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Review

The adoption of digital technologies in the manufacturing world and their evaluation: A systematic review of real-life case studies and future research agenda

Leonardo Maretto *, Maurizio Faccio, Daria Battini

Department of Management and Engineering, University of Padova, Stradella San Nicola, 3, 36100 Vicenza, Italy

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ABSTRACT

In the last decade, digitalization has transformed industrial systems worldwide and digital technologies have increasingly been implemented in many different ways in the manufacturing sector. Despite the large number of theoretical investigations in this field, there is still a lack of clarity regarding the cost-benefit analysis of the adoption of digital technologies in manufacturing. In addition, the majority of the literature reviews published in the last years do not focus on real-life case studies of digital technologies implementation. This review makes a unique selection of 229 case studies and categorize them according to four main dimensions: the different types of applied digital technologies, their level of application within the industrial layout, the performance measurement of digital technologies and the economic benefit analysis of their implementation. Five new research directions emerge as a result of this work.

1. Introduction

Digital transformation was defined by Vial [1] as "a process that aims to improve an entity by triggering significant changes to its properties through combinations of information, computing, communication, and connectivity technologies".

The digital transformation is generating fundamental changes in the manufacturing sector: digital technologies enable the retrieval and analysis of data in real time and, above all, allow to connect machines and elements of the physical world, that can now communicate with each other; moreover, these technologies are being increasingly used to support humans, from strategic decision-making to assembly activities.

As a consequence of the digital transformation, manufacturing companies should be able to increase productivity and, at the same time, increase their responsiveness and adaptation ability to both demand and productive mix. As a result, manufacturing companies are pressured into adopting digital technologies in order to stay relevant and competitive and to better respond to external market forces. However, as highlighted by Ivanov et al. [2], there is still a lack of clarity regarding the real economic benefit of the implementation of digital technologies within industrial plants. Additionally, in the same study researchers and practitioners point out a scarcity of academic works that deal with operational and real-life aspects, such as performance measurement and cost-benefit analysis. According to the researchers' and practioners' opinion, the most appropriate methodology to address these topics is represented by case studies.

Industry 4.0 and digitalisation have already received a large degree of attention by the academic world. However, due to the vastness of the topics, the landscape of scientific research remains fragmented [3]. Consequently, a certain number of systematic literature reviews (SLRs) related to Industry 4.0 and digitalisation have started to appear, aiming to set in order the existing body of knowledge: e.g., the works of Serrano et al. [4], Mittal et al. [5] or Osterrieder et al. [6]. Many of the existing SLRs tend to focus on specific declinations or aspects of the Industry 4.0 paradigm: Winkelhaus and Grosse [7] examined the world of Logistics 4.0; Rosa et al. [8] conducted an in-depth study of the contributions dealing with the relation between Circular Economy and Industry 4.0; Zonta et al. [9] provided an overview of predictive maintenance initiatives within Industry 4.0 programs; Kadir et al. [10] studied the integration of human factors, ergonomics and Industry 4.0. In this context, how have SLRs been used to address the aspects highlighted by the findings of Ivanov et al. [2]? First of all, only two reviews followed an approach based on case studies: Liao et al., [11] and Zheng et al., [12]. [11] focused on mapping the technological implementation

* Corresponding author.
E-mail address: leonardo.maretto@phd.unipd.it (L. Maretto).

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through a keywords count and provided a brief and qualitative overview of laboratory and industrial applications of Industry 4.0 technologies. [12] limited the analysis to the effect of the adoption of digital technologies on manufacturing business processes, without performance or economic evaluation. Secondly, other review works attempted to collect different performance metrics and tried to link them with the application of Industry 4.0 and digital technologies. However, all these reviews focused on specific and limited sectors: Moeuf et al. [13] limited their research work only to case studies in SMEs, Prashar et al. [14] considered only contributions related to production scheduling, Coronado et al. [15] collected and classified a large number of metrics that were related to the evaluation of Human-Robot Interaction while Fatorchian and Kazemi [16] studied the impact of Industry 4.0 on the performance of the supply chain. Finally, to the best of our knowledge, no SLRs have surveyed elements of economic evaluation related to the adoption of digital technologies.

The findings of [2] and the aforementioned gaps that exists in the landscape of SLRs of digital technologies implementation represent the starting point of this research: the purpose of this paper, in fact, is to provide an overview on the real-life adoption of digital technologies within industrial plants, as shown by case studies produced by academic literature, as well as to understand how these case studies have been evaluated, both in terms of performance and economic viability. We aim to offer an overview on how the concepts of Industry 4.0 and digitalization have been translated into real-life case studies and how they have been evaluated by academic literature: the desired final result would be a collection of digital technologies adopted in real-life case studies alongside their level of penetration within the industrial layout, as well as a survey of the main Key Performance Indicators (KPIs) and economic indexes used to evaluate the performance and economic impact of these technologies. Finally, the results of Ivanov et al. [2] were obtained with a survey submitted at the 9th IFAC MIM 2019 Conference in Berlin: we want to confirm the perception, shared by a large number of researchers and practitioners, that academic literature has not devoted enough attention to the topics of performance measurement and economic benefit analysis in real-life cases of Industry 4.0 application. In essence, with this contribution we try to answer the following research questions:

1. Which digital technologies have been adopted in real-life case studies reported by academic literature and what is their layout level of application?
2. How have digital technologies been evaluated in terms of performance in real-life case studies?
3. How have digital technologies been evaluated in terms of economic benefit in real-life case studies?

To address these questions, a systematic literature review approach was adopted. 154 papers were selected from the published literature, containing a total of 229 real-life case studies of application of digital technologies in industrial plants or university laboratories. This work introduces elements of novelty both in the research approach and the addressed topics:

1. It is one of the very few works that provide an overview of real-life case studies of the adoption of digital technologies in the manufacturing world.
2. To the best of our knowledge, it is the first work to provide an overview of the layout level of adoption of digital technologies in real-life case studies.
3. To the best of our knowledge, it is the first work to provide an overview of KPIs used for the performance measurement of the adoption of digital technologies in real-life case studies, without limitation related to sector or setting.
4. To the best of our knowledge, it is the first work to provide an overview of economic evaluation indexes used for the economic assessment of the adoption of digital technologies in real-life case studies.

The paper is organized as follows: Section 2 presents a description of the terminology and the classifications that were adopted to survey the existing literature; Section 3 introduces the methodology of the systematic literature review; Section 4 presents the main bibliographic and descriptive results; Section 5 reports all the results related to digital technologies, both as single elements as well as groups; Section 6 collects results related to both performance measurement and economic evaluation; Section 7 explores the limitations of this work and presents new possible research directions emerging from the previous results; Section 8 concludes the paper with the usual closing remarks.

2. Preface and terminology description

This section provides a detailed description of the selection process for the classification of digital technologies and the classification of layout levels that were used as the basis for the research work.

2.1. Classification of digital technologies

Before presenting the methodology, it is fundamental to agree on which classification tool to use for the categorisation of the selected papers. In order to have a list of the technologies that are responsible for the digitalization process in the industrial and manufacturing sector, a decision was made to look within the extant literature for classifications of the enabling technologies of the Fourth Industrial Revolution. This approach can be justified since digitalization is listed among the technology-push approaches behind the development of Industry 4.0, according to Lasi et al. [17]. Basing the list on the existing Industry 4.0 classifications, however, is not as immediate as it may look: as shown by Culot et al. [18], the absence of a clear-cut definition of Industry 4.0 and the heterogeneity of the existing sources, generate a vast landscape of technological components, with different levels of detail. [18] can be considered a good starting point since it provides a methodological approach for the definition of Industry 4.0 and its constitutive elements while also presenting a clear categorization of the sources. [18] introduces two main groups of sources: academic and non-academic contributions. The latter group is additionally divided into other five categories: 1) country-specific sources; 2) intergovernmental sources; 3) consulting firms; 4) international-standard setting bodies; 5) multinational companies. Country-specific sources represent a particularly important reference since they are issued by administrative bodies who can shape the way in which the concept of Industry 4.0 is interpreted in a certain country. With regards to country-specific sources, another interesting contribution is provided by Radanliev et al. [19], which collected and reviewed the national Industry 4.0 initiatives of 11 countries. The country-specific documents that were analysed in the two previously mentioned works are shown in Table 1.

As it emerges from Table 1, each country has its own Industry 4.0 reference document. In many cases, a country has more than one Industry 4.0 program (USA, UK, Japan, France) with different reference documents. In other cases there can be different documents referring to the same program (China, USA, Germany). A common approach among these government initiatives is to tie the concept of Industry 4.0 to a predefined set or list of technologies, which are seen as integral to the definition of Industry 4.0 itself. For example, in UK's Made Smarter Review [20] 11 key technologies are identified: 1) Robotics and process control automation, 2) Industrial Internet of Things, 3) Additive Manufacturing, 4) Augmented and Virtual Reality, 5) Simulation, 6) Data and systems integration, 7) Big Data and Analytics, 8) Industrial Security, 9) Cognitive Computing and Artificial Intelligence, 10) Mobility and Wearables, 11) Cloud based platforms. The Italian Ministry of Economic Development introduced a similar list in a survey, the MISE Report [21], that is complementary to the national Industry 4.0 plan: 1)

Table 1
Classification of country-specific documents for Industry 4.0.

Country	Radanliev et al. [19]		Culot et al. [18]	
	Private or Public Program Name	**Source**	**Private or Public Program Name**	**Source**
Germany	Industrie 4.0	GTAI, [23]	Industrie 4.0	Kagermann et al., [24]
USA	AMP (Advanced Manufacturing Partnership)	NIST, [25]	Advanced Manufacturing	NIST, [25]
	Industrial Internet Consortium	IIC, [26]		
UK	Catapults	John, cited in [19]	Fourth Industrial Revolution	HM Government, [27]
	UK Digital Strategy	DCMS, [28]		
	Made Smarter Review 2017	Siemens, [20]		
Japan	Industrial Value Chain Initiative	IVI, [29]	Society 5.0	Prime Minister of Japan and His Cabinet, [30]
	New Robot Strategy (NRS)	METI, [31]		
	Robot Revolution Initiative (RRI)	METIJ, [32]		
France	New Industrial France or Nouvelle France Industrielle (NFI)	NIF, [33]	Factories of the Future	Usine du Future, [22]
Netherlands	Smart Industry or Factories of the Future 4.0	Bouws et al. [34]	-	-
Belgium	Made Different	Sirris and Agoria, [35]	-	-
Spain	Industria Conectada 4.0	MEICA, [36]	-	-
Italy	Fabbrica Intelligente	MIUR, [37]	Piano Nazionale Industria 4.0	MISE, [38]
China	Made in China 2025	SCPRC, [39]	Made in China 2025	State Council of China, [40]
Russia	National Technology Initiative (NTI)	ASI, [41]	-	-
Korea	-	-	Manufacturing 3.0	MOTIE, [42]

Advanced Manufacturing Solutions (interconnected and collaborative robots), 2) Additive Manufacturing (AM), 3) Augmented Reality (AR), 4) Simulation, 5) Smart materials and nanotechnology, 6) Industrial Internet of Things, 7) Horizontal Integration, 8) Vertical Integration, 9) Cloud, 10) Big Data/Analytics, 11) Cyber Security. With regards to France, in Usine du Future [22], the enabling technologies are divided into two groups: the first one is transversal and collects all the technologies that enable the connection and integration of the technologies of the second group. The first group is composed of: 1) Modelling and Simulation, 2) Software for a digital factory, 3) Interfaces and protocols for systems communication, 4) Cybersecurity, 5) Internet of Things, 6) Cloud Computing and 7) Big Data; the second group is composed of: 1) Additive Manufacturing, 2) Flexibility of Conventional Production Processes, 3) Surface Functionalization, 4) Intelligent machines and tools, 5) Collaborative robots, 6) New materials and composites, 7) Innovative welding processes, 8) Sensors and actuators and 9) Control, surveillance and traceability.

With regards to the non-academic sources, the contributions of consulting firms also deserve a mention. Rüßmann et al. [43] developed a highly influential work for the Boston Consulting Group. This work, that has more than 800 citations on Scopus, introduced nine building blocks of Industry 4.0, which support its implementation: 1) Advanced Manufacturing Solutions, 2) Additive Manufacturing, 3) Augmented Reality, 4) Simulation, 5) Horizontal/Vertical Integration, 6) Industrial Internet, 7) Cloud, 8) Cyber-security, and 9) Big Data and Analytics.

