Computers & Industrial Engineering 149 (2020) 106774

Contents lists available at ScienceDirect

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie

Smart production planning and control in the Industry 4.0 context: A systematic literature review

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ARTICLE INFO

Keywords:
Smart capabilities
Industry 4.0
Internet of things
Cyber-physical systems
Big data and analytics
Systematic review

ABSTRACT

Scholars and practitioners have considered Industry 4.0 a comprehensive set of emerging technologies that establish a new industrial perspective based on the "Internet of Things". As smart manufacturing is at the core of the Industry 4.0 concept, production planning and control (PPC) should play a key role in Industry 4.0 activities. Prior research has mainly focused on technological issues of Industry 4.0, while little is known about how PPC is influenced by digital capabilities and how it operates in this new context. We conduct a systematic literature review to develop an analytical framework that explains how PPC in the Industry 4.0 context is influenced by smart capabilities from five base technologies (Internet of Things, Cyber-Physical Systems, Big Data and Analytics/Artificial Intelligence, and Additive Manufacturing), and how this is related to manufacturing system performance indicators, and environmental factors. The review includes studies from 2011 (when the Industry 4.0 concept was coined) to October 2019. Our findings provide a complete list of 18 smart capabilities (e.g., real-time capabilities, adaptability and dynamicity, visibility and traceability, autonomy, smart scheduling, PPC-as-a-service); 13 performance indicators (e.g., manufacturing flexibility, agility, reliability); and environmental factor conditions (e.g., product, demand, and manufacturing process). We also propose a future agenda with 10 research directions for PPC's study in the Industry 4.0 context.

1. Introduction

Production planning and control (PPC) activities aim to define what, how much, and when to produce, buy, and deliver so that the company can match manufacturing performance with customer demands (Bonney, 2000). Therefore, PPC is a value-adding process of the manufacturing activity (Wiendahl, Von Cieminski, & Wiendahl, 2005). PPC needs to continually adapt to operational and strategic environments, complex customer requirements, and new supply chain opportunities (Vollmann, Berry, Whybark, & Jacobs, 2005; Yin, Stecke, & Li, 2018). Thus, PPC needs to be dynamic, adaptive, and integrative (Adamson, Wang, & Moore, 2017; Helo & Hao, 2017; Ivanov, Dolgui, Sokolov, Werner, & Ivanova, 2016; Kong, Fang, Luo, & Huang, 2015).

The rapid industrial environmental changes impose an evolutionary and integrative perspective in operations management and, consequently, in the PPC function (Olhager, 2013; Olhager & Rudberg, 2002). Thus, the PPC function considers, for example, material requirements planning (MRP), enterprise resource planning (ERP), just-in-time manufacturing, and collaborative planning, forecasting, and replenishment, among other activities (Jacobs, Berry, Whybark, & Vollmann, 2018; Rondeau and Litteral, 2001). In recent years, the PPC function has been strongly supported by information and communication technology (ICT) (Shamsuzzoha, Toscano, Carneiro, Kumar, & Helo, 2016). ICT supports planning and control for core aspects of production, e.g., forecast demands, sales and operations planning (S&OP), MRP, master production scheduling (MPS), and production scheduling (Nahmias & Olsen, 2015). PPC function can also include interface activities such as procurement, shipment, capacity analysis, input/output control, and ordering systems (Chapman, 2006).

With the advent of the Internet of Things (IoT) and cyber-physical systems (CPS) in industrial contexts, digital capabilities have provided the opportunity for creating a new PPC context (Moeuf, Pellerin, Lamouri, Tamayo-Giraldo, & Barbaray, 2018; Rojko, 2017; Thürer et al., 2019; Wang, Altaf, Al-Hussein, & Ma, 2018). Emerging digital

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https://doi.org/10.1016/j.cie.2020.106774

