Internet service with high flexibility, scalability and cost efficiency [49], making these terms strongly connected within one cluster.

In cluster 4 (yellow) “industrial internet of things” enables “predictive maintenance” [44], while “cyber physical system” and “augmented reality” are widely applied technologies and concepts in manufacturing companies [50-52]. Application of “cyber physical system” in manufacturing companies enables “predictive maintenance” [52].

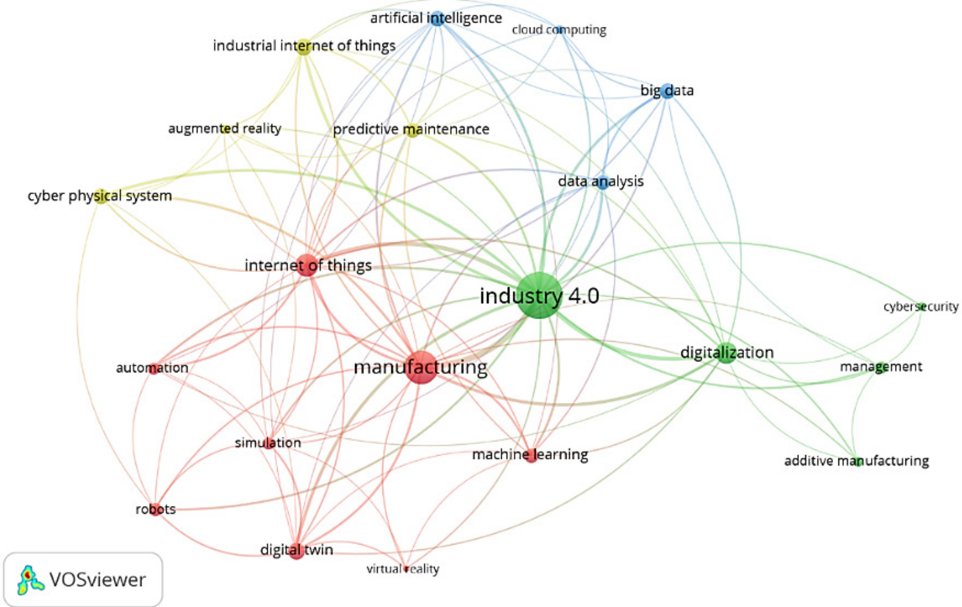


Fig. 3 Scopus database keywords clusters from VOSviewer software

Table 1 presents a list of all source titles (Journals) where the analysed articles were published. Based on the analysis, it can be concluded that this topic is of interest to many journals since 35 journals have published articles on this topic. Journals “Computers and Industrial Engineering”, “International Journal of Advanced Manufacturing Technology” and “Sustainability (Switzerland)” have the highest number of published articles on this topic, with three articles per journal.

Fig. 4 shows the distribution of articles per publication year. This topic was the most popular in 2021, when there was a peak of 16 published articles, while afer that year, the trend has been slowly decreasing. This peak may be the reason for COVID-19. For instance, many articles were sent in 2020 but were not published then because of interruptions in publishing by COVID-19. In 2020, internationally collaborative publications had a significant drop [53]. Some of the reasons could be a break or delay in publishing because of the extraordinary situation in which COVID-19 affected the whole world, so some articles intended for publishing in 2020 were published in 2021.

Regarding 2024, the database was established in February 2024, and by that month already three articles had been published in 2024. It is assumed that more articles will be published in 2024. Also, from Fig. 4 it can be concluded that the number of published articles shows a cumulative increase, indicating that the topic is still popular and applicable to manufacturing companies.

Table 1 Source titles where the analysed articles were published

No.	Source Title	No. of articles (%)
1	Three articles per Journal: *Computers and Industrial Engineering, International Journal of Advanced Manufacturing Technology, Sustainability (Switzerland)*	9 (20.01 %)
2	Two articles per Journal: *Applied Sciences (Switzerland), IEEE Access, Journal of Manufacturing Systems, Journal of Manufacturing Technology Management*	8 (17.76 %)
3	One article per Journal: *Academic Journal of Manufacturing Engineering, Acta Astronautica, Acta Logistica, Advances in Production Engineering And Management, AI and Society, Applied Computer Science, Business Strategy and the Environment, Computers in Industry, Eksploatacja i Niezawodnosc, Elektrotechnik und Informationstechnik, Engineering Research Express, Expert Systems with Applications, Frontiers in ICT, IEEE Transactions on Industrial Informatics, International Journal of Production Economics, Journal of Computing and Information Science in Engineering, Journal of High Technology Management Research, Logistics, Management and Production Engineering Review, Management Revue, Proceedings of the Estonian Academy of Sciences, Sensors, Sensors (Switzerland), Sustainable Production and Consumption, Technological Forecasting and Social Change, Technology in Society, Technovation, Thunderbird International Business Review)*	28 (62.23 %)
Total	35 Journals	45 articles (100 %)

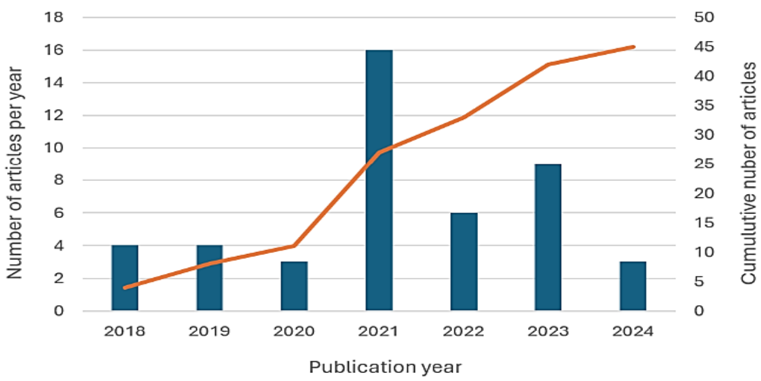


Fig. 4 Distribution of the 45 analysed articles by publication year (2018–2024)

Table 2 Number of citations of articles

No.	Number of citations	Number of cited articles (%)
1	Over 1000	1 (2.22 %)
2	501-1000	0 (0 %)
3	100-500	4 (8.89 %)
4	51-100	3 (6.67 %)
5	11-50	15 (33.33 %)
6	1-10	13 (28.89 %)
7	0	9 (20 %)
	Total	45 (100 %)

Table 2 shows the number of citations and cited articles. Interestingly, there are five articles cited over 100 times, which are [48, 54, 55, 66], while one article stands out with 1457 citations, namely [57]. Nine articles have not yet been cited.

