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Simulation in industry 4.0: A state-of-the-art review

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Abstract

Simulation is a key technology for developing planning and exploratory models to optimize decision making as well as the design and operations of complex and smart production systems. It could also aid companies to evaluate the risks, costs, implementation barriers, impact on operational performance, and roadmap toward Industry 4.0. Although several advances have been made in this domain, studies that systematically characterize and analyze the development of simulation-based research in Industry 4.0 are scarce. Therefore, this study aims to investigate the state-of-the-art research performed on the intersecting area of simulation and the field of Industry 4.0. Initially, a conceptual framework describing Industry 4.0 in terms of enabling technologies and design principles for modeling and simulation of Industry 4.0 scenarios is proposed. Thereafter, literature on simulation technologies and Industry 4.0 design principles is systematically reviewed using the preferred reporting items for systematic reviews and meta-analyses (PRISMA) methodology. This study reveals an increasing trend in the number of publications on simulation in Industry 4.0 within the last four years. In total, 10 simulation-based approaches and 17 Industry 4.0 design principles were identified. A cross-analysis of concepts and evaluation of models' development suggest that simulation can capture the design principles of Industry 4.0 and support the investigation of the Industry 4.0 phenomenon from different perspectives. Finally, the results of this study indicate hybrid simulation and digital twin as the primary simulation-based approaches in the context of Industry 4.0.

Keywords: Discrete-Event Simulation, Agent-Based Simulation, System Dynamics, Virtual Reality, Augmented Reality, Artificial Intelligence

1. Introduction

The Industry 4.0 (I4.0), i.e., the Fourth Industrial Revolution, is a term conceived at the Hannover Fair in 2011 as part of Germany's long-term strategy to strengthen the competitiveness of its manufacturing sector (Liao et al., 2017). From *Industrie 4.0* working group, it "will lead to the emergence of dynamic, real-time optimized, self-organizing value chains that can be optimized based on criteria such as cost, availability, and resource consumption" (Kagermann et al., 2013, p. 20). After 2013, I4.0 gained worldwide recognition and became a hot topic in scientific literature (Lasi et al., 2014; Liao et al., 2017; Xu et al., 2018). Moreover, it was the main subject of discussion at the 2016 World Economic Forum owing to its high relevance to the manufacturing sector (Schwab, 2017). A global survey with over 2,000 participants proposes that approximately 5% of a companies' annual revenue will be invested in digitalization projects. In turn, companies expect to reduce their operational costs by 3.6% per year (PwC, 2016). These studies reinforce the argument that the digitalization of production systems will drive innovation over the next decades (Kagermann et al., 2013).

There is no standard definition for the term I4.0 in literature (Liao et al., 2017). Particularly, over a hundred definitions of I4.0 have been developed (Moeuf et al., 2018). I4.0 is often described as a set of design principles and enabling technologies to guide researchers and practitioners to implement I4.0 scenarios in companies (Hermann et al., 2015; Ghobakhloo, 2018). Overall, I4.0 is considered as a new socio-technical paradigm that depends on further development, access, and integration of information and communication technologies (ICT) with automation technologies to promote end-to-end systems integration across the entire value chain (Kagermann et al., 2013). It "is a collective term for technologies and concepts of value chain organization" (Hermann et al., 2015, p. 11), having implications on value creation, business models, services, and work organization (Kagermann et al., 2013; Schwab, 2017; Xu et al., 2018).

A revolutionary aspect of I4.0 is the accessibility to its enabling technologies, made possible by the lowering price and widespread use of sensors throughout value chains (Dalenogare et al., 2018), which aids in removing barriers to effective supply chain integration and management (Cragg & McNamara, 2018; Ralston & Blackhurst, 2020; Hofmann et al., 2018). Nonetheless, from Li et al. (2017), the novelty of I4.0 is classified into three axes: (1) technological advances and integration; (2) scaling of the access and robustness of the internet, and (3) convergence of digital, physical, and biological technologies together with its widespread and influence in the dynamics of business,

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economy and social development. This is consistent with the definition of I4.0 provided by Schwab (2017). Schneider (2018) also explained that the feasibility of I4.0 differentiates it from previous initiatives because of the increasing number of available technologies, the growth of companies' digital capabilities, and intra and cross-company integration through a complex value chains network, consistent with Hofmann & Ruesch (2017) and Xu et al. (2018).

Several initiatives related to I4.0 have been launched worldwide to strengthen the competitiveness of the manufacturing sector, predominantly through bi- or tripartite collaboration from a triple helix (university-industry-government) collaboration (Liao et al., 2017). Examples of these initiatives include the manufacturing USA program, also known as national network for manufacturing innovation (NIST, 2019); Canada's advanced manufacturing supercluster (Elci et al., 2019); the project evolution of networked services through a corridor in Quebec and Ontario for research and innovation - ENCQOR (ISED, 2019); German high-tech strategy 2020 (Kagermann et al., 2013); factories of the future in the European union's (Liao et al., 2017); and made in China 2025 (Xu et al., 2018).

Although some literature report several ongoing projects, I4.0 is nonetheless in its infancy, and most examples are either in the planning stage or are pilot projects (Liao et al., 2017; Xu et al., 2018; Alcácer & Cruz-Machado, 2019). Furthermore, research on risks, costs, revenue potential, and implementation barriers of I4.0 is scarce. Additionally, there is a lack of support to companies desiring to use this new social-technical paradigm (Hofmann & Ruesch, 2017). In this context, simulation techniques play major roles because they offer the possibility to evaluate multiple I4.0 scenarios through the development of planning and exploratory models of complex systems, which can aid addressing partly the aforementioned problems (Kagermann et al., 2013; Lugert et al., 2018).

Modeling and simulation are relevant techniques in the fields of industrial engineering, operations, and supply chain management (Shafer & Smunt, 2004; Negahban & Smith, 2014; Scheidegger et al., 2018). It is an enabling technology of I4.0 for managing complex systems (Ghobakhloo, 2018; Moeuf et al., 2018; Alcácer & Cruz-Machado, 2019). Moreover, an empirical research (Jeong et al., 2018) and patent analysis (Han et al., 2018) proposed modeling and simulation as critical technologies to produce innovations and develop the I4.0.

In manufacturing and logistics systems, which is the primary focus of this study, modeling and simulation denote a set of methods and technological tools that allows the experimentation and validation of products, processes, systems design and to predict system performance. It also supports decision making, education and training, aiding to reduce costs and development cycles (Negahban & Smith, 2014). Moreover, modeling and simulation are robust methods in science and developing theories (Davis et al., 2007), which can be used for different purposes, such as prediction, proof, explanation, prescription, and empirical guidance (Harrison et al., 2007).

Furthermore, the application of simulation technologies is a component of industry leaders' initiatives and strategy for implementing I4.0, such as General Electric's (GE) brilliant factory (Thilmany, 2017), and Siemens' digital factory (Shih, 2016), which addresses manufacturing plant virtualization, visualization, and simulation. Siemens and GE hold different patents related to new simulation techniques (Tao et al., 2019). From Tao et al. (2019), examples of industrial applications include the use of simulation by Siemens for systems planning, operation, and maintenance; the application of simulation by GE for asset management and optimization; and the employment of simulation by Airbus to monitor and optimize production processes. In addition, most leading simulation software vendors (e.g., AnyLogic, MathWorks, Siemens, Arena, Dassault Systèmes, Autodesk, Flexin, Simul8, Aspen Technology, AVEVA, Simio) are investing in the development of commercial solutions for I4.0 (Martin, 2019; AnyLogic, 2020), following the increasing interest from companies in modeling and simulation technologies (Deloitte, 2018).

Nevertheless, advancements in I4.0 and its enabling technologies introduce new challenges to the field of simulation owing to the increasing complexity of systems to be modeled (Vieira et al., 2018; Tao et al., 2018; Martin, 2019; Zhou et al., 2019; Uriarte et al., 2019). Therefore, this study aims to investigate the state-of-the-art of research at the intersection between the emerging field of Industry 4.0 and the field of simulation. The research question (RQ) addressed in this study are the following:

- RQ1 – What are the simulation-based approaches being employed in the context of I4.0?
- RQ2 - What are the purposes, empirical nature, and applications area of studies on simulation in I4.0?
- RQ3 – What are the design principles of I4.0?
- RQ4 - Which I4.0 design principles are captured by each simulation-based approach?

Although there are several reviews on simulation, they either are not in the context of I4.0 (Jahangirian et al., 2010; Negahban & Smith, 2014), focus on a specific simulation technique (Rodič, 2017; Vieira et al., 2018; Tao et al., 2019), or have a different scope/design from this research (Mourtzis, 2019). To the best of our knowledge, this is the first article providing a general overview and comparison between simulation technologies and design principles of I4.0. Furthermore, the time considered in this study extends the dates of coverage of existing reviews, including more recent publications. Additionally, whereas comparing the reference list of this study with the reference lists of existing review articles, through a bibliographic coupling analysis (Van Eck & Waltman, 2014), it overlaps maximum in 6%, indicating that this study introduces new and important insights for those striving to understand the state-of-the-art of research at the intersection of I4.0 domain with the simulation domain.

The main contributions of this study are threefold. First, it presents a broad coverage of the specialized literature using a quantitative and qualitative approach, identifying the simulation approaches used relative to the I4.0. Second, it extends the list of I4.0 design principles provided by Ghobakhloo (2018) and establishes a link between simulation technologies and I4.0 design principles. Third, it provides a comprehensive classification of simulation studies relative to I4.0.

The remainder of this study is organized as follows. Section 2 describes the research methodology used to review the literature. Section 3 and 4 present the quantitative and quantitative analyses, respectively. Section 5 presents the discussion. Section 6 introduces the limitations and opportunities for future research. Finally, conclusions are outlined in Section 7.

2. Methodology

2.1. Conceptual framework

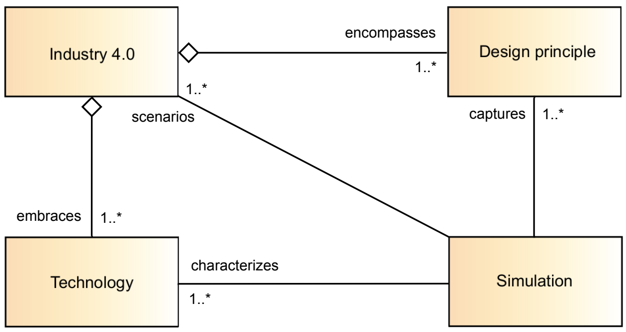


Figure 1: Conceptual framework

Fig. 1 presents the conceptual framework to guide the systematic review, represented as a unified modeling language (UML) class diagram, which describes the system's components and the different types of static relationships among them (Bersini, 2012). As shown in Fig. 1, I4.0 can be described in terms of its design principles and enabling technologies (Hermann et al., 2015, 2016; Ghobakhloo, 2018). The simulation characterizes one or more enabling technologies of I4.0 (Kagermann et al., 2013; Ghobakhloo, 2018), which can be used to evaluate multiple I4.0 scenarios (Houston et al., 2017; Martin, 2019; Tao et al., 2018; Gajsek et al., 2019).