As pointed out by Cohen et al. [44], compared to governments and practitioners, academic literature shows a different approach to the definition of the enabling technologies of Industry 4.0. Going back to the German definition of Industry 4.0, coming from the country that introduced the term for the first time, it appears that there are no predefined long lists of technologies which establish a clear-cut boundary between what is I4.0 and what is not: the emphasis is put instead on the connection and networking of different elements along the industrial value chain as well as on the technological components that empower the connection. In the seminal work of Kagermann et al. [24], drafted for the German National Academy of Science and Engineering, Industry 4.0 is defined as the technological evolution that involves the technical integration of Cyber-Physical Systems (CPS) into manufacturing and logistics and the use of the Internet of Things and Services, which networks resources, information, objects, and people, in industrial processes. Germany Trade & Invest, GTAI [23], defined Industry 4.0 as a technological evolution from embedded systems to cyber-physical systems. Put simply, Industry 4.0 represents the coming fourth industrial revolution on the way to an Internet of Things, Data and Services. This approach to the definition of Industry 4.0 is shared by some of the most cited academic works on the topic. Hermann et al. [45] presented Industry 4.0 as the Fourth Industrial Revolution, which is characterized by a paradigm shift from centrally controlled to decentralized production processes. Moreover, I4.0 is based on three key components: IoT, CPS and Smart Factories. Lu [46] introduced a definition of Industry 4.0 derived from the literature: it is as an integrated, adapted, optimized, service-oriented, and interoperable manufacturing process which is correlated with algorithms, big data and high technologies. The author then expanded on these high technologies, defining a set of techs that are behind the I4.0 revolution: mobile computing, cloud computing, big data and the Internet of Things (IoT). Xu et al. [47] defined the Fourth Industrial Revolution as the integration of the worlds of production and network connectivity through IoT and CPS. The authors also clarified the difference between the Third and Fourth Industrial Revolution: although the former is also focused on the automation of machines and processes, the latter is more directed to the end-to-end digitalization and the integration of the digital industrial ecosystems by seeking completely integrated solutions. Collecting contributes from the literature, it is also stated that Industry 4.0 is mainly represented by CPS, IoT and cloud computing, while also relying on business process management (BPM) and smart devices.

In summary, the two main groups of sources, academic and non-academic, seem to adopt two different approaches to the definition of the technologies that are part of the Industry 4.0 framework:

1. Listing technologies with no specific distinction within the list. This approach is usually preferred by government initiatives and practitioners.
2. Defining a set of enabling technologies that empower the implementation of Industry 4.0 through the connection of all the elements involved in the industrial process, which is seen as the core of the Fourth Industrial Revolution. These core baseline technologies enable the adoption and full exploitation of other digital technologies. The enabling technologies are often listed alongside others, but with no differentiation, in the previous approach.

Two examples of the combination of these two approaches are represented by the already cited [22] and the work of Cohen et al. [44]. In the latter, Industry 4.0 is defined as the comprehensive transformation of the entire industrial production through the merging of Internet, and information and communication technologies with traditional manufacturing processes. According to [44], Industry 4.0 is enabled by 6 different technologies: 1) IoT, 2) Vision systems, 3) Ubiquitous computing, 4) Cloud computing, 5) CPS, 6) ICT Enterprise architecture and application integration. Moreover, the authors provided a second list of technologies, in addition to the previous one, which includes all the technologies that have more recently made their way into the assembly line shop floor, allowing to develop the assembly declination of Industry 4.0, "Assembly 4.0″: 1) 3D Printing, 2) Augmented Reality (AR), 3) Cobots, 4) Autonomous mobile material handling vehicles, 5) Self Awareness of sensors, parts, machines and systems. The technologies of the first list lay out the basis for the successful development of the technologies of the second list.

An even more structured example is provided by Frank et al. [48]. Industry 4.0 technologies are separated in two layers, according to their main objective: the lower level, or "base technologies", enables the Industry 4.0 revolution, differentiating it from previous industrial stages, and includes technologies that provide connectivity and intelligence to the upper level. The "base technologies" are: 1) Internet of Things, 2) Cloud services, 3) Big Data and 4) Analytics. The upper level is represented by the so-called "front-end technologies". This name comes from the fact that the four dimensions that are enabled by these technologies are concerned with operational and market needs. These dimensions are characterized by the word Smart and each one of them represents a specific subset of technologies:

1. Smart Manufacturing. It includes technologies that have an impact on the production system, which means on how the products are processed. Within Smart Manufacturing there is another intermediate level, called "Categories", that groups together similar technologies that respond to the same purpose.

a. Vertical Integration: 1) Sensors, actuators and Programmable Logic Controllers (PLC), 2) Supervisory Control and Data Acquisition (SCADA), 3) Manufacturing Execution System (MES), 4) Enterprise Resource Planning (ERP), 5) Machine-to-machine communication (M2Ma).
b. Virtualization: 6) Virtual commissioning, 7) Simulation of processes (e.g., digital manufacturing), 8) Artificial Intelligence for predictive maintenance, 9) Artificial Intelligence for planning of production.
c. Automation: 10) Machine-to-machine communication (M2Mb), 11) Robots (e.g., Industrial Robots, Autonomous Guided Vehicles, or similar), 12) Automatic nonconformities identification in production.
d. Traceability: 13) Identification and traceability of raw materials, 14) Identification and traceability of final products.
e. Flexibility: 15) Additive manufacturing, 16) Flexible and autonomous lines.
f. Energy Management: 17) Energy efficiency monitoring system, 18) Energy efficiency improving system.

2. Smart Products. It includes technologies related to how the products are offered: product's connectivity, product's monitoring, product's control, product's optimization and product's autonomy.
3. Smart Working. It includes emerging technologies that aid workers in their activities: 19) Remote monitoring of production, 20) Remote operation of production, 21) Augmented reality (AR) for maintenance, 22) Virtual reality (VR) for workers training, 23) Augmented and virtual reality (A&VR) for product development, 24) Collaborative robots.
4. Smart Supply Chain. It includes technologies that improve the way raw materials and finished products are offered: 25) Digital platforms with suppliers, 26) Digital platforms with customers, 27) Digital platforms with other company units.

For a detailed description of each technology, we redirect the reader to the original publication. This is the classification that was adopted for this research work, because of the following reasons: 1) it is one of the most cited papers on Industry 4.0, being in the 99th percentile in Scopus with more than 800 citations 2) it is rather wide and comprehensive, listing up to 36 different digital technologies (having a wide range of classified technologies permits to classify existing case studies more directly and with less room for interpretation); 3) it is a combination of the two described approaches to the definition of Industry 4.0 technologies. Moreover, the "front-end" technologies are not simply listed but they are divided into groups according to their similarity and purpose. This can help to better visualize the connections and relations between different sets of technologies. Moreover, a decision was made not to include the technologies belonging to the group "Smart Products" since the focus of this work is exclusively on the digitalization of industrial plants. Therefore, technologies related to the digitalisation of the products were not considered. This reduced the available technologies for the classification of the papers to 27: in the list above, the selected technologies are numbered from 1 to 27.

2.2. Classification of facility layout levels

The analysis of the layout level of application is based on the classification proposed by Peron et al. [49] with regards to facility layout planning. The layout of an industrial system can be divided into three different levels: plant (or macro), department, and workstation (or micro). The plant (or macro) level is meant as the layout level where the location, size and shape of each department is defined. The department level details the location of all the equipment within each department. Finally, the workstation level comprehends the detailed arrangement of tools, parts, bins etc. in each workstation. Additionally, a fourth level was added to this classification: inter-plant. This allows to examine the application of digital technologies along the supply chain and outside the boundaries of a single plant.

3. Methodology

The first research trials resulted in a very large number of papers that dealt with the implementation of Industry 4.0 and digitalisation within industrial plants: the number of contributions was considered too high to be handled in reasonable time. In order to select only the most relevant research outputs in a systematic way, a decision was made to follow the methodology adopted by Andriolo et al. [50]: this methodology introduces an ingenious approach based on a Pareto analysis of the citation count to select a relevant sample of the literature. The original methodology was adjusted in order to fit the current research needs: the overall research procedure is summarised in Table 2.

The literature search was conducted using Scopus database in March 2023. With regards to the years selection, only papers from 2015 onwards were considered: it is 4 years after the first introduction of the term Industry 4.0 at the Hannover Messe in 2011 and respectively 2 and 1 year after the publication of two of the main sources for I4.0 definition, [24] and [23], which formalized the concept in official documents. In this way it is possible to exclude papers that do not have enough degree of maturity because they were developed and published before a formal definition of the Fourth Industrial Revolution. After that, the remaining years were split in two time periods: 2015–2021 and 2022. The first time period was further divided in two timeframes: 2015–2018 and 2019–2021. These two timeframes then saw the application of the Pareto-analysis-based approach, described in detail in Section 3.1. The additional split of the 2015–2021 time period was done in order to adopt slightly different Pareto-based exclusion criteria for the two timeframes (since the number of papers in the 2019–2021 interval is more than three times the number of papers in the 2015–2018 interval) and to reduce the influence of the works of the first timeframe on the overall number of citations (if a strategy with only one time interval going from 2015 to 2021 was adopted, the older papers would be overrepresented

Table 2
Review methodology and resulting papers and case studies.

Step	Keywords	Years	Selection Criteria	Selection Criteria	Papers Found
1	("industry 4.0" OR digitalisation OR digitalization OR "I4.0" OR "smart factory" OR "smart manufacturing") AND ("application" OR "case stud*" OR "laboratory" OR "real-life") AND NOT (survey OR "literary review" OR "literature review" OR review OR "state of the art") IN TITLE, ABSTRACT, KEYWORDS				15007
2		2015–2018			2485
3			■ Subject Area: ENGI, COMP, BUSI, DECI ■ Document Type: Article ■ Source Type: Journal ■ Language: English		533
4			Citation number: papers contributing to 80% of total citations		132
5				Content Analysis Crit. a), b)	**46**
6	("industry 4.0" OR digitalisation OR digitalization OR "I4.0" OR "smart factory" OR "smart manufacturing") AND ("application" OR "case study" OR "laboratory" OR "real-life") AND NOT (survey OR "literary review" OR "literature review" OR review OR "state of the art") IN TITLE, ABSTRACT, KEYWORDS				15007
7		2019–2021			7934
8			■ Subject Area: ENGI, COMP, BUSI, DECI ■ Document Type: Article ■ Source Type: Journal ■ Language: English		2017
9			Citation number: papers contributing to 60% of total citations		298
10				Content Analysis Crit. a), b)	**83**
11	(“industry 4.0″ OR digitalisation OR digitalization OR “I4.0″ OR “smart factory” OR “smart manufacturing”) AND (“application” OR “case study” OR “laboratory” OR “real-life”) AND NOT (survey OR “literary review” OR “literature review” OR review OR “state of the art”) IN TITLE AND KEYWORDS	2022	■ Subject Area: ENGI, COMP, BUSI, DECI ■ Document Type: Article ■ Source Type: Journal ■ Language: English		264
12				Content Analysis Crit. a), b), c)	**25**
Total papers 2015–2022					**154**
Total case studies 2015–2022					**229**

in the Pareto distribution of the number of citations). Conversely, the Pareto-analysis-based approach could not be applied to the papers published in 2022. Therefore, a different methodology was followed (described in Section 3.2). 2463 papers were found in the timeframe between 2015 and 2018, while 7744 were found in the interval 2019–2022.

3.1. Pareto analysis for the timeframes 2015–2018 and 2019–2021

The literature search started by searching the following set of keywords within title, abstract and keywords: ("industry 4.0" OR digitalisation OR digitalization OR "I4.0" OR "smart factory" OR "smart manufacturing") AND ("application" OR "case stud*" OR "laboratory" OR "real-life") AND NOT (survey OR "literary review" OR "literature review" OR review OR "state of the art"). In particular, the keywords “application", "case stud* ", "laboratory" and "real-life" were adopted because the aim of the paper is to focus exclusively on case studies of real-life applications of digital technologies. This was reinforced by excluding from the results anything that contained the keywords ”survey”, “literary review”, “literature review”, “review” and “state of the art”. Moreover, to categorise the papers using the classification introduced in Section 2.1, a detailed description of the case study is required: due to a simple matter of space, reviews and surveys were considered unsuitable to contain detailed descriptions of real-life case studies. The adopted search string yielded a total of 15007 papers.

The subsequent filtering through the two timeframes yielded the following results: 2485 papers were found in the timeframe between 2015 and 2018 while 7934 were found in the timeframe 2019–2021.

The results were further limited to the following subject areas: Engineering, Computer Science, Business, Management and Accounting and Decision Sciences. It was also decided to limit the results only to scientific articles published in journals in English, thereby excluding conference papers, articles in press etc. This was done in order to keep only the case studies that were reported with the highest methodological rigour. The selection criteria were the same for both time intervals. The results of this filtering process were 533 papers for 2015–2018 and 2017 for 2019–2021.