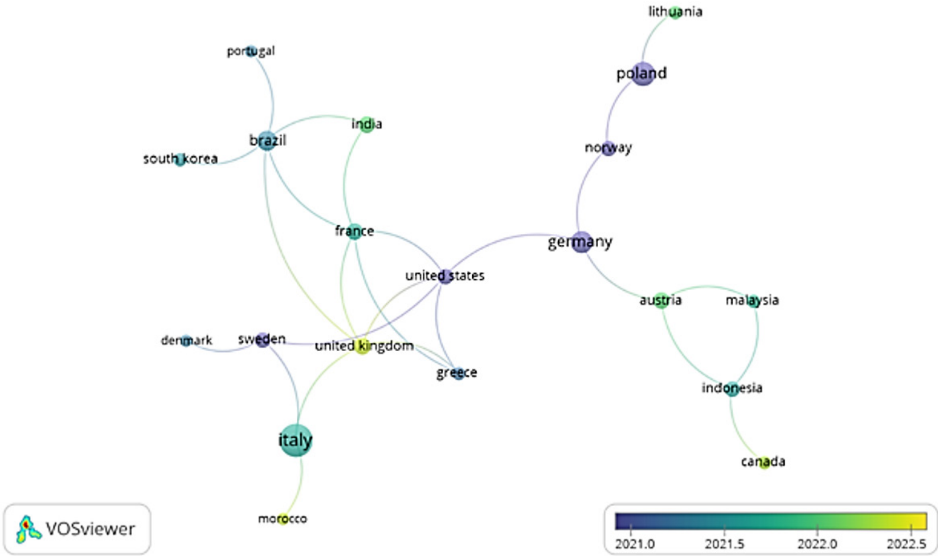
Regarding author profile analysis, not surprisingly, 34 articles (75.56 %) are written by academics (from universities, institutes, and business schools), 10 articles (22.22 %) are written in cooperation between academics and practitioners, pointing out the real application of technology implementation, while one article (2.22 %) is written by a practitioner. The classification of analysed articles by research method is presented in Table 3.

Table 3 Classification of analysed articles per research method

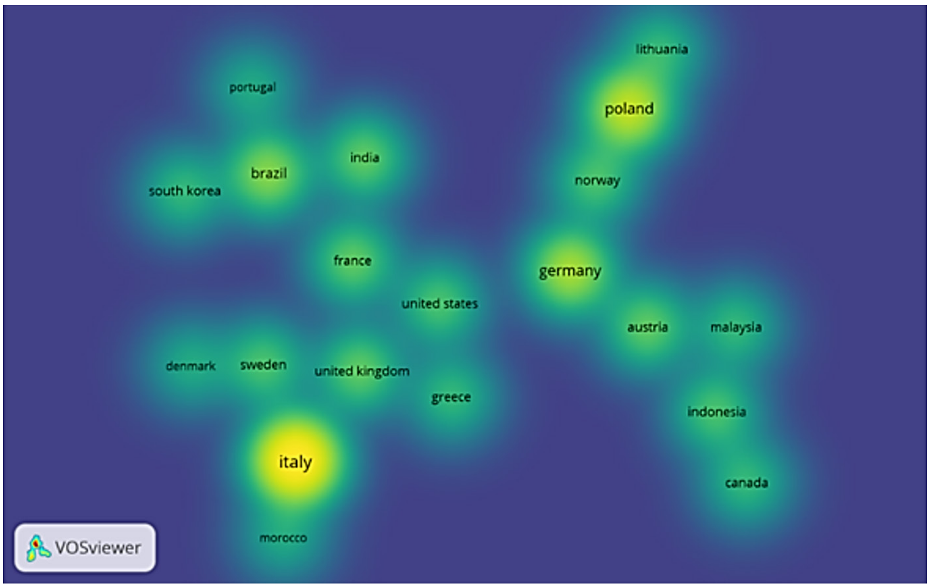
No.	Research method	Number of articles (percentage)
1	Case study (CS)	27 (60 %)
2	Survey (S)	10 (22.22 %)
3	Literature review (LR)	4 (8.89 %)
4	Interview (I)	2 (4.44 %)
5	Case study and interview (CS&I)	1 (2.22 %)
6	Case study, interview and survey (CS, I&S)	1 (2.22 %)
	Total	45 (100 %)

A total of 27 (60.00 %) articles presented Case studies and results of the applied technologies in manufacturing companies, 10 articles (22.22 %) presented results of surveys conducted in manufacturing companies, 4 articles (8.89 %) presented results of a literature review and 2 articles (4.44 %) present results of interviews done in manufacturing companies. One article (2.22 %) presented the results of an applied Case study and interview, while also one article (2.22 %) presented the results of a Case study, an interview, and a survey in a manufacturing company.

For additional sample analysis, a deeper analysis of the selected articles was conducted. First, an analysis of the authors' origins was performed, as presented in Fig. 5.



(a)



(b)

Fig. 5 VOSviewer – overlay (5a) and density visualization (5b) of countries of the authors of the articles

As presented in Fig. 5a, Germany, Poland, Norway, the United States, and Sweden are the countries with the oldest articles (2021). This was expected for Germany, since the concept of I4.0 was first introduced in 2011 at the Hannover Fair [58], where industrial global transformation was highlighted [59]. The biggest circles (representing the number of authors per country) are observed for Italy, Germany, and Poland, respectively. The countries whose authors are the most connected (five connections) are Brazil (connected with South Korea, Portugal, India, France, and the United Kingdom), France (connected with India, Brazil, the United Kingdom, Greece, and the United States), the United Kingdom (connected with Brazil, France, the United States, Greece, and Italy), and the United States (connected with France, the United Kingdom, Sweden, Greece, and Germany). The least connected countries are Portugal, South Korea, Denmark, Morocco, Canada, Lithuania, Poland, and Norway, with only one connection per country.