Available online 24 August 2020

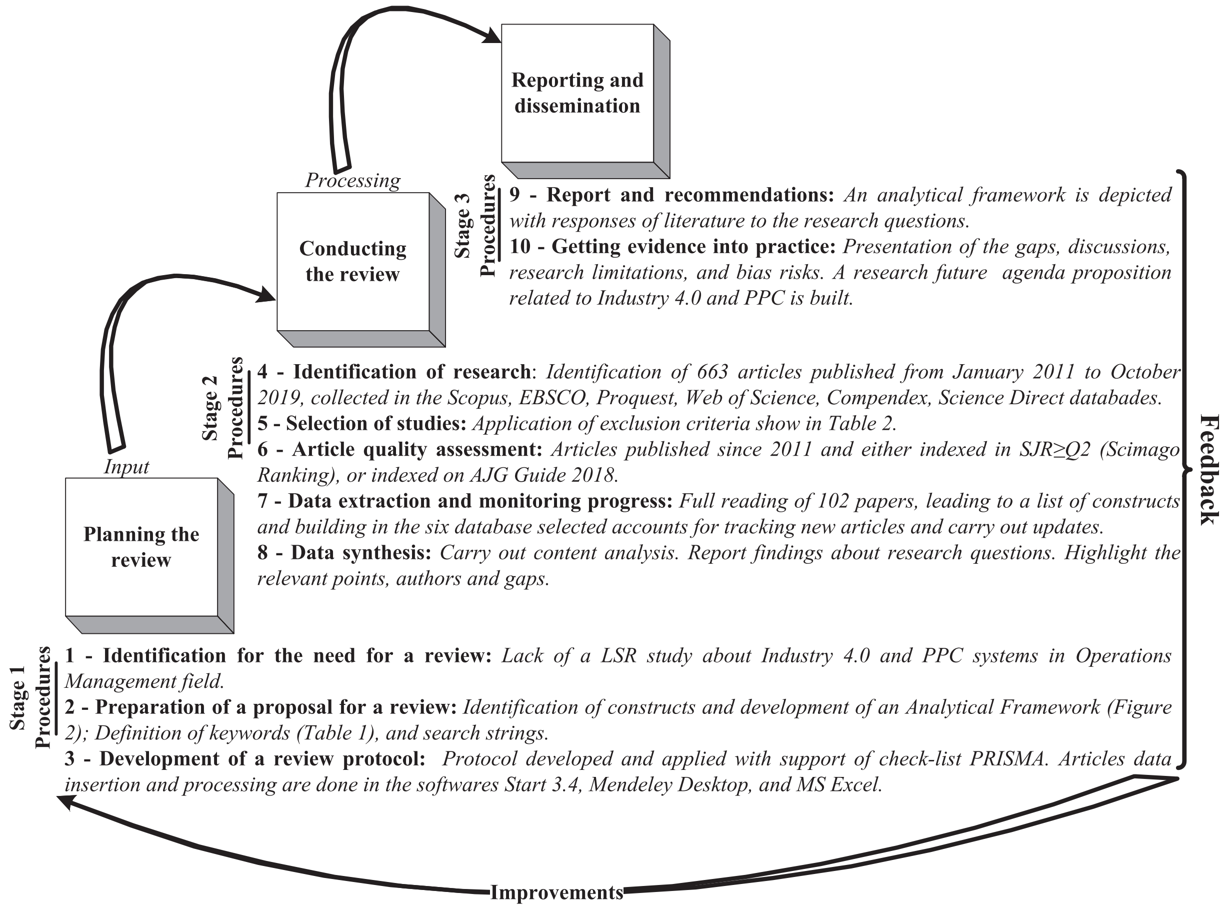


Fig. 1. Systematic literature review (SLR) using mixed guidelines from Tranfield et al. (2003), and Levy and Ellis (2006).