To consider the most relevant works, only the papers that represented a specific share of the total number of citations were selected with a Pareto analysis: selecting the most cited contributions allowed to focus on the most influential set of literature, the one that most likely shaped the way in which the implementation of digital technologies in industrial plants has been interpreted by the academic world. For the time interval 2015–2018 132 papers were selected, representing 80% of the total citation count, as shown in Fig. 1. For 2019–2021, selecting the papers contributing to 80% of the total number of citations would have resulted in 639 results, a number which was considered too high to be handled in reasonable time. Therefore, the citation threshold was reduced to 60%, resulting in a total of 298 papers (shown in Fig. 2).

Finally, in the last step of the selection process, the resulting papers were carefully examined through a content analysis, starting from title, abstract, introduction, conclusions and specific case study section. Two exclusion criteria were applied:

a) Exclude all papers that do not describe case studies of actual real-life application of digital technologies in the industrial and

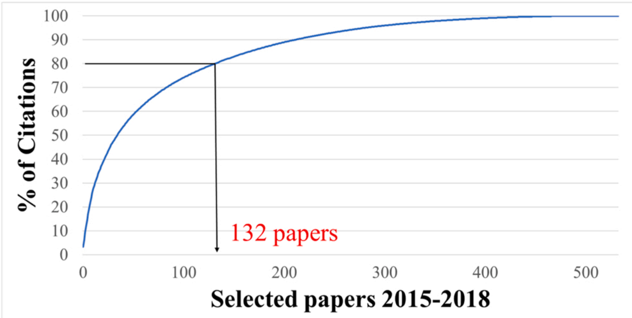

Fig. 1. Pareto analysis of the 533 papers selected for 2015–2018.

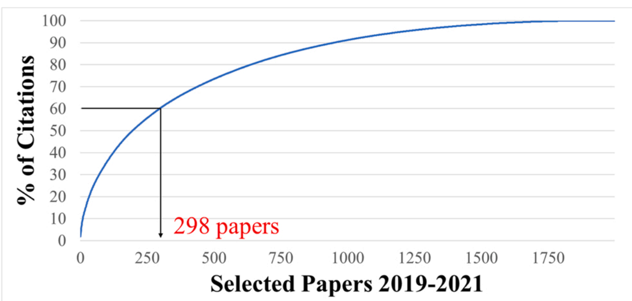

Fig. 2. Pareto analysis of the 2017 papers selected for 2019–2021.

manufacturing sector or in university laboratories. Therefore, case studies describing applications of digital technologies in hospitals, in the construction sector etc. were excluded. In order to select only real and not simulated case studies, a set of specific clues was looked for such as the name of the company or the university laboratory where the implementation was conducted, pictures of the equipment, etc. Finally, the last step consists in the exclusion of all the papers that focused exclusively on the technology itself rather than focusing on the effect of the technology on the industrial setting.

b) Exclude all papers in which the case studies are not detailed enough. To be classified as "detailed enough" a case study must have the two following characteristics:
   i. It must report at least one of the digital technologies listed in the classification proposed by [48].
   ii. The applied technologies must be associated to an explicitly mentioned layout level of application or to a specific productive/manufacturing process. In case this is not verified, in order to be selected the case study must include at least two digital technologies and the paper must clearly mention the name of the company (and the respective productive sector) or the laboratory where the study was developed.

After the content analysis, the final paper count is 46 for the 2015–2018 interval and 83 for 2019–21.

3.2. Research approach for 2022

A different methodology had to be adopted for the selection of the papers published in 2022. Searching with the original search key within title, abstract and keywords and filtering for year (2022), subject area, document type, source type and language yielded a remarkable number of results: 1217. It is almost a 36% increase with respect to the results for 2021, as shown in Fig. 3. This result is a testament to the increasing research attention towards the adoption of digital technologies. However, it represents a problem from a methodological point of view. As a matter of fact, it is not possible to conduct a Pareto analysis on the citation count in order to limit the number of contributions: the papers are too recent, they did not have time to accumulate enough citations to be relevant and the selected works would be significantly skewed in favour of open access publications. For this reason, a different methodology was adopted: the original search key was researched only within title and keywords, in order to select the papers that are more explicitly aimed at reporting real-life case studies of the adoption of digital technologies. This procedure yielded a more manageable number of articles: 264. Finally, these results went through a thorough content analysis. The adopted exclusion criteria were a), b) (already introduced in Section 3.1) and (c), an additional criterion related to journal relevance:

c) Exclude all papers published in journals that have an Impact Factor lower than 1, as proposed by Zheng et al. [12].

After the content analysis, the final paper count for 2022 is 25.

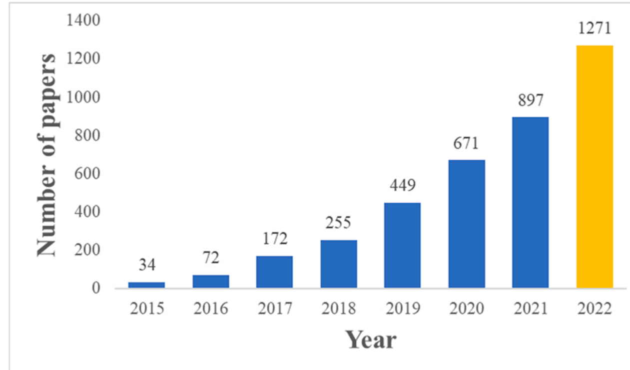

Fig. 3. Number of papers per year after filtering the results of the search key through subject area, document type, source type and language.

3.3. Final results of the literature search procedure

The final paper count is 46 for 2015–2018, 83 for 2019–2021 and 25 for 2022, a total of 154 selected papers. Since multiple papers report more than one case study, the final number of collected case studies is 229.

4. Bibliographical and descriptive results

Fig. 4 shows the distribution of the selected papers over the years. It is possible to recognise an ascending trend until 2020. The reduction in the number of papers in 2021 can be explained with the fact that more recently published papers did not have time to collect enough citations to be included in the 60% Pareto threshold. The number of papers in

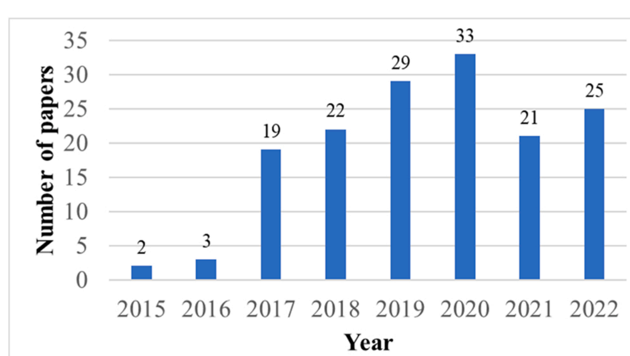

Fig. 4. Distribution of the 154 selected papers over the years.

2022 is a consequence of the different adopted methodology, as explained in Section 3.

Table 3 lists the journals where the selected papers were published. The top three journals are: Journal of Manufacturing Systems (17 papers), International Journal of Advanced Manufacturing Technology (12 papers) and International Journal of Production Research (11 papers). It appears that the main case studies of digital technologies implementation in industrial plants are somewhat dispersed across literature (58 total journals), with no big clusters of publications.

It has already been mentioned that the digitalisation of industrial plants is a process that is also guided by Industry 4.0 national plans so it can be interesting to look at the geographical distribution of the authorship of the studies. Table 4 lists the most represented countries in terms of the nationality of the researchers that contributed to the development of the case studies. Fig. 5 represents the number of authors for each country with different shades of colour. Five countries (China, Italy, Spain, United States of America and Germany) make up almost 60% of the total number of authors, indicating a particular attention of the Chinese, Italian, Spanish, American and German academic world towards the study of real-life applications of digital technologies.

The selected case studies were also classified according to the specific environment in which they were developed. Fig. 6 distinguishes between laboratory/university environment and industrial environment: it appears that scientific literature focused significantly more on case studies set in an industrial environment, with 162 instances. However, the number of studies conducted and developed in a university or research laboratory is still relevant, with up to 49 reported cases. In 17 cases it was not possible to discern whether the study was conducted in a company or in a research laboratory.

The case studies were further classified according to their specific productive or research sector. The numbers are reported in Fig. 7. A university laboratory was the main setting for a real-life Industry 4.0 or digitalization case study, with 39 occurrences. Other non-industrial case studies were set in a generic research laboratory (9 cases) and in a model factory (1 case). In terms of industrial case studies, the most represented sector is automotive and its supply chain, with 26 analysed cases: it is not a surprising result, since automotive is often seen as one of the driving sectors of the industrial and manufacturing world. Other highly frequent sectors are Mechanical Parts Manufacturing (19 cases), Electronics (13 cases) and Food and Beverage (10 cases). In general, there is a rather wide array of diverse industrial sectors, ranging from Jewellery Manufacturing [51] to Biomedical ([52–54]) or Furniture Manufacturing ([51, 54, 55]). The classification of the research and productive sectors was derived from the description of the case studies provided in each paper and later finalized after four rounds of simple coding.

Table 3
List of journals that published the 154 selected papers.

Source title	Frequency
Journal of Manufacturing Systems	17
International Journal of Advanced Manufacturing Technology	12
International Journal of Production Research	11
Computers in Industry	10
Robotics and Computer-Integrated Manufacturing	8
IEEE Access	7
Sensors (Switzerland)	6
Journal of Cleaner Production	6
Computers and Industrial Engineering	5
IEEE Transactions on Industrial Informatics	4
International Journal of Computer Integrated Manufacturing	4
International Journal of Production Economics	3
Advanced Engineering Informatics	3
Journal of Ambient Intelligence and Humanized Computing	3
Engineering	3
Production Planning and Control	3
Sustainability (Switzerland)	3
5 journals	2
36 journals	1

Table 4
Nationality of the researchers who authored the selected case studies.

Country	Frequency
China	148
Italy	99
Spain	45
United States	43
Germany	32
Greece	26
South Korea	22
Sweden	19
India	18
Portugal	17
United Kingdom	17

5. Technology application and layout

In this section, the digital technologies adopted in the 229 selected case studies are categorised according to the classification proposed by [48]. The frequency of each technology is analysed first. Then, the analysis of the layout penetration of each technology is presented. Finally, the section concludes with a clustering of the adopted digital technologies, based on their co-occurrence in the same case study.

5.1. Digital technologies frequency

First of all, the single technologies were analysed according to their frequency (the number of case studies in which a technology is present), as shown in Table 5. Since the average frequency is around 32, the technologies were first separated in two main groups: above and below average. Then, two other categories were created in order to better represent the level of research attention.

The first category is called “Research-Leading Technologies” since it comprises the 5 most frequent technologies. How to interpret this result? If a technology belongs this top 5, it does not mean that it is one of the most researched digital technologies in general. It means that the digital technology in question was implemented very frequently in the most cited case studies, produced by academic literature, which were focused on digital technologies implementation in industrial plants. Therefore, it is possible to state that the single digital technology that was most frequently applied in real-life cases of Industry 4.0 implementation is represented by PLC, sensors and actuators, with 86 instances (more than 1/3 of the total number of case studies). This should not be a surprising result, since sensorisation (the introduction within industrial plants of sensors that are able to extract and elaborate vast amount of data) is at the basis of the concept of Industry 4.0 and smart manufacturing [56].