As presented in the density visualization from VOSviewer in Fig. 5b, most articles are written by authors from Italy, followed by Germany and Poland, while the fewest are from Portugal, South Korea, Denmark, Morocco, Greece, Canada, Indonesia, Malaysia, and Lithuania. By analysing 45 articles, most authors are from Italy (10 authors), while a total of 18 authors are from Germany and Poland (9 authors per country). Only one author per country is from Algeria, Estonia, India, Kazakhstan, Lithuania, Slovakia, South Africa, and the United Kingdom. Overall, the selected articles include a total of 95 authors from 29 countries, as presented in Table 4.

Comparing results from VOSviewer and the authors' analysis, differences can be noticed. By adding articles through forward–backward analysis, more countries are included in the analysis, such as China (5 authors), Spain (4 authors), Taiwan (3 authors), Australia, Hungary, Romania, and Turkey (2 authors per country), as well as Algeria, Estonia, Kazakhstan, Slovakia, and South Africa, with one author per country.

Table 4 Countries of the authors of analysed articles

No.	Countries	Number of authors per country (%)
1	Italy	10 (10.53 %)
2	Germany, Poland	9 (18.94 %)
3	Brazil	8 (8.42 %)
4	Austria	7 (7.37 %)
5	Denmark	6 (6.32 %)
6	China	5 (5.26 %)
7	Spain	4 (4.21 %)
8	Norway, South Korea, Taiwan	3 (9.48 %)
9	Australia, Canada, France, Greece, Hungary, Malaysia, Portugal, Romania, Sweden, Turkey	2 (21.10 %)
10	Algeria, Estonia, India, Kazakhstan, Lithuania, Slovakia, South Africa, United Kingdom	1 (8.40 %)
Total	29 countries	95 authors (100 %)

3.2 Research results from selected articles

Within the detailed analysis of each article, Table 5 presents a list of the selected 45 articles, together with the keywords of the papers (authors' keywords) and the purpose of each article, divided by research method from Table 3: CS, S, LR, I, CS&I, CS, I&S. The first column in the table, Reference numbers (Ref. No.), presents the ordinal number of the reference list.

Table 5 Selected 45 articles with keywords of the paper and the purpose of the study and article

Ref. No.	Study purpose	Author keywords	Purpose of the article
[39]	CS	Additive manufacturing; COVID-19 pandemic; Digitalization; Industry 4.0; Manufacturing systems; Operator 4.0; Resilience; Supply chain disruption	To analyse the impact of COVID-19 on workforce and supply resilience by implementing three I4.0-driven solutions, such as Plug-and-Play worker, the Remote Operator 4.0 and the Predictive Health of the Operational Staff.
[50]	CS	Augmented Reality; Engineered-to-Order; Industrial PSS; Intelligent Product Service System; Maintenance; Product Service System (PSS)	To design and develop an Intelligent Product Service System, a method based on servitization principles to deliver an intelligent and adaptable maintenance service aided by AR, by an optimizing algorithm for adjusting the stakeholder schedules on the energy supplier predictions.

Table 5 (Continuation)

[40]	CS	Digital twin simulation; Industry 4.0; Layout problem for RMS; Reconfigurable manufacturing system (RMS)	To integrate several I4.0 technologies and concepts (IIoT, AI, advanced robotics, simulation, digital twin) and optimizing them to create a smart layout design system for Reconfigurable Manufacturing Systems (RMS), introducing a new approach to automate the reconfiguration process of RMS.
[36]	CS	Business process; Digitalization; Industry 4.0; Internet of Things; SmartFactory; SmartPlanner	To present manufacturing company renovation phases, serving as a foundation for future digital technology developments, such as the integration of sensor-based data on the operational status of production machines and the available warehouse supplies (SmartFactory), creation of Web-based tool (SmartPlanner) for improved organization of production, without complex calculations for the duration estimation of production orders.
[60]	CS	Control scheme; Industrial robot; Open-loop and closed-loop simulations; PID controller	To present open and closed-loop simulation of the industrial robot with six axes manipulator arms using PID (Proportional–Integral–Derivative) controller and comparing results, providing desired trajectory of robot arm.
[54]	CS	Augmented Reality; Cyber-physical systems; Identification; Industrial augmented reality; Industrial Internet of Things; Industry 4.0; Internet of Things; Smart factory; Traceability	To present the application of industrial AR (IAR) in shipbuilding, to evaluate their performance in a shipyard workshop and inside a ship under construction.
[59]	CS	Blockchain technology; Execution integrity; Industry 4.0; Production system; Smart device	To present and explain a blockchain-based execution protection scheme (NoSneaky), a low-cost simple integration scheme for production systems used for protection of the production line from getting sabotaged by cybercriminals.
[12]	CS	Artificial intelligence; Digital Twin; Discrete event simulation; Fast fashion; Industry 4.0; Operational planning	To present the improvement of operational decision-making considering I4.0.
[62]	CS	Internet of Things—IoT; Methodological framework; Production line performance; Simulation; Wearable devices	To propose a methodological framework using wearable IIoT devices, such as wearable sensors and simulation tools (and creating a Digital Twin of observed processes), supports the analyses of production line performance parameters by considering numerical and experimental data, enabling continuous monitoring of the line balancing and performance as production demand fluctuates.
[57]	CS	Digital transformation; Industry 4.0; Manufacturing companies; Smart Manufacturing	To propose a conceptual framework for I4.0 technologies, showing levels of technology adoption and implications for manufacturing companies.
[41]	CS	Assembly cycle; Collaborative assembly; Collaborative robotics; Human-robot interaction; Industry 4.0	To propose a task scheduling method that determines the optimal assembly cycle considering the primary features of the process and product, as well as allocating tasks between robots and humans.
[51]	CS	Augmented reality; Pick-by-Vision system; Smart glasses; Warehouse management	To present results of the application of AR technology (device: "smart" glasses) in warehouse management.
[14]	CS	Autoencoder; Characteristics importance; Decision tree; Feature importance; Injection molding; Machine learning; Quality prediction; Regression	To present research findings on the applicability of ML for quality prediction challenges in injection molding industry, by implementing ML algorithms for prediction and identifying factors that influence molding products quality.
[52]	CS	Collaborative Software Engineering; Cyber-Physical Production Systems (CPPS); Industry 4.0 (I4.0); ISO/IEC/IEEE 42010:2011	To describe fundamental principles of tool, that integrates established and emerging reference models, standards and methodologies from software engineering, production automation and I4.0, embedded within a novel collaborative engineering model for CPPS, emphasizing its innovative aspects and sharing insights gained during its development and implementation in industrial scenario.