To better understand these relationships in Fig. 1, the design principles that serve as the foundation of I4.0 and existing simulation-based approaches used relative to I4.0 will be systematically reviewed. Simulation techniques serve different purposes (Harrison et al., 2007) and apply to different areas (Jahangirian et al., 2010), which can enable easy examination of the I4.0 phenomenon from different perspectives. Therefore, the uses of simulation, the application areas, and the relationship between the simulation approaches and I4.0 design principles will also be investigated.

2.2. The systematic review strategy

To ensure a robust and rigorous systematic literature review, the preferred reporting items for systematic review and meta-analysis (PRISMA) methodology (Moher et al., 2009), consisting of a 27-item checklist and a four-phase flow diagram (see Fig. 2), was adopted. From Moher et al. (2009), the PRISMA's checklist provides guidelines to conduct a systematic literature review (e.g., title, abstract, method, results, discussion) and the PRISMA flow chart describes the information flow through the different phases of the systematic literature review (i.e., identification, screening, eligibility, inclusion). With thousands of citations on the web of science, Scopus, and Google scholar, this approach is widely used across different research fields to guide the development of systematic reviews, including I4.0 (Liao et al., 2017).

2.2.1. Sampling

Table 1: Search protocol

SP1	Data source:	Web of Science and Scopus
	Search string:	"simulation" AND ("model*" OR "framework") AND ("Industry 4.0" OR "Industrie 4.0" OR "Fourth Industrial Revolution"OR "4th Industrial Revolution")
	Search fields:	Title, abstract, and keywords
	Period:	From 2011 to December 31, 2019
	Language:	English
	Document:	Journal articles
SP2	Data source:	Web of Science and Scopus
	Search string:	("design principle*" OR "requirement*") AND ("Industry 4.0" OR "Industrie 4.0" OR "Fourth Industrial Revolution"OR "4th Industrial Revolution") AND ("literature review" or survey or state-of-the-art)
	Search fields:	Title, abstract, and keywords
	Period:	From 2011 to December 31, 2019
	Language:	English
	Document:	All types

The data collection follows a two-phase process to enable the cross-analysis of concepts (see Fig. 2). The first phase systematically identifies studies that use simulation-based approach relative to I4.0, whereas phase two systematically identifies publications that analyze or review the design principles of I4.0. The search protocol adopted in each phase were built in three steps (see Table 1). First, the electronic data sources Web of Science Core Collection and Scopus, broadly covering the management and engineering research literature, were selected. Second, the search string was constructed based on the objectives of the research. Third, four eligibility criteria were applied: (1) date of coverage: the search period ranges from the beginning of 2011, with the emergence of the term Industry 4.0 (Liao et al., 2017), to December 31, 2019; (2) Search fields: title, abstract, or keywords of articles in the data sources; (3) Document types: in the first search protocol, only journal articles were included as they were considered more reliable owing to the rigor of the evaluation process and because they predominantly provide significant details about the methodology, which is essential to the development of this study. However, in the second search protocol, all types of documents were considered; (4) Language: consider only studies published in English.

After defining the search strategy, articles were identified, screened, and assessed for eligibility, to develop the final sample. A summary of the systematic review strategy, based on PRISMA methodology, is exhibited in Fig. 2.

The identification phase consisted of applying the search protocol in each data source, combining the articles into a single database, and removing duplicates using EndNote X9 and double-checking references. The screening phase consisted of analyzing the title, abstract, and keywords of articles in the sample, applying the exclusion criteria in Table 2. In the eligibility phase, the remaining full-text articles remaining in the sample

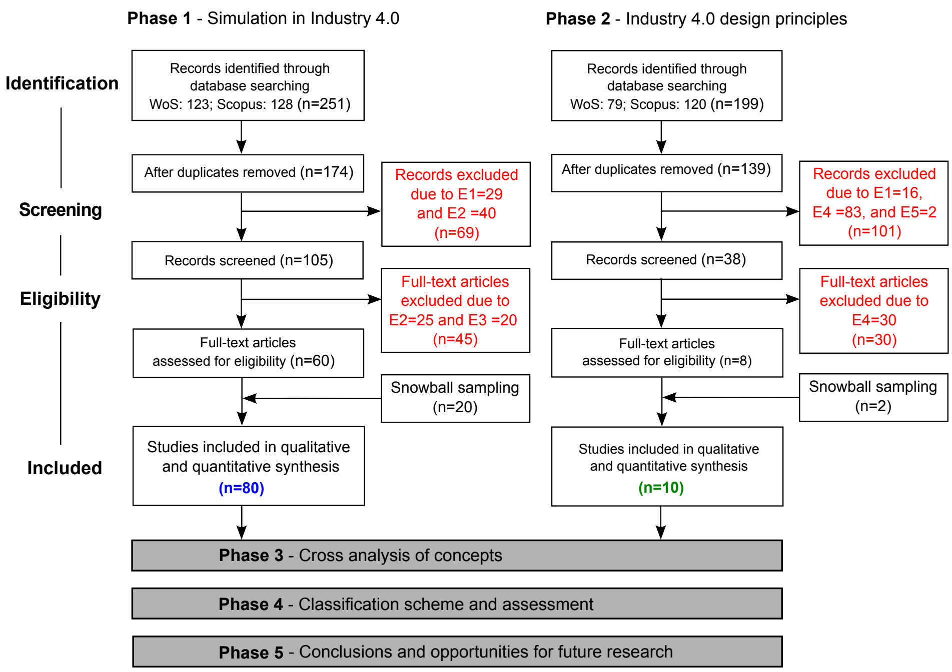


Figure 2: Systematic review strategy

Table 2: Inclusion and exclusion criteria with the total number of occurrences

Criteria	Description	Total occurrences	
		Phase 1	Phase 2
Exclusion (E)	E1: Industry 4.0 or Simulation is used only as a keyword, example fact, or cited expression.	29	16
	E2: Does not fit with the scope of the research.	65	N/A
	E3: Industry 4.0 or Simulation is only used to describe some challenges, trends, or recommendation.	20	N/A
	E4: The paper does not focus on the analysis or review of Industry 4.0 design principles.	N/A	113
	E5: Full-text could not be assessed or is not in English.	N/A	2
Inclusion (I)	I1: Simulation and Industry 4.0 are part of the main research effort.	80	N/A
	I2: The paper analyze or review the design principles of Industry 4.0	N/A	10

were assessed for qualification. Only articles matching the inclusion criteria in Table 2 were accepted in the sample. Next, the backward and forward snowball sampling technique was applied to these articles to determine if any relevant references was missed in the sample. Snowballing is an important search technique to develop systematic review studies (Wohlin, 2014). It uses an article's reference list (backward snowball sampling) or the citations to the article (forward snowball sampling) to identify additional references to include in the sample of articles to be reviewed (Wohlin, 2014). Finally, in the inclusion phase, articles in the sample after eligibility analysis plus articles identified through the snowball sampling were included in the quantitative and qualitative analysis.

Phase 1 initially resulted in 251 articles. After duplicate removal, the sample reduced to 174 articles. The titles, abstracts and keywords were thereafter analyzed and exclusion criteria E1 and E2, set out in Table 2 were applied, reducing the sample from 174 to 105 articles. At this stage, the 62 articles excluded owing to E2 occurred mainly because they focused on other areas (e.g., energy, healthcare, construction, telecommunication), alternate to on manufacturing or logistics systems. After assessing the full text of the articles, the other 45 articles were excluded owing to E2 and E3, resulting in a sample with 60 articles. By performing the snowball sampling, 20 additional articles were identified. Hence, a total of 80 articles were included in the final sample for the quantitative and qualitative analysis. A third researcher, an expert in the field, double-checked the reference lists (articles excluded and included in the sample) to reduce potential bias. The underlying principle was, whenever a disagreement about the inclusion or exclusion of an article occurs (which were very few cases), we appended the article to the sample to prevent missing possible relevant studies in the sample.

In phase 2, we repeated the four step procedure in Fig. 2 to identify studies describing the principles of I4.0, resulting in a sample of 10 articles, included in qualitative analysis. Here, most of the 113 articles were excluded owing to E4 because they used design principles or requirements only as a keyword, cited expression, or example fact, and did not focus on the analysis or review of the design principles of Industry 4.0.

2.2.2. *Data analysis*

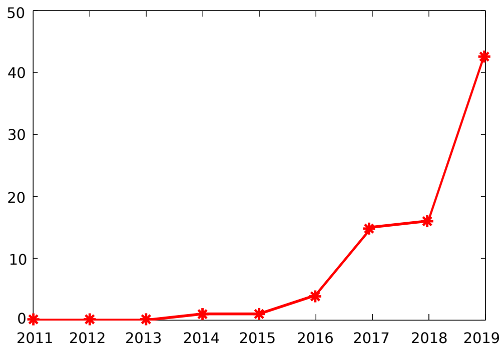
Adhering to the PRISMA guidelines (Moher et al., 2009), this research uses a mixed-method systematic review, combining quantitative and qualitative approaches. Accordingly, the data analysis was divided into two stages. First, we performed a quantitative synthesis through graphical and tabular methods of descriptive statistics. Thereafter, we conducted a qualitative content analysis, which involves decontextualization, recontextualization, categorization, and compilation of data (Bengtsson, 2016).

Overall, the research design is divided into four phases, as depicted in Fig. 2. Firstly, studies at the intersection of I4.0 and simulation fields are selected to identify the simulation-based approaches used relative to I4.0. Secondly, reviewed articles related to I4.0 are analyzed to identify the design principles of I4.0, i.e., essential constructs for the development of I4.0 models. Now, a quantitative analysis of the simulation-based studies is performed, and the simulation approaches in I4.0, and the design principles of I4.0, introduced. Thirdly, a cross-analysis of concepts that establishes the relationship between the simulation-based approaches and the design principles of I4.0 is presented. Next, a classification scheme (coding) with five categories, subdivided into 61 subcategories, is developed to guide further content analysis. The 80 articles included in the final sample of phase 1 were next classified, and the results reported. Lastly, gaps and opportunities for future research are discussed.

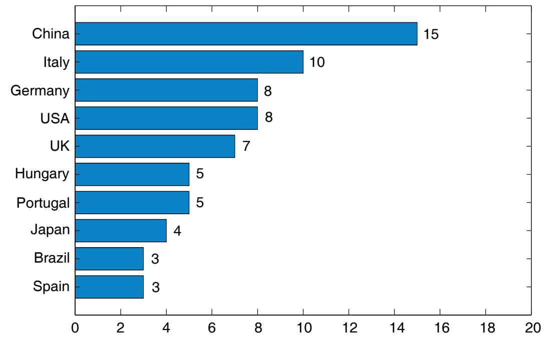
3. Quantitative analysis

The sample size of phase 1 comprises of 80 journal articles, used for both quantitative and qualitative analysis (see Appendix A). Fig. 3a displays the distribution of these publications over time, showing an upward trend in the number of scientific publications in the fields of I4.0 and simulation. It is observed that more than 70% of the articles were published in the last two years. Fig. 3a indicates that the research field at the intersection of the I4.0 domain with the simulation domain is new and under-explored, considering the potential of simulation to develop I4.0 and vice versa, as highlighted by the academic, and industry professionals and other organizations (Kagermann et al., 2013; Shih, 2016; Thilmany, 2017; Lugert et al., 2018; Tao et al., 2018; Martin, 2019; AnyLogic, 2020).