capabilities of the "Fourth Industrial Revolution" (i.e., Industry 4.0) can create new opportunities for PPC. The German conceptualization of Industry 4.0 focused on establishing and sustaining real-time optimized value networks (Kagermann, Helbig, & Hellinger, 2013), setting out multiple actors, and covering autonomous manufacturing resource networks (Bitkom et al., 2016). Many other extensions and broader perspectives have been proposed after this initial concept coined in Germany (Frank, Dalenogare, & Ayala, 2019). However, we follow the traditional view of the German model, which has been consolidated worldwide as the dominant view of the fourth industrial revolution. This view considers the manufacturing process as the core activity of Industry 4.0 (Dalenogare, Benitez, Ayala, & Frank, 2018). In this sense, the PPC function, which is a central part of the manufacturing system, may also face changes with the advent of Industry 4.0 technologies (Cattaneo, Fumagalli, Macchi, & Negri, 2018; Dombrowski & Dix, 2018; Moeuf et al., 2018; Vollmer, Zhou, Heutmann, Kiesel, & Schmitt, 2017). Dombrowski and Dix (2018) stated that managerial functions, including the PPC, could be transformed by using digital technologies, being more integrated, and automated. Traditional activities of PPC can be affected by concepts such as the vertical integration of physical and digital production environments (Wang, Gunasekaran, Ngai, & Papadopoulos, 2016), which considers cyber-physical systems and digital twins (Gilchrist, 2016; Graessler & Poehler, 2017; Zhong, Xu, Klotz, & Newman, 2017) and the integration of ERP, manufacturing execution systems, and machine-to-machine approaches for ordering systems (Howaldt, Kopp, & Schultze, 2017).

Although Industry 4.0 technologies are assumed to support PPC activities, the Industry 4.0 literature has not investigated yet specific characteristics of this crucial function of the production systems. The literature on this topic is widespread, and it lacks a holistic view that clarifies the relationships between Industry 4.0 and PPC functions, showing how Industry 4.0 affects PPC activities through new smart capabilities. Therefore, this study's main objective is to investigate the relationship between PPC and Industry 4.0 through a systematic literature review (SLR). We relate PPC with Industry 4.0 in a conceptual framework representing the intersections and studies addressing several perspectives. As a prerequisite, the key constructs are introduced, and the relationships postulated between them are presented. Furthermore, our research identifies three main research streams and presents key findings in each area. Based on this, a research agenda for future studies are proposed.

2. Research method: A systematic literature review

Our research method follows an SLR approach, which aims to ensure replicability by using transparent procedures and steps (Tranfield, Denyer, & Smart, 2003). Therefore, as shown in Fig. 1, we followed the recommendations of Levy and Ellis (2006), Tranfield et al. (2003), and Webster and Watson (2002), which served as methodological and operational guides for the research.

2.1. Stage 1: Planning the review

After identifying the research gap (absence of reviews showing the relationships between PPC and Industry 4.0), the first step was to determine the nature of Industry 4.0 and its means of realization as well as what is PPC and its scope and activities. Then, we developed constructs, keywords, and search strings. Thus, an analytical framework

