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# The impact of Industry 4.0 on bottleneck analysis in production and manufacturing: Current trends and future perspectives

Ehsan Mahmoodi [a], Masood Fathi [a,b,*], Morteza Ghobakhloo [b,c]

[a] Division of Intelligent Production Systems, School of Engineering Science, University of Skövde, 54128 Skövde, Sweden
[b] Division of Industrial Engineering and Management, Department of Civil and Industrial Engineering, Uppsala University, Sweden
[c] School of Economics and Business, Kaunas University of Technology, Kaunas, Lithuania

A R T I C L E I N F O

*Keywords:*
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A B S T R A C T

Bottleneck analysis, known as one of the essential lean manufacturing concepts, has been extensively researched in the literature. Recently, there has been a move towards using new Industry 4.0-based concepts and technologies in the development of bottleneck analysis. However, the interrelations between bottleneck analysis and Industry 4.0 have not been studied thoroughly. The present study addresses this gap and performs a systematic literature review on articles available in major scientific databases (i.e., Web of Science and Scopus) to investigate the impact of Industry 4.0 on the advancement of bottleneck analysis in production and manufacturing. Bibliometric analysis and content review were performed to extract the quantitative and qualitative data. Results revealed that only five out of 15 design principles and five out of eleven technologies of Industry 4.0 were addressed previously in developing bottleneck analysis methods. In addition to highlighting the existing gaps in the literature and proposing topics for future research, several potential development streams are proposed by studying the design principles and technologies of Industry 4.0, which have not been considered in bottleneck analysis before.

## 1. Introduction

Manufacturing industries are constantly striving to improve the productivity of their processes (Schmenner, 2015). Productivity improvement is mainly centered around increasing throughput, which can be defined as the pace at which parts pass through a production line (Lai et al., 2021). The throughput of a production system is constrained by one or more resources, known as “throughput bottleneck(s)” (Possik et al., 2021). In production and manufacturing, it is known that bottlenecks are responsible for up to 30 % of throughput losses (Alavian et al., 2019). Given the impact of bottlenecks on the productivity of manufacturing systems, bottleneck analysis (BA) has attracted considerable interest among academics and practitioners.

Theories developed for BA focus on the identification of bottlenecks, their elimination, as well as the resolution of their root causes. According to Goldratt & Cox (1986), bottlenecks should be identified and eliminated cyclically to improve throughput continuously. Nevertheless, it is difficult to identify and eliminate bottlenecks in practice, requiring practitioners to rely on their experience and intuition when conducting BA (Zhang et al., 2021). In order to provide the industry with the appropriate tools for BA, researchers have developed analytical and discrete event simulation models (Thürer et al., 2021). The limitation of analytical and simulation models is that they must be continually revised and adjusted to reflect changes happening in the real system (Lai et al., 2021). Consequently, maintaining analytical and simulation models represents a significant challenge to practitioners. Fortunately, the emerging manufacturing digital transformation under Industry 4.0 appears to offer important implications for addressing challenges associated with BA.

The term Industry 4.0, which stands for the fourth industrial revolution, originates from the German initiative launched in 2011 to empower the manufacturing sector via digitalization (Lasi et al., 2014). Hence, Industry 4.0 has been primarily understood as the application of the most advanced digital technologies for boosting manufacturing operations (Ghobakhloo, 2018). The definition of Industry 4.0 has evolved significantly during the past decade. The scope of digital transformation under Industry 4.0 nowadays extends beyond the four walls of factories, involving the digital transformation of organizations and their value network across various industries (Culot et al., 2020). For the manufacturing sector, Industry 4.0 entails transformation toward a

* Corresponding author at: Division of Intelligent Production Systems, School of Engineering Science, University of Skövde, 54128 Skövde, Sweden.
*E-mail addresses:* masood.fathi@his.se, fathi.masood@gmail.com (M. Fathi).

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hyperconnected manufacturing ecosystem involving the seamless integration of production facilities, smart warehouses, suppliers, intralogistics, and even customers (Ching et al., 2021). Industry 4.0 is a technology-driven phenomenon, meaning the smart factories of Industry 4.0 rely on integrating disruptive technological innovations such as artificial intelligence within the existing production infrastructure, operations technologies, and processes (Büchi et al., 2020). The technologies of Industry 4.0 are labeled disruptive as they redefine or significantly restructure manufacturing operations (Benitez et al., 2020). Among other disruptive changes, Industry 4.0 transforms lean processes and allows manufacturers to become digitally leaner (Ghobakhloo and Fathi, 2020). In doing so, Industry 4.0 offers important implications for bottleneck analysis, which is one of the continuous improvement tools under the lean production philosophy (Tu and Zhang, 2022).

In recent years, data-driven approaches have been developed whereby shop floor data is directly used to identify bottlenecks without relying on any models (West et al., 2022). Real-time bottleneck analysis can be utilized by applying Industry 4.0 (I4.0) technologies, such as sensors and advanced communication technologies (Tu et al., 2021). This is the most obvious way in which I4.0 has transformed BA. There is, however, another way in which I4.0 has influenced BA. I4.0 has enabled advanced manufacturing systems to become more flexible and agile by implementing cyber-physical systems (Su et al., 2022). This flexibility and agility in manufacturing processes are essential to handle fluctuations in demand caused by mass customization (Espinoza Pérez et al., 2022). Nevertheless, as manufacturers become more flexible and agile due to the ever-increasing market turbulence, bottleneck dynamics and shiftiness increase, making the BA increasingly complex (Zhang et al., 2021).

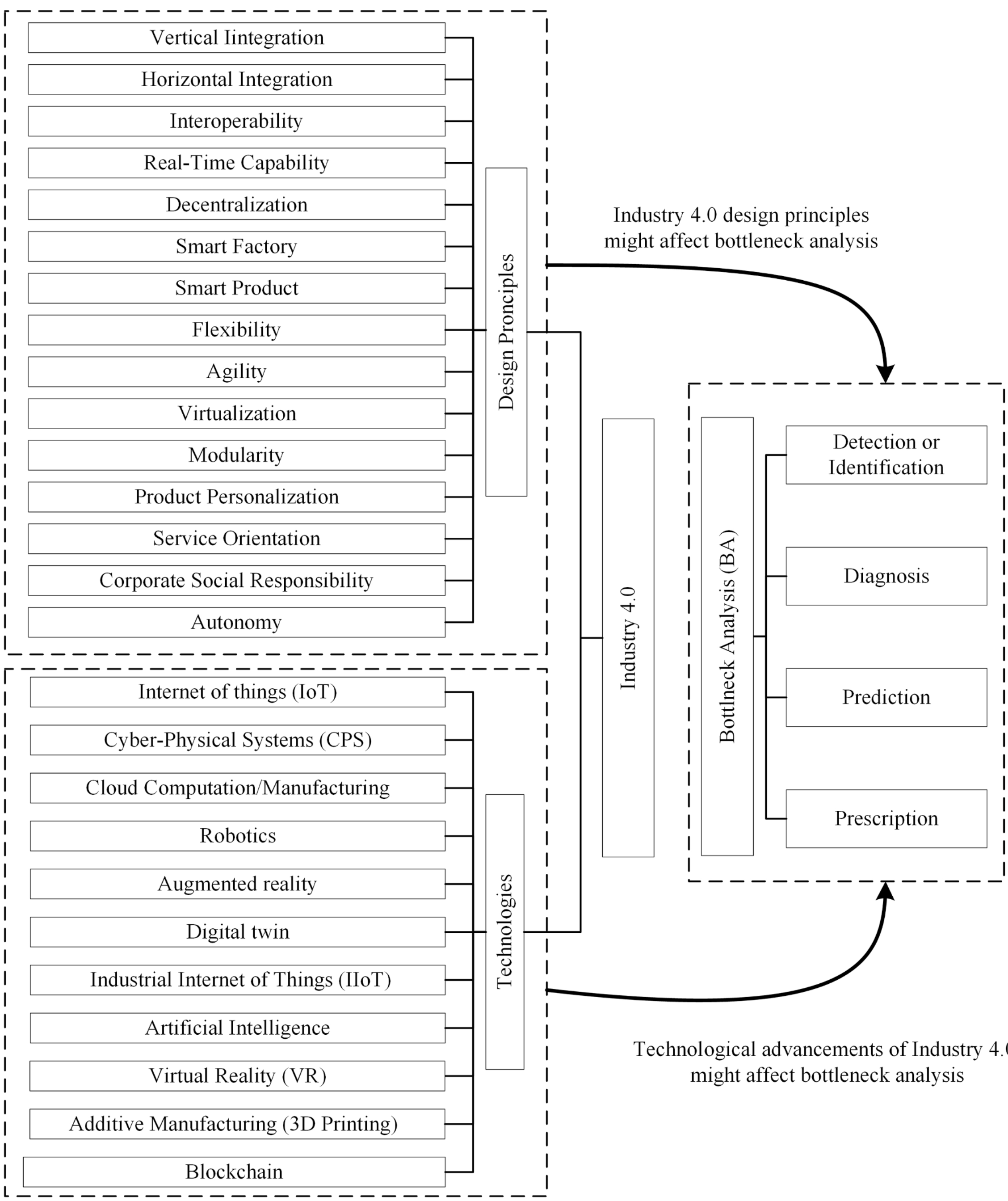



**Fig. 1.** Identified relationships between I4.0 and BA.

In general, BA is influenced by I4.0 in two ways. First, BA becomes more complicated in advanced production systems of I4.0 due to more flexibility and frequent planned and unplanned changes (Lai et al., 2021). Second, new capabilities provided by I4.0 will lead to the invention of novel BA methods (Subramaniyan et al., 2021). To address this controversial role of I4.0, it is crucial to find how BA might change with or benefit from the building blocks of I4.0.