The geographical distribution of the publications is presented in Fig. 3b. The top 10 most frequent were considered. Another 25 countries were represented in the sample, with up to two publications. The institution and location information from the affiliation of all authors of each article was considered. Therefore, a publication with authors from different institutions and countries were computed separately. In total, the 80 articles analyzed involved 322 authors, 161 institutions, and 35 countries, with an average of 4.03 authors per article and a standard deviation of 1.55. Almost 70% of the research articles were co-authored by four or more researchers. In total, 61 articles (78.75%) involved one or more institutions of a single country, whereas 17 articles (21.25%) involved institutions in different countries, suggesting that it remains considerable room for international collaboration. Considering the distribution by continent, we find: Europe (54 articles; 66%); Asia (34 articles; 41%); North America (7 articles; 9%); and South America (6 articles; 8%). There is a higher concentration of publications linked to European institutions, mainly from Germany, Italy,



(a) Number of publications per year



(b) Geographic distribution of publications

Figure 3: Publication count by year and country

and the UK, following a similar pattern of I4.0 publications, as presented in Liao et al. (2017).

Table 3: Keywords frequency analysis

Keyword	n	%
Manufacturing	53	66.3
Cyber-Physical Systems	41	51.3
Agent-Based Simulation	30	37.5
Decision Making	21	26.3
Smart manufacturing	17	21.3
Digital Twin	15	18.8
Virtual Reality	14	17.5
Internet of Things	11	13.8
Discrete Event Simulation	9	11.3
Big Data	8	10.0

The keyword analysis is important to initially identify the primary constructs addressed in the content of the studies. In total, 871 keywords were collected from the 80 studies. Table 3 presents the 10 most common keywords, excluding the two used in the query (i.e., simulation, Industry 4.0) and the ratio based on the absolute number (n) of articles in the sample.

The keywords in Table 3 suggests that most of the studies (62%) are within the manufacturing context, which is in the scope of this study. Furthermore, it indicates three core enabling technologies of I4.0, i.e., the Internet of Things (IoT), Cyber-Physical Systems (CPS), and Big Data, as described by Kagermann et al. (2013). In addition, it indicates that: 35% of the studies in the sample may adopt agent-based modeling and simulation (ABMS) or multi-agent systems (MAS), con-

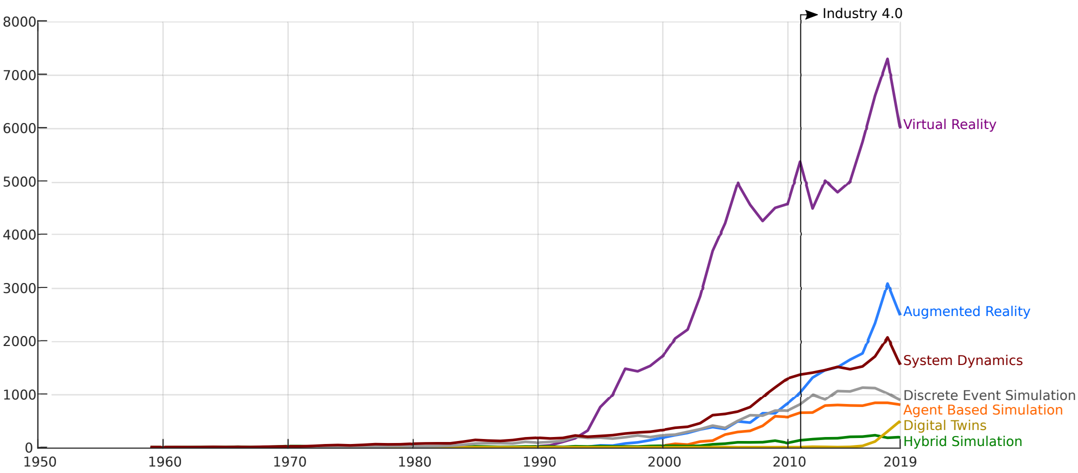


Figure 4: Evolution of the number of publications per simulation approach

Table 4: Articles by journal and period

Journal	IF	SJR	Articles published per year						Total	Percent
			14	15	16	17	18	19		
International Journal of Production Research	4.577	1.78	0	0	0	3	2	4	9	11.3%
Computers & Industrial Engineering	4.135	1.47	1	0	0	2	1	5	9	11.3%
International Journal of Computer Integrated Manufacturing	2.861	0.66	0	0	0	1	2	5	8	10.0%
Computers in Industry	3.954	1.01	0	0	1	0	2	4	7	8.8%
International Journal of Advanced Manufacturing Technology	2.633	1.00	0	0	0	1	3	3	7	8.8%
Simulation Modelling Practice and Theory	2.219	0.61	0	0	0	0	0	4	4	5.0%
Journal of Manufacturing Systems	5.105	2.11	0	1	0	1	0	1	3	3.8%
CIRP Annals-Manufacturing Technology	3.641	2.54	0	0	0	1	1	1	3	3.8%
Sustainability	2.576	0.58	0	0	0	0	0	3	3	3.8%
International Journal of Simulation Modelling	2.492	0.62	0	0	0	0	1	2	3	3.8%
IEEE Transactions on Industrial Informatics	9.112	2.35	0	0	0	0	1	1	2	2.5%
International Journal of Production Economics	5.134	2.38	0	0	0	0	0	2	2	2.5%
IEEE Access	3.745	0.78	0	0	0	2	0	0	2	2.5%
Social sciences	N/A	0.24	0	0	0	0	0	2	2	2.5%
Systems	N/A	0.40	0	0	0	2	0	0	2	2.5%
Applied Soft Computing Journal	5.472	1.41	0	0	0	0	0	1	1	1.3%
IEEE Transactions on Automation Science and Engineering	4.938	1.50	0	0	0	0	1	0	1	1.3%
Engineering with Computers	3.938	0.66	0	0	0	0	1	0	1	1.3%
Production Planning & Control	3.605	1.39	0	0	0	0	0	1	1	1.3%
Journal of Computational Design and Engineering	3.408	0.74	0	0	1	0	0	0	1	1.3%
IEEE Transactions on Human-Machine Systems	3.374	1.19	0	0	1	0	0	0	1	1.3%
Computer Networks	3.111	0.85	0	0	1	0	0	0	1	1.3%
Applied Sciences	2.474	0.42	0	0	0	0	0	1	1	1.3%
Processes	1.963	0.85	0	0	0	0	0	1	1	1.3%
Mathematics	1.747	0.24	0	0	0	0	0	1	1	1.3%
Journal of Simulation	1.214	0.87	0	0	0	1	0	0	1	1.3%
Production and Manufacturing Research	N/A	0.64	0	0	0	0	1	0	1	1.3%
Machines	N/A	0.42	0	0	0	0	0	1	1	1.3%
Organizacija	N/A	0.22	0	0	0	1	0	0	1	1.3%
		Total	1	1	4	15	16	43	80	100%

sidering that both terms are often used interchangeably (Barbati et al., 2012); that 17% of studies may address digital twin (DT); 16% virtual reality; and 10% discrete-event simulation (DES). This analysis also indicates the other three simulation approaches: system dynamics (3%), augmented reality (3%), and hybrid simulation (5%).

The articles were published in 29 different scientific journals (see Table 4), covering the leading journals of industrial engineering and simulation fields, based on the journal citation reports (JCR) and SCImago journal rank (SJR). Table 4 considers initially the total number of articles per journal, followed by the journal's impact factor (IF), based on the JCR, and SJR. The number of publications per journal per year and the proportion of articles per journal in the sample is also presented.

Although publications are spread over 29 journals, 50% are from five journals: Computers & Industrial Engineering (11.3%), International Journal of Production Research (11.3%), International Journal of Computer Integrated Manufacturing (10%), Computers in Industry (8.8%), and International Journal of Advanced Manufacturing Technology (8.8%). Moreover, a bibliographic coupling analysis indicates that the 80 articles in the sample are closely related, with more than 80% sharing minimum 3 and maximum 49 references. Note that "the larger the number of references two publications have in common, the stronger the bibliographic coupling relation between the publications" (Van Eck & Waltman, 2014, p. 287). The bibliographic coupling analysis and co-occurrence keyword analysis, two of the most commonly studied types of bibliometric networks (also referred to as science mapping), were carried out using VOSviewer software, highly used for visualizing bibliometric networks and text mining (Van Eck & Waltman, 2014).

To understand how the use of simulation approaches changed over time, particularly before and after the emergence of the I4.0, we observed the time series associated with the seven simulation technologies provided by the keyword analysis using Google Ngram Viewer (http://books.google.com/ngrams) and Scopus. On one side, Google Ngram is a data-mining tool based on a rich data set of words/phrases from millions of digitized books published between 1500 and 2008, widely used in data science (Skiena, 2017). On the other side, Scopus is one of the largest abstract and citation databases of scientific publications. The time series produced with Google Ngram viewer and Scopus datasets presented similar patterns up to 2008, except for Digital Twins, which Google Ngram returns no results. Fig. 4 shows the time series of each simulation approach based on the Scopus database. Each term was searched individually, and filtered by five subject areas closely related to the scope of this research: engineering, computer science, mathematics, decision science, and business management. Articles containing the terms in either the titles, abstracts, or keywords were retrieved.

Fig. 4 indicates that virtual reality, together with augmented reality, concentrates the higher number of publications. System dynamics and discrete-event simulation are the oldest methods, both with more than 50 years old. Concerning the evolution of publications, simulation-based approaches experienced a significant increase after the 1990s. However, the distribution of publications slightly changed after 2011. In the last three years, digital twin' publications increased exponentially, agent-based simulation and hybrid simulation were stable, whereas the other approaches presented a high variation.

4. Qualitative analysis

4.1. Simulation in Industry 4.0

Simulation is defined as the process of designing a model of a real or hypothetical system to describe and analyze the behaviors of the system (Scheidegger et al., 2018). The key components of this definition are: modeling – the process of creating a model; model - an abstract and simplified representation of a system, composed of a set of assumptions, which is often represented by a mathematical or logical relationship; system - the process that is analyzed; process – a collection of interrelated elements; and simulation – the operation of a model over time (Banks, 1998).

Simulation is a primary methodology for analyzing complex production systems and an essential problem-solving methodology (Negahban & Smith, 2014). A reason for using simulation are the high cost associated with the development of experiments with the actual system, to observe the behavior of processes in the real world, or with the building of a physical model (Scheidegger et al., 2018). Additionally, a model can be significantly complex to be analyzed analytically (Banks, 1998). Advantages in using simulation approaches includes: conducting tests rapidly and cheaper without disrupting the real system (risk-free environment), compressing or expanding time for a particular observation, and use of animation (visualization of dynamic systems) to facilitate communication and models validation (Banks, 1998; Borshchev, 2013; Scheidegger et al., 2018). Whereas the main disadvantages are the lack of professionals, high salaries of simulation engineers, the high cost of software licenses, and time to develop models (Banks, 1998; Kagermann et al., 2013).