Table 5 (Continuation)

[63]	CS	Buffer time control; Due date control; Industry 3.5; Industry 4.0; Theory of constraints	To present a Due Date Control (DDC) system linked with I4.0 technologies, aimed at accurately collecting real-time data for integration with production systems, tailored for controlling process plans through an M2M communication approach. Additionally, it involves creating a Work-in-Process (WIP) alert system utilizing an M2M communication method within I4.0 to address the challenge of enhancing delivery performance.
[37]	CS	Automation; Computer vision; Industry 4.0; Internet of things; Production interface; Smart manufacturing	To propose ORiON Production Interface (OPI) unit, to improve existing factories and their equipment.
[64]	CS	Artificial intelligence; Automated production; Digital twin; Machine learning; Robotic assembly; Satellite production; Teleoperation	To present an approach to an in-orbit factory of small satellites, encompassing a digital process twin, AI-based fault detection and teleoperated robot control, with responses regarding the application of AI and robots to enhance the robustness, fault-tolerance and autonomy of the production process, with the focus on achieving an automated production system for small satellites in orbit.
[65]	CS	CPPS; IoT; Manufacturing systems; Process and data modelling	To develop CPPS-based modelling technologies and suggest a concept for upgrading a conventional production system.
[66]	CS	Condition-based maintenance; Extreme learning machine; Induction motor; Industry 4.0; Predictive maintenance	To present results of an industrial AI to Condition-Based Maintenance within a wooden piece manufacturing company, that involves temperature prediction of the ten induction motors in the extraction system utilizing a methodology based on Extreme Learning Machines, enabling dynamic model prediction.
[67]	CS	N/A	To present a machine-tool monitoring system for shopfloor control following the IoT paradigm.
[38]	CS	3D printing; Additive Manufacturing (AM); Balanced scorecard; Competitive advantage; Empirical research; Industry 4.0; Management; Smart manufacturing; Strategy	To develop a new management approach by incorporating AM technology and best practices, using the comprehensive literature reviews and empirical research conducted across 250 Polish manufacturing enterprises.
[43]	CS	Catalyst; Digital twin; Industry 4.0; Machine learning; Process industry; Virtual reality	To present a framework for constructing ML-based DTs aimed at real-time prediction of critical process parameters within the process industry, offering insights into benefits of employing ML-based DTs in process industry and highlighting challenges associated with their implementation.
[55]	CS	Cyber-Physical Production System; Functionality; Human; Industry 4.0; Manufacturing; Performance; Social sustainability	To respond to questions regarding the application of CPPS on health and learning and operative performance of human employees.
[49]	CS	Artificial neural network; Extreme learning machine; Hybrid fore-casting; Maintenance; Production planning; Quality control; Support vector machine	To propose a new hybrid forecasting model that integrates AI-based approaches with conventional time series techniques for production planning, maintenance and quality control, with a focus on solving the constraint of restricted access to independent variables, introducing algorithm for evaluating the forecasting accuracy and selecting an optimal method tailored for industrial companies.
[47]	CS	AGV (automated guided vehicles); AMR (autonomous mobile robots); Computer simulation; Digital twin; Industry 4.0; IoT	To present the application of DT technology for testing the operating environment of an Autonomous Mobile Robot.
[44]	CS	Embedded solutions; Industrial IoT; Industry 4.0; Low-cost; Prototyping; Retrofitting solutions	To present rapid, low-cost prototyping solution tailored for manufacturing companies with legacy machinery, for transition to I4.0 paradigm through a low-risk initial approach.
[68]	CS	Artificial intelligence; Cloud computing; Industry 4.0; Smart factory	To present AI applications in a Cloud-assisted Smart Factory (CaSF), introducing the primary concerns and technical challenges with AI integration in the CaSF systems, proposing solutions to address these challenges.

Table 5 (Continuation)

[48]	S	Artificial intelligence; Big data; Circular economy; Industry 4.0; Sustainable manufacturing	To present institutional pressures on resources and their implications for adopting BD Analytics powered by AI (BDA-AI) and to assess how this influences the capabilities of sustainable manufacturing and circular economy practices under the moderating impacts of organizational flexibility and industry dynamism in the automotive industry with significant progress of digitalization.
[42]	S	Human–robot collaboration; Industrial robots; Intention to use; Negative attitudes; Trust	To present survey results about the attitudes of employees towards robots and their willingness to work with robots.
[5]	S	Artificial intelligence; Benefits; Degree of implementation; Industry 4.0; Manufacturing; Sustainable development	To present the level of I4.0 implementation principles in Romanian manufacturing companies, used for the establishment of critical premises for sustainability.
[69]	S	Industry 4.0; Innovation; Management; Organization; Process; Progress; Technologies	To present main characteristics of Germany and Poland manufacturing companies that strive for digital maturity.
[52]	S	Artificial intelligence (AI); Digital skills; Industry 4.0; Machine learning (ML); Technology adoption; Technology-organization-environment framework	To present a survey results of 655 companies from manufacturing industry to explain the main drivers of AI adoption and the influence of various Technological, Organizational and Environmental (TOE) prerequisites essential for the successful adoption of AI in manufacturing companies.
[15]	S	Circular economy; Digitalization; Empirical study; Industry 4.0; Survey; Sustainable production	To present the degree and stage of implementation of four key enabling digital technologies (IoT, DA, AI and blockchain) for a sustainable circular economy by the survey of 31 manufacturing companies.
[47]	S	Dynamic capabilities view; Empirical study; Industry 4.0; Statistical model; Vertical and horizontal collaboration	To present the impact of inter-organizational collaboration practices on a company's circular economy initiatives and outcomes (sustainability and economic performance), as well as investigating the potential enabling role of emerging digital technologies on both aspects, based on a survey conducted among 112 Austrian manufacturing firms.
[70]	S	Data management; Industry 4.0; Industry 4.0 exploration; Internet of things; Manufacturing firms; Policy	To present results of qualitative research and discussion regarding current practice and challenges in I4.0 implementation in Malaysian manufacturing companies.
[16]	S	Additive manufacturing; Bayesian network; Petri nets; Process modelling	To apply the Bayesian Network in the planning of technology AM implementation in manufacturing company.
[1]	S	3D printing; Additive manufacturing; Industry 4.0; Production development; Production engineering	To determine the trajectory of the 3D printing industry development in Poland companies, the study seeks insights from survey respondents regarding opportunities and threats associated with the implementation of the I4.0 concept (focused on offering and applying 3D) in company.
[13]	LR	Industrial performance; Industry 4.0; Manufacturing technology; Technology	To propose five collaborative networks combining technologies associated with I4.0: (1) smart manufacturing; (2) technological platforms; (3) market reactiveness; (4) smart products and (5) flexibility.
[71]	LR	Digitalisation; Employment; Industry 4.0; Manufacturing; Skills; Technological change	To present the impacts of digitalization on employment, analysing the positive and negative sides of digitization.
[72]	LR	Creativity and innovation; Digital innovation; Industry 4.0; Innovation management; Sustainability	To present the results of a deep literature review to explain the importance of digital innovation in companies to survive in an era of I4.0.
[73]	LR	Artificial intelligence; Industry 4.0; Machine Learning	To present a literature review results regarding the adoption of AI in the context of I4.0 Industrial AI (IAI) in different industry sectors.
[74]	I	Ambidexterity; Industry 4.0; Innovation; Manufacturing; Skill formation	To present results of interviews in mechanical engineering company regarding the organization of introduction and development of digital technologies in a company as well as their impact on organizational structure and practice.