For the purpose of this study, I4.0 and BA are classified into their respective building blocks to provide a better understanding of their interrelationships (see Fig. 1). According to the literature (e.g., de Paula Ferreira et al., 2020; Ghobakhloo et al., 2021), I4.0 is classified into two main building blocks, namely "design principles" and "technologies". Alternatively, BA consists of four distinguishable building blocks: detection, diagnosis, prediction, and prescription (West et al., 2022).

The technologies of Industry 4.0 refer to the innovative and disruptive technological innovations that drive the digital transformation of manufacturing firms under Industry 4.0 (Ching et al., 2021). Although these technologies were introduced years ago (the genesis of some Industry 4.0 technologies dates back to the third industrial revolution), these technologies have become functionally mature and commercially viable in the past decade. Previous studies offer diverse classifications of Industry 4.0 technologies (Zheng et al., 2021). This study follows the most widely accepted classifications for the technological constituents of Industry 4.0 (e.g., Frank et al., 2019; Ghobakhloo, 2018; Senna et al., 2022) and reports the most relevant technologies as the ones listed in Fig. 1. Alternatively, the design principles of Industry 4.0 denote the techno-functional conditions that allow Industry 4.0 technologies to deliver their intended values optimally (Hwang et al., 2017). For example, real-time capability principles of Industry 4.0 entails that in order for the smart factory to operate appropriate, various smart components and technologies such as 3D printers, machinery, industrial controllers, manufacturing execution systems, enterprise systems, and cyber-physical systems should have the ability to communicate with each other seamlessly and in real-time, when needed (Ching et al., 2021). While the literature recognizes a long list of design principles for Industry 4.0, this study follows the most frequently acknowledged categorization (e.g., Cañas et al., 2021; Ghobakhloo et al., 2021) and lists the design principles of Industry 4.0, as shown in Fig. 1.

As presented in Fig. 1, the interrelationship between BA and I4.0 could be studied from two points of view: first, the effect of the design principles of I4.0 on BA, and second, the modern capabilities provided by I4.0 technological constituents to improve and design new methods for BA.

A large number of papers have studied I4.0, and there is also a vast literature focused on BA. However, the intersection of I4.0 and BA has not been rigorously studied. This paper contributes to the literature on BA in two ways. First, the study identifies I4.0 design principles and technologies previously considered in the BA background. Second, the study provides insights into how BA could benefit from I4.0 in the future. The contributions of the paper are persuaded by conducting a systemic literature review and answering the following three research questions: Which I4.0 design principles have already been considered in BA? Which I4.0 technologies have already been considered in BA? How will I4.0 shape the future of BA?

The remainder of this paper is organized as follows: Section 2 provides a background on BA. Section 3 describes the research methodology used to review the literature. Section 4 presents a bibliometric analysis. Section 5 describes the I4.0 design principles and technologies employed in BA. Section 6 discusses the first two research questions and answers them. Section 7 is devoted to answering the third research question by describing opportunities for future developments. Finally, Section 8 provides the conclusion of the study.

## 2. BA background

The BA can be viewed and discussed from different perspectives. This section provides a brief description of the steps involved in BA and the challenges involved in performing BA.

### 2.1. BA steps

BA is divided into detection, diagnosis, prediction, and prescription (West et al., 2022), briefly explained in the following paragraphs.

*Bottleneck detection* or identification methods are employed to locate the bottleneck(s) of a system. There are numerous bottleneck detection methods in the literature. Several studies, including research conducted by Lai et al. (2021), Subramaniyan, Skoogh, Gopalakrishnan, & Hanna, 2016, Subramaniyan, Skoogh, Gopalakrishnan, Salomonsson, et al., 2016, and Fang et al. (2020), classified bottleneck detection methods into three main groups, namely analytical, simulation-based, and data-driven approaches.

*Bottleneck diagnosis* is performed to find and prioritize the root causes of bottlenecks. According to the literature, process variabilities (e.g., stochastic arrival times, setup times, processing times, and unplanned stops) and their resulting disturbances during the production process are responsible for bottlenecks (Wang et al., 2016). These disturbances are divided into two types: dominant disturbances causing immediate suspension of the production process; and recessive disturbances causing gradual deterioration of the production process (Fang et al., 2020). Although the latter does not directly affect production, they significantly decrease throughput in the long run.

*Bottleneck prediction* methods help decision-makers become aware of future bottlenecks based on historical data. Bottleneck prediction methods generally assume the availability of shop floor data and machine logs and are mainly built using simulation modeling in combination with predictive analytics (Li et al., 2011; Tang et al., 2018), network analysis (Lai et al., 2018; Zhang et al., 2021; Zhu et al., 2019), or neural networks (Huang et al., 2019).

*Bottleneck prescription* is performed to prescribe a set of recommendations, based on results generated during descriptive and prescriptive analytics for future improvement (Lepenioti et al., 2020). To the best of our knowledge, only one research study on bottleneck prescription was published by Subramaniyan et al. (2019). However, bottleneck prescription is an up-and-coming research area and needs further investigation in the future (West et al., 2022).

### 2.2. BA in practice

There are a number of complexities involved in BA that makes it a challenging task for both researchers and practitioners alike. The first challenge for doing a BA, specifically in real-world problems, is the fact that there are several different interpretations and definitions of bottlenecks. Second, bottlenecks have a variety of root causes, which makes it difficult to identify the main reason for bottlenecks. The third challenge relates to the dynamic behavior of bottlenecks in a production line. In Sections 2.3.1–2.3.3, these challenges are elaborated.

#### 2.2.1. Bottleneck definition

Determining the definition of bottleneck is a preliminary step to BA. Generally, the bottleneck is defined as the resource limiting the production capacity. However, the definition of bottleneck is still a controversial issue on which there is no consensus among researchers. Tang et al. (2018) categorized different bottleneck definitions into four groups: 1) resource with the highest work in process, 2) resource with slowest processing rate, 3) resource with the highest effect on the system's main performance indicator, usually throughput, and 4) resource with the capacity lower than demand. Each of these definitions has proven useful and captures certain aspects of production systems, such as throughput, quality, cost, and market demand. However, the results of the analysis may differ depending on which definition is utilized. As an example, the machine that is considered the bottleneck depends on the definition applied. This confusion affects the first step of BA, i.e., bottleneck detection. As a result, it is critical for researchers to identify which definition they are referring to when performing a BA.

#### 2.2.2. Bottleneck Root-Causes

The second challenge of BA centers on identifying the root causes of bottlenecks. This challenge affects the diagnosis step in BA. Research on bottleneck diagnosis focuses on both identifying the causes of bottlenecks in a manufacturing system and determining the order in which those causes should be addressed (West et al., 2022). Generally, stochastic disruptions that occur during a pre-scheduled production plan cause bottlenecks. According to Fang et al. (2020), there are two categories of production line disturbances: dominant disturbances, which result in an immediate suspension of production, and recessive disturbances, which cause production to deteriorate gradually. Even though the latter does not directly affect production, they substantially impact throughput (Wang et al., 2018). Studying sources of possible process variabilities leads to finding the root causes of bottlenecks. However, a large number of process variabilities (e.g., stochastic arrival times, setup times, and processing times, as well as unplanned stops) results in an exponential growth of the number of different root causes found for a bottleneck. Thus, preparing an action plan to remove the bottlenecks is difficult.

#### 2.2.3. Bottleneck shiftiness

The third challenge is associated with the dynamic nature of bottlenecks, referred to as "bottleneck shiftiness". As a result of bottleneck shiftiness, it becomes more difficult to predict when and where bottlenecks will occur (Rocha & Lopes, 2022). The reason is that the methods used for predicting bottlenecks in a production line are mainly based on historical data on the system's behavior. If there is a fundamental change in the production plan, product sequence, or system configuration, the predictions may not be realistic enough to apply to real-world systems. Furthermore, bottleneck shiftiness makes it difficult for researchers to formulate definite recommendations or prescriptions for practitioners (Tu et al., 2021). However, BA will not be able to meet its ultimate goal and unleash its full potential unless it provides prescriptions that can be applied to real-world situations (Thürer et al., 2021).

## 3. Research methodology

The present study followed the PRISMA protocol (PRISMA 2021) to conduct the systematic literature review, which involves the following steps: (i) defining the research questions, (ii) determining the sources of information, (iii) clarifying the search strategy, (iv) describing eligibility criteria, (v) data extraction, and (vi) discussion.

### 3.1. Research questions

Considering that the industry is moving at an ever-growing speed towards the implementation of I4.0, the following research questions are developed to clarify the relationship and interconnection between BA and I4.0.

RQ1: Which I4.0 design principles have already been considered in BA?
RQ2: Which I4.0 technologies have already been considered in BA?
RQ3: How will I4.0 shape the future of BA?

### 3.2. Sources of information and search methodology

The papers were searched in two major scientific peer-reviewed databases, Scopus and Web of Science. The search string is composed of three parts. As shown in Fig. 2, these three parts of the search string are linked using the "And" operator to be searched simultaneously. In the first part of the search string, "bottleneck" was included to search the "title" of the articles. Since the word "bottleneck" is a general keyword that appears in many different fields of study, the "manufactur*" and "product*" keywords were included to be searched in the "title, abstract, and keyword" fields as the second part of the search string.