There are several simulation-based approaches available in literature. Fig. 5 provides an overview of the simulation-based approaches being employed in the context of I4.0, based on the studies in the sample. A description of each simulation approach and an indication of key references are provided next.

Agent-based modeling and simulation (ABMS): is considered a "relatively new approach to modeling complex systems composed of interacting, autonomous agents" (Macal & North, 2010, p. 151). ABMS or Multi-Agent Systems (MAS) is also defined as "a set of elements (agents) characterized by some attributes, which interacts with each other through the definition of appropriate rules in a given environment" (Barbati et al., 2012, p. 6020). An agent is defined as a complex software unit able to operate autonomously, pursuing a set of specific goals (Frayret, 2011; Abar et al., 2017). It can represent different things, whether material or not, such as sensors, machines, products, people, and innovation (Borshchev, 2013). Generally, an ABMS model consists of a set of agents, the agents' environment, and a set of agents relationships (Macal & North, 2010). There is also a strong notion of an agent, which includes not just characteristics like autonomy, social ability, reactivity, proactiveness, but also human-like attributes such as knowledge, belief, intention, and emotion (Wooldridge & Jennings, 1995). ABMS plays an important role in I4.0 as a modeling paradigm for CPS and simulation method (Houston et al., 2017). A review of the industrial applications of agent technology in CPS is presented in Leitão et al. (2016). A detailed software tool list for ABMS is presented in Abar et al. (2017).

Discrete Event Simulation (DES): is defined as "one in which the state variables change only at those discrete points in time at which events occur" (Banks, 1998, p. 8). The event consists of an occurrence that alters the system's state, while a state variable of a system represents all the information necessary to describe the system's behavior at a certain point in time. As an example, the number of products in a queue waiting for a quality check may be considered a state variable, and a product that is entering or leaving the queue, an event (Da Costa et al., 2017). Other key elements of DES models are passive entities (or objects), resources, locations, queues (or processing lists), source and sink blocks, and path network (Scheidegger et al., 2018). DES is process-oriented, mainly developed using process flowchart, and operates in discrete times. The abstraction

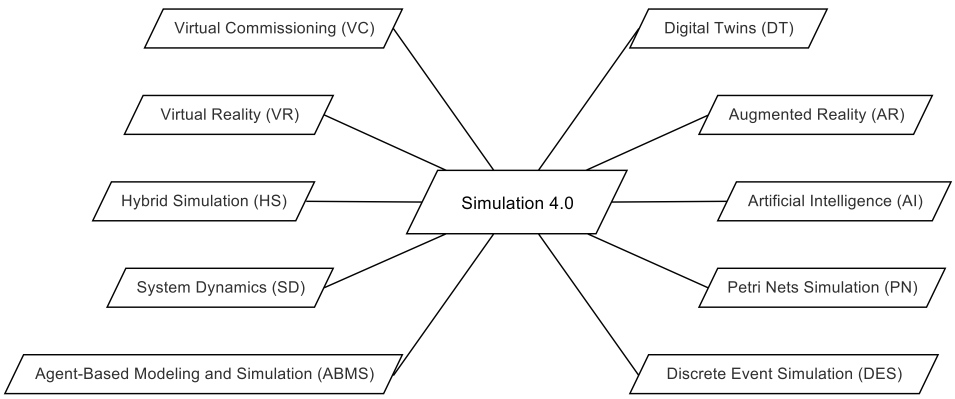


Figure 5: Simulation-based approaches applied in the context of Industry 4.0

level of DES models is usually medium to low. A review of DES in the scope of I4.0 is provided by Vieira et al. (2018).

System Dynamics (SD): is a continuous simulation approach to analyses dynamic systems over time, using stock and flows and feedback loops diagrams and differential equations to represent systems' components relationships (Scheidegger et al., 2018). SD has two modeling approaches (Kunc, 2017). The use of stock and flow diagrams implies a quantitative approach (hard modeling), while the qualitative approach, which is also referred to as soft operational research, involves only the use of influence (feedback loop) diagrams. SD is considered a more strategic modeling approach, where the models usually present a high abstraction level (Borshchev, 2013).

Virtual Reality (VR): is a virtual experience in which a user is immersed in a responsive virtual environment (Turner et al., 2016). It refers to a set of ICT technologies (i.e., expression technology, interaction technology, authoring technology, collaboration technology) that enables the user to experience a virtual environment in an experimental simulation (Choi et al., 2015). VR has a wide range of applications in the manufacturing industry (Berg & Vance, 2017).

Augmented Reality (AR): is a set of technologies (e.g., capturing device, visualization devices, interaction device, tracking system) that allows the direct or indirect view of the physical world environment in real-time to be augmented (i.e., enhanced) by adding virtual computer-generated devices to it (Bottani & Vignali, 2019). AR systems in manufacturing can increase a user's perception and interaction with the real world, supporting different activities such as training, assembly, and maintenance (Longo et al., 2019; Pérez et al., 2019).

Artificial Intelligence (AI): is a domain of computer science relating to the simulation of intelligent behavior in computers. Its subfields include machine learning, deep learning, natural language processing, computer vision, cognitive computing, and more (Carvalho et al., 2019; Lolli et al., 2018). AI can also be described as a set of techniques for modeling and simulation of environmental systems, which includes artificial neural networks, fuzzy models, reinforcement learning, cellular automata, and meta-heuristics (Chen et al., 2008).

Petri Nets simulation (PN): is a discrete-event graphical and analytical tool used to model and simulate flexible manufacturing systems (Başak & Albayrak, 2014; Pisching et al., 2018). In other words, PN formalism is suitable for representing concurrent, asynchronous, distributed, parallel, and stochastic systems (Guo et al., 2017; Drakaki & Tzionas, 2015). There are different extensions to PN. Overall, a PN consists of four elements: places - represented by circles, transitions - represented by rectangles, edges - represented by direct arrows, and tokens - represented by small solids (Pisching et al., 2018).

Hybrid Simulation (HS): is characterized by the combination of two or more simulation methods, i.e., multi-paradigm model (Scheidegger et al., 2018; Brailsford et al., 2019) or combination of simulation with optimization approaches, i.e., simulation-optimization (de Sousa Junior et al., 2019). The introductory guide for HS presented in Scheidegger et al. (2018) compares in detail the three of the main simulation methods in industrial engineering, i.e., DES, ABMS, and SD. Another key reference on HS is the literature review conducted by Brailsford et al. (2019), which also presents a conceptual framework to guide the development of HS projects. According to the authors, there are four types of hybridization: sequential - the output of one model is the input to another model; enriching – narrow use of another method by one dominant; interaction – the models interact cyclically without dominance; and integration – where it is not easy to distinguish the beginning of one method and the ending of another method. They also provide guidelines to combine simulation methods with optimization approaches (e.g., exact or heuristic methods). There are different kinds of HS models in the literature, such as DES-ABMS (Farsi et al., 2019), SD-ABMS (Nassehi & Colledani, 2018), DES-VR (Turner et al., 2016), ABMS-Data Science (Houston et al., 2017), Simulation-Big data (Vieira et al., 2019b), PN-AI (Drakaki & Tzionas, 2017), and multi-level simulation (Delbrügger et al., 2019). Most authors employ the term HS to describe their models, even though the taxonomy for classifying simulations with multiple models proposed by Lynch & Diallo (2016) may be considered in future research.

Digital Twins (DT): refers to the digital representation of a physical system and the seamless integration between the physical and digital spaces (Cimino et al., 2019). DT is commonly defined as "a multi-physics, multi-scale, probabilistic, ultra-fidelity simulation that reflects, in a timely manner, the state of a corresponding twin based on historical data, real-time sensor data, and physical model "(Tao et al., 2019, p. 2406). It was initially developed within the aerospace industry than extended to the manufacturing field (Rodič, 2017; Tao et al., 2019). Essentially, DT is a hybrid approach, built into four levels: geometry, physics, behavior, and rule (Tao & Zhang, 2017). The first two levels involve mainly kinematics and geometric simulation, also referred to as continuous simulation (Klingstam & Gullander, 1999), which is based on computer-aided technologies, such as computer-aided design (CAD), computer-aided engineering, and computer-aided manufacturing as well as finite element analysis (Dankwort et al., 2004). Levels three and four involve different simulation approaches, such as DES, ABMS, and AI techniques (Schluse et al., 2018). Tao & Zhang (2017) and Tao et al. (2019) review the role of DT in the manufacturing industry. A review of the influence of I4.0 on the development of DT is presented in Rodič (2017).

Virtual Commissioning (VC): is a digitalization method to speed up the commissioning of a new production process through a virtual environment (Lechler et al., 2019). It is a testing method that makes use of simulation models and emulated controllers during the development and validation of new manufacturing systems (Ahrens et al., 2018). VC integrates different technologies, such as 3D CAD, DES, and PLC. DT models have also been incorporated into the process of virtual commissioning. DT models, along with PCL design, give an even more accurate view of how automated systems design will perform prior to physical commissioning when hardware and PLCs are put together. A brief review of VC can be found at Lechler et al. (2019) and Putman et al. (2017).

4.2. Industry 4.0 design principles

Defining constructs clearly, in a desegregate approach, is essential to advance scientific research in the intersection of I4.0 and simulation fields, because it aids identifying variables and operational definitions for modeling, simulation and the development of theories (Davis et al., 2007; Harrison et al., 2007). It is important to support companies in identifying and implementing I4.0 projects (Hermann et al., 2015).Although there is no consensus on the definition of I4.0, some of its core technological components and design principles can be identified and used to support the implementation of I4.0 scenarios in companies (Hermann et al., 2015, 2016), and model and simulate those scenarios in a risk-free virtual environment prior to real implementation. Similar strategies have been used to characterize other important managerial approaches, such as Lean Production. In summary, I4.0 design principles are fundamental concepts that describe the I4.0 phenomenon and support its implementation (Ustundag & Cevikcan, 2017).

Ten articles describing the I4.0 design principles were selected for analysis, following the search protocol and eligibility criteria described in Section 2.2.1 (Kagermann et al., 2013; Lasi et al., 2014; Hermann et al., 2015, 2016; Ustundag & Cevikcan, 2017; Ghobakhloo, 2018; Mabkhot et al., 2018; Mittal et al., 2018; Ruppert et al., 2018; Tavcar & Horvath, 2019). Fig. 6 and Table 5 provides an overview of the 17 design principles of I4.0 identified from these articles, extending the list provided by Ghobakhloo (2018).