Table 5 (Continuation)

[56]	I	Digital transformation; German companies; Implementation; Industrial Internet of Things; Industry 4.0; Qualitative research	To present a deeper understanding of the implementation steps of I4.0.
[10]	CS&I	Industry 4.0; Portugal; Technology adoption; Technology management; Technology provider companies	To present the challenges and opportunities associated with embracing I4.0 from the viewpoint of technology provider companies.
[46]	CS,I&S	Digital twin; Industry 4.0; Manufacturing planning; Optimisation; Simulation; Virtual factory; Virtual manufacturing; Virtual reality	To present the demonstration results, as well as evaluation, discussion and argument of industry experts of previously introduced DT-based virtual factory framework designed to support modelling, simulation and evaluation of complex manufacturing systems, utilizing multi-user collaborative VR learning/training scenarios.

Table 6 List of technologies mentioned in the articles with number of technologies per article and frequency of technology appearance in the articles

Refs.	IoT	CS	CPS	CC	BD	R	M2M	AR	VR	BI	ML	AI	AM	No. M
[10]			1	1	1			1					1	5
[73]	1			1							1	1	1	5
[1]	1		1		1	1							1	5
[13]	1		1	1	1									4
[71]	1				1	1		1						4
[72]			1	1				1				1		4
[68]	1			1		1						1		4
[39]								1	1				1	3
[54]	1		1					1						3
[15]	1				1							1		3
[47]	1				1							1		3
[50]	1							1						2
[48]					1							1		2
[57]	1				1									2
[14]											1	1		2
[75]											1	1		2
[64]						1						1		2
[65]	1		1											2
[43]									1		1			2
[40]												1		1
[36]	1													1
[60]						1								1
[61]							1							1
[42]						1								1
[12]												1		1
[62]	1													1
[5]												1		1
[41]						1								1
[51]								1						1
[69]						1								1
[52]			1											1
[74]												1		1
[63]							1							1
[37]	1													1
[66]												1		1
[67]	1													1
[38]													1	1
[55]			1											1
[49]												1		1
[45]					1									1
[70]	1													1
[16]													1	1
[56]	1													1
[44]	1													1
[5]									1					1
F	18	0	8	5	9	8	2	7	3	0	4	15	6	

We have analysed two types of data: (1) what is the most mentioned technology in articles (Table 6) and (2) what is usually a set of technologies mentioned together (Table 7). Table 6 presents a list of technologies mentioned and the total number of technologies per article (No M), while the last row presents the frequency of technology appearance in selected articles (F).

The most mentioned technologies in I4.0 in manufacturing companies are IoT (18 appearances, 40 %) and AI (15 appearances, 33.33 %). BD follows with 9 appearances (20 %), CPS and R with 8 appearances each (17.78 %), AR with 7 appearances (15.56 %) and AM with 6 appearances (13.33 %). It can be concluded that these technologies are mostly applied in manufacturing companies. There were no examples of the implementation of technologies CS and BI (0 appearances, 0 %), so it can be concluded that these technologies are not usually used in manufacturing companies, or that their use is not yet the subject of academic research. By analysing technologies in the 45 articles, the frequency of technologies mentioned together is presented in Table 7: IoT is combined with BD (6 articles), CPS (4 articles) and AI (4 articles); CPS is combined with CC (3 articles), BD (3 articles) and AR (3 articles), while AI is combined with IoT (4 articles), CC (3 articles), BD (3 articles) and ML (3 articles).

Other combinations are two or fewer articles. According to these analyses, it can be concluded that IoT is the most suitable technology for application and combination with other technologies in manufacturing companies. It is interesting that VR is only combined with AR. In the same table, technologies CS, M2M, and BI were not presented, because they had no combination with some other technology in analysed articles. It can be concluded that these technologies are not easily suitable for combining or are not usually applied or combined with other technologies.

Table 7 Combinations of applications of technologies in selected articles

Technology	CPS	CC	BD	R	AR	VR	ML	AI	AM
IoT	4	3	6	3	3		1	4	2
CPS		3	3	1	3			1	2
CC			2	1	2		1	3	2
BD				2	2			3	2
R					1			2	1
AR						1		1	1
VR							1		
ML								3	1
AI									1

4. Discussion

To properly respond to all three RQs defined in this paper, the main benefits and barriers to I4.0 technology application, as well as the advantages and disadvantages of technology applications in manufacturing companies, are presented in this chapter.