The second most represented technology, with 84 instances, is the remote monitoring of production. For example, Chen et al. [57] developed a smart packing production line, that was completed, at the terminal layer of the smart factory architecture, by a set of devices which enabled the visualization of the results of the cloud processing and the monitoring of the real-time state of the production. Tao and Qi [58] developed their case study in a dairy company producing buffalo milk: through the combination of automation equipment and IoT, the status data of the entire production process is collected, allowing the real-time monitoring of operating data and the identification of bottlenecks in production and other disturbances, prompting an immediate reaction in the production scheduling. Stark et al. [59] created a smart factory cell, coupled with a digital production twin, which includes a pick-and-place robot, a milling machine and a manual assembly area: every step of the manufacturing process is monitored and recorded, which not only allows to control production from remote but also to simulate parts of the process in real-time. The prominence of remote monitoring of

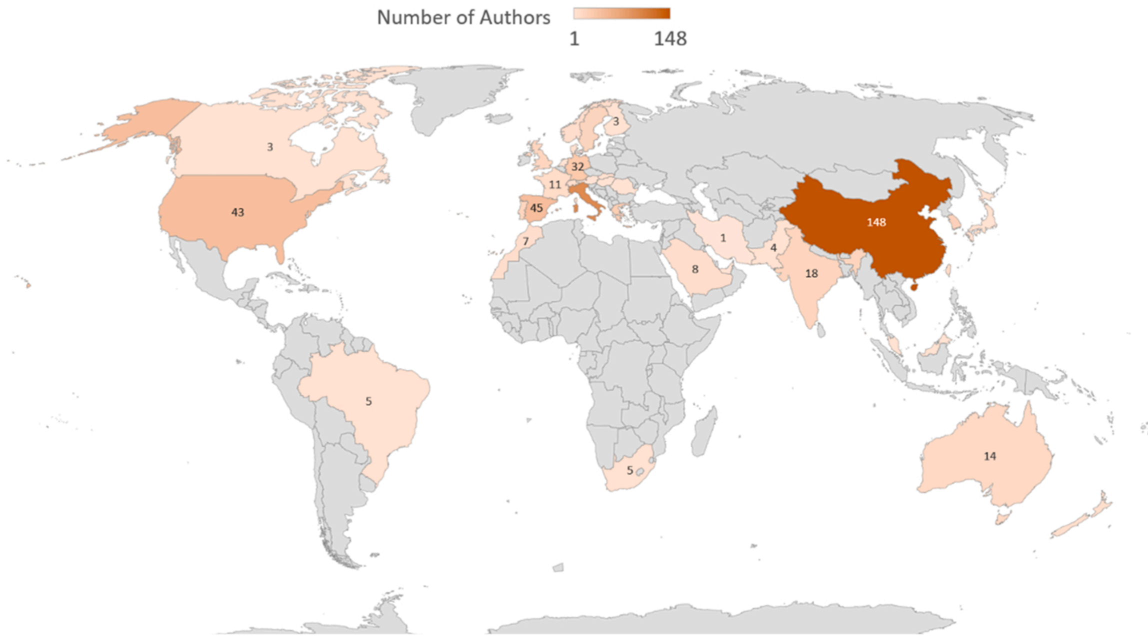

Fig. 5. World map that uses different shades of colour to represent the number of researchers per country that contributed to the development of the case studies. The numbers that were used to draw the map are the ones listed in Table 4.

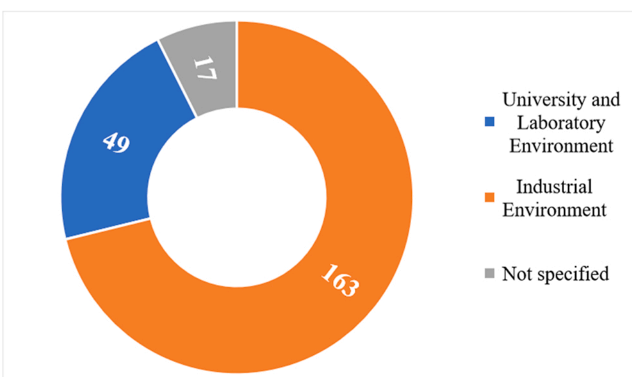

Fig. 6. Setting of the 229 selected case studies.

production, which collects information from the plant and makes it available for reading and interpretation, is a testament to the enduring centrality of the human role, even in a highly technological and automated manufacturing process. The destination of the data collection and elaboration process, in fact, is still human decision-making. The third place in the frequency ranking is occupied by Industrial Robots. This result might be explained with the fact that robotization was already one of the trends of the Third Industrial Revolution, hence the diffusion of the technology at an advanced level of application. In most cases, [60, 61, 62] or [63], robots are traditional handlers, manipulators, pick-and-place robots and AGVs and the research effort is focused on their connection with other elements of the plant. The work of Fernàndez-Caramés et al. [64] is an interesting contribution that does not follow the previous trend. In this study, UAVs (Unmanned Aerial Vehicles) were used to perform inventory in a warehouse, by in-flight scanning RFID tags on a wide variety of items. The other two Research-Leading Technologies, almost tied at 67 and 66 cases, are Traceability of raw materials and ERP, respectively. It is worth considering that all but one of the case studies that included the ERP technology came from the industrial world. The reason could be found in the high implementation cost of this technology, which can be prohibitive for an educational institution. As a matter of fact, the only exception to this trend is represented by the work of Mantravadi et al. [65]: in order to study the interaction between cyber-physical production systems and mass customization at the Aalborg University's Smart Production Lab, the authors adopted Odoo, an open-source enterprise software which can fulfil the role of an ERP.

Four technologies are part of the "Highly Researched" category: Traceability of final products (58), Simulation of processes (54), MES (52), and Automatic nonconformities identification (44). With regards to the application setting, MES and ERP follow a similar pattern: 47 out of 52 application cases are set in an industrial environment. The cases in which the MES software was applied in a university laboratory are only five: Schluse et al. [61]; Urbina Coronado et al. [66]; Negri et al. [67]; the aforementioned work of Mantravadi et al. [65]; Kahveci et al. [68]. In [66] the study was implemented at the Advanced Manufacturing Pilot Facility (AMPF) of the Georgia Institute of Technology. [67] integrated MES with a digital twin and tested its implementation at the Industry 4.0 Laboratory of the School of Management of the Politecnico di Milano. [68] reproduced a battery module assembly system at WMG, University of Warwick, using MES to coordinate AGVs movements.

Artificial Intelligence is listed at the top of the third category: Researched and Under-Researched Technologies. The main field of real-life application of AI within industrial and manufacturing plants is predictive maintenance, with 28 cases (e.g., Li et al. [69]). The application of AI to production planning appears less often, with 21 cases (e.g., Stricker et al. [70], Wang et al. [71]). Additive Manufacturing and Augmented Reality for Maintenance also show a slightly below average number of case studies. Real-life applications of Augmented Reality for Maintenance are split almost equally between industrial and research settings, with 13 and 11 cases, respectively (and an additional non-specified case). Additive Manufacturing, on the other hand, was investigated by scientific literature mainly in industrial case studies: only three cases ([60] [62] and [72]) studied the real-life implementation of Additive Manufacturing from a digitalization perspective within a university laboratory. Other technologies that belong to the Researched and Under-Researched category are Energy efficiency monitoring systems (24 cases); Digital platform with customers (24 cases) and with suppliers (22 cases); Cobots (19 cases); Flexible and autonomous lines (18 cases). Cobots are another emerging technology that has been understudied in terms of its real-life application in a

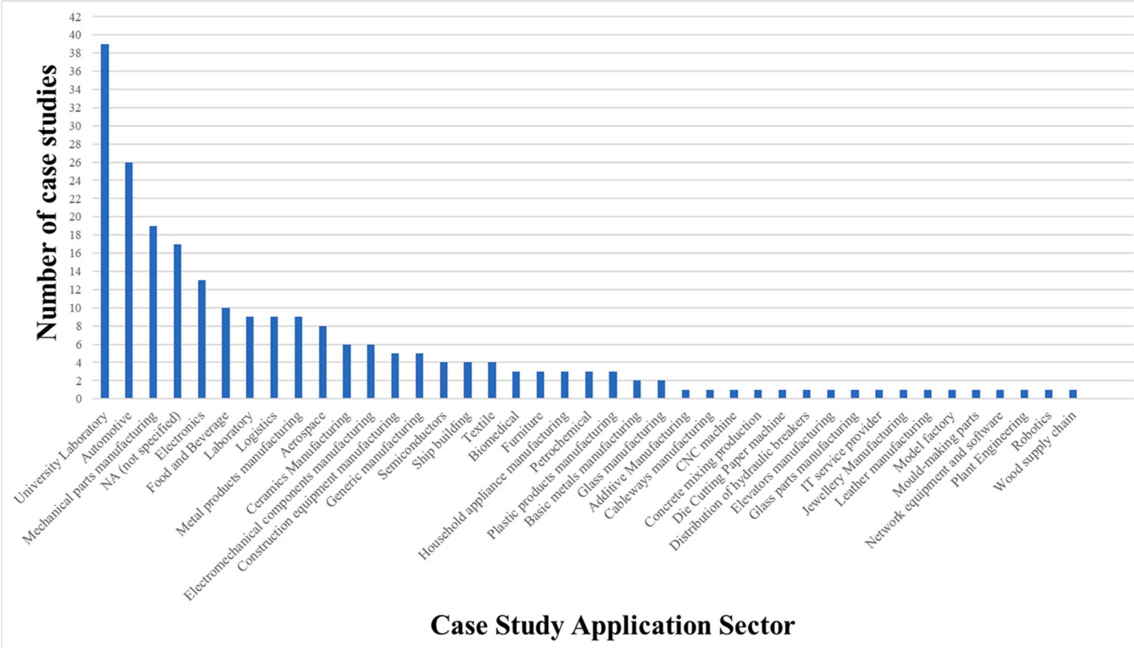

Fig. 7. Classification of the research or industrial sector of the 229 case studies of implementation of digital technologies.

Table 5
Frequency of digital technologies in industrial and laboratory case studies.

Technology	Technology Dimension	Frequency	Research Category
1. PLC, sensors and actuators	Vertical Integration	86	Research-Leading Technologies
19. Remote monitoring of prod.	Smart Working	84	
11. Robots	Automation	74	
13. Traceability of raw materials	Traceability	67	
4. ERP	Vertical Integration	66	
14. Traceability of final products	Traceability	58	Highly Researched Technologies
7. Simulation of processes	Virtualization	54	
3. MES	Vertical Integration	52	
12. Aut. nonconf. identification	Automation	44	
8. AI for predictive maintenance	Virtualization	28	Researched and Under-Researched Technologies
15. Additive Manufacturing	Flexibility	27	
21. AR for maintenance	Smart Working	25	
17. Energy eff. Monitoring syst.	Energy Management	24	
26. Digital plat. with customers	Smart Supply Chain	24	
25. Digital plat. with suppliers	Smart Supply Chain	22	
9. AI for planning of production	Virtualization	21	
24. Cobots	Smart Working	19	
16. Flex. and aut. lines	Flexibility	18	
2. SCADA	Vertical Integration	15	Highly Under-Researched Technologies
27. Dig. plat. with company units	Smart Supply Chain	15	
5. M2Ma	Vertical Integration	12	
20. Remote operation of prod.	Smart Working	12	
6. Virtual Commissioning	Virtualization	11	
10. M2Mb	Automation	11	
22. VR for workers training	Smart Working	10	
18. Energy eff. Improving syst.	Energy Management	6	
23. A&VR for prod. development	Smart Working	6	

digitalization context within manufacturing plants. It is noteworthy that the majority of the selected case studies including cobots were conceptualized and developed in Italy (13 out of 19 case studies).

The last category, Highly Under-Researched Technologies, comprises all the technologies that were present at maximum in 15 case studies. SCADA appeared exactly in 15 instances and was always coupled with either a PLC or an MES system. Digital platforms with other company units were adopted in fewer case studies (15) in comparison with the other kinds of digital platforms. In a similar way, the remote operation of production, as seen in Adamson et al. [73], Liu et al. [74] or Amjad et al. [75], was implemented in far less case studies than its close relative in the technological dimension of Smart Working, the remote monitoring of production. (12 v. 84). This might be explained with the additional complexity that is brought by an infrastructure that not only monitors production from remote but is also able to control it. Machine-to-Machine communication was adopted in 23 cases, 12 times for Vertical Integration purposes and 11 times from an Automation perspective. Virtual Commissioning also appeared 11 times, and in two case studies it was applied alongside one single technology: Guo et al. [76], where Virtual Commissioning and the Simulation of Processes contributed to the design of the new layout of a Chinese paper cup factory, and Dammacco et al. [77], that adopted Virtual Commissioning and Virtual reality to design and commission the production line of the electronic axle of heavy-duty vehicles. Virtual Reality appeared in real-life case studies only 16 times in total, 10 times as a support system for workers training and 6 times as a tool to re-design a specific machine or process. For example, VR was used to re-design a woodworking processing centre in Peruzzini and Pellicciari [78] or the assembly process of a tractor at CNH Industrial in Peruzzini et al. [79]. Finally, systems that are able to not only monitor energy efficiency but also to improve it, such as in Majeed et al. [80] and Ma et al. [81], were recorded in only 6 cases.

As shown by Benitez et al. [82], Tortorella and Fettermann [83] and Tortorella et al. [84], the real value-added of digitalisation and Industry 4.0 does not lie exclusively in the application of a specific set of technologies but also in the interconnection of those technologies alongside different resources within an industrial plant. One way to reflect on this topic is to look at the frequencies of the Technology Dimensions of the classification of Frank et al. [48]. The Technology Dimensions are an attempt to group similar technologies according to their purpose. The first technology dimension, Smart Manufacturing, is divided into six sub-categories, which are directly related to the purpose of the technologies. It was decided to consider those six sub-categories at the same level of the other two remaining Technology Dimensions, in order to increase the granularity of the data. The results of this evaluation are collected in Table 6.