A seminal reference in I4.0 is the final report of the *Industrie 4.0* working group (Kagermann et al., 2013), which initially described its vision, potential, research requirements, and priorities for further research. From this report, the essential building blocks of I4.0 are vertical integration, smart factories, horizontal integration, and end-to-end digital integration of engineering. Additionally, Lasi et al. (2014) indicates flexibility, product personalization, decentralization, virtualization, and corporate social responsibility as main drivers and fundamental concepts of I4.0. Hermann et al. (2015) systematically reviewed the critical features of I4.0, identifying six design principles for I4.0 implementation: modularity, interoperability, real-time capability, virtualization, decentralization, and service orientation. These six principles were also analyzed in Mabkhot et al. (2018) and Ruppert et al. (2018). An aggregate analysis is presented in Hermann et al. (2016), which describes four I4.0 design prin-

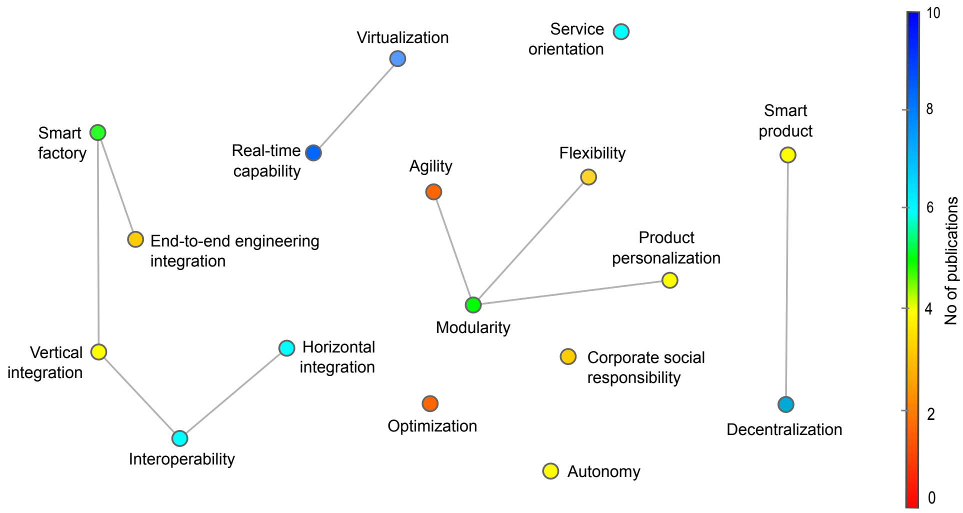


Figure 6: Design principles of Industry 4.0. Each node represents a design principle of Industry 4.0. The color of the node indicates the number of articles in the sample. The edge (line) represents a key relationship between principles.

Table 5: Description of the desigh principles of Industry 4.0

Principle	Description
Vertical integration:	is the integration of different ICT systems within a company at the different hierarchical levels, i.e., physical, software application, business processes (Kagermann et al., 2013). It refers to intra-company integration and networked manufacturing systems (Alcácer & Cruz-Machado, 2019), following a bottom-up automation pyramid approach, which is mostly described in terms of five levels: 1 - field level (devices, sensors and actuators); 2 - control levels (programmable logic controllers - PLC); 3 - supervisory level; 4 - planning level; and 5 - management level (Snatkin et al., 2013; Schlechtendahl et al., 2014; Wang et al., 2016a).
Horizontal integration:	consists of inter-company integration of IT systems (Alcácer & Cruz-Machado, 2019), both within and across an organization (Kagermann et al., 2013), enabling collaborative networks of companies share resources, capabilities, and information in real-time across the value chain (Brettel et al., 2014).
End-to-end engineering integration:	it refers to the digital integration of system engineering across the entire value chain, including product design and development, production planning, production engineering, production, and services (Kagermann et al., 2013; Wang et al., 2016a). It implies a holistic system engineering approach and digital product life-cycle management, encompassing both the production process and the manufactured product (Kagermann et al., 2013; Tao et al., 2018).
Smart factory:	refers to extensively integrated and collaborative manufacturing systems, which are capable of responding in real-time to changes in demands and conditions in the factory (Mabkhot et al., 2018). It consists of a network of smart objects or interconnected cyber-physical systems, and its main features include comprehensive connection, deep convergence, and reliance on data-driven simulation-optimization (Wang et al., 2016a,b; Kusiak, 2018).
Interoperability:	indicates the capacity of two or more systems to coexist, interact (exchange information), and interoperate, i.e., share resources (Gorkhali & Xu, 2016; Schlechtendahl et al., 2014). It refers to the ability of CPS components and IT systems having different standards to connect and communicate with each other (Mabkhot et al., 2018).
Modularity:	is an engineering concept that refers to the degree in which a product or system can be decomposed in re-combinable modules (Mabkhot et al., 2018) that are units "composed of a set of components with a set of specific interfaces" (Efatmaneshnik et al., 2018, p. 365). Modularity applies to the different stages of the production cycle (e.g., design, fabrication, assembly), enabling mass customization, and flexible and agile manufacturing systems (Hermann et al., 2015; Mabkhot et al., 2018; Efatmaneshnik et al., 2018; Ghobakhloo, 2018).
Real-time capability:	refers to data collection and analysis in real-time to support data-driven decision making (Tavcar & Horvath, 2019). It can be subdivided into three categories: real-time monitoring, real-time data analysis, and real-time decision-making (Mabkhot et al., 2018). The main technological enablers for real-time systems capabilities are industrial automation, IoT, CPS, cloud computing, big data, and simulation (Kagermann et al., 2013).
Virtualization:	refers to the virtual replication of a physical system by linking sensors and actuators data with digitized factory model (Hermann et al., 2016), in which a virtual system can be used to monitor, simulate and control its physical counterpart (Mabkhot et al., 2018). Virtualization is mainly related information transparency and to enabling technologies such as CPS, virtual reality, augmented reality, digital twin, and virtual commissioning (Hermann et al., 2015; Ghobakhloo, 2018; Mabkhot et al., 2018).
Decentralization:	means that the system network, where the decision is made, is not centrally controlled. It is directly related to the idea of self-organization and emergent behaviors, where lower-level components act on local information to achieve global goals (Kamdar et al., 2018; Oh et al., 2015; Tang et al., 2018).
Autonomy:	generally means that a system can operate and make decisions autonomously, without external instructions or intervention (Kamdar et al., 2018). It also suggests self-leaning capabilities, i.e., the ability of a system to learn and adapt (Tavcar & Horvath, 2019). Autonomy equips a production system with the capacity to respond to unforeseen events intelligently (Kagermann et al., 2013). However, a system may have different degrees of autonomy (Santa-Eulalia et al., 2012; Tavcar & Horvath, 2019).
Optimization:	is related to resource productivity and efficiency (Kagermann et al., 2013). It usually refers to prescriptive models used to find an optimum or near-optimum solution for a problem described in terms of a function and a set of constraints, ensuring the higher performance of a system, e.g., operational, economic, and environmental performance (de Souza Dutra et al., 2020). It "consists of searching the best solution, according to a given criterion, among a set of feasible solutions" (Barbati et al., 2012, p. 6021). It is also related to self-adjust and self-optimize functions (Ruppert et al., 2018; Tavcar & Horvath, 2019).
Flexibility:	refers to the ability of manufacturing systems and supply chains network to adapt and respond (proactively or reactively) to turbulent demand and changing environments (Lasi et al., 2014; Yu et al., 2015).
Agility:	is mainly related to responsiveness and speed to respond to changes. It is the capability of systems to be agile and to respond to unexpected or unplanned events quickly (Taylor et al., 2015). It is characterized by visibility, short lead times, and rapid detection and reaction (Giannakis & Louis, 2016).
Service orientation:	refer to new business models, such as factory as a service (FaaS), were organizations shift the focuses of obtaining profit from selling products to selling services (Mabkhot et al., 2018). "In this environment, complex manufacturing tasks can be accomplished collaboratively by several manufacturing services from different companies" (Ghobakhloo, 2018, p. 922).
Smart product:	refers to uniquely identifiable and all times located products that carry information about itself, about its environment, and its users (Kagermann et al., 2013; Mabkhot et al., 2018). Smart products are also referred to sensor-embedded products, and can be implemented through RFID tags, which allow storing and transmitting all information required for its production to machines (Hermann et al., 2015; Li et al., 2017).
Product personalization:	refers to production based on customized orders (lot size-1), where buyers dictate the conditions of the trade (Lasi et al., 2014). Product personalization also means that customer-specific criteria can be incorporated into the different phases of product development and that later modification in orders can be easily managed (Kagermann et al., 2013).
Corporate and social responsibility:	refers to environmental sustainability, resource efficiency, and labor regulations (Lasi et al., 2014; Ruppert et al., 2018). I4.0 will create new social infrastructures in the workplace, affecting job creation, competence profiles, training strategies, and increasing the participation of workers in the innovation process (Kagermann et al., 2013). Moreover, I4.0 emphasizes that sustainability and resource productivity and efficiency should be at the center of the design and operations of industrial manufacturing processes (Lasi et al., 2014).

ciples (i.e., interconnection, technical assistance, decentralized decisions, and information transparency). Other key feature that characterizes the I4.0 includes autonomy, smart product, optimization, and agility (Ustundag & Cevikcan, 2017; Mittal et al., 2018; Tavcar & Horvath, 2019).

4.2.1. Key relationships between I4.0 design principles

All I4.0 design principles are related to some extent. Although it is beyond the scope of this study to analyze all relationships and or dependencies between principles, it is important to highlight some key relationships described in the analyzed papers, represented by the arcs in Fig. 6. They are:

- Interoperability enables vertical and horizontal integration (Burke, 2017; Mabkhot et al., 2018).
- Modularity enables flexibility, agility, and product personalization (Hermann et al., 2015; Mabkhot et al., 2018; Efatmaneshnik et al., 2018; Ghobakhloo, 2018).
- Vertical integration enables smart factory (Ustundag & Cevikcan, 2017; Tavcar & Horvath, 2019).
- Smart manufacturing enables digital end-to-end engineering (Kagermann et al., 2013).
- Virtualization of production systems depends on real-time capabilities (Hermann et al., 2015; Ghobakhloo, 2018).
- Decentralization can be achieved through smart products (Kagermann et al., 2013; Hermann et al., 2015, 2016).

There are different levels of interoperability (i.e., technical, syntactic, semantic, organizational) and interoperability technologies, such as AutomationML (Automation Markup Language) and OPC UA (Open Platform Communications Unified Architecture), which are part of the reference architecture model for Industrie 4.0 (RAMI4.0) (Mabkhot et al., 2018; Ghobakhloo, 2018). These technologies enable vertical and horizontal integration by providing semantic interoperability for connected systems, allowing multi-vendor heterogeneous devices, machines, processes, and systems to communicate and information to flow seamlessly from field level to business level (Burke, 2017; Mabkhot et al., 2018).

Modularity allows achieving product personalization through combination, modification, or addition of modules, in a modular design of products (Duray et al., 2000; Efatmaneshnik et al., 2018; Ghobakhloo, 2018). Modularity also enables increased flexibility and agility of production systems to respond to fluctuating demands by reducing lead-time through a fast (plug & play) combination of modules with compatible software and hardware interfaces (Hermann et al., 2015; Li et al., 2019), wherein functionalities can be added or removed more quickly from a system (Efatmaneshnik et al., 2018; Mabkhot et al., 2018), as in modular and reconfigurable manufacturing systems (Kim et al., 2019).