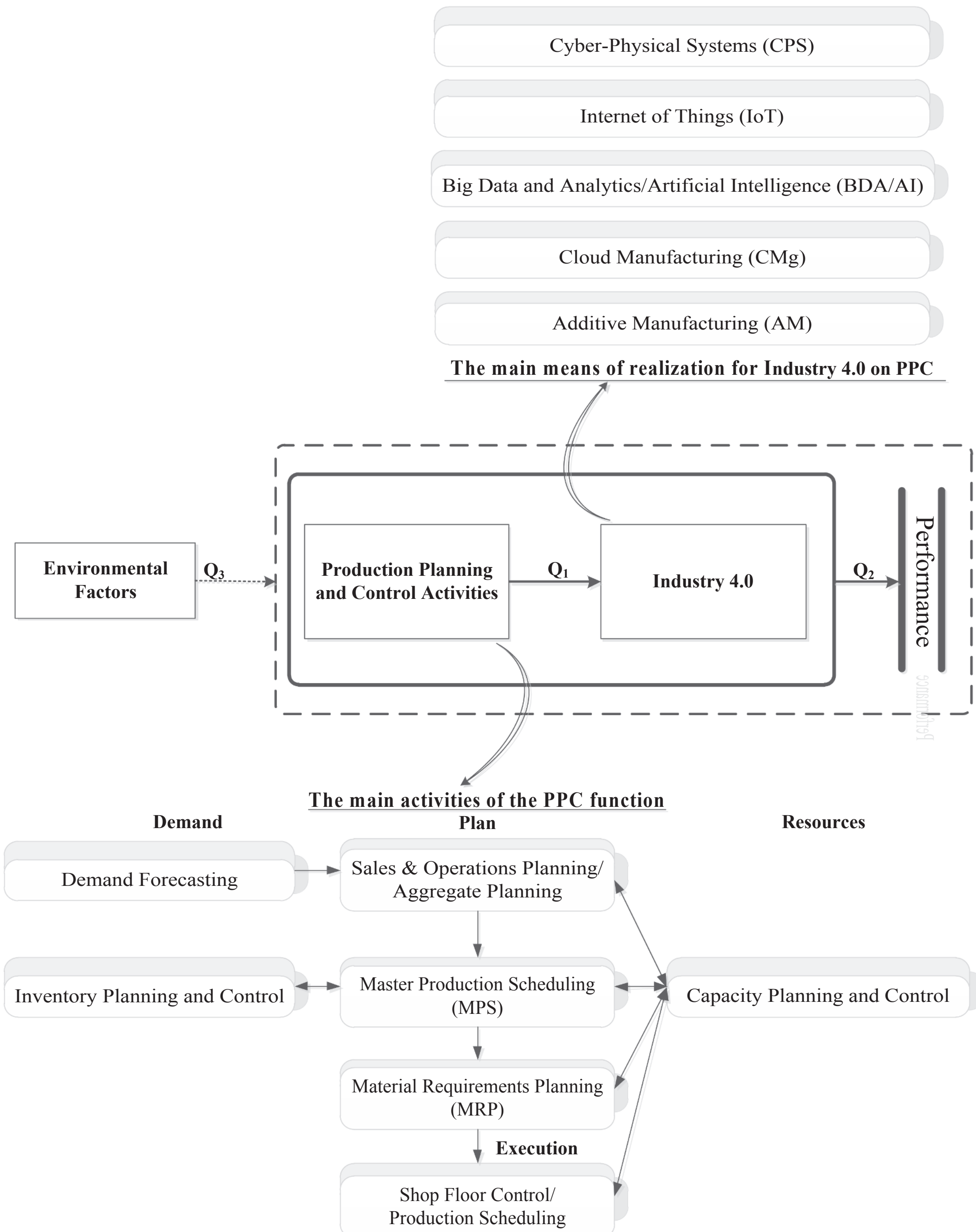


Fig. 2. Analytical framework.

with three research questions was consolidated (see the next subsection, i.e., "Analytical Framework"). We used this framework to create a research protocol that sets the details for conducting Stage 2 (SLR processing).

2.1.1. Analytical framework

In this study, a preliminary collection of references and exploration of the literature found no accessible SLR-type papers related to the functional relationships between Industry 4.0 and PPC, approaches to smart capabilities and performance, or environmental factors moderating on the relationship of PPC with performance.

The analytical framework of Fig. 2 presents the different theoretical points of view regarding the relationships between Industry 4.0, PPC, performance, and environmental factors. A similar framework was presented in Buer, Strandhagen, and Chan (2018) to study the links between Industry 4.0 and lean manufacturing, which we used as a reference. The purpose of our framework was to establish a relationship reference for a subsequent summary of the results for each PPC activity, as well as the respective smart capabilities and attributes provided by leading technologies in Industry 4.0. Using this framework, we also aimed to investigate the changes toward smart PPC, i.e., what structural changes are necessary to introduce new smart capabilities for the PPC function in the Industry 4.0 context. Based on this, a framework with three research questions is detailed below.

The three research questions of the present study are as follows:

Q_1. The PPC function and its activities are evolutionary, integrative, and capable of adapting activities, methods, tools, and structures to support the impacts of Industry 4.0. *Therefore, what are the smart capabilities necessary for PPC that can be provided by Industry 4.0?*

In this study, smart capabilities are defined as capabilities and resources that leverage the PPC function and its activities toward digitalization, integration, and automation (Arbix, Salerno, Zancul, Amaral, & Lins, 2017) through the exploration of smart technologies, as well as the mechanisms of networking power, applied in smart manufacturing planning and control.

Q_2. The integration between the PPC function and Industry 4.0 can affect different manufacturing system performance dimensions. *Does the integration of PPC with Industry 4.0 determine performance implications?*

Q_3. Moderating factors are likely to influence the integration potential between the PPC function and Industry 4.0, as well as the performance resulting from this integration. *What are the environmental factors which influence the development of smart capabilities for PPC?*

Each of the constructs of Fig. 2 is explained below, considering: the means of realization for Industry 4.0, PPC function, performance implications, and environmental factors.