Since the scope of this paper was BA in the context of I4.0, the keywords included in the third part of the search string were chosen to cover the related concepts, technologies, and aspects of I4.0, which were searched in the "title, abstract, and keyword" fields. As shown in Fig. 2 and Fig. 3, two different search strings were developed to distinguish between the design principles and technologies of I4.0. This was necessary to draw clear lines while analyzing I4.0 and BA relationships. The keywords relevant to the design principles of I4.0 are vertical integration, horizontal integration, interoperability, real-time capability, decentralization, smart factory, smart product, flexibility, agility, virtualization, modularity, product personalization, service orientation, corporate social responsibility, and autonomy. The keywords related to I4.0 technologies are Internet of Things (IoT), Cyber-physical Systems (CPS), Cloud Computing, Robotics, Augmented Reality (AR), Digital Twin, Industrial Internet of Things (IIoT), Artificial Intelligence (AI), Virtual Reality (VR), Additive Manufacturing (3D printing), and Blockchain. "Industry 4.0" and "digitalization" were added to the third part of the search string to find papers that have directly mentioned I4.0 or its equivalent term "digitalization." The study did not apply any time limit to the systemic search of databases while acknowledging that the Industry 4.0 phenomenon was publicized in 2011. While it is true that the technologies and principles listed above have matured and commercialized since 2011, their diffusion and limited industrial applications date back to the 1980s (Ghobakhloo et al., 2021).

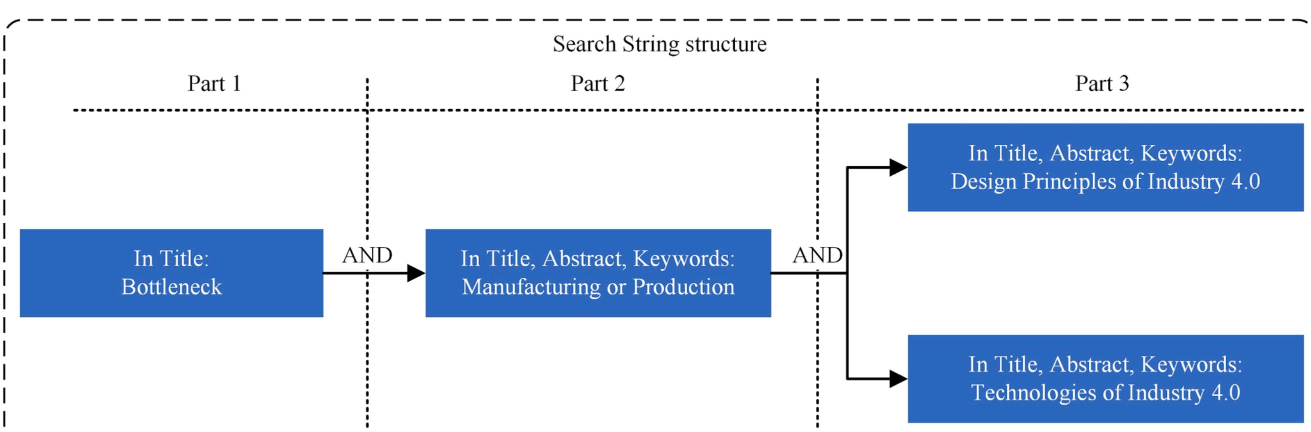



**Fig. 2.** Structure of search string.

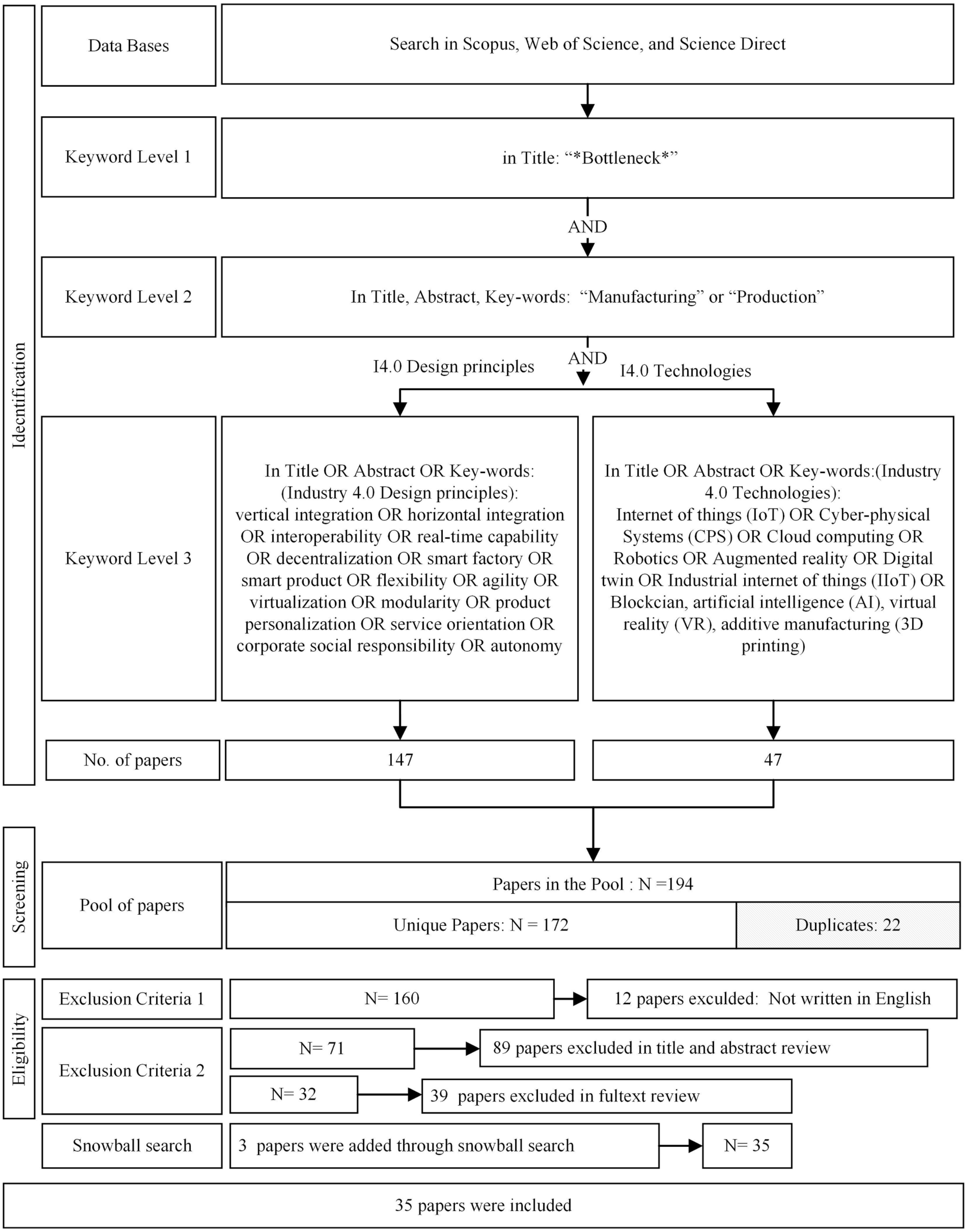



**Fig. 3.** The process of paper selection using PRISMA.

### 3.3. Eligibility criteria

The criteria for paper inclusion and exclusion are listed in Table 1. Papers not written in English were excluded according to the first exclusion criteria. According to the second exclusion criteria, papers appearing in search results with keywords in the title and abstract but without sufficient relevance to the subject of the study in the full text were excluded.

### 3.4. Screening and paper selection

The resulting search strings and the number of papers found are shown in Fig. 3. Of 194 papers found in the search, 22 were duplicates and thus removed from the study. 12 papers that were not written in

**Table 1**
The exclusion and inclusion criteria.

| Criteria | Description |
|---|---|
| Exclusion | 1. The body of the paper is not written in English<br>2. Search keywords show up merely in the abstract or title, and the paper is not related to BA or I4.0. |
| Inclusion | 1. The article is formally published in open access or subscription-based peer-reviewed resources<br>2. A scientific resource of any acknowledged categories (e.g., original research, review, letter, case study, book chapter)<br>3. The main subject of the article is focused on BA<br>4. I4.0 design principles or technologies are mentioned in the article |

English were also removed. Out of the remaining 160 papers, 89 more papers were excluded in the 'title and abstract' scanning step as most of them studied subjects other than production or manufacturing. In the next step, the full text of 71 remaining papers was studied, out of which 36 papers were excluded as they did not include the design principles or technologies of I4.0 in the full text.

### 3.5. Snowball search

The term snowballing refers to the process of identifying additional papers using the reference list or citations of a paper (Wohlin et al., 2022). After screening and finding the relevant papers, a snowball search, was performed to find related studies not discovered in the first search. This resulted in the finding of two new relevant papers. Finally, 34 papers were included in the systematic literature review. The exclusion and inclusion criteria are shown in Table 1. The paper selection process is also presented in Fig. 3.

## 4. Bibliometric analysis

The frequency of papers published each year is depicted in Fig. 4. As shown in Fig. 4, the papers which used I4.0 design principles and technologies to identify, diagnose, or predict bottlenecks in a production or manufacturing system were first published in 2004, even before the term "Industry 4.0" was introduced in 2011. This reveals the importance of dividing "Industry 4.0" into its building blocks while conducting this study. Some of the I4.0 building blocks, including real-time capability and visualization, were employed in BA before they were categorized under the umbrella term of I4.0. According to Fig. 4, a growing trend in the number of papers that developed an I4.0-based method for BA is evident, with most being published from 2019 to 2021.

Fig. 5 shows a connection map generated using VOSviewer software to analyze the co-occurrence of keywords and main focus areas in BA. There are three major sections in Fig. 5: sections (a), (b), and(c). For clarity, section (c) is divided into three subsections, namely, (c-1) to (c-3). As evident in the map, there is a shift between central subjects and keywords in the papers published between 2004 and 2021. Based on this data, subjects such as productivity, throughput, line balancing, and reliability through techniques like scheduling and resource management, using analytical models and optimization methods, were more discussed from 2004 to 2012 (Fig. 5 (a)). Then, a shift from analytical models to simulation can be seen in Fig. 5, from 2013 to 2015 (Fig. 5 (b)). From 2016 to 2018, the emergence of a new set of keywords was discovered, including digitalization, learning factory, data-driven, bottleneck prediction, maintenance, and quality control (Fig. 5 (c)).