The vertical integration of hierarchical subsystems serves as a backbone for implementing the smart factory, by connecting sensors and actuators in the field level up to management level (Wang et al., 2016b; Ustundag & Cevikcan, 2017; Tavcar & Horvath, 2019), which in turn supports end-to-end digital integration by allowing vertical networking of smart production systems (Kagermann et al., 2013; Wang et al., 2016a) endowed with reasoning, learning, adapting, and evolving capabilities (Tavcar & Horvath, 2019), which is crucial to support mass product personalization (Wang et al., 2016a).

Virtualization suggests that cyber-physical systems can monitor physical processes, which rely on real-time capabilities, such as real-time data collection (Ghobakhloo, 2018). It is associated with digital twins, wherein "sensor data are linked to virtual plant models and simulation models" (Hermann et al., 2015, p. 15) to monitor, analyze and optimize the physical process in real-time (Mabkhot et al., 2018; Tao et al., 2019).

Decentralization can be achieved through smart products due to smart products' capability to store and exchange data with smart processes throughout its lifetime and to actively control the manufacturing process (Kagermann et al., 2013; Kagermann, 2015; Hermann et al., 2015; Alqahtani et al., 2019). Decentralized controlled production systems based on smart products can produce by following the specifications and instructions recorded in an RFID tag embedded or attached to the product or product carrier (Kagermann et al., 2013; Wang et al., 2016b; Li et al., 2017; Mabkhot et al., 2018).

4.3. Linking simulation approaches with I4.0 design principles

After identifying the simulation-based approaches used relative to I4.0 and the design principles of I4.0, we proceeded with the cross-analysis of the concepts. To understand the I4.0 design principles that are captured by each simulation-based approach, we assessed all studies in the sample (see Appendix A). Initially, the articles were grouped by the simulation approaches used. Thereafter, key terms (i.e., I4.0 design principles) were searched in the text. Subsequently, the context wherein the string is invoked was analyzed to identify any explicit relationship between the simulation approach and the I4.0 design principle established by the authors. Thereafter, full-text articles were assessed relative to model conception, implementation, and analysis to identify implicit relationships. To increase the validity and reliability of the analysis, a triangulation by investigators (Bengtsson, 2016) was performed. Two investigators performed the analysis separately and thereafter, discussed their results at weekly meeting to obtain consensus. If no consensus was reached, a third investigator was consulted to reach the final decision. Tab. 6 summarizes the main relationships between simulation approaches and I4.0 design principles, from the authors' perspective, where the symbols mean that the I4.0 design principle is captured (●), partially captured (◑), or non-captured by a simulation approach (○).

Vertical integration (P1) and horizontal integration (P2) can be modeled using ABMS (Wang et al., 2016b) or PN formalism (Haag & Simon, 2019; Pisching et al., 2018; Guo et al., 2017). Other approaches, such as VR, DT, and VC, also depicts these principles. The DT-based model proposed by Zhang et al. (2017), Zhou et al. (2019), and Schluse et al. (2018) integrates intra-company level data from sources, such as human workers, sensors/actuators, manufacturing execution systems, and kinematics/dynamics. At inter-company level, Vieira et al. (2019a) and Vieira et al. (2019b) proposed a decision support system that integrates different supply chain' data sources and reproduces material and information flow using a hybrid data-driven simulation model, allowing supply chain disruption scenarios to be evaluated.

DT together with VR are two promising technologies to deploy end-to-end engineering integration (P3) across a value chain, by allowing the combination of a physical entity with a

Table 6: Linking simulation-based approaches with the design principles of Industry 4.0

SM approach	I4.0 design principle																
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15	P16	P17
ABMS	●	◑	○	◑	●	●	●	◑	●	●	●	●	●	◑	◑	◑	◑
DES	○	◑	○	○	○	○	◑	◑	○	○	●	●	●	●	○	○	◑
SD	○	◑	○	○	○	○	◑	◑	○	○	●	●	○	◑	○	◑	○
VR	◑	○	○	◑	○	○	●	●	○	○	●	●	○	●	●	●	◑
AR	○	○	○	◑	●	○	●	●	◑	○	●	●	◑	●	●	◑	○
VC	●	◑	◑	◑	◑	◑	◑	◑	○	○	●	●	◑	●	◑	◑	○
PN	●	◑	○	◑	◑	◑	◑	◑	○	○	●	●	◑	○	○	◑	○
AI	◑	○	○	●	◑	◑	●	●	●	●	●	●	◑	●	●	◑	○
DT	●	●	◑	●	●	●	●	●	◑	◑	●	●	◑	●	◑	◑	◑
HS	●	●	◑	●	●	◑	●	●	●	●	●	●	●	●	◑	◑	◑

The symbols mean I4.0 desing principle captured (●), partialy captured (◑), or non-captured (○) by the simulation approach. The abbreviations are: P1 - Vertical integration; P2 - Horizontal integration; P3 - End-to-end engineering integration; P4 - Smart factory; P5 - Interoperability; P6 - Modularity; P7 - Real-time capability; P8 - Virtualization; P9 - Decentralization; P10 - Autonomy; P11 - Optimization; P12 - Flexibility; P13 - Agility; P14 - Service orientation; P15 - Smart product; P16 - Product personalization; P17 - Corporate and social responsibility; ABMS - Agent Based Modeling and Simulation; DES - Discrete Event Simulation; SD - System Dynamics; VR - Virtual Reality; AR - Augmented Reality; VC - Virtual Commissioning; PN - Petri Nets Simulation; AI - Artificial Intelligence; DT - Digital Twins; HS - Hybrid Simulation;

high-fidelity virtual counterpart and creation of immersive virtual environments. The potential application of DT throughout the product-life-cycle is indicated in several studies (Tao & Zhang, 2017; Rodič, 2017; Tao et al., 2019; Cimino et al., 2019). However, there are several challenges to be addressed to make it feasible, as listed in Tao et al. (2018). However, some studies proposed addressing these principles partially. Sierla et al. (2018) combines DT with product-centric control, wherein the virtual counterpart of a product (developed from the virtual product description) inquires its own manufacturing services, allowing potential manufacturing suppliers to be involved in the product design phase and assembly planning. The authors present two example cases as a proof-of-concept. Cecil et al. (2019) proposed an IoT-based CPS framework, wherein a VR-based collaborative environment is used to support distributed micro-devices assembly planning. The authors developed a testbed to demonstrate the feasibility of their approach.

A smart factory (P4) is often modeled as a multi-agent system. Wang et al. (2016b) proposed a smart factory framework, modeling physical resources as different types of agents, forming a self-organized MAS system with feedback and coordination based on Big Data. Nagadi et al. (2017) presented a framework for smart factory assessment using ABMS to determine a machines' behaviors and DES to mimic process flows.

The principles interoperability (P5) is explored by different approaches, such as ABMS, HS, DT, and VC models. Laurindo et al. (2019) proposed an integration mechanism for HS or VC approach, by allowing online communication and high-level data exchange between DES and the dynamic system simulation software. From the authors, the integration between the DES model and the control system enables the validation of PLC logic and other different operational aspects of a production system. Vieira et al. (2020) presented a simulation-based approach to address problems related to the integration of big data, from different data sources, into supply chain simulation models. Schluse et al. (2018) introduced the concept of experimentable digital twins that combines DT with model based systems engineering and simulation technology, wherein its components communicate through a simulated communication infrastructure, mirroring the real communication infrastructure of its physical counterparts. A general approach to transform legacy systems into Industry 4.0-ready by connecting production systems with different interfaces is presented in Schlechtendahl et al. (2014).

Modularity (P6) links to the strategy of modular simulation, used to reduce the model building complexity, and to the capacity to reuse and share sub-models (Delbrügger et al., 2019). It is an important feature of agent systems (Heydari & Dalili, 2015; Rodrigues et al., 2018). Farsi et al. (2019) proposed a modular HS framework, combining DES with ABMS for a modular manufacturing system design, which considers different abstraction levels. Zhang et al. (2017) uses 3D reference models and modular encapsulation to aid individualized designs and virtual assembly. Zhou et al. (2019) and Delbrügger et al. (2019) integrated several simulation modules. To achieve modularity, Tan et al. (2019) proposed the smart assembly units, which encapsulate assembly functions and data-drive capabilities, enabling decomposition and reconfiguration of assembly processes, implemented in an event-driven multi-agent reinforcement learning approach.

Real-time capability (P7) and Virtualization (P8) are mainly related to the capacity to collect and integrate CPS/ IoT-data (or big data) into the simulation models. Saez et al. (2018) used an HS approach to assess the performance of production systems in real-time, monitoring and analyzing machines' continuous and discrete variables in virtual environments operating synchronously to factory floor equipment. Turker et al. (2019) present a decision support system for dynamic job-shop scheduling that collects data from an IoT system and act on jobs processing orders, testing the system under different demand scenarios through a DES model. Houston et al. (2017) combined ABMS with data science to evaluate the return on investment of installing an IoT system, used to collect continuous real-time data in support of predictive maintenance. A multi-view of a DT real-time data synchronization logic to link a physical system with and virtual simulation model is described in Zhang et al. (2017).

Decentralization (P9) is captured through an ABMS, which enables distributed decision making at different levels, i.e., machine level, system level, or to create collaborative enterprise networks. Kaihara et al. (2017) proposed a simulation model to evaluate the effectiveness of crowdsourced manufacturing using ABMS and DES, wherein business entities share their manufacturing resources based on their demand and available capacity. A continuation of this study is presented in Kádár et al. (2018), wherein the authors propose a bi-level simulation model to support asset sharing in a large federated network of manufacturers. In their model, each factory agent integrates a DES model and has an interface to communicate with an agent-based collaboration platform, which establishes the negotiation mechanism. Similarly, a distributed approach based on ABMS and DES for multi-machine preventive maintenance scheduling is proposed in Upasani et al. (2017). Other examples include the VR-based simulation approach for evaluation and validation of manufacturing assembly planning from distributed locations, proposed by Cecil et al. (2019), and a DT-based distributed approach is presented in Liu et al. (2018).

Autonomy (P10) is determined by agent design (i.e., ABMS), wherein system entities are modeled as autonomous intelligent agents. The intelligence of the agent is usually modeled in terms of ”if-else” statements, optimization methods, or following an AI technique. UML statechart and sequence diagram are employed as a conceptual modeling tool to describe the behaviors and communications between agents. An ABMS with reinforcement learning for intelligent planning and scheduling is described in Tan et al. (2019). Grundstein et al. (2017) proposed an autonomous production control method for complex job shop manufacturing using heterarchical structures, validated through a DES model. Other examples of simulation models with intelligent mechanisms can be found in Ghadimi et al. (2019) and Carvajal-Soto et al. (2019).