PPC Function: The PPC function is responsible for making decisions regarding planning, starting, controlling, monitoring, scheduling, and reprogramming of a production planning, and ensuring the delivery of the products of a manufacturing company (Bonney, 2000). The framework depicted in Fig. 2 lists the PPC function's main activities, as triggered by strategic manufacturing planning. This PPC structure is based on Vollmann et al. (2005), Chapman (2006), and Jacobs et al. (2018), and often comprises a hierarchical structure. The main activities of a generic PPC are also shown: demand forecasting (DFO), S&OP/aggregate planning, MRP, MPS, inventory and capacity planning and control (INV; CAP), production scheduling and shop floor control of production (SFC) activities.

The means of realization for Industry 4.0: The "means of realization" for Industry 4.0 is the term used in this study to refer to any smart technology or mechanisms in the literature that constitutes a method to developing an Industry 4.0 concept inside the PPC perspective. This term is based on Moeuf et al. (2018). The means of realization for Industry 4.0 can be impactful and can boost and suitably sustain the

Table 1
The keywords used in this research.

Industry 4.0 construct		Production planning and control (PPC) construct
'industry 4.0' OR		
'industrie 4.0' OR		
'the fourth industrial revolution' OR		
'the 4th industrial revolution' OR		'planning and control'OR
'smart manufacturing' OR		
'smart production'OR		
'smart factory' OR		
'cyber-physical system' OR		
'cyber-physical production system' OR	AND	
'internet of things' OR		
'industrial internet' OR		'demand forecasting' OR
'big data and analytics' OR		'sales and operations planning' OR
'artificial intelligence' OR		'aggregate planning' OR
'digitalization' OR		'materials requirement planning' OR
'digitization' OR		'master production scheduling' OR
'additive manufacturing'OR		'production scheduling' OR
'cloud manufacturing'OR		'inventory planning and control' OR
'digital factory'		'capacity planning and control'

development of a smart PPC function (Dombrowski & Dix, 2018; Moeuf et al., 2018). Accordingly, we surveyed 50 current references to delimit the scope and the means of realization for Industry 4.0 from the PPC perspective.

The subject exploration revealed that the scope of research involving manufacturing planning and control with Industry 4.0 can be divided into five essential means of realization that may occur alone or in clusterings, namely the CPS, IoT, big data and analytics with artificial intelligence (BDA/AI), cloud manufacturing (CMg), and additive manufacturing (AM). This systematic review uses these key five technologies as potential vectors for the realization of Industry 4.0 inside manufacturing planning and control.

Performance implications: Current OM literature has already noted the performance dimension implications regarding the relationships between PPC and Industry 4.0 (Dalenogare et al., 2018). For example, Moeuf et al. (2018) identified flexibility, cost reduction, quality improvement, reduction of delivery time, and productivity improvement as linked to the PPC practices for small and medium-sized enterprises (SMEs). Buer et al. (2018) identified cost, flexibility, productivity, quality, reduced inventory, and reliability as the manufacturing system performance dimensions affected by integrating lean manufacturing with Industry 4.0. Both reviews found evidence justifying an analysis of the literature regarding the performance effects achieved by integrating manufacturing and Industry 4.0. This relationship will be approached from the strategic performance dimensions of operations linked to smart capabilities for manufacturing planning and control (Jacobs et al., 2018).

Moderating factors: Our article considers a contingency theory (Sousa & Voss, 2008) as the theoretical basis for the third question (Q_3) regarding manufacturing planning and control moderator factors. This viewpoint considers environmental variable effects on both the integration and operations performance of PPC and Industry 4.0. In this way, the contingency theory supports investigating how organizations can adapt their PPC structures to fit into environments to develop superior performance (Sousa & Voss, 2008). Often, this adaptation also concerns production planning environments and methods; therefore, in this review, moderator factors are defined as *identifiable elements in the environment* (Buer et al., 2018) *that can moderate the applicability of Industry 4.0 in an organizatioń's operations and can harness smart capabilities*