Between 2019 and 2021, a newer generation of keywords has been used in the literature. This set of keywords mainly connects the bottleneck to I4.0. Around the lower right corner of Fig. 5 (c-1), we can find a cluster that is formed using deep learning, sustainability, digital transformation, AI, and machine learning, which are connected to keywords related to BA and I4.0 technologies like smart manufacturing or CPS. Another cluster of keywords in the upper right corner (Fig. 5 (c-2)) connects keywords like cloud manufacturing and computer-aided manufacturing to BA through predictive analytics and quality control. This shows that a growing trend through the use of capabilities provided by I4.0 has been forming in the literature of BA in recent years. The most recent set of keywords, located at the right end of Fig. 5 (c-3), is related to bottleneck prediction, which is an emerging field in BA.

## 5. Review results and findings

For the classification of the reviewed papers, related segments of the papers were coded using MaxQda software. Then the codes were merged and categorized to reach insightful classifications. Since the papers published in the BA field are diverse and many different methods were used to address this problem, using an unstructured coding system to extract related content and categorize them could help researchers get a more comprehensive view of the literature. The reviewed papers were categorized based on the BA types addressed in each paper using the coding system. As a result, four categories appeared; 1) bottleneck detection, 2) bottleneck diagnosis, 3) bottleneck prediction, and 4) papers with bottleneck-based scheduling, sequencing, or dispatching.

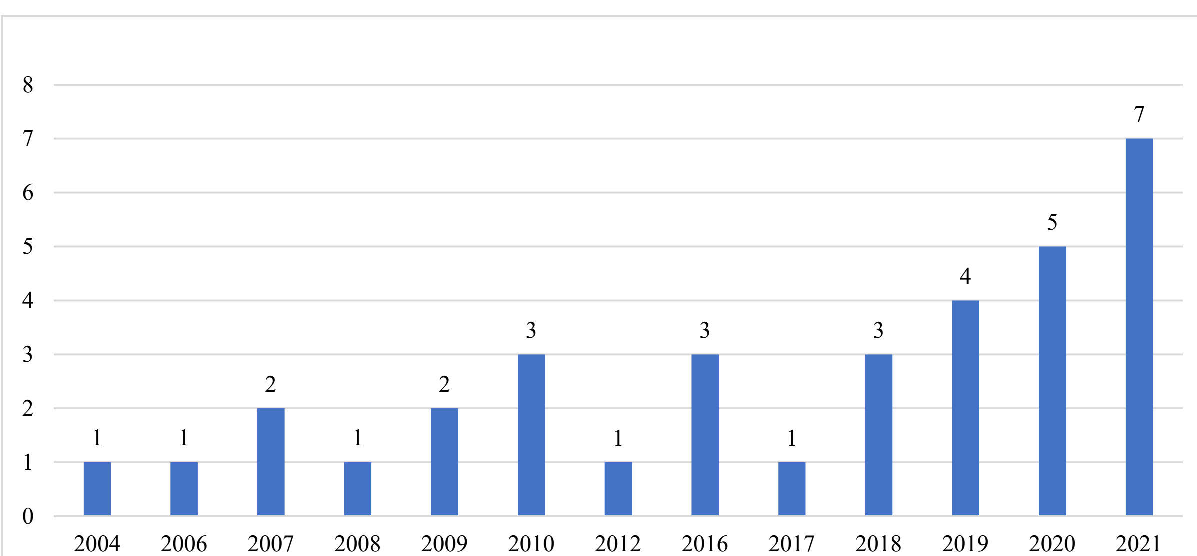



**Fig. 4.** Frequency of studies published on the I4.0-based method for BA.

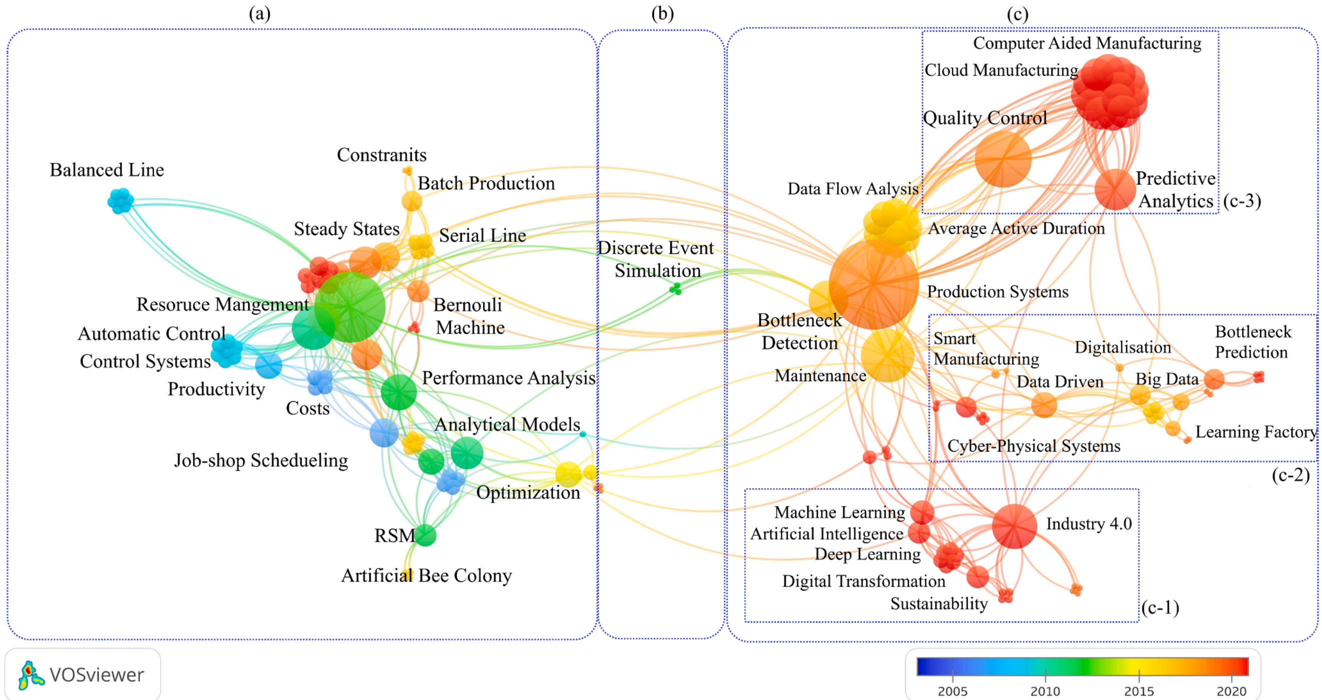



**Fig. 5.** Network and relationships between keywords generated by VOSviewer.

Fig. 6 shows the papers in each category. The frequency of papers in each category, from 2004 to 2021, is depicted in Fig. 7. It is worth mentioning that papers by Wedel et al. (2015), Huang et al. (2019), Jia et al. (2021), and Subramaniyan, Skoogh, Salomonsson, Bangalore, & Bokrantz (2018) belong to more than one category. Therefore, the total number of records in Fig. 6 and Fig. 7 is more than the number of papers selected for systematic literature review. As shown in Fig. 7, 20 papers addressed bottleneck detection, nine papers focused on scheduling, sequencing, or dispatching tasks to improve throughput, four papers addressed bottleneck prediction, and four papers dealt with bottleneck diagnosis.

Based on the extracted codes, papers were also categorized by (1) design principles of I4.0 employed in BA, (2) technologies of I4.0 employed in BA, (3) modeling approaches, and (4) objectives. Using Maxqda lexicographic search, design principles of I4.0 were searched one by one in papers included in the study to ensure that these terms were really addressed and not just mentioned. This process was repeated while studying the I4.0 technologies in BA. The resulting content analysis findings are provided in Section 5.1 and Section 5.2 separately. Modeling approaches and objectives addressed are presented in Sections 5.3 and 5.4, respectively.

### 5.1. *BA and design principles of I4.0*

In this section, the design principles of I4.0, which were considered in BA, are explained. According to the data presented in Table 2, six out of 15 I4.0 design principles were considered by authors while performing BA in a production system. These principles are explained in more detail in Sections 5.1.1–5.1.6.

#### 5.1.1. *Real-Time capability*

Based on the data presented in Table 2, real-time capability has been applied to BA since 2007. Recently, the emergence of technologies that provide real-time data from the shop floor highlighted the importance of BA in real-time, both from theoretical and practical points of view (Zhang et al., 2021). Fig. 8 illustrates the frequency of the keyword "real-time" in BA. As depicted in Fig. 8, a rising trend toward developing models with real-time capability is evident in BA literature. While a yearly comparison might not provide a coherent conclusion, the rising trend since 2015 shows a solid interest in using the real-time capability in BA that emerged with the popularity of I4.0 worldwide. This trend becomes more evident when knowing that the use of the keyword "real-time" in BA literature in 2016 alone (43 times) is almost the same as the sum of all years from 2007 to 2015 (49 times). Moreover, the use of this keyword in 2021 (97 times) is more than the sum of its past three years from 2018 to 2020 (86 times).

A bottleneck moves from one machine to another in real-world production systems, and for that reason, it is called a dynamic or shifting bottleneck (Roser et al., 2021). Therefore, methods developed to detect, diagnose, or predict the bottleneck of a production system must be able to mitigate the challenge of dynamic bottlenecks by receiving real-time data and producing results in real-time (Llopis et al., 2021).

It is also essential to distinguish between real-time capability and data-driven methods in BA. There are several data-driven approaches for BA that cannot work in real-time (Subramaniyan et al., 2021). These methods are not qualified to be included in applicable approaches for I4.0 since they lack real-time capability.