All 10 simulation-based approaches can capture optimization (P11) and flexibility (P12) principles by adjusting the parameters in the models in multiple evaluation scenarios or by incorporating mathematical optimization approaches into the models. Trebuna et al. (2019) combined the value stream mapping (VSM), a Lean manufacturing tool, with a DES model to identify improvement opportunities that optimize production flows and increases the flexibility and productivity of a production system. Frazzon et al. (2018) proposed an HS model to optimize production scheduling and transport planning in supply chains by combining a mixed-integer programming model, a DES model, and a genetic algorithm iteratively. Zhang et al. (2017) describes how DT models can perform real-time optimization of production systems. In addition, Zhou et al. (2019) proposed a knowledge-driven DT framework that enables self-optimizing manufacturing systems. Human-robot collaboration in the physical and virtual space is another promising technology of I4.0 to improve manufacturing flexibility. In this regard, Pérez et al. (2019) presented a VR-based framework to support training, simulation, and VR-operated robotic systems through an immersive virtual environment.

Simulation models capture agility (P13) in approaches such as, by supporting multiple scenarios evaluations, distributed collaboration and by increasing information transparency. Schönemann et al. (2015) proposed an HS model, that combines DES with ABMS, to evaluate the development of agile manufacturing systems based on redundant job shop work stations and flexible product routing. In Vieira et al. (2019a), disruptive events were triggered in different geographic locations in supply chain simulation run time to analyze system' performance impact related to terms of stock levels and unfilled orders. To address the need for agile manufacturing, Sierla et al. (2018) combined DT with product-centric control, proposing a framework to aid collaborative product design and factory planning.

Service orientation (P14) can be achieved through data-driven simulation, wherein users can develop and run simulation models with minimum or no knowledge in programming, in a self-contained service. This enhances the model maintainability, reusability, and ability to support decision making in complex systems (Guizzi et al., 2019). An example is presented in Goodall et al. (2019), which proposed a data-driven simulation approach for remanufacturing operations using DES and object-oriented programming paradigm. Their simulation model predicts material flow in a generic and reusable manner, reflecting changes in real systems without manually change the simulation construct. Moreover, the concept of software as a service (SaaS) is applied in Kádár et al. (2018).

Smart product (P15) enables data-driven simulation approaches. Alqahtani et al. (2019) developed a DES model to predict an optimal warranty policy for remanufactured products and components, wherein an end-of-life product is equipped with RFID sensors to collect and transfer critical product pieces of information. Furthermore, modeling as an agent system, Benotsmane & Kov (2019) and Benotsmane & Kov (2019), described a model that considers iterative smart working pieces.

Product personalization (P16) also implies smart production lines. Zhang et al. (2017) and Zhang et al. (2017) proposed a DT-driven platform for rapid individualized designing of production systems, which combines a reference model, distributed simulation, and multi-objective optimization models to support the quality of design and quality of conformance. From Park et al. (2019), a mean to achieve customization/personalization is operating factory as a service (FaaS) in a distributed manufacturing system. To achieve this, they proposed a DT-based approach. Tamás (2017) proposed a DES model to improve the performance of intermittent production systems, to enable managing several product variants, in a customer-oriented approach.

Corporate and social responsibility (P17) can be analyzed in terms of impact analysis and resource efficiency. Ghadimi et al. (2019) proposed a framework for sustainable supplier evaluation and selection in the I4.0 supply chain using agent technology. Charnley et al. (2019) explored the relationship between circular economy and I4.0 through an HS approach, combining a DES and an SD model to enable a data-driven circular economy, focusing on remanufacturing processes in the automotive industry. Yazdi & Azizi (2019) considered the concept of manufacturing sustainability, thus, proposed a DES model to evaluate an improvement project before implementation, showing an impact on production systems' operational performance and energy consumption. Longo et al. (2019) proposed a VR-based system for emergency response training in industrial sites, applicable to emergency management and disaster/risk preparedness enhancement, as well as to support companies comply with security norms and reduce environmental risks.

4.4. Classification scheme and assessment

To aid further content analysis, and assess central aspects of the studies employing a simulation-based approach in I4.0, a classification scheme with five categories, subdivided into 61 subcategories was proposed (see Fig. 7). The dataset used to display the results in Fig. 7 is available in the Appendix A.

The first category represents the simulation-based approaches identified through quantitative and qualitative analysis, as described previously. The second category, adapted from Jahangirian et al. (2010), is used to assess the empirical nature of the studies. Here, real problem solving (RPS) refers to models that use real data gathered from real processes to solve a real problem. In contrast, hypothetical problem solving (HPS) uses artificial data (e.g., randomly generated instances) to solve a real-life problem. The RPS has a stronger internal validity compared to HPS, which subsequently presents a stronger external validity, focusing on providing solutions that can be generalized.

The third category, adapted from Harrison et al. (2007), classifies the purpose (or use) of simulation models into seven categories: (1) prediction – analysis of variables relationships through simulation output, which can also be seen as hypotheses subject to empirical testing; (2) proof – relates to resulting system behavior, used to show that the system modeled can yield specific types of behaviors; (3) discovery – identification of unexpected behaviors through system entities interaction analysis; (4) exploration – analysis of the conditions wherein a particular behavior is produced; (5) critique – examination of a pre-existing theoretical explanation for a phenomenon; (6) prescription - recommendations to improve operations effectiveness; (7) empirical guidance – support the development of new theories and empirical research.

Category four, adopted from Harrison et al. (2007) and Jahangirian et al. (2010), is used to classify the studies per area of application related to the field of industrial engineering. The fifth category groups the design principles of I4.0 identified through the qualitative analysis of studies included in phase 2 of the systematic review. The key results from the content analysis were thereafter computed using the defined classification scheme, summarized in Fig. 7, where each publication can be classified into no, one, or multiple categories.

Overall, 10 simulation-based approaches and 17 design principles of I4.0 were identified. The more significant part of the simulation-based studies (over 55%) employs hybrid simulation or digital twin (see Fig. 7a). DES and ABMS also play a vital role in I4.0, being applied in 20% of the sample. In addition to that, most HS models integrate DES and/or ABMS approach. Other approaches are represented in the sample as follows: SD (4 articles, 5%); AI techniques (4 articles, 5%); VR (3 articles, 3.8%); AR (3 articles, 3.8%); PN (1 article, 1.3%). As concerns model implementation, the studies use very different software tools. Of these, the most frequent are AnyLogic (8 articles, 10%), Arena (7 articles, 8.8%), Tecnomatix plant simulation (6 articles, 7.5%), and MATLAB/Simulink (5 articles, 6.3%). In terms of programming languages, Java stands out with 19 articles, representing 23.8% of the sample size. Furthermore, AnyLogic is also based on Java programming.

For the empirical nature (see Fig. 7b), the majority of these studies (42 articles, 52.5%) used artificial data based on hypothetical cases or randomly generated instances. In contrast, 29 studies (36.3%) used real-data. Additionally, 6 review articles (7.5%) and 3 theoretical-conceptual articles (3.8%) were identified. In general, the review articles focused on a specific simulation method. Rodič (2017), Tao et al. (2019) and Cimino et al. (2019) focus on DT. Vieira et al. (2018) center on DES, and Turner et al. (2016) on DES-VR. Mourtzis (2019) emphasizes the historical evolution of simulation technologies. They all have a different scope and design compared to this research. For applications (see Fig. 7d), most of the studies (57.5%) focused on process engineering manufacturing, scheduling, or production planning and inventory control. Together, supply chain management, maintenance, education/training represents 25% of the sample. Nevertheless, 10 out of 23 areas related to the field of industrial engineering are unexplored. Lastly, Fig. 7e shows that all 17 design principles of I4.0 identified can be captured by simulation technology. However, the extensiveness wherein the design principles are captured varies depending on the simulation approach. HS and DT consider a higher number of I4.0 principles. End-to-end engineering integration, smart product, and corporate social responsibility are the principles least addressed by these studies.

5. Discussion

This review's results reveal an increasing trend in the number of publications on simulation in I4.0 in the last 4 years. This result reinforces the importance and potentials of simulation technologies to support the implementation of I4.0, as indicated by other academics, industry experts, and leading simulation software vendors (Kagermann et al., 2013; Shih, 2016; Thilmany, 2017; Tao et al., 2018; Lugert et al., 2018; Jeong et al., 2018; Han et al., 2018; AnyLogic, 2020; Ghobakhloo, 2018; Martin, 2019). It is consistent with the recommendations in the final report from the German *Industrie* 4.0 working group to develop the I4.0, which is a primary reference on I4.0. It is also consistent with the findings of the empirical research conducted by Lugert et al. (2018) with 170 industry experts, which reveals simulation as an essential technique to enhance continuous improvement tools to plan and guide companies' transition to I4.0. Moreover, the use of simulation technologies is incorporated as part of industry leaders' strategy (e.g., General Electric, Siemens, Bosch, Airbus) on the path to I4.0 digital transformation (Tao et al., 2019; AnyLogic, 2020; Vieira et al., 2019b,a; Deloitte, 2018). Furthermore, from the ABI research group, I4.0 stimulates investments (in billions of dollars) in plant simulation software (Martin, 2019). The global survey conducted by Deloitte (2018) with 361 executives about