4.1 Analysis of the advantages and disadvantages of technologies for digitalization and automation in manufacturing companies

The main advantages and disadvantages of technology according to the analysed articles are presented in Table 8. It must be noted that not every article has highlighted an advantage or disadvantage or a barrier to the application of technologies, and for that reason, not all articles are referenced. In most articles, disadvantages and barriers are excluded because the authors were mostly focused on technology application improvements in manufacturing companies.

IoT represents a technology that enables process and product innovation with positive employment effects [71], with a direct influence on flexible production lines [13]. It enables data to be stored within a connected database [66], significant cost and time reductions, improved quality control of products, real-time detection and response to errors in production, as well as optimized resource utilization by minimizing unproductive setup times of production lines [36]. IoT reduces the costs of connecting new machines, technology installation, and development [44]. It is a reliable and inexpensive solution that can be easily installed, with low implementation costs that enable better communication with operators [44, 67].

CPS enables unrestricted navigation between collaborative consolidation phases and individual modelling, favoring teams performing engineering processes rather than individuals [52]. The application of CPS can improve employee satisfaction, accelerate information delivery, and improve operator learning, increase the level of knowledge, competencies, and skills, decrease human errors due to lack of knowledge, improve communication quality and internal quality control processes, expand time flexibility, and achieve cost efficiency through higher utilization and lower testing process costs [55].

Table 8 Advantages and disadvantages of technology applications per technology

No.	Techn.	Advantages	Disadvantages/barriers
1	IoT [15,36,67]	Cost reduction; Improved quality control; Real-time detection and reaction to production errors; Optimized employment; Easy installation; Data collection from production processes;	Not specifically stated;
2	CS	Not specifically stated;	Not specifically stated;
3	CPS [52,55,65]	Flexible engineering process; Operator learning; Human error incidence; Higher human capital; Employee satisfaction; Rich information capital; Improved communication quality; Expansion, market and routing flexibility; Higher productivity; Improved internal quality; Time, cost efficiency;	Not specifically stated;
4	CC [68]	Interfaces for multiple data types;	Specific format of input data;
5	BD [15,48,51, 57,71]	Innovation of processes and products; Positive employment effects; Integrated with AI; Collection of data from different sources; Enhanced collaboration in the supply chain; Improved recycling options, resource life cycle and more efficient processes; Competitive advantage; Demand forecasting and customer analysis;	Continuous involvement of senior management to improve decision-making;
6	R [41,42,64, 68,71]	Industrial Collaborative Robots (ICR): a safe physical and human-machine interaction; Optimal scheduling of the assembly cycle; Improved quality, efficiency (energy, time, cost), productivity; Reduced waste and errors; Repeated steps and higher precision compared to humans; Working in humanly unacceptable conditions; Decrease in the number of injuries and risks at work: Mimic human behaviour; Better handling of components in assembly lines; A multi-modal shared control approach at the assembly lines;	Negative effect on employment; Financial support for efficient implementation of this technology; Fear of employees to be replaced and resistance to change; Need for qualified employees for technology implementation;
7	M2M	Not specifically stated;	Not specifically stated;
8	AR [39,50,51, 57,71]	Process and product innovation; Integrated with VR, employees remotely manage an automated, digital and robotic workforce; Support to remote maintenance assistance; Increased safety; Faster picking; Speed of training; Increase in productivity; Reduced error rate; Reduces the number of injuries of employees; Application of easy-to-use devices that enable vision picking and hands-free working; Increases the speed, performance, accuracy and flexibility of an employee;	Investment could be costly and unnecessary for small companies; Longer wearing of AR devices can cause headaches and poor vision; "Smart" glasses have limited battery capacity, durability and product life;
9	VR [39,46,57]	Integrated with AR, employees remotely manage an automated, digital and robotic workforce; Improves productivity of employees; Enables creation of virtual factory;	Not specifically stated;
10	BI	Not specifically stated;	Not specifically stated;
11	ML [14,43, 66,73]	ML-based algorithms identify and assist in data processing, validation and acquisition; Understanding of quality problems; Quality prediction; Reduce quality monitoring costs; Reduce the employee's time for machine control; Increase the production level; Integration with AI enables to achieve innovation, improve maintenance, control and supervision of industrial processes; Integration with VR enables automatic repeating of training process; Optimization of the manufacturing process;	Not specifically stated;

Table 8 (Continuation)

12	AI [12,15,48, 57,64,66, 68,71,73, 74,75]	Enable sustainable production, improved quality control, zero downtime, customized products and decrease of production costs; Return on investment; Improved production and product management of individually designed products; Improves factory performances and operational aspects (system intelligence, efficiency, flexibility and reliability of manufacturing; Integrated with DT, ML, BD; Applied for predictive maintenance and inventory management;	High investment; Required skills, knowledge and specialist with digital skills to successfully implement; Concerns regarding model training, data processing, and testing, data acquisition and model interpretation; Combination of constraints of tight financing and radical innovations regarding client projects; Integrated with BD requires constant monitoring by senior management for better decision-making; Human skills as a barrier to technology implementation;
13	AM [1,16, 38,39]	Automation processes; Increase in efficiency; Minimizing shutdowns; Ensuring high product quality; Fast access to data and possibility of analysing them; Exclude needs for new interaction between humans and machines; Planning, design and production of elements or products with complex geometry, in any shape, that is not possible to do with conventional production; A high possibility to personalize elements or products to customer needs; Enable the company's significant competitive advantage, flexible production and fulfilment of individual customer requests and needs; Improved software and new, different materials for 3D printing; Waste reduction (time and resources); Reduction in human participation in production and assembly processes; Not expensive technology;	The lowest correlation between competitive advantage and effectiveness, as well as employee reduction and waste or energy reduction; The costs of personnel training and purchasing machines are high; Specific materials cannot be used; The lack of sufficient skills and knowledge among employees implies new specialists;

One of the advantages of **CC** is the availability of cloud platforms with interfaces for multiple data types, while the disadvantage is the requirement of a specific input data format. A challenge is to improve real-time performance and system robustness, since data in different and specific formats can be stored [68].