#### 5.1.2. *Flexibility*

According to data provided in Table 2, BA in flexible manufacturing was the focus of three studies, Yan et al. (2010), Jia et al. (2021), and Tu et al. (2021). However, due to the emergence of I4.0, the investigation of BA methods in flexible manufacturing systems is essential. This is because, in a flexible manufacturing system, the traditional assumption of steady-state and long production runs of a single variant is no longer valid (Jia et al., 2021; Tu et al., 2021).

Jia et al. (2021) developed a mathematical model considering the completion time bottleneck to manage the real-time performance of a manufacturing line with closed Bernoulli machines and finite buffers. Based on the definition, a manufacturing line with the parts transferred between machines using transporters (e.g., AVGs) is called a closed line. Scholars used the concept of completion time bottleneck for systems with finite production runs. The analysis revealed that the bottleneck retrieved as a steady-state production bottleneck was sometimes

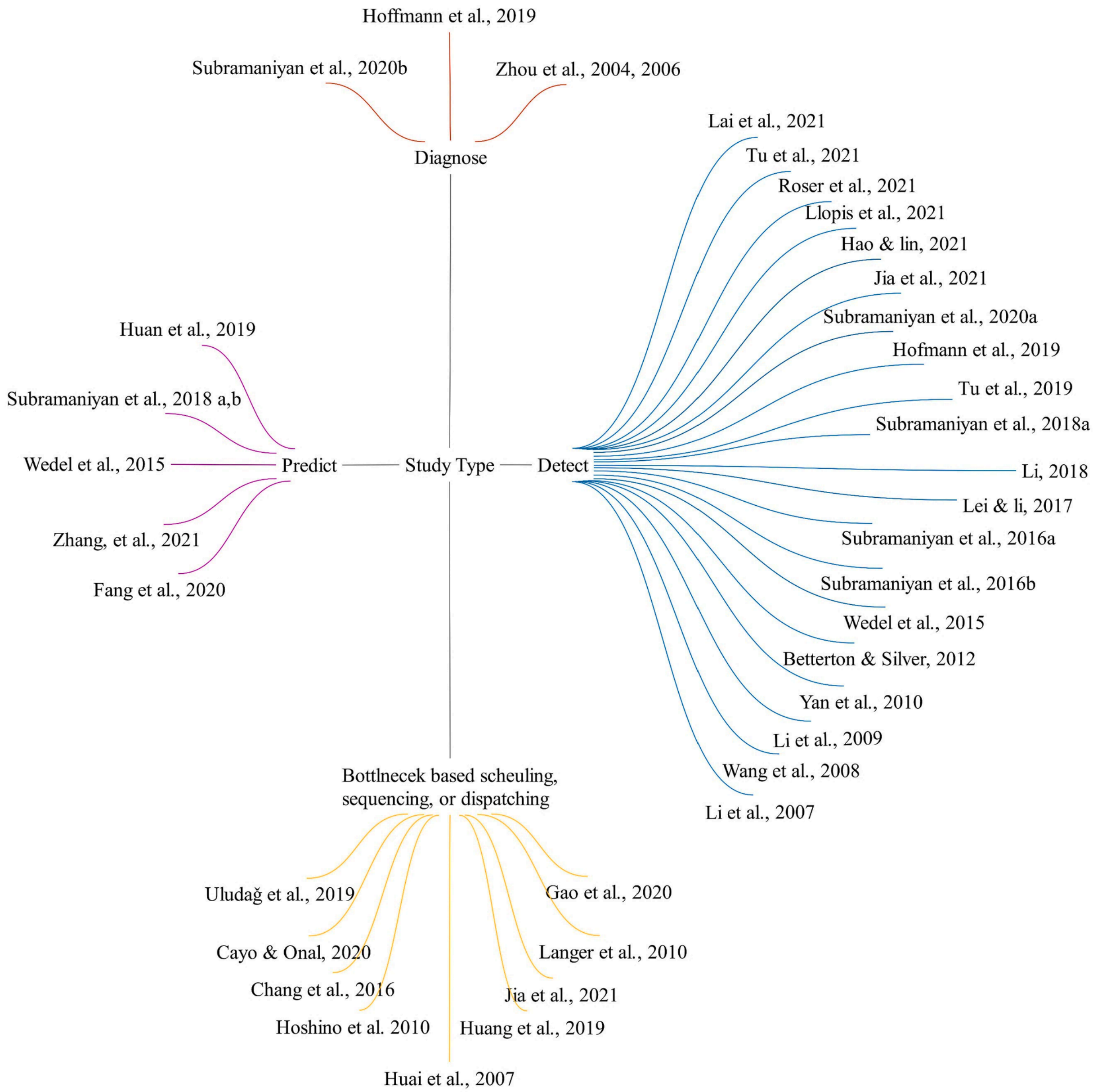



**Fig. 6.** Code-Subcode-Segment diagram for the classification of papers using unstructured coding.

different from the real bottleneck of the system with infinite production runs, depending on other factors like the length of the production line (number of machines) and the time duration of the production.

Tu et al. (2021) have also reported the problems arising from sticking to the steady-state assumption and believed that the solutions presented in the literature have been mostly static rather than dynamic. The authors argued that possible improvements to bottleneck stations might be applied dynamically during a single production run. For example, a strategy that is not unusual in the case of engine production companies is that different types of engines are introduced into the system in a short period. As a result, different stations might turn into a bottleneck for different engines. In this situation, several operators are allocated to the stations with the highest workload, and if the bottleneck place changes during production, workers can be reallocated to different stations (Tu et al., 2019). This type of resource is not handled while using steady-state assumptions.

Non-validity of steady-state assumption in manufacturing systems is significant while discussing how some I4.0 principles might result in dramatic changes to traditional definitions of bottleneck in a manufacturing system. In the following years, mass customization will replace mass production. However, the quality of this change might differ from industry to industry (Espinoza Pérez et al., 2022). Therefore, it is necessary to re-assess the assumption of steady-state while developing BA methods, specifically in terms of bottleneck definition.

### 5.1.3. *Virtualization*

Virtualization provides decision-makers with a powerful tool to make complex decisions in a manufacturing system. Using virtualization, one can see the results of decisions before they are implemented by analyzing different scenarios. Thus, virtualization helps managers reduce the costs and time required for improving a manufacturing system, leading to better production management and control (Martins et al., 2019). One of the applications of virtualization in a manufacturing system is BA. Zhou et al. (2004) proposed a method based on virtual manufacturing technologies to diagnose bottlenecks of a production system. The authors used a simulation model combined with a dynamic 3D visualization graphical tool to detect and diagnose bottlenecks rapidly. Zhou et al. (2006) generalized their proposed method as a three-

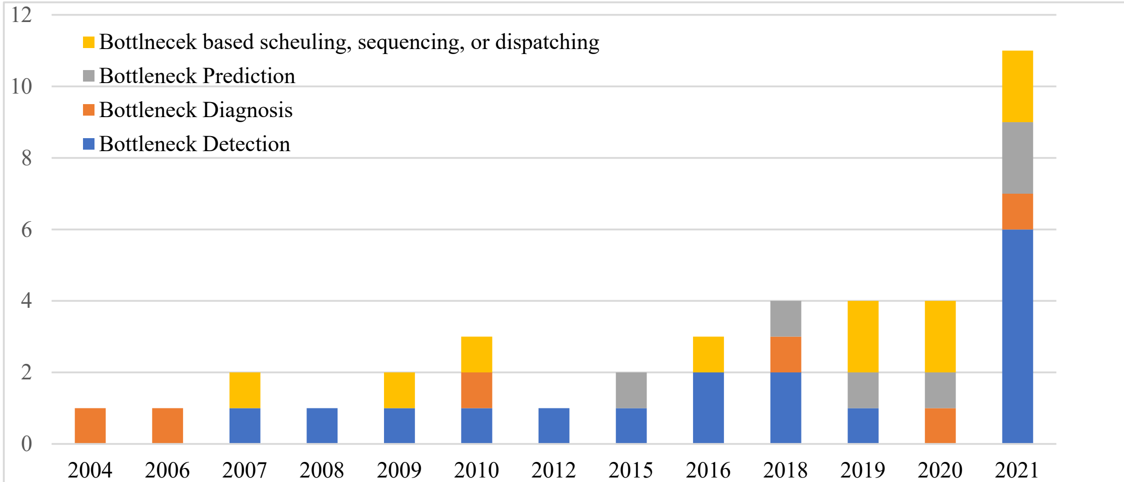



**Fig. 7.** Frequency of papers in bottleneck detection, bottleneck diagnosis, bottleneck prediction and bottleneck-based scheduling, sequencing, or dispatching.