The “Frequency” column of Table 6 reports the total number of instances in which a technology belonging to a certain Dimension was adopted in the recorded case studies. It appears that the most researched category is Vertical Integration, with 231 occurrences, followed at a distance by Smart Working with 156 instances. It is worth considering that Vertical Integration is a sub-category of Smart Manufacturing while Smart Working was classified as a Dimension by itself. Moreover, more than half of the occurrences recorded for Smart Working are related to a single technology, the Remote monitoring of production, as shown in Table 5. Automation, Traceability and Virtualization were sufficiently investigated by academic literature in terms of real-life applications, with 129, 125 and 115 instances, respectively. The last three categories, Smart Supply Chain, Flexibility and Energy Management, appear to be partly neglected in terms of real-life case studies.

However, since the categories include different number of technologies, it could be interesting to also look at the “relative” frequency. To this purpose, the relative frequency was defined as the ratio between the absolute frequency and the total number of available case studies for a certain Technology Dimension. The number of available case studies is calculated by multiplying the number of technologies of a single category by the total number of selected case studies (229). For example, Vertical Integration includes 5 technologies. Therefore, the total number of available case studies amounts to $229 \times 5 = 1145$, as shown in the column “Total Cases” of Table 6. The “Relative Frequency” column of Table 6 shows that Traceability (with 125 occurrences out of 458 total available cases) is in fact the most frequently adopted Technology Dimension in relative terms, followed by Vertical Integration. Smart Working, which was in second place in absolute terms, drops to the fifth place. Automation keeps its rank while Virtualization climbs to the fourth place. Looking at the under-researched dimensions, Flexibility and Smart Supply Chain exchange position while Energy Management remains under-researched even in relative terms.

5.2. Technologies, layout and connectivity level

This section examines how different layout levels were impacted by the application of digital technologies and their respective connectivity levels.

The layout levels have already been described in Section 2.3. The current section aims to count how many times each technology was applied or described at each level of the industrial layout. A paradigmatic example for each layout level is provided below:

- Workstation Level. Bruno and Antonelli [85] developed two case studies of dynamic task assignments for human-robot collaboration in workcells. Both cases focused on a single assembly cell that included a cobot, therefore the technology “Cobots” was counted as applied twice at “Workstation” level.
- Department Level. Ruppert and Abonyi [86] studied the integration of location systems into digital twins in the wire-harness assembly line of an automotive supplier. The technologies implemented in the study were MES, Simulation of processes, Traceability of raw materials and final products and Remote monitoring of production. These five technologies were counted as being applied at “Department” level.
- Plant Level. Strandhagen et al. [55] studied the Industry 4.0 implementation process at four companies. One of them, Brunvoll AS, produces thruster systems for propulsion of different types of advanced vessels. The company adopted ERP, Industrial Robots, Additive Manufacturing and Remote monitoring of production, to a varying degree of maturity, all across its productive plant. Therefore, these technologies were considered as applied at “Plant” level.
- Inter-Plant Level. Gottge et al. [87] investigated the impact of Industry 4.0 on the purchasing process in the automotive sector. In two of the three presented industrial case studies, the companies adopted a system of traceability of raw materials and a digital platform to connect with suppliers. These two technologies were considered as implemented at “Inter-Plant” level.

In the vast majority of the cases (179 out of 229), the implementation of digital technologies was limited, or mainly focused, to one single layout level. In the remaining case studies, the application of digital technologies was more thorough and it impacted more than one level at the same time. Moreover, when multiple technologies were connected together, it was considered that their impact extended beyond the layout level of physical application. An example of this type of technology implementation is the work of Chen et al. [88]. This contribution analysed a power equipment circuit breakers manufacturing plant that was transformed into a smart factory using a novel framework. A very wide set of interconnected digital technologies was applied in the smart

Table 6
Total and relative frequency of digital technology dimensions in industrial and laboratory case studies.

Technology Dimensions	Sub-category	Frequency	Rank	Total Cases	Relative Frequency	Rel. Rank
Smart Manufacturing	Vertical Integration	231	*1*	1145	0,202	*2*
	Virtualization	114	*5*	916	0,124	*4*
	Automation	129	*3*	687	0,188	*3*
	Traceability	125	*4*	458	0,273	*1*
	Flexibility	45	*7*	458	0,098	*6*
	Energy Management	30	*8*	458	0,066	*8*
Smart Working		156	*2*	1374	0,114	*5*
Smart Supply Chain		61	*6*	687	0,089	*7*

factory throughout all internal layout levels: PLC, Simulation of processes, AI for predictive maintenance, AI for production planning, Machine-to-Machine communication, Industrial Robots, Traceability of raw materials, Traceability of final products, Additive Manufacturing, Energy efficiency monitoring systems and Remote monitoring of production. Since all these technologies were connected and communicated among each other, their impact reached outside the layout level of physical implementation. Therefore, all these technologies were considered to be applied at "Workstation", "Department" and "Plant" level.

The results of this classification effort are collected in Table 7: the columns show how many times each technology was applied at a certain layout level. The first observation that can be derived from Table 7 is that the most impacted layout level is the Plant level, with 531 occurrences of technology application. In second place there is the Department level (310), closely followed by the Workstation level (300). Finally, Inter-Plant level appears to be the least impacted layout level, with only 153 instances. Looking at Table 7 it is also possible to identify different implementation patterns. A limited number of technologies were applied almost evenly across the internal layout levels: Simulation of processes, Energy efficiency monitoring systems, Remote operation of production and VR for workers training. The majority of the listed digital technologies were applied mainly at Plant Level: PLC, sensors and actuators, SCADA, MES, ERP, Machine-to-Machine communication for Vertical Integration, AI for planning of production, Robots, Automatic nonconformities identification, Traceability of raw materials and final products, Additive Manufacturing, Energy efficiency improving systems, Remote monitoring of production and Digital platforms with other company units. Three technologies were applied mainly at Workstation level: Virtual Commissioning, AR for Maintenance and Cobots. Intriguingly, the technologies that were applied mainly at Workstation level belong to either the group of Under-Researched or Highly Under Researched Technologies introduced in Table 5. It is not surprising that Flexible and autonomous lines were applied mainly at Department Level. Another restricted group of technologies shows an uneven application pattern, with more instances at Workstation and Plant level and less instances at Department level: AI for predictive maintenance, Machine-to-Machine communication for Automation and A&VR for product development. As expected, Digital platforms with suppliers and customers were applied mostly at Inter-Plant level.

Table 7 can also be read vertically, in order to see which technology was most frequently at each level of layout:

- At Workstation level, the top 3 is represented by Remote monitoring of production (36 occurrences), PLC, sensors and actuators (31) and Simulation of processes and AR for maintenance (tied at 22).
- At Department level, the three most applied technologies are Remote monitoring of production (39), PLC, sensors and actuators (33) and Industrial Robots (28)
- At Plant level, the top 3 is composed of ERP (54), Remote monitoring of production (46) and Traceability of raw materials (45)
- At Inter-Plant level, the three main technologies are Digital platforms with suppliers (21), Digital platform with customers (18) and ERP (16).

This point of view highlights the importance and transversality of the application of the Remote monitoring of production, PLC sensors and actuators and ERP.

The same exercise seen in Table 6 was conducted again in this section, grouping the technologies according to their purpose following the classification of Frank et al. [48]. The results are collected in Table 8. The first interesting observation is that there is correspondence between the purpose of certain technology dimensions and the layout level of application. Smart Supply Chain technologies, in fact, were applied and impacted mainly the Plant and Inter-Plant level: the Inter-Plant level, in fact, was added in order to capture the effect of the application of digital technologies along the supply chain. This is also true for Smart Working technologies. Smart Working technologies were defined by [48] as a set of technologies which aim to provide help to human workers in order to increase their productivity: human operators perform their tasks at Workstation level, while the human decision-making process, supported by the data made available by the Remote monitoring of production, is usually performed at Plant level. Smart Working technologies were indeed applied mostly at Workstation (86 times) and Plant (76 times) level. With regards to the sub-categories of the Smart Manufacturing dimension, Vertical Integration, Automation, Traceability and Energy

Table 7
Impact of digital technologies on layout levels.

Technology Dimension	Technology	Layout Level			
		Workstation	Department	Plant	Inter-Plant
Vertical Integration	1. PLC, sensors and actuators	31	33	41	2
	2. SCADA	3	2	13	1
	3. MES	14	13	42	10
	4. ERP	11	15	54	16
	5. M2Ma	4	3	8	1
Virtualization	6. Virtual Commissioning	5	4	2	0
	7. Simulation of processes	22	21	26	5
	8. AI for predictive maintenance	15	5	11	2
	9. AI for planning of production	8	11	14	2
Automation	10. M2Mb	6	2	6	1
	11. Robots	21	28	42	8
	12. Aut. nonconf. identification	12	14	29	6
Traceability	13. Traceability of raw materials	18	27	45	15
	14. Traceability of final products	15	22	43	13
Flexibility	15. Additive Manufacturing	8	10	18	3
	16. Flex. and aut. lines	3	15	4	0
Energy Management	17. Energy eff. Monitoring syst.	9	12	11	1
	18. Energy eff. Improving syst.	1	2	5	0
Smart Working	19. Remote monitoring of prod.	36	39	46	9
	20. Remote operation of prod.	6	4	7	0
	21. AR for maintenance	22	5	6	2
	22. VR for workers training	7	5	6	3
	23. A&VR for prod. development	3	0	2	2
	24. Cobots	12	7	9	4
Smart Supply Chain	25. Digital plat. with suppliers	4	4	13	21
	26. Digital plat. with customers	2	4	16	18
	27. Dig. plat. with company units	2	3	12	8
Total for Layout Level		300	310	531	153

Table 8
Total and relative impact of digital technology dimensions on layout levels.

Technology Dimensions	Sub-category	Layout Level				Layout Level (Relative)			
		Workstation	Department	Plant	Inter-Plant	Workstation	Department	Plant	Inter-Plant
Smart Manufacturing	Vert. Int.	63	66	158	30	0,055	0,058	0,138	0,026
	Virtualization	50	41	53	9	0,055	0,045	0,058	0,010
	Automation	39	44	77	15	0,057	0,064	0,112	0,022
	Traceability	33	49	88	28	0,072	0,107	0,192	0,061
	Flexiblity	11	25	22	3	0,024	0,055	0,048	0,007
	En. Mgmt	10	14	16	1	0,022	0,031	0,035	0,002
Smart Working		86	60	76	20	0,063	0,044	0,055	0,015
Smart Supply Chain		8	11	41	47	0,012	0,016	0,060	0,068

Management had an impact mostly at Plant Level. Virtualization technologies, conversely, were applied mainly at Workstation and Plant level, while Flexibility technologies were focused mostly on Department and Plant level.

Reading Table 8 vertically, the most frequently applied group of technologies for each level are:

- At Workstation level, Smart Working (86 occurrences)
- At Department level, Vertical Integration (66)
- At Plant level, Vertical Integration (158)
- At Inter-Plant level, Smart Supply Chain technologies (47)

Finally, the relative impact of the Technology Dimensions was calculated adopting the same approach used in Table 6: the results are collected in the last four columns of Table 8. In relative terms, the most frequently applied Technology Dimension at Workstation, Department, and Plant level is Traceability, while at Inter-Plant level is Smart Supply Chain.