The application of **BD** in manufacturing companies is highly important for achieving competitive advantage [57], positively affects employees, and provides numerous opportunities for product and process innovation [71]. It has high applicability in customer analysis and demand forecasting [15]. Usually, this technology is integrated with AI and enables many improvements in manufacturing, such as collecting a significant amount of data from various sources, empowering machines to make decisions autonomously, improving the flexibility of manufacturing processes and collaboration throughout the supply chain, and reducing the risk of supply network disruptions [48]. Integrated with AI, BD implies continuous involvement of senior management in applying analytical and data visualization methods to improve decision-making [51].

The main improvements **robots** have made in manufacturing include "improvement of system robustness and accuracy, high-precision classification of workpieces, path adaptability and resolution of time and space conflicts, shortened path length, and the ability of robots to avoid intersecting with obstacles" [68]. Applied in production, robots improve productivity, efficiency (energy, time, cost), and quality; reduce waste, the number of errors, and production labour costs; mimic human behaviour and repeat tasks; can work in humanly unacceptable conditions; and are more precise than humans, decreasing the risk and number of injuries in production [42]. Robots are force-sensitive and enable better handling of components in assembly lines, improving the production process and replacing humans with a multi-modal shared control approach [64]. The disadvantages of robot implementation can be seen in their negative effect on employment, as robots can substitute human labour [71], leading to poor adoption of this technology, negative attitudes, and resistance to change among employees [42]. Also, this technology requires highly qualified personnel, which can be costly and sometimes hard to find [64], as well as financial support to be efficiently implemented [41].

The application of **AR** in manufacturing companies has many advantages, such as innovation in products and processes, implying positive effects on employees [71]; increases workers' productivity [57]; provides remote maintenance assistance to manage unforeseen malfunctions [50]; enables faster picking and faster responses; ease of use; fast training; vision picking; reduces the risk of errors by employees; and increases productivity, speed, performance, accuracy, and flexibility, while enabling application in noisy environments [51]. Integrated with VR, these technologies can positively influence employees to remotely manage an automated, digital, and robotic workforce safely and efficiently [39], including through easy-to-use devices ("smart" glasses, tablets, etc.). One of the disadvantages of this technology is that investment can be unnecessary and costly [51]. Even though AR applications through "smart" glasses enable employees to work hands-free, more efficiently and ergonomically, without work administration, decreasing the number of injuries and reducing errors, these devices have limited battery capacity, durability, and product life, while long-term use can cause headaches and poor vision [51].

VR, integrated with AR, can positively influence employees to remotely manage an automated, digital, and robotic workforce safely and efficiently [41], improving employee productivity [57] and shortening manufacturing lifecycles [46].

The main advantages of **ML** include improved understanding of quality problems, application and monitoring of quality prediction compared with real measurements, reduction of quality monitoring costs and employee time for machine control, and increased production levels [14, 43]. Algorithms based on ML technology are used for identification and assistance in processing, validation, and acquisition of data [73]. In the analysed articles, ML is mostly integrated with VR and AI. Integrated with VR, ML models automatically reinitiate training when the manufacturing process changes, eliminating the need for human intervention and optimizing the manufacturing process [43]. Integrated with AI and using a data-driven approach, ML improves the maintenance, supervision, and control of industrial processes [66].

AI enables the achievement of sustainable production, improved quality control, zero downtime, customized products, reduced production and system costs, and improved return on investment [73], overall improving operational aspects of the factory [57] and the performance of the "smart" factory (intelligence, efficiency, flexibility, and reliability) [68], as well as early detection of pollution or defects in production [64]. AI is used for predictive maintenance and inventory management [15], improving "product and production management of individually designed and complex solutions and products, the management and control of the inherent complexity of order, production, and distribution planning processes, and generating competitive advantages", enabling "fine-slicing" of manufacturing [75]. AI can be integrated with ML and, using a data-driven approach, improves the maintenance, supervision, and control of industrial processes [66]. Mostly integrated in DT, AI recognizes demand patterns and forecasts them to provide dashboards with automated commands, more accurate input data, and user-friendly interfaces [12]. Integrated with BD, AI collects larger quantities of data from different sources, enabling machines to make autonomous decisions, enhancing flexibility and circularity in manufacturing processes, providing more recycling options, longer resource life cycles, waste reduction, and better adjustment towards more efficient processes [48]. The disadvantages of implementing AI technology in manufacturing companies include [73, 75]: lack of data, high investment requirements, false positives, required knowledge, skills, and technical expertise for successful adoption, fear of insufficient benefits, and security concerns. AI also brings "tight financing constraints and the challenge of combining radical innovations with client projects at a very early stage" [74]. Another challenge of AI application "is the qualification of employed AI methods for practical usage" [64]. One of the barriers to AI implementation is the existence of human skills unique to humans, such as common sense, judgement, flexibility, and the ability to identify the purposiveness of objects [71].

The implementation of **AM** in manufacturing enables many advantages, the most important of which are [1]: increased efficiency, minimized shutdowns, ensured high product quality, fast access to data, and the possibility of analysing them. AM decreases or even eliminates the need for specific or new interactions between humans and machines [39], reduces waste (time and resources), and enables planning, design, and production of elements or products with complex geometry that is not possible using conventional production methods [38]. It enables companies to gain significant competitive advantage, flexible production, and fulfilment of individual customer requests and needs [16]. Regarding disadvantages, although AM uses many new and different materials, not every material can be used in this type of production; the costs of AM machines and personnel training remain high; and this technology still shows low correlation between competitive advantage and effectiveness, employee reduction, and waste or energy reduction [38], as well as a lack of knowledge and skills among employees, implying the need for new specialists [1].

For technologies **CS**, **M2M**, and **BI**, advantages and disadvantages are not clearly stated in the analysed articles.

4.2 Responses on RQs

To respond to the defined RQs in this paper, a critical qualitative discussion supported by a systematic literature review was used.