**Table 2**
I4.0 design principles in BA.

| Author | Real-time capability | Virtualization | Flexibility | Smart Manufacturing | Decentralization | Agility |
|---|---|---|---|---|---|---|
| Zhou et al. (2004) | | ✓ | | | | |
| Zhou et al. (2006) | | ✓ | | | | |
| Zhang et al. (2007) | ✓ | ✓ | | | | |
| Li et al. (2007) | ✓ | | | | | |
| Wang et al. (2008) | ✓ | | | | | |
| Li et al. (2009) | ✓ | | | | | |
| Hoshino et al. (2010) | ✓ | | | | ✓ | |
| Yan et al. (2010) | | | ✓ | | | |
| Langer et al. (2010) | ✓ | | | | | |
| Betterton & Silver (2012) | ✓ | | | | | |
| Wedel et al. (2015) | ✓ | | | | | |
| Chang et al. (2016) | ✓ | | | | | |
| Subramaniyan, Skoogh, Gopalakrishnan, & Hanna (2016) | ✓ | | | | | |
| Subramaniyan, Skoogh, Gopalakrishnan, Salomonsson, et al. (2016) | ✓ | | | | | |
| Lei & Li (2017) | ✓ | | | | | |
| Li, (2018) | ✓ | | | | | |
| Subramaniyan, Skoogh, Salomonsson, Bangalore, & Bokrantz (2018) | ✓ | | | | | |
| Subramaniyan, Skoogh, Salomonsson, Bangalore, Gopalakrishnan, et al. (2018) | ✓ | | | | | |
| Hofmann et al. (2019) | ✓ | ✓ | | | | |
| Huang et al. (2019) | ✓ | | | ✓ | | |
| Uludağ et al. (2019) | ✓ | | | | | |
| Tu et al. (2019) | ✓ | | | | | |
| Cayo & Onal (2020) | ✓ | | | | | |
| Subramaniyan et al. (2020a) | ✓ | | | | | |
| Subramaniyan et al. (2020b) | ✓ | | | | | |
| Fang et al. (2020) | ✓ | | | | | |
| Gao et al. (2020) | | | | | | ✓ |
| Hao & Lin (2021) | ✓ | | | | | |
| Zhang et al. (2021) | ✓ | | | | | |
| Lai et al. (2021) | ✓ | | | ✓ | | |
| Tu et al. (2021) | ✓ | | ✓ | | | |
| Llopis et al. (2021) | ✓ | | | | | |
| Roser et al. (2021) | ✓ | | | | | |
| Jia et al. (2021) | ✓ | | ✓ | | | |
| Frequency | 30 | 4 | 3 | 2 | 1 | 1 |

step framework, with the steps being visual modeling, simulation, and diagnosis study. Although Zhou et al. (2004) and Zhou et al. (2006) employed virtualization for BA, their method does not work in real-time. Zhang et al. (2007) used virtualization to assess dynamic bottleneck dispatching policies. The authors compared the performance of their proposed dynamic dispatching rules with static dispatching rules for bottleneck management in a virtually simulated semiconductor fab with a capacity of 30 thousand wafers per month. Zhang et al. (2007) also pointed out that integration of the virtual dispatching method with the manufacturing execution system (MES) could be used for scheduling.

Hofmann et al. (2019) employed virtualization in an AR-based solution to detect bottlenecks of a production system. Using this method, one can bring a regular smart device, including a smart tablet, smartwatch, or smartphone, to the shop floor and see the required key performance indicators (KPIs) on each machine. This method became viable through the high computing power available in recent years to perform

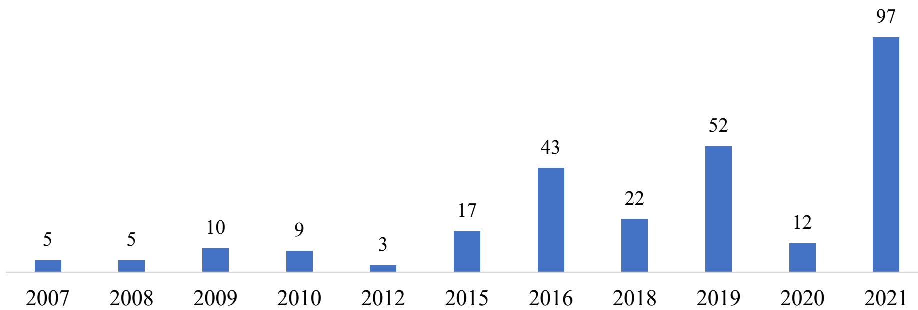



**Fig. 8.** Frequency of "real-time" keyword in BA literature.

image processing and receive real-time data from each machine on the shop floor and send the required data to devices through the internet. Although virtualization seems to be of great value for BA purposes in a real manufacturing system, a few papers in bottleneck literature used this method.

#### 5.1.4. *Smart manufacturing*

BA in a smart manufacturing environment uses real-time data provided by CPS to detect and predict bottlenecks in real-time and provide prescriptions. Huang et al. (2019) developed a bottleneck-based proactive task-dispatching method in a smart factory. The authors developed an IoT-based tool combined with a radio frequency identification (RFID) framework to gather the required data from the manufacturing line in real-time. The required structure for data gathering was designed based on the RFID cuboid proposed by Zhang et al. (2015). After preparing the data, a bottleneck prediction method was designed, which combines deep neural networks and time series and can propose dispatching rules considering future bottlenecks. This model was verified with a simplified model from a real case study. Li et al. (2007) proposed a real-time bottleneck detection method by extending the use of the "turning point" method to smart manufacturing systems with complex structures. These structures include closed-loop, parallel, and rework-loop manufacturing systems. Their method proved to be successful in terms of increasing overall equipment effectiveness after a one-year pilot study.

#### 5.1.5. *Decentralization*

Decentralization is the process of giving authority to manufacturing elements for making decisions considering the situation instead of following fixed predefined rules (Brettel et al., 2014). Decentralization was employed by Hoshino et al. (2010) to overcome the bottleneck of a robotic batch manufacturing system. In this system, there were two types of robots, 1) material handling robots (MHR) and 2) material processing robots (MPR). In the manufacturing system studied by Hoshino et al. (2010), a bottleneck in one of the processes led to congestion in MHRs. To solve this problem, a behavior control method was developed in which MHRs were equipped with controllers to get the required data about the position of other robots. Using this control method, MHRs keep their distance from other robots to avoid congestion.

#### 5.1.6. *Agility*

One of the design principles of I4.0 is agility in manufacturing. The main goal of the agile paradigm is to understand market behavior and respond to customer needs quickly. Therefore, the agile manufacturing system aims to decrease the response time of the system to satisfy market demand (Mathiyazhagan et al., 2021). Gao et al. (2020) studied the agile design of a manufacturing system using a bottleneck-based method to design the topology of the production line. One of the most important aspects of agile design in a manufacturing system is finding a near-optimal solution for buffer allocation problems in a reasonable amount of time. In their study, Gao et al. (2020) used variable neighborhood searches to reach a solution with low computational time and high quality. Using this method, different bottleneck-based topologies of the production line were evaluated to reach a near-optimal design.

### 5.2. *I4.0 technologies in BA*

In this section, I4.0 technologies used in BA are reviewed and explained. According to the data presented in Table 3, only five out of 11 I4.0 technologies were considered while performing BA in a production system.

#### 5.2.1. *IoT in BA*

IoT devices of a smart factory, which are divided into two categories of sensors and data transmission systems, provide the possibility of interconnection between machines and other resources on the shop floor. Using these interconnections, each resource of a smart factory can adapt itself to the the-real time changes on the shop floor to prevent bottlenecks (Wang et al., 2018). Recently, IoT-based bottleneck prediction methods were studied by Huang et al. (2019) and Fang et al. (2020).

**Table 3**
Technologies of I4.0 used in BA.

| Author | Internet of things (IoT) | Cloud | Augmented reality (AR) | Cyber-physical Systems (CPS) | Artificial Intelligence (AI) |
|---|---|---|---|---|---|
| Lei & Li (2017) | | | | | ✓ |
| Hofmann et al. (2019 | | | ✓ | | |
| Tu et al. (2019) | | | | | |
| Uludağ et al. (2019) | | | | ✓ | |
| Huang et al. (2019) | ✓ | | | | |
| Cayo & Onal (2020) | | | | | |
| Subramaniyan et al. (2020a) | | | | | ✓ |
| Fang et al. (2020) | ✓ | | | | |
| Gao et al. (2020) | | | | | |
| Hao & Lin (2021) | | | | | ✓ |
| Tu et al. (2021) | | | | | |
| Zhang et al. (2021) | | ✓ | | | |
| Hao & Lin (2021) | | ✓ | | | |
| Subramaniyan et al. (2021) | | | | | ✓ |
| | 2 | 2 | 1 | 1 | 4 |

Huang et al. (2019) implemented IoT technologies, including sensors RFID and WI-FI, as the first step of a BA method for a smart factory. The role of IoT was to provide real-time data from the shop floor. Using data provided by IoT, a deep neural network (DNN) combined with time series was employed to predict the bottlenecks in real-time. This method was tested on a valve manufacturing company and successfully improved system throughput. Fang et al. (2020) used the data provided by IoT systems of a large-scale job-shop for machining parts of an aero-engine in China. The real-time data was fed to a Parallel gated recurrent unit (P-GRUs) network in which the data of the present bottlenecks were analyzed to predict future bottlenecks.

#### 5.2.2. Cloud manufacturing in BA

Cloud manufacturing is one of the technologies utilized to predict bottlenecks in a manufacturing system. Zhang et al. (2021) combined a series of traditional with state-of-the-art technologies to provide a real-time bottleneck detection tool. These authors employed simulation to model processes and dispatching rules. Since real-time BA is highly sensitive to the amount of data available from the manufacturing system, a cloud-based service was established to provide real-time data. The data were fed to a simulation model to schedule production based on bottleneck machines using dynamic programming and fuzzy method.

Lai et al. (2021) used cloud-based bottleneck detection based on the “turning point” method in an automotive smart manufacturing system. A cloud-based solution was developed to detect bottlenecks and visualize results. To this aim, the daily records of the manufacturing shop were stored in the cloud using an algorithm developed in Python, and the resulting predicted bottlenecks were sent to frontline experts using the internet. This program runs in the background continuously on the data stored in the cloud. When new data arrive, the feature extraction algorithm and bottleneck detection run results update in the cloud. The one-year pilot use of this method resulted in a 30 percent improvement in Overall Equipment Effectiveness (OEE).

#### 5.2.3. AR in BA

Hofmann et al. (2019) used AR and real-time data to propose an augmented go-and-see approach. “GO & See” is one of the bottleneck detection techniques developed under lean manufacturing. Using this method, one can walk through the production line and draw applicable conclusions about the production flow. AR is one of the technologies rooted in I4.0 that could significantly help this lean-based bottleneck detection approach. However, the lack of real-time data processing power while using added reality has imposed limitations on growing such methods. With higher processing power, such technologies are nowadays turning into reality. Hofmann et al. (2019) proposed some KPIs to detect bottlenecks with AR. Based on the bring-your-own-device principle and image processing techniques, an application was developed to detect the cycle time and work in process (WIP) of the production line. This application was developed by Apple ARKit and employed RFID tags on entities to detect each machine’s cycle time (leaving time - enter time) and buffer level (exiting parts of a station - entries to the next station). Using these data together with real-time KPI values for each station, root causes of the bottlenecks could be easily determined. The results revealed that the use of the Augmented “GO & See” method by line managers led to significantly better performance than the traditional version. Augmented “GO & See” is classified as level 3 in ACATECH Industry 4.0 maturity model (Zeller et al., 2018).