5.3. Digital technologies clustering

As mentioned in Section 5.1, digitalisation achieves its purpose when multiple technologies and different elements of an industrial plant are connected and communicate with each other. Another way to look at

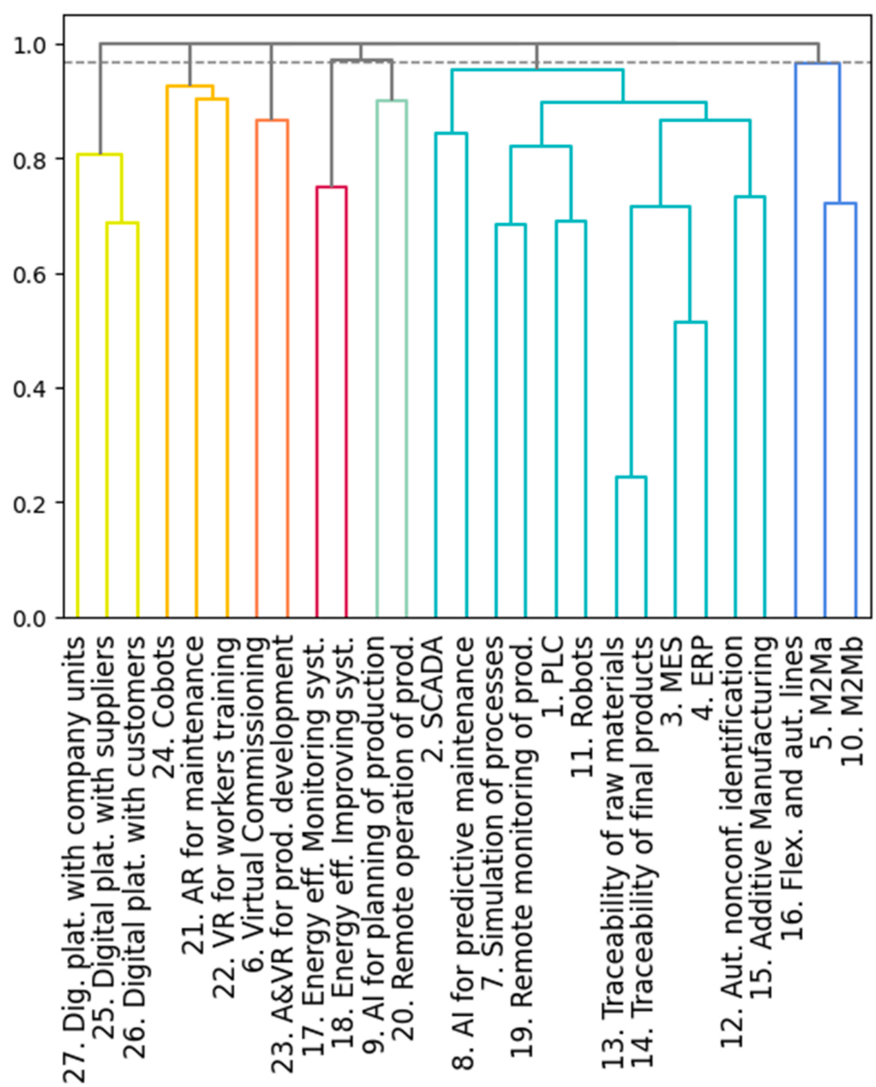

Fig. 8. Dendrogram showing with different colours the different clusters of digital technologies adopted in real-life case studies reported by academic literature.

this factor is to verify how the selected case studies combined the digital technologies of the classification of Frank et al. [48]. In order to do this, a matrix was constructed starting from the data extracted from the case studies. In the matrix, the lines represent the case studies and the columns represent the 27 digital technologies listed in Section 2.1. Each element of the matrix is either 0, if the technology is not adopted in a given case study, or 1, if the technology is present. To identify existing groups of technologies that were more frequently adopted together, a hierarchical cluster analysis was performed on the database matrix. Since the dataset is binary, it was decided to adopt the complete linkage method with Dice coefficient as similarity measure, as per Everitt et al. [89] and Tamasauskas et al. [90]. The result of the procedure is shown in Fig. 8: with a threshold value of 0.968, it is possible to identify seven different clusters. The resulting clusters are listed below, alongside the single digital technologies that belong to them:

1) Digital platforms with other company units, Digital platform with suppliers, Digital platform with customers
2) Cobots, AR for maintenance, VR for workers training
3) Virtual Commissioning, A&VR for product development
4) Energy efficiency monitoring systems, Energy efficiency improving systems
5) AI for planning of production, Remote operation of production
6) It is useful to divide it into three other sub-clusters:
   a. SCADA, AI for predictive maintenance
   b. PLC, Industrial Robots, Simulation of processes, Remote monitoring of production
   c. Traceability of raw materials, Traceability of final products, MES, ERP, Automatic nonconformities identification, Additive Manufacturing
7) Flexible and autonomous lines, Machine-to-Machine communication

The results of the clustering show that the implementation of groups of digital technologies in real-life case studies did not always follow a purpose-oriented approach. 4 out of 7 clusters (or 6 out of 9, if the sub-clusters of Cluster 6 are considered) are composed of technologies that belong to different Technology Dimensions, which, according to [48], are groups of technologies that pursue the same purpose.

The proposed clustering is clearly different from the one developed in [48]. The database used by [48] included data from 92 companies belonging to the Brazilian Machinery and Equipment Builders' Association (ABIMAQ-Sul), while the matrix used in our work includes 229 case studies, developed either in industry or in laboratory, selected from academic literature. Moreover, the database in [48] included the self-assessed level of implementation of each technology belonging to the Smart Manufacturing dimensions, while in this work the technologies (also belonging to the Smart Working and Smart Supply Chain dimensions) were only considered as either present or not (although their level of implementation can be considered to be relatively high, given the needs of a thorough case study). Finally, the clustering in [48] was methodologically more well-rounded, with a second stage that included non-hierarchical k-means clustering followed by a demographic analysis: the purpose of this procedure was to identify visible patterns of implementation of digital technologies within Brazilian manufacturing companies, based on the self-assessed level of development of each single technology. The clustering proposed in this section aims to provide a simpler overview of how digital technologies were combined in case studies developed by academic literature: rather than the implementation level, the focus is shifted on how digital technologies were grouped together in order to leverage the value-added brought by communication and interconnection.

6. Performance and economic evaluation

This section provides an overview on how real-life case studies of adoption of digital technologies were evaluated in terms of operational and economic performance. As already mentioned in the introduction, one of the areas that, according to academics and practitioners, is in most urgent need for academic attention is the performance measurement and cost-benefit analysis of the implementation of Industry 4.0 technologies [2]: measuring performance through a specific set of KPIs is a step towards understanding how the benefit is captured, while surveying forms of economic evaluation provides the groundwork for an effective cost-benefit assessment. This is all the more important for the case of Industry 4.0, where the revolution is happening not only through the spontaneous adoption of digital technologies by industrial companies but also through the active push of national and international institutions via specific plans (as shown in Section 2.1). For these reasons, the selected case studies were carefully examined in order to find elements of performance and economic evaluation. The first interesting result is shown in Fig. 9: out of 229 case studies, only 94 (41%) provided a form of performance evaluation of the implemented technologies and even less contributions (30, around 13% of all case studies) included a form of economic assessment. The complementary result is that more than half of the case studies of the selected sample of academic literature simply did not evaluate the performance of the presented technological system: works such as Wang et al. [91], Kolberg et al. [92], Urbina Coronado et al. [66], Tao and Qi [93], Mittal et al. [51] and Jiang et al. [94] provide a detailed description of the case studies and the implemented technologies but do not evaluate the effect of their application with specific KPIs or economic indexes. Only 20 papers include both performance and economic evaluation: Choi et al. [95], Fernàndez-Caramés et al. [96], Ma et al. [97], P è rez et al. [98], Foresti et al. [99], Ghobakhloo and Fathi [100], Halawa et al. [101], Ma et al. [102], Margherita and Braccini [54], P è rez et al. [103], Peruzzini et al. [79], Sundarakani et al. [104], Leng et al. [105], Fraga-Lamas et al. [106], Belli et al. [107], Ma et al. [108], Singh et al. [109], Matsunaga et al., [110] Tripathi et al. [111] and Stefanini and Vignali [63]. The trend reported in Fig. 9 shows that the ratio between the total number of case studies, the number of case studies with performance evaluation and the number of case studies with economic evaluation has not changed significantly over the years.

6.1. Operational performance evaluation

The Key Performance Indicators adopted in the 94 case studies with elements of operational performance assessment were collected and put together in a list. The resulting set of KPIs went through five steps of simple coding, which aimed at combining together the indicators that measured similar or highly related quantities or properties. The coding phase resulted in a final list of 21 KPI categories, which are described in detail below:

1) Case Specific: it includes the KPIs that cannot be generalised since they measure parameters and properties that are specific for the single case study of application (e.g., the number of assistance request generated by an operator using a VR system or the level of traceability of a bill of materials).
2) Commissioning Time: the KPIs that measure the duration of a commissioning process.
3) Cost: the instances in which the monetary cost is used as a performance indicator on the same level as other operational parameters.
4) Emissions: the KPIs that measure the level of environmental emissions such as CO_2 emissions, Level of Climate Damage, etc.
5) Energy Consumption: the KPIs that measure the energy consumed by the productive system.
6) Ergonomics Indexes: RULA, REBA, OWAS, etc.
7) Human workload: the KPIs that estimate the workload of human workers, such as Man Hours or mental workload assessments.
8) Maintenance: the KPIs that are related to the maintenance function, such as Mean Time Between Failure, Mean Time To Repair, Remaining Useful Life, etc.

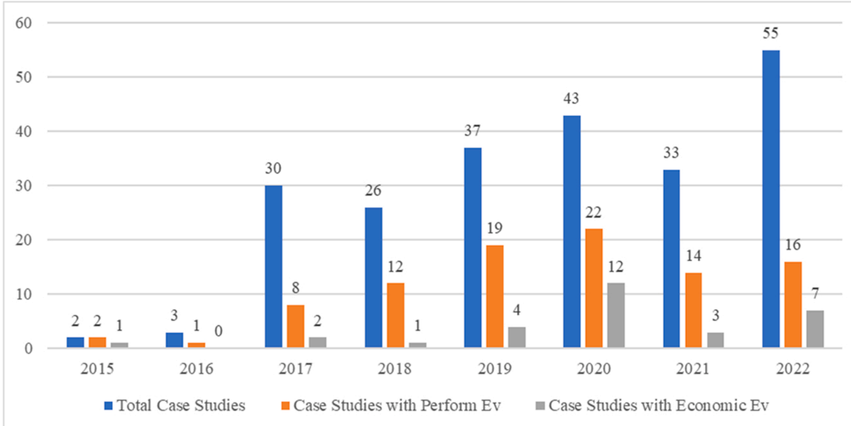

Fig. 9. Number of case studies with Operational Performance Evaluation and Economic Evaluation over the years.

9) OEE: the instances in which the Overall Equipment Effectiveness was used to evaluate operational performance in the reported case studies.
10) Operator's physical parameters: the KPIs that measure physical parameters of a human operator, such as spaghetti charts of worker's movements, maps of hand positions, etc.
11) Paperwork: the instances in which the amount of paperwork was considered as an evaluation criteria in the selected case studies
12) Process Specific KPIs: the KPIs that are specific of a given production process (e.g., value-added time and non-value-added time measured before and after the introduction of digital technologies)
13) Process Time: the KPIs that measure the duration of a productive process, such as throughput time, makespan, etc.
14) Quality: the KPIs that measure the quality of a given product or process, such as number of errors, number of defects, etc.
15) Resource Utilization: the KPIs that measure the availability of a given production resource.
16) Six Sigma Indexes: the instances in which Six Sigma KPIs were used to evaluate performance in the reported case studies.
17) Space Utilization: the instances in which spatial measurements, such as occupied m^2, were used to evaluate performance in the reported case studies.
18) System Productivity: the KPIs that collect the productive capacity of the system, such as pieces per hour, etc.
19) Technical: the KPIs that measure properties that are specific of the applied technologies and are not related with the application environment (e.g., the speed of AGVs).
20) User Response: the instances in which the response of human workers (measured in terms of usability, etc.) was used to evaluate performance in the reported case studies.
21) Work Environment: the KPIs the measure the environmental conditions for human workers, such as temperature, humidity, etc.

After the end of the coding phase, the frequency of the KPI categories was calculated: Table 9 lists the 21 KPIs categories according to the number of case studies in which they were recorded.

Table 9 shows that the most frequently adopted KPI category in real-life case studies of digital technologies implementation in industrial plants is represented by Case Specific KPIs (30 occurrences). This should not be a surprising result: the complexity of the applied technologies and their interaction with the productive process often require specifically tailored performance indicators. The second most frequent KPI category is Process Time KPIs (27 occurrences): this indicates that the preferred generic (as in "non-case-specific") approach to estimate the operational benefit of the introduction of digital technologies is to evaluate if they

Table 9
Frequency of adoption of Key Performance Indicator categories within case studies with performance evaluation.

KPI Category	Frequency	Rel. Freq. to the no. of case studies with Perf. Ev. (%)	Rel. Freq. to the total no. of case studies (%)
Case Specific	30	31.9	13.1
Process Time	27	28.7	11.8
Process Specific KPIs	18	19.1	7.9
Quality	17	18.1	7.4
Technical	16	17.0	7.0
Maintenance	13	13.8	5.7
User Response	12	12.8	5.2
Resource Utilization	11	11.7	4.8
Energy Consumption	9	9.6	3.9
System Productivity	9	9.6	3.9
Human Workload	7	7.4	3.1
Operator's Physical Parameters	6	6.4	2.6
Emissions	4	4.3	1.7
Commissioning Time	4	4.3	1.7
Space Utilization	3	3.2	1.3
OEE	3	3.2	1.3
Paperwork	3	3.2	1.3
Cost	3	3.2	1.3
Ergonomics Indexes	2	2.1	0.9
Work Environment	2	2.1	0.9
Six Sigma Indexes	1	1.1	0.4

can guarantee a reduction in process times. Other frequently adopted KPI categories are Process Specific KPIs (18 cases), Quality KPIs (17) and Technical KPIs (16). The main conclusion that can be derived from Table 9 is the relative scarcity of KPIs that are typically used to evaluate industrial performance (Lindberg et al., [112]): even if Process Time KPIs, Process Specific KPIs or Quality KPIs are ranked high in the table, their frequencies are still significantly low when compared with the number of case studies with performance evaluation (94) and even lower when compared with the total number of case studies (229). These results confirm the perceptions of academics and practitioners collected in the survey of Ivanov et al. [2]: there is indeed a need for academic attention towards the performance measurement of Industry 4.0 implementation because the topic has been vastly neglected by scientific literature so far, as shown in Table 9.