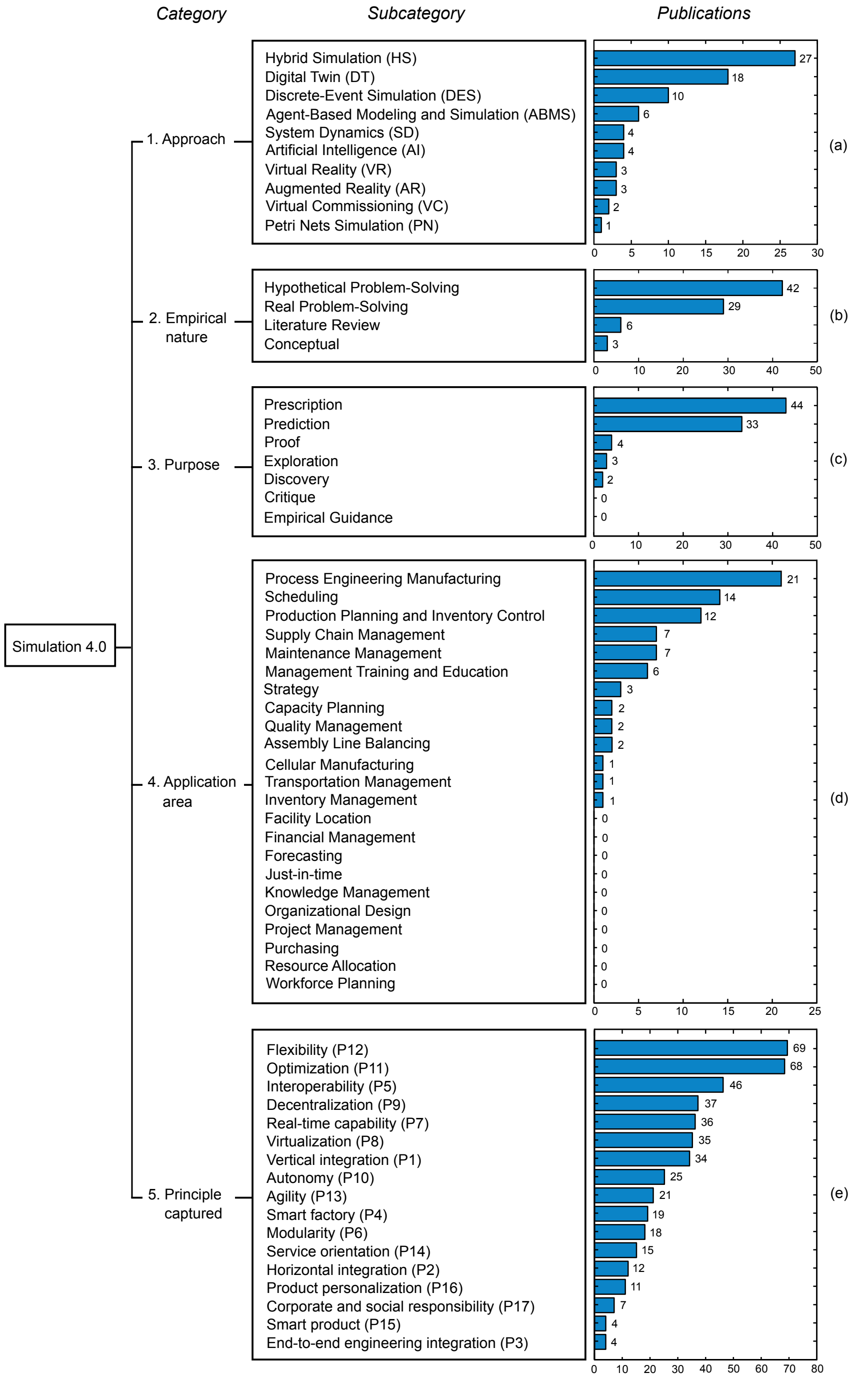


Figure 7: Classification scheme and assessment results

I4.0 also indicates companies' investments to adopt advanced simulation and modeling technologies to access, analyze and leverage data from assets. We can therefore infer that the research area at the intersection of I4.0 and simulation fields will continue to grow in the coming years owing to its relevance to industry.

5.1. RQ1 - *What are the simulation-based approaches being employed in the context of I4.0*

In addressing the first research question, 10 simulation-based approaches are used in the context of I4.0: DES, SD, ABMS, HS, PN, AI, VR, AR, VC, and DT. This result indicates that traditional simulation techniques (e.g., DES, SD) and software tools (e.g., Arena, Anylogic, Simulink) are still applicable in I4.0. The results also indicate hybrid simulation and digital twin as the main simulation approaches in the context of I4.0. This result is consistent with the increasing trend to adopt hybrid modeling and simulation as a mean to meet the complex systems identified by Jahangirian et al. (2010). It is also consistent with the rising profile of digital twin along to the advancement of I4.0 identified by Tao et al. (2018).

5.2. RQ2 - What are the purposes, empirical nature, and applications areas of studies on simulation in I4.0?

To address the second research question, the main purpose of the simulation-based studies in I4.0 is prescription and prediction for an improved mode of operations. However, most studies use artificial data or hypothetical cases (i.e., hypothetical problem-solving). This finding may be partly due to the novelty of I4.0 and the early development stage of simulation in I4.0. It may also be explained by the fact that it is often difficult and time-consuming to collect primary data from physical systems that are usable for simulation-based research or owing to restrictive confidentiality agreements.

For application areas, we found that studies on process engineering manufacturing, scheduling, and production planning and control are predominant. This result is in partially consistent with those obtained in Shafer & Smunt (2004) and Jahangirian et al. (2010), which features scheduling as a dominant research topic in simulation.

5.3. RQ3 - What are the design principles of I4.0?

For the third research question, the results indicate 17 design principles characterizing the I4.0 (see Fig.6). This result extends the list of principles identified in Ghobakhloo (2018), revealing other important research constructs, such as flexibility, agility, and autonomy, widely investigated in operation and supply chain management literature. This result is significant to guide companies in identifying and implementing I4.0 scenarios in a more practice-oriented manner, considering that it still lacks a clear understanding of the I4.0 concept (Hofmann & Ruesch, 2017; Moeuf et al., 2018). It is also important to support the development of modular and reusable simulation frameworks for a set of problems based on a library of software components that can be built upon the principles of I4.0.

5.4. RQ4 - Which I4.0 design principles are captured by each simulation-based approach?

Finally, for the fourth research question, the results suggest that simulation can fully or partially capture all design principles of I4.0. This result indicates that simulation can support the investigation of the I4.0 phenomenon from multiple perspectives (e.g., strategic, tactical, operational), suggesting a broader set of applications from the ones already reported in the literature. This result is essential to foster the simulation's adoption to capture and solve problems that emerge in the context of I4.0, to support the assessment and guide the implementation of I4.0, wherein there is still a lack of tools for practitioners and managers, as pointed by Hofmann & Ruesch (2017). However, the extensiveness wherein I4.0 principles are captured varies according to each simulation-based approach. In this regard, hybrid simulation and digital twin stand as the most promising approaches for I4.0 because they are able to capture most principles of I4.0. However, traditional simulation approaches such as DES are still valid and will continue to evolve driven by I4.0, as discussed by Vieira et al. (2018), which proposes a research agenda for DES in I4.0.

6. Limitations and future research

Similar to other studies, this review has its limitations, one of which relates to the search strategy. As discussed by Liao et al. (2017), there are other similar I4.0 initiatives, such as the Industrial Internet of Things (IIoT), developed in the USA, a term that could be used in queries considering that some authors use these terms interchangeably (Hofmann & Ruesch, 2017). However, these issues were partially addressed using the backward and forward snowball sampling technique (Wohlin, 2014) and by including a high number of articles in the sample, compared to other reviews in the field of I4.0 and simulation, such as the ones developed by Moeuf et al. (2018) and Vieira et al. (2018). Furthermore, the study focuses only on peer-reviewed journal articles. Other document types, sources of data and languages could be considered in the search protocol. Moreover, this study is not an exhaustive review of each simulation-based approach. Future studies can focus on a particular simulation technique, such as the one developed by Vieira et al. (2018), which proposed a research and development agenda for DES in I4.0.

A limitation of this study related to analysis is that content analysis (i.e., categorization and compilation of data) involves subjective judgment calls. However, by using the PRISMA statement (Moher et al., 2009), triangulation by investigators (Bengtsson, 2016), and existing classification categories (Harrison et al., 2007; Jahangirian et al., 2010) we have minimized the potential bias of reviewers. In addition, this study does not investigate all the relationships (and or dependencies) and aggregation levels between the design principles of I4.0. This can be addressed in future studies.

The analysis of the results also reveals issues and opportunity areas for future research:

- Hybrid modeling and simulation: different forms of model hybridization (e.g., multi-methods, multi-models, composite models) can be explored in future researches to manage the increasing complexity of I4.0 manufacturing systems. However, problems such as incompatibilities between simulation software tools, conflicts between distributed heterogeneous data sources, interface incompatibility, incompatible runtime models and multiple representations of time, bases of value, bases of behavior and resolutions (Mustafee et al., 2015; Eldabi et al., 2018; Tao et al., 2018), related to models interoperability and synchronization will require addressing.
- Data-driven and real-time simulations: incorporating real-time data or big data into the simulation models and developing real-time optimized simulations is a research trend that can advance I4.0 towards its vision of real-time self-optimized production systems. In this regard, there are several opportunities to integrate artificial intelligence techniques (e.g., genetic algorithms, artificial neural networks, reinforcement learning) as well as other machine learning and deep learning techniques into simulation models. Simulation models can embed artificial intelligence components to allow testing, calibration, forecasting, optimization, learning, or adaptive behavior and to increase the speed of large-scale models (Wallis & Paich,

2017).

- Real problem solving: most simulation-based studies in I4.0 use either artificial data or hypothetical cases. Therefore, the development of real cases using real-world data from industry is required to increase the practical relevance of simulation research in the context of I4.0 and to bridge the gap between academic studies and industry practices. Because most companies are not Industry 4.0-ready, as discussed by Schlechtendahl et al. (2014), the use of learning factories (or living labs) to develop testbeds and or proof-of-concept experiments can be considered, as applied in Zhou et al. (2019) and Schluse et al. (2018).
- The purpose of using simulation: most studies analyzed center on prediction or prescription (see Fig. 7c). There is a lack of models used for exploration, discovery, proof, critique, and empirical research guidance. In this regard, it is also important to highlight that simulation is a robust methodology to advance theory development (Harrison et al., 2007; Davis et al., 2007), and there remains sufficient room for simulation-based research in I4.0.
- Application areas: the lack of simulation studies in I4.0 related to critical areas of industrial engineering, operations, and supply chain management (e.g., just-in-time, cellular manufacturing, capacity planning, quality management) revels other future research avenues. An approach to partly address these problems, whereas using companies' capabilities is to combine Lean production practices with simulation techniques, which is consistent with earlier research (Lugert et al., 2018; Uriarte et al., 2019).
- Principles captured: the summary of I4.0 design principles described by the simulation models analyzed (indicated in Fig. 7e) introduces other research opportunities owing to the lack of models to describe principles such as smart products, corporate and social responsibility, horizontal integration, and end-to-end engineering integration, which requires significantly holistic approaches.
- Classification of models: the development of a new typology and or taxonomy for modeling and simulation in I4.0 is another promising avenues for future research because it can help reduce complexity (grouping several concepts into a small number of types) and make more accessible for researchers and practitioners to identify terminologies, define and categorize their models more accurately.

7. Conclusions and implications

Simulation is a key technology of Industry 4.0 to support the development of planning and exploratory models to optimize decision making, the design, and operations of complex systems. It also has the potential to aid the assessment and implementation of Industry 4.0 in companies by evaluating multiple scenarios. However, advancements in Industry 4.0 and its enabling technologies (e.g., the Internet of Things, Cyber-Physical Systems, Big Data) introduces new challenges to the field of simulation owing to the increasing complexity of systems to be modeled. This study aimed to provide a state-of-the-art review of simulation in the context of Industry 4.0.

This study shows an increasing trend in simulation-based research in Industry 4.0 within the last four years and suggests that the research area at the intersection of Industry 4.0 and simulation fields will likely continue to grow owing to its increasing relevance to the industry. In total, 10 simulation-based approaches employed in Industry 4.0, and 17 design principles characterizing the Industry 4.0 were identified. A cross-analysis of concepts show that all design principles of Industry 4.0 can be fully or partially expressed through simulation. Moreover, our findings suggest that hybrid simulation and digital twins are currently the two primary simulation approaches in Industry 4.0.

The findings from this study have implications for researchers, practitioners, and managers. The results suggest that simulation-based approaches can aid the investigation of the Industry 4.0 phenomena from different perspectives (e.g., strategic, tactical, operational). Furthermore, the use of simulation techniques can equip organizations with means to evaluate Industry 4.0 principles and technologies in a virtual environment to enhance technology investment decision-making and aid the transition toward the 4th Industrial Revolution.

Finally, despite the limitations of this review, we believe it will contribute to the work of researchers and practitioners striving to understand the state-of-the-art of research at the intersection between the emerging field of Industry 4.0 and the field of simulation by identifying, characterizing and analyzing simulation-based research developed in the context of Industry 4.0 and by discovering opportunities for future research.

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Appendix A. Supplementary material

Supplementary data associated with this article is available in the online version.

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