#### 5.2.4. CPS in BA

The role of CPS in resolving the bottleneck problem by decreasing the cycle time and increasing resource utilization rates of a train wagon manufacturing system was studied by Uludağ et al. (2019). These authors did not implement the CPS in a real manufacturing system; however, they developed a simulation model to compare the performance of the manufacturing system with and without CPS. The main bottleneck of this manufacturing system occurred between welding and cutting shops. Uludağ et al. (2019) examined the effect of resource sharing, which became feasible using CPS. They found that CPS implementation can be a solution for mitigating the bottleneck.

#### 5.2.5. AI in BA

Technologies that are usually categorized under the umbrella term AI are big-data analytics, machine learning (supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning), neural networks, pattern recognition, decision support systems, language processing techniques (text mining and speech recognition), and computer vision (Zhang & Lu, 2021). Among these, big-data, machine learning, neural networks, and text mining were used by scholars to analyze production bottlenecks. Applications of AI in BA are briefly explained in the following paragraphs.

- Big-data technologies come to play when real-time data from the shop floor are gathered, stored, and interpreted. Big-data technologies mainly prepare data infrastructure and guarantee the smooth flow of large amounts of data generated from machine logs (Zhang et al., 2021). These data will later be fed to other AI-based BA tools, including machine learning algorithms or neural networks, for further analysis.
- Machine learning algorithms used in BA were employed for two purposes: extracting features of bottleneck machines using machine log data (Subramaniyan et al. 2020b) and classifying machines into bottlenecks and non-bottlenecks (Lei & Li 2017).
- Neural networks were used in both bottleneck detection and prediction. Huang et al. (2019) used a deep neural network (DNN) combined with a time-series to predict the bottlenecks of the production system. Fang et al. (2020) developed a Parallel gated recurrent units (P-GRUs) network to detect shifting bottlenecks and corresponding correlations between present bottlenecks to predict future ones.
- Text mining was used by Hao & Lin (2021) to detect bottlenecks in a three-phase scheduling procedure. The text mining algorithm, namely the *N*-gram modeling approach, which is a simple but powerful text mining algorithm, was used in the second phase. Using this approach, the machine logs data were analyzed to find resources that were prone to turn into bottlenecks in the near future.

More detailed information about AI methods in BA could be found in the study by Subramaniyan et al. (2021). However, the use of text mining in detecting bottlenecks (Hao & Lin 2021), which was not reviewed in Subramaniyan et al. (2021), was identified in the present study as one of the interesting AI applications in BA.

## 6. Discussion

This section discusses the design principles and technologies used for BA and answers the first and section research questions.

I4.0 *design principles in BA:* The first research question of this study is to investigate the intersection between I4.0 design principles and BA. Fig. 9, generated based on the conducted literature review, presents the network of relationships between I4.0 and the building blocks of BA. In Fig. 9, the line thickness drawn between boxes is proportional to the number of related papers. Lines that do not have text demonstrate the relationships with one study. The heat maps for I4.0 design principles and BA as well as I4.0 technologies and BA are presented in Fig. 10(a) and Fig. 10(b), respectively.

According to Fig. 9, among I4.0 design principles, real-time applicability, decentralization, smart manufacturing, flexibility (flexible manufacturing), agility, and virtualization were previously considered in BA.

Based on the data presented in Fig. 9, the strongest relationship was identified between real-time capability and bottleneck detection, with 18 papers. Real-time bottleneck detection has gained importance since

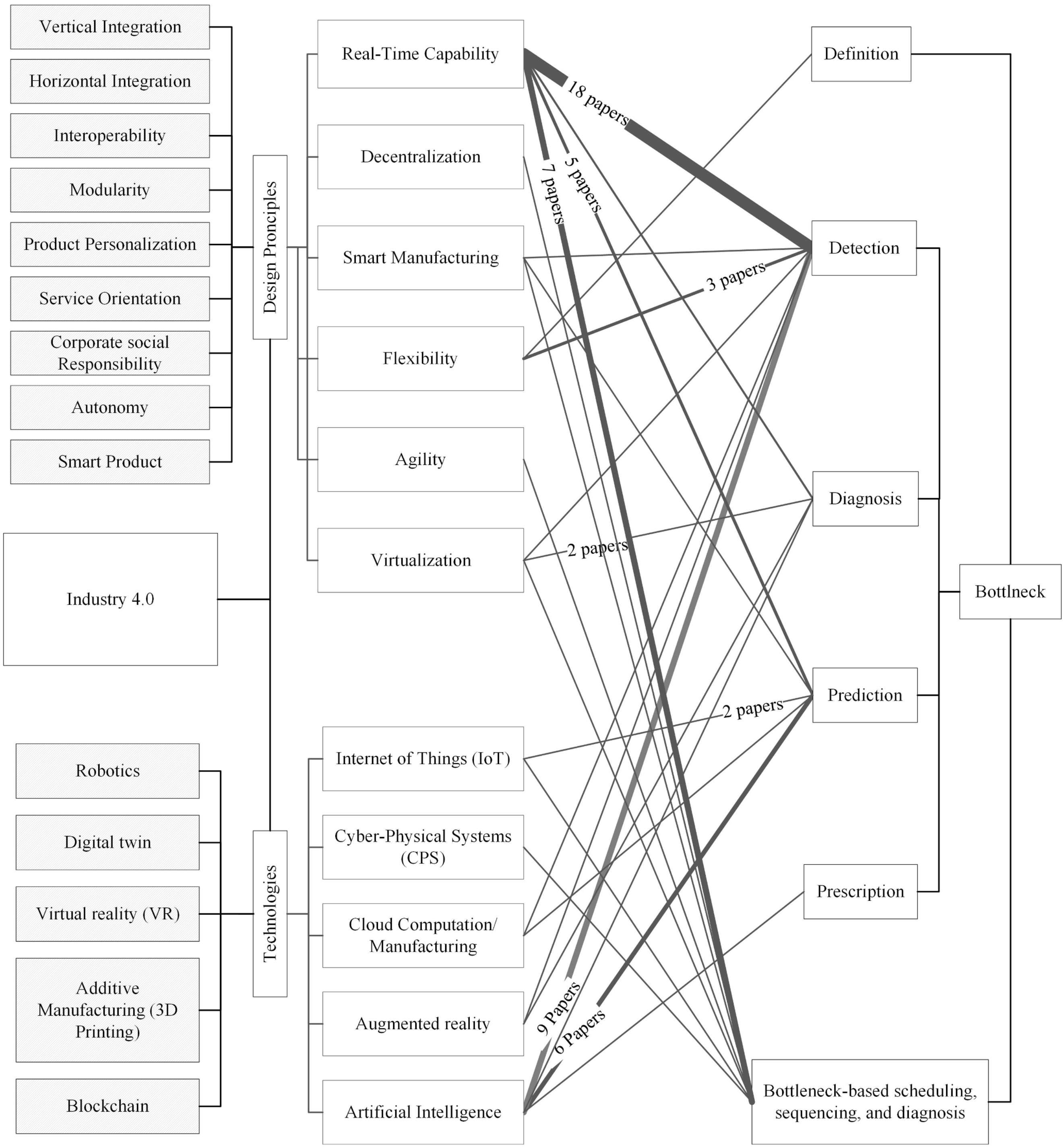
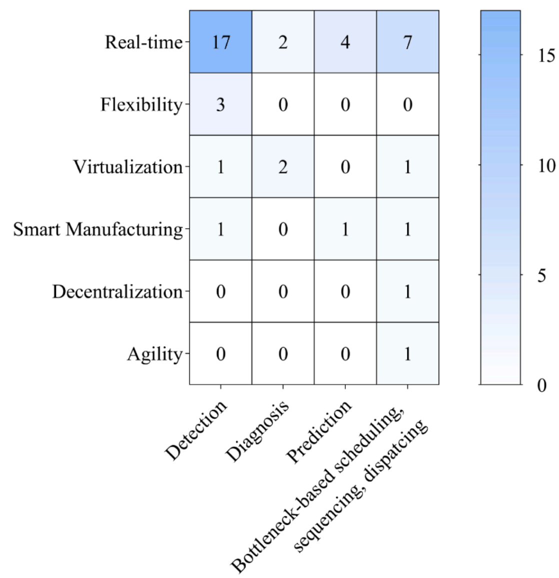


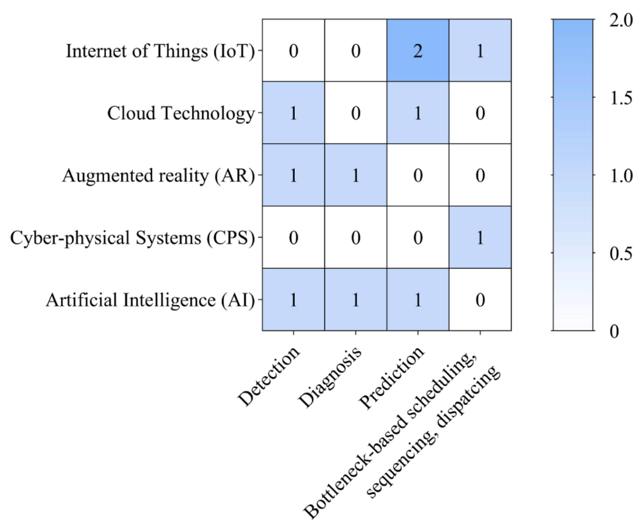

**Fig. 9.** Network of relationships between I4.0 and BA.

the dynamic nature of the throughput bottleneck became apparent in the literature. Thereafter, related terms including dynamic bottleneck, moving bottleneck, and short-term bottleneck appeared in the production engineering literature. The focus of seven papers was on developing bottleneck-based planning methods. In bottleneck-based planning of a production line, the bottleneck machine is prioritized in resource allocation to prevent the bottleneck from starvation (Huang et al., 2019). Since the bottleneck changes continuously in the production line, detecting real-time bottlenecks and providing dynamic plans are critical to improving productivity (Cayo & Onal, 2020). This could be why all bottleneck-based planning methods were equipped with the ability to detect bottlenecks in real-time. In the case of bottleneck prediction methods, including real-time capability is not optional. This is because if a prediction is supposed to be used in a real production facility, the required calculations must be performed in real-time and updated based on changes happening continuously in the production system (Zhang et al., 2021).