To look at the collection of KPI categories from another perspective, they were mapped with the aid of VOSViewer: the map, shown in Fig. 10, is based on the co-occurrence of KPI categories in the 94 reported case studies, adopting the full-counting approach as per Perianes-

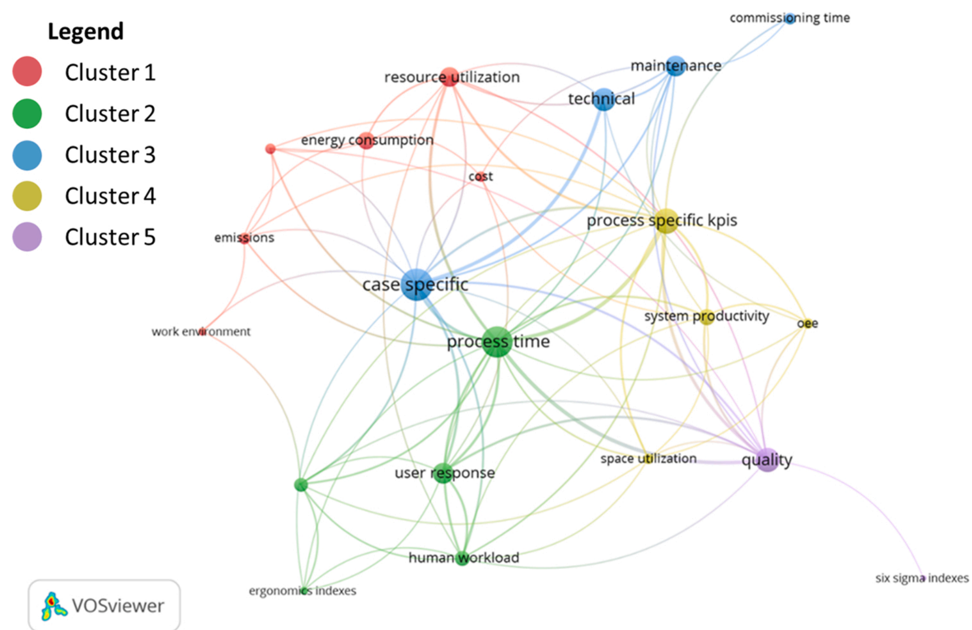

Fig. 10. Text map of Key Performance Indicators categories applied in real-life case studies of digital technologies implementation in the industrial sector (developed with VOSViewer).

Rodriguez et al. [113].

The KPI categories were combined in five clusters, which are shown in different colours in Fig. 10. The clusters are listed below:

1) *Environment and Sustainability KPI Cluster:* it includes the KPI categories of Cost, Emissions, Energy Consumption, Paperwork, Resource Utilization and Work Environment.
2) *Human Factors and Process Time KPI Cluster*: it includes the KPI categories of Ergonomics Indexes, Human Workload, Operator's Physical Parameters, User Response and Process Time
3) *Technology Oriented KPI Cluster:* it includes the KPI categories of Case Specific, Commissioning Time, Technical and Maintenance
4) *Overall Process Health Cluster:* it includes the KPI categories of OEE, Process Specific KPIs, Space Utilization and System Productivity.
5) *Quality Cluster:* it includes the KPI categories of Quality and Six Sigma Indexes

It is very interesting to observe how the clusters are composed of very closely related KPI categories. For example, Cluster 2) includes KPI categories that, aside from Process Time, are all related to the Human Factors area. This result could be partly attributed to the effects of the coding exercise. However, it can also be explained with the approach to the design of the case studies and their subsequent performance assessment: it is possible that academic literature conducted the performance evaluation of real-life case studies of digital technologies implementation mainly from the point of view of single subject areas or topics, rejecting a more comprehensive outlook. However, this is contrast with the main characteristics of digitalisation and Industry 4.0: they are complex socio-technical processes that require a more holistic approach to performance evaluation.

6.2. Economic evaluation

As shown in Fig. 9, the case studies containing elements of economic evaluation are only 30. Therefore, given the low number of contributions, it was decided to conduct only a qualitative assessment of the content of the selected works.

4 papers include only hints to forms of economic evaluation, without using precise numbers or references. In three of the four cases, the element of evaluation was the cost of the technologies. Fernández Caramés et al. [96] conducted a study where Augmented Reality was combined with information coming from MES and ERP using a fog-computing based architecture. Only a rough estimate of the cost of Microsoft HoloLens smartglasses (around $3000), used to implement Augmented Reality in the study, was provided in the paper. No other elements or indexes were adopted to evaluate the entire proposed system. Augmented Reality was also at the centre of the work of Peruzzini et al. [79], where its effects on human workers were studied at CNH Industrial, a manufacturer of agriculture and industrial vehicles. Here, some of the proposed solutions were evaluated with the terms “cheap” or “very expensive”, which are a reference to their perceived cost. However, no numbers were provided. P é rez et al. [98] focused on a digitalised workstation where an Industrial Robot and Virtual Reality glasses were combined. The human-machine interface that allowed to control the robot was developed in two different ways: through a traditional console and with the aid of VR glasses. These two options were compared, among other things, based on their acquisition cost. The actual cost was not reported but the VR-based interface was presented as the cheaper solution. Finally, more complex indexes were introduced by Alexopoulos et al. [114]: while discussing the opportunity of adopting digital twins in dynamic production environments, Cost-Benefit and Return on Investment (ROI) analyses were proposed as main parameters of choice. However, no actual analyses were performed in the case study.

Among the 26 cases with actual elements of economic evaluation, cost was again the most used index, appearing 13 times in total. Ma et al. [97] developed a Smart Lean Automation Engine enabled by Cyber Physical Systems (SLAE-CPS) at a model factory within the Department of Industrial Engineering at Tsinghua University, combining technologies such as PLC, Automatic nonconformities identification, Traceability of raw materials and Remote monitoring of production. The SLAE-CPS was compared to a traditional Jidoka integrated architecture. Among other parameters, the two systems were compared based on their hardware cost: Jidoka had a total cost of 380000 RMB (Chinese Renminbi), while the total cost of the SLAE-CPS system was 210000 RMB, almost a 50% reduction. Ma et al. [102] studied Company X, a cooperative ceramics manufacturing company located in Foshan, China. The study focused on ball mills involved in the grinding process, which showed unusual energy consumption problems. The combination of sensors, production data extracted from the ERP and an Energy efficiency monitoring system, allowed to compute the energy cost of two mills: the electricity cost for mill-25 was 1391.698 CNY (Chinese Yuan), while for mill-26 the cost was 1497.272 CNY. Since the energy consumption was also known, it was possible to calculate the average cost per kWh: due to lower energy prices, mill-26 had a lower average cost at 0.0505 CNY/kWh, compared with 0.7797 CNY/kWh of mill-25. Foresti et al. [99] registered a reduction in training costs of internal personnel of (36 $\pm$ 16) % after the application of advanced diagnostics smart maintenance assistants based on the combination of data retrieved by PLCs and AI for predictive maintenance. The study was conducted on the production lines of 12 international bottling companies over a period ranging from 12 to 38 months. P é rez et al. [103] examined a case study in the aerospace industry, focusing on the assembly process of the rib of an aircraft wing. The traditional process based on manual labour was compared with a new approach based on human-robot collaboration, which relied on PLC, Automatic nonconformities identification and Cobot technologies. The elements of economic evaluation were the so-called non-recurrent costs, which dropped 30% compared to the traditional assembly procedure. The already cited work of Halawa et al. [101] used cost as a parameter for technology selection: four types of real-time location systems (UWB, RFID, Wi-Fi and Vision Systems) were compared, among other parameters, according to their acquisition cost calculated as the average price over 15 different supplying companies. The acquisition cost was then combined with other criteria using the analytical hierarchical process (AHP), resulting in the choice of UWB. Shivajee et al. [115] attempted to reduce the manufacturing conversion costs of an automotive two-wheeler manufacturing company by applying a combined approach. The adopted strategy included the contemporary application of quality control tools, cause & effect diagrams and real-time digitalization of the productive plant. The latter was achieved thanks to the combination of PLC, SCADA, MES, Automatic nonconformities identification and Remote monitoring of production. First, the manufacturing conversion cost determinants were recorded in great detail and listed in a dedicated table, which included all the examined processes (ranging from welding and painting to assembly etc.). After the implementation of the proposed solution, all the conversion costs were recalculated and compared with the *ex-ante* situation, resulting in 24.18 INR (Indian Rupee) of savings per vehicle, for a total of US$ 2.27 million annual savings. Other more recent examples of the use of cost as an economic evaluation element are the works of Sundarakani et al. [104], Fraga-Lamas et al. [106], Zhou et al. [116], Ma et al. [108], Eugeni et al. [117], Singh et al. [109] and Tripathi et al. [111].

Belli et al. [107] and Matsunaga et al. [110] used the generated savings to evaluate the economic benefit of the introduction of digital technologies. [107] studied the digitalization process of a plastic hose manufacturing company: the application of a combination of ERP, remote monitoring of production and digital platforms with other company units resulted in a reduction of errors and non-conformities, quantified in a saving range between €10,000 and €20,000 per year. [110] showed that using the data generated by an energy efficiency monitoring system to optimise the production scheduling can generate up to R$ 28.980 (Brazilian Real) in savings per year.

Stefanini and Vignali [63] adopted a more sophisticated approach to cost computation: in order to evaluate the economic feasibility of the introduction of AGVs into a food processing facility, the authors employed life cycle costing. Life cycle costing requires to estimate multiple sources of cost: initial investment, operating cost, maintenance cost and end of life cost.

Income was used as the main economic indicator by Yuan et al. [118]. Studying the application of smart manufacturing through the implementation of MES, ERP and AI for production planning in two Chinese petrochemical plants, an improvement of overall income of 25.12 million and 41.94 million CNY per year was recorded, respectively. Revenue was also adopted in the works of Sundarakani et al. [104] and Arcidiacono et al. [119].

The break-even point was adopted as the principal economic assessment indicator by Mittal et al. [51]. The case of a jewellery manufacturing company was presented: newly acquired 3-D printing machines were introduced in the manufacturing process. The effect was even better than expected, with the break-even point being reached in eight months instead of ten. The break-even point was also used alongside cost by Zhou et al. [116].

Only three works presented a combination of more complex economic indexes: Choi et al. [95], Margherita and Braccini [54] and Ghobakhloo and Fathi [100].

Choi et al. [95] presented the case of Company D, the largest parts manufacturer in South Korea, producing parts ranging from electronic components to mechanical parts. Between 2009 and 2012, the company underwent a virtualization and digitalization process of its plants. The adopted technologies were mainly MES, ERP, Simulation of processes and Traceability of raw materials and final products. A financial and productivity analysis was conducted, comparing the following indexes between 2009 and 2012:

- Sales increased by almost 40%, from 6105 billion KRW (South Korean won) in 2009 to 8645 billion KRW in 2012
- The operating profit increased from 512 billion KRW in 2009 to 833 billion KRW in 2012
- Gross Value Added increased from 17.1% in 2009 to 20.0% in 2012
- Profit-sharing ratio increased from 51.2% in 2009 to 60% in 2012
- Capital Costs to the Gross Added Value increased from 39.7% in 2009 to 45% in 2012

Moreover, the new digital architecture of the factory was applied to the project of new plants as well as to the expansion and improvement of existing facilities, leading to expected savings of US$10.5 million.