Response to RQ1 – How do the I4.0 technologies impact production management in manufacturing companies? Digital innovations save energy and time and enable employees to devote more time to innovation and creativity, while digital technology maintains the environment as sustainable and healthy and fulfils customer demands [72], enabling green and sustainable solutions [69]. Innovation within I4.0 brings the linking of traditional manufacturing expertise with new forms of knowledge in technologies such as IoT, AI, and others [74]. The application of digital technologies positively affects inter-organizational collaboration [47]. Organizational factors positively impact the implementation of digital technologies in manufacturing companies, and these companies are usually knowledge-based, research-intensive, and service-oriented [75]. This confirms that I4.0 technologies have a positive impact on production management, as already published in many articles, such as: I4.0 technologies enable improvements in production [76]; I4.0 technologies have a positive impact on production management, indicating that the implementation of I4.0 technologies in production management can serve as a strategic approach to address challenges from competition and changes in market demands [20]; I4.0 technologies have a significant positive impact on production performance [77], and others. Based on the analysed articles and compared with results from other articles that were not included in the analysis, it can be concluded that I4.0 technologies positively impact production management in manufacturing companies, with numerous advantages.

Response to RQ2 – Does the application of I4.0 improve production management? The application of I4.0 improves production management, where the main benefits are [10, 13, 69, 72]: improvements in (industrial) productivity, automation and automated logistics and supply chains, production resilience, flexibility, efficiency, cybersecurity, decision processes, quality of products and services, cost reduction, profit increase, and skilled personnel, as well as overall improved performance of the manufacturing system and simplified automated production systems. These findings confirm conclusions from Fasuludeen Kunju *et al.* [76], where it is stated that the implementation of I4.0 "leads to an increase in production, asset utilization, quality, reduced machine downtime in industries, and maintenance". Authors Rosin *et al.* [78] showed that I4.0 has a strong and positive impact on Lean principles in manufacturing companies, such as Just-in-Time and Jidoka, which are designed to enhance productivity. Authors Fatorachian and Kazemi [77] reported that I4.0 significantly enhanced performance not only in production but also in procurement, retailing, and inventory management. Authors in [20] concluded that I4.0 enhances production efficiency, reduces operational costs, and decreases response times to changes in market demands. Overall, I4.0 improves production management.

Response to RQ3 – What are the most applied, i.e. key I4.0 technologies in manufacturing companies? According to the analyses and results presented in Table 6, the most applied, i.e. key, I4.0 technologies in manufacturing companies are IoT, AI, BD, CPS, robots, AR, and AM. The top three most applied technologies are IoT, AI, and BD. Chen, Yati, and Beldiq [20] present these three technologies as those that "become crucial for enhancing the efficiency and effectiveness of production processes". Results regarding IoT and BD are confirmed by research presented in [18], which shows that IoT and BD are widely used technologies in manufacturing companies and encompass a broad range of processes, while AI is considered an important technology with a "significant role in modern manufacturing" [79]. CPS and robots are also frequently used in manufacturing companies. In [17], CPS was selected as the main key technology for I4.0, while in recent years it has been IoT, as presented in this paper. The reason could be that company needs and technological improvements have shifted the focus toward IoT as a more important technology in production management than CPS. Regarding robots, results from these articles confirm the statement from [3] that "robots will be more dominant in manufacturing". AR and AM also have an important role in manufacturing. For AR, this is confirmed in [80] based on a literature review analysis (covering the period from 2006 to 2017), which highlights its great potential for application in industrial operations, assembly, and maintenance, while emphasizing that AR is still in the initial adoption phase. This could explain why this technology ranks sixth. The same authors conclude that "it is expected that AR systems will become even more widespread in the near future". AM is considered a very important technology for manufacturing, where AM's capabilities, such as design freedom, computer-aided design, and free-form build, make it crucial for I4.0 and manufacturing companies [19]. AM has brought a major change in manufacturing, enabling substantial modifications of parts [81].

The results presented in this paper differ from those reported in [79], where the authors conducted a literature review analysis over two periods (1979–2010 and 2011–2019), indicating that the most crucial technologies were CPS, BD, and IoT, respectively. Results presented in [82] show that key I4.0 technologies more frequently used are Blockchain, BD, AI, ML, and IoT. These differences can be explained by the time frame of analysis. This paper analysed technologies in manufacturing companies published between 2018 and 2024, while other studies analysed earlier periods, leading to the conclusion that in recent years technologies such as IoT and AI have become more popular and widely applied in manufacturing companies. IoT connects "physical objects using electronics, sensors, software, and communication networks" [83], while AI enables "higher value-added manufacturing by accelerating the integration of manufacturing and information communication technologies, including computing, communication, and control" [84]. One of the latest technological achievements is AI-based IoT systems for Industry 5.0, where AI-based systems are a crucial component of IoT technology [85]. AI is considered a technology whose application enables improvements in production operations and processes [86]. This change in the ranking of technology application can be explained by technological development, which has led to improvements and changes in technologies, making some technologies more popular and widely applied in practice, while others become outdated or replaced by newer solutions that bring greater benefits to manufacturing companies. The reasons why some technologies have been more frequently applied in recent years include different company preferences, capacities, technological capabilities, and market demands, all of which have a significant impact on technology adoption. It should be emphasized that continuous improvement of these technologies, as well as employee training for their use, is crucial for their successful integration and acceptance in companies [87].

5. Conclusion

This paper presents a systematic literature review regarding digitalization and automation in manufacturing companies, using the Scopus database. The literature review suggests that there is a growing interest in digitalization and automation in manufacturing companies and that I4.0 technologies save costs, energy, and time, and generally improve production management. In addition, this paper presents the top three most applied technologies in manufacturing companies, namely IoT, AI, and BD.

The first limitation of the study is that the database was extracted from only one scholarly database (Scopus), meaning that more articles on the topic could be found in other scholarly databases, such as WoS (Web of Science), Google Scholar, IEEE Xplore, and others. The second limitation is that the database was extracted in February 2024, so the results presented for 2024 are not representative of the entire year. The third limitation is that this article focuses on I4.0 technologies for digitalization and automation in manufacturing companies, so many other applications of these technologies may exist in different industries.

The future directions of the authors' research include conducting a survey in manufacturing companies to examine the level of application of technologies for digitalization and automation, to explore the level of their application, the level of interest in their application, and the expected results of the application of these technologies in production management, as well as to analyse the impact of industry size, sector, and technological maturity on the adoption and implementation of I4.0 technologies. Another future direction of the authors' research is to analyse the impact of cultural, regulatory, and economic factors on the adoption of I4.0 technologies.

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