Flexibility also seems to be significant, apart from real-time capability, which is the strongest linking chain between I4.0 and BA. The importance of flexibility comes from its effect on bottleneck definition. In a highly flexible manufacturing system with short production runs, the underlying assumptions of steady-state will no longer be valid, and this causes a severe challenge to BA methods in terms of bottleneck definition. Although researchers have recently studied this issue (e.g.,




**(a) I4.0 design principles versus BA.**




**(b) I4.0 technologies versus BA.**

**Fig. 10.** Heat maps of I4.0 design principles and technologies versus BA.

Jia et al., 2021; Tu et al., 2021), it needs further investigation.

Moreover, access to real-time data from the shop floor coupled with recent advancements in processing power has resulted in novel visual and virtual BA methods (Hofmann et al., 2019). Virtualization is new to BA and was employed once by Hofmann et al. (2019). However, based on its practical applications in a production line, there is a high potential for developing solutions that can analyze the bottlenecks of a real production system and provide the results visually. Developing real-time BA solutions equipped with a visual interface is achievable by implementing new technologies, including blockchain and cloud (Akter et al., 2022).

BA was studied in the smart manufacturing context along with real-time capability, flexibility, and virtualization (Huang et al., 2019; Lai et al., 2021). Smart manufacturing systems provide interesting features regarding real-time capability in BA. IoT-Based technologies and sensors, RFID, and cloud manufacturing provide real-time data from the shop floor. However, a smart manufacturing system has more noticeable aspects, including self-learning (Yan et al., 2010), self-organization, and self-adaptivity (Estrada-Jimenez et al., 2021), which could be utilized to develop auto-corrective systems to mitigate and prevent bottlenecks in production facilities.

Decentralization and agility are other design principles of I4.0 studied in BA. BA is complicated in a decentralized manufacturing environment because independent decision-making units make the decision. Therefore, the design of decision-making processes might lead to logical bottlenecks in such systems (Grassi et al., 2020).

Agility was also studied in BA through the bottleneck-based topology design of a manufacturing system (Gao et al., 2020). Agile manufacturing's main objective is increasing flexibility through manufacturing configuration and production volume (Sharifi & Zhang, 2001), both of which cause new bottlenecks in the system. Hence, more research is required to provide practical insights for developing BA methods in decentralized or agile manufacturing systems. Since flexibility and agility are tied to the physical configuration of the system, BA in reconfigurable manufacturing systems also needs to be studied.

As shown in Fig. 9, some of the design principles of I4.0, namely horizontal and vertical integration, smart product, agility, personalization, service orientation, corporate social responsibility, and autonomy, are not considered or mentioned in BA. There could be two reasons for this. The first is that some design principles might not be considered relevant, e.g., smart product or service orientation. The second reason is that some other principles are inherent in BA, for instance, corporate social responsibility. Mitigating bottlenecks and improving production throughput results in more efficient use of existing production facilities. As a result, managing production bottlenecks contributes to fewer environmental problems, which coincide with corporate social responsibilities. This might introduce another potential area of research to investigate the role and importance of BA in sustainable manufacturing (Grassi et al., 2020).

I4.0 *technologies in BA:* The second research question of this study addressed the intersection of I4.0 technologies and BA. According to Fig. 9, amongst I4.0 technologies, IoT, CPS, cloud manufacturing, AR, and AI were previously used in BA. The main applications of I4.0 technologies in BA are categorized as follows: (1) providing real-time data through the implementation of IoT (Fang et al., 2020; Huang et al., 2019; Wang et al., 2018), cloud manufacturing (Lai et al., 2021; Zhang et al., 2021), and CPS (Uludağ et al., 2019); (2) visualization and virtualization (Hofmann et al., 2019), (3) data-driven and AI methods instead of analytical and simulation methods (reviewed by Subramaniyan et al. (2021)). Including I4.0 technologies in BA dates back to 2018, indicating that the work in this area of research has begun recently. Thus, both academics and practitioners have a long way to go to fulfill the potential of BA using state-of-the-art technologies.

## 7. Opportunities for future developments

The third research question of the present study concerned the future of the BA methods regarding I4.0 design principles and technologies. To find a proper answer to this question, the design principles and technologies that were not employed in BA and their potential applications are discussed here. Amongst the design principles, vertical and horizontal integration might significantly influence the definition of BA. The realization of vertical integration, defined as the integration of intra-company systems (Alcácer & Cruz-Machado, 2019), might lead to BA methods that take all departments involved in production (e.g., human resource management, financial management, IT management, sales department, and procurement) into account while defining the bottleneck of the system. The horizontal integration might also have a significant effect on BA. Information sharing between different levels of a value chain in real-time (Brettel et al., 2014) will lead to BA methods for the whole value chain, i.e., supply and distribution, as well as production. Some researchers have pinpointed that the main bottlenecks were shifted to the logistics and distribution sides (Nchanji et al., 2021). Thus, it is expected that the realization of horizontal integration would push

BA towards more holistic BA methods by defining a bottleneck index similar to the approach used in the study by Tang et al. (2018).

In addition to horizontal integration, product personalization was among the design principles not addressed directly in BA (Fig. 9). Personalization of industrial products can be considered the main characteristic of customer demand in the era of I4.0 (Wang et al., 2017). The more customized products and their specifications are, the more agility and flexibility will be required in the production process to fulfill ever-changing customer demands in a reasonable amount of time. As such, it can be concluded that personalization will increase the need for agility and flexibility in production, resulting in a higher degree of shiftiness and greater challenges for BA.

Amongst I4.0 technologies not previously mentioned in BA, virtual reality and digital twins seem to have the potential for further investigation. The use of virtual reality resulted in solutions like the Augmented Go & See method presented in the study by Hofmann et al. (2019). Using a VR headset might obviate the need to bring a smartphone, smartwatch, tablet, or laptop to the production line by providing engineers and practitioners with a real-time virtual version of the manufacturing system. VR-based technology combined with real-time BA equipped with self-adaptive systems of smart manufacturing will bring about highly flexible and efficient solutions. The digital twin also has the potential to improve BA methods. A digital twin consists of a simulation model fed by real-time data (Lugaresi & Matta, 2021), holding a substantial potential to contribute to bottleneck diagnosis and prediction. Training an AI to the real-time simulation model can be a powerful tool in bottleneck prescription.

As discussed in this section, the potential methods for BA were proposed by studying I4.0 technologies that have not been considered in BA previously. However, the literature on BA still lacks a structured and step-by-step methodology to deal with the advanced technologies of I4.0, highlighting the need to develop a BA framework compatible with I4.0.

## 8. Conclusion

This study conducted a systematic literature review using the PRISMA method to investigate the intersection of BA and I4.0. In this study, probable I4.0 effects on underlying assumptions and methods of BA were investigated and highlighted to provide theoretical and practical insights into developing novel technology-driven BA methods. The results of the research provide practitioners with insights into the advancements and opportunities of existing BA methods to improve manufacturing productivity. This study may also be useful for researchers in establishing future research opportunities using I4.0 technologies to develop novel approaches for BA.

The results of the systematic literature review revealed that some of the design principles of I4.0, such as real-time applicability, decentralization, smart manufacturing, flexibility, virtualization, and agility, have been previously studied in the literature of BA. It has also been found that real-time capability was the main characteristic of most BA methods. The strongest relationship was found between real-time capability and the bottleneck detection block of BA. Overall, the systematic review identified a growing trend toward considering I4.0 design principles in the BA context. It has also been noticed that some I4.0 technologies have already been employed in BA, including IoT, cloud, AR, CPS, and AI. These technologies were mainly used to compile and analyze real-time data from the manufacturing shop floor. The literature review also showed that I4.0 technologies application in BA is a young and growing field. Finally, the ways I4.0 might revolutionize the BA were discussed.

Based on the results of this study, following future directions could be suggested, some of which would concentrate on theoretical aspects of BA, while others would be more practical in approach. The proposed future research directions include developing: 1) vertically integrated BA methods that can detect and mitigate bottlenecks not just at the operational level but in other functions of a manufacturing company, 2) horizontally integrated BA methods to detect and mitigate bottlenecks not just inside the manufacturing plant but in other levels of a supply chain, i.e., supply, logistics, and reverse logistics 3) digital twins-based BA methods, 4) VR-based real-time BA methods, 5) methods compatible with high-mix/low-volume production systems, and 6) a general framework for BA that incorporates the principles and techniques of I4.0. The results of this study indicate that BA has the potential to enhance manufacturing performance and productivity, while I.40 takes this potential to its fullest extent. In the same way, I4.0 may significantly contribute to other domains experiencing bottlenecks, such as agriculture, health care, and service industries.

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## Declaration of Competing Interest

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

## Data availability

No data was used for the research described in the article.

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