Margherita and Braccini [54] conducted a thorough analysis of four case studies based on Italian manufacturing companies: Company A, a sanitary ceramics manufacturing company, Company B, a kitchen furnishings manufacturing company, Company C, a leather manufacturing company and Company D, an orthopedic prothesis manufacturing company. The case companies were selected because of their adoption of Industry 4.0 technologies for the purpose of achieving Flexible Manufacturing. The digital technologies in use included PLC, Industrial Robots, Traceability, Flexible and autonomous lines and Remote monitoring of production. Three main parameters were used for the economic assessment: Sales, EBITDA and Net Profit. A table for each company reported the monetary value of the three indexes between 2012 and 2018. For Company A, the focus was on the stability of the EBITDA. Company B saw an increase of EBITDA, Sales and Net Profit after the adoption of Industry 4.0 technologies. In Company C, the transition to Flexible Manufacturing empowered by Industry 4.0 was completed in 2017: at the end of process, EBITDA and Sales increased while Net Profit remained stable. Company D started the transition in 2017, witnessing an increased EBITDA and Net Profit and a slight reduction in Sales.

Ghobakhloo and Fathi [100] developed probably the most complete real-life case study with both operational performance evaluation and economic evaluation. The case company is KKCO, which produces and supplies fasteners to major automotive manufacturers. Aided by a consultancy firm, the company underwent a digitalization project that spanned from January 2013 to December 2017. A wide set of digital technologies were either introduced or developed: PLC, SCADA, MES, ERP, AI for productive maintenance, Traceability of raw materials and final products and Remote monitoring of production. The economic value of this transformation was evaluated in a specifically dedicated section of the paper. In the first year of the digitalization project (2013), the company invested 68% of its 2012 revenue in technological and human IT resources. The investment share decreased in 2014 and 2015 to 38.2% and 41.5%, respectively. Four financial indexes were tracked during the evaluation period 2013–2017: ROS (Return on Sales), ROA

(Return on Assets), ROIC (Return on Invested Capital) and Sales Growth. All four indexes showed a clearly increasing trend. The total investment cost and net value of the digitalization project were calculated, resulting in a reported ROI average of 3.59% in the evaluation period as well as an annual ROI value of 0.7%. The project broke even just before the end of the evaluation period in late 2017. It was also reported that Balanced Scorecard was applied to establish a link between digitalization investments and operational performance indicators: 6 out of 23 operational KPIs (product quality, maintenance efficiency, product delivery timeliness, inventory management accuracy, waste avoidance and production rate accuracy) reportedly showed a positive correlation with digitalization investments.

As it appears from the few contributions reported in this section, especially in comparison to the total number of selected case studies, academic literature did not dedicate enough attention to the economic evaluation of the implementation of digital technologies in industrial plants. This finding further confirms the results of the survey conducted by Ivanov et al. [2]. When economic evaluation is present, it applies mainly a single indicator like cost or revenue, which does allow to have a full picture of the actual economic impact of digital technologies. Only three reported case studies adopted a more complex set of financial and economic indexes. Moreover, with the exception of cost (which appeared in 13 out of 30 reported papers), there seems to be no standardized approach for the economic evaluation of the adoption of digital technologies.

7. Discussion, future research directions and limitations

The 229 selected case studies provide an overview on how academic literature has addressed the issue of the real-life implementation of digital technologies in the manufacturing world. The subsequent quantitative and qualitative analysis allowed to identify new possible research directions and to substantiate with actual data the widespread perspective among researchers of an urgent need for academic research on the performance measurement and cost-benefit analysis of Industry 4.0 [2]. The new research directions are detailed below, with the research direction (RD) presented in italics followed by its description.

RD1: develop new real-life case studies of industrial applications of the Highly Under-Researched Technologies

The frequency analysis of Section 5.1 identified different groups of technologies according to their frequency in case studies reported by academic literature. Research-Leading Technologies as PLC, sensors and actuators, Remote monitoring of production, Industrial Robots, Traceability of raw materials and ERP can be seen as almost synonymous of digitalization and Industry 4.0. Conversely, it is possible to identify two other groups of digital technologies that are either under-reported in academic literature or under-tested in real-life case studies: Under-Researched Technologies (AI for predictive maintenance, Additive Manufacturing, AR for maintenance, Energy efficiency monitoring systems, Digital platforms with customers and suppliers, AI for planning of production, Cobots and Flexible and autonomous lines) and Highly Under-Researched Technologies (SCADA, Digital platforms with company units, Machine-to-Machine communication, Remote operation of production, Virtual Commissioning, VR for workers training, Energy efficiency improving systems and A&VR for product development). As consequence of these results, more real-life case studies of these two categories of digital technologies are needed.

RD2: real-life case studies of different combinations of digital technologies should follow a standardized approach, possibly derived from new literature

This review also attempted to map how technologies were combined together in real-life case studies. In Section 5.1, a pre-existing classification was adopted to group technologies according to their purpose, as per [48]. In terms of absolute frequency, Smart Supply Chain, Flexibility and Energy Management technologies show a lack of attention from academic literature, while in relative terms also Virtualization and Smart Working technologies seem to require more reported case studies. Section 5.3 analysed how digital technologies were actually combined in real-life case studies, identifying 7 different clusters. These clusters do not necessarily match the Technology Dimensions classification taken from the literature: subcluster 6b, for example, includes four technologies that belong to four different Technology Dimensions (PLC, sensors and actuators belong to Vertical Integration, Industrial Robots to Automation, Remote monitoring of production to Smart Working and Simulation of processes to Virtualization). This shows how the practical implementation of digital technologies in groups or bundles appears to be a still fragmented research area: to capture the effect of these technological combinations on both operational and economic performance, a more standardised approach is needed in real-life case studies. This approach should be derived from a general theoretical framework which should be able to provide guidance to both academic and industrial managers during the implementation of technology bundles.

RD3: evaluate the impact of digital technologies on industrial systems with KPIs that are able to measure industrial performance as well as system sustainability, resilience and workers' safety and wellbeing

Section 6.1 analysed how case studies of industrial applications of digital technologies were evaluated by academic literature. First of all, only 94 out of 229 (41%) selected case studies actually included elements of performance evaluation. When performance evaluation was present, a total of 21 different KPI categories were applied. The most used operational KPI category was Process Time, which appeared in 27 cases. However, compared to the total number of case studies, Process Time KPIs were employed in relatively few instances: only in 11.8% of the use cases. This is true also for other KPI categories commonly used to capture industrial performance, such as Resource Utilization or System Productivity, which appear even less often. Therefore, the general lack of performance evaluation in case studies of digital technologies implementation is compounded by an additional scarcity of a more specific evaluation of industrial performance. Moreover, performance evaluation is becoming a crucial aspect not only for a technology-driven process such as Industry 4.0, but also for the transition towards the value-driven Industry 5.0 [120,121]. Nevertheless, as discussed in Section 6.1, the selected case studies showed a relatively limited adoption of KPIs related to the main aspects of Industry 5.0 such as system sustainability, resilience [122] or workforce safety, wellbeing and inclusivity [123]. These results emphasizes one of the main concerns regarding the recent Industry 5.0 paradigm: the general awareness that sustainability, resiliency and human-centricity should be better assessed and evaluated in digital technologies implementation projects. Finally, the results of the clustering show that academic literature focused mainly on assessing the performance of digital technologies within specific subject areas, lacking the holistic approach that would be required to evaluate the modern productive systems which, thanks to Industry 4.0 (and the upcoming Fifth Industrial Revolution), have transformed into complex socio-technical systems.

RD4: study the economic impact of the application of digital technologies in industrial plants by using appropriate financial and economic indexes

Section 6.2 shows how the economic evaluation of the application of digital technologies in industrial plants was even rarer than performance evaluation. Out of 229 selected case studies, only 30 included elements of economic evaluation. 4 out of 30 cases used only extremely basic elements of economic evaluation, without reporting actual numbers. Out of the remaining 26 cases, only 3 adopted a wide set of refined economic and financial indexes. This qualitative analysis shows how academic literature is in dire need for case studies that include robust economic evaluation of the implementation of digital technologies in industrial plants. This gap is at the core of the fourth research direction.

RD5: Develop new decision support systems and adequate models to combine different kinds of performance evaluation in order to conduct an effective cost-benefit analysis of the adoption of digital technologies

Finally, the combined lack of performance and economic evaluation lead to the absence of any form of cost-benefit analysis, except for the case of Ghobakhloo and Fathi [100] where investments in digitalization were linked with operational performance using the Balanced Scorecard. This finding confirms the urgent need for academic research on cost-benefit analysis of Industry 4.0 implementation, as shown in [2], giving the input for the last research direction. Future studies should provide decision support systems and multi-criteria decision-making models that are able to support managers in conducting a complete cost-benefit analysis of the implementation of digital technologies in industrial systems by considering technical, economic, social and environmental KPIs. A few of these models already exists, such as Almeida et al. [124] and Dreyer et al. [125], but the results of this review call for more extended and wide-ranging approaches.

We acknowledge that our study has some limitations. First of all, the choice of focusing exclusively on case studies clearly reduced the selected body of research. However, this was done because of three main reasons:

1) To reduce the total number of results to a manageable amount.
2) Case studies allow a deeper examination of the applied technologies and the layout level of implementation. Moreover, real-life applications permit more realistic performance and economic evaluations, which were among the objectives of this work.
3) Case studies are considered by researchers as the most appropriate tool for Industry 4.0 and digitalization research, as per [2].

The keywords selection and the Pareto thresholds had an impact on the results. For example, real-life case studies of single specific technologies might not include terms such as "Industry 4.0″, "digitalization" or "smart manufacturing" in their title, abstract and keywords, thus excluding them from the results. In addition, using thresholds at 80% for 2015–18% and 60% for 2019–21 excluded portions of existing literature. Both thresholds were set in order to limit the number of possible results: using higher thresholds would have made a thorough examination of each case unfeasible. Using Scopus as the main database for the research limited the number of relevant contributions. Finally, as already mentioned in Section 5.3, the proposed technology clustering should be considered a simple mapping of how digital technologies were combined in case studies reported by academic literature.

Not with standing the limitations, our work introduces elements of novelty in the extant literature of digitalisation of industrial plants and Industry 4.0. To the best of our knowledge, this is the first work to provide a wide mapping of case studies of Industry 4.0 applications reported by academic literature. A similar effort was conducted by Liao et al. [11]: dating back to 2017, however, this well-grounded and extensive work is now relatively old, missing five years of new research. Moreover, the section dedicated to real-life applications is limited to a brief qualitative description and the technology analysis was mainly based on keywords rather than a content analysis. In their review work, Zheng et al. [12] studied multiple applications of digital technologies in the manufacturing sector but decided to analyse them from the perspective of their impact on different industrial business processes. Counting the frequencies of appearance of single digital technologies in academic literature was performed by Culot et al. [18], focusing on papers that attempted to define the concept of Industry 4.0. In our work, on the contrary, the technology count was based on real-life case studies. Our work is also the first to examine the link between digital technologies and layout level of application. Peron et al. [49], who partly inspired our paper, described how digital technologies can be used at different layout levels but only for the purpose of facility layout planning. Literature has already produced interesting works that try to link digital technologies and operational performance, such as Dalenogare et al. [126] or Gillani et al. [127]. As already mentioned in Section 1, other review works provided collections of KPIs related to the application of digital technologies. However, these works had a more limited scope: [13] focused on SMEs, [14] on production scheduling and [15] on Human-Robot Interaction. Therefore, our work is the first to offer a mapping of the KPIs adopted to capture and measure the industrial performance of digital technologies using an inductive approach that starts from generic real-life case studies. Finally, to the best of our knowledge, this paper is the first to include a survey of the economic indexes used to evaluate the economic benefit of the implementation of digital technologies in industrial systems.

8. Conclusions

This work provides an overview of how academic literature treated the real-life implementation of digital technologies in industrial plants as well as their performance measurement and economic evaluation. Following the methodology adopted by Andriolo et al. [50], 154 papers from 2015 to 2022 were collected, including a total of 229 case studies. First of all, a set of bibliographic results was reported, ranging from journals of publication to the countries where the research work was conducted. After categorising the selected case studies according to a version of the classification of Industry 4.0 technologies introduced by [48], it was possible to identify which digital technologies were most frequently applied as well as how multiple digital technologies were combined in real-life case studies: four different groups of digital technologies were identified according to their degree of research attention. The impact of single technologies and groups of technologies on different levels of the industrial layout (workstation, department, plant and inter-plant) was also analysed. Then, the study examines how real-life applications of digital technologies were evaluated in terms of performance measurement. Only 94 out of 229 case studies included elements of performance evaluation, showing the need for more rigorous research on the topic of performance measurement of digital technologies. The KPIs employed by the recorded case studies were also carefully analysed and clustered. Even less case studies (30) presented elements of economic evaluation, confirming the existing research gap in terms of economic benefit analysis of the implementation of digital technologies. Given the low number of available cases, only a qualitative assessment of the adopted economic indexes was conducted. Combining the findings of the different analyses that were conducted on the selected case studies, five new research directions were identified.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. : Papers selected by the systematic literature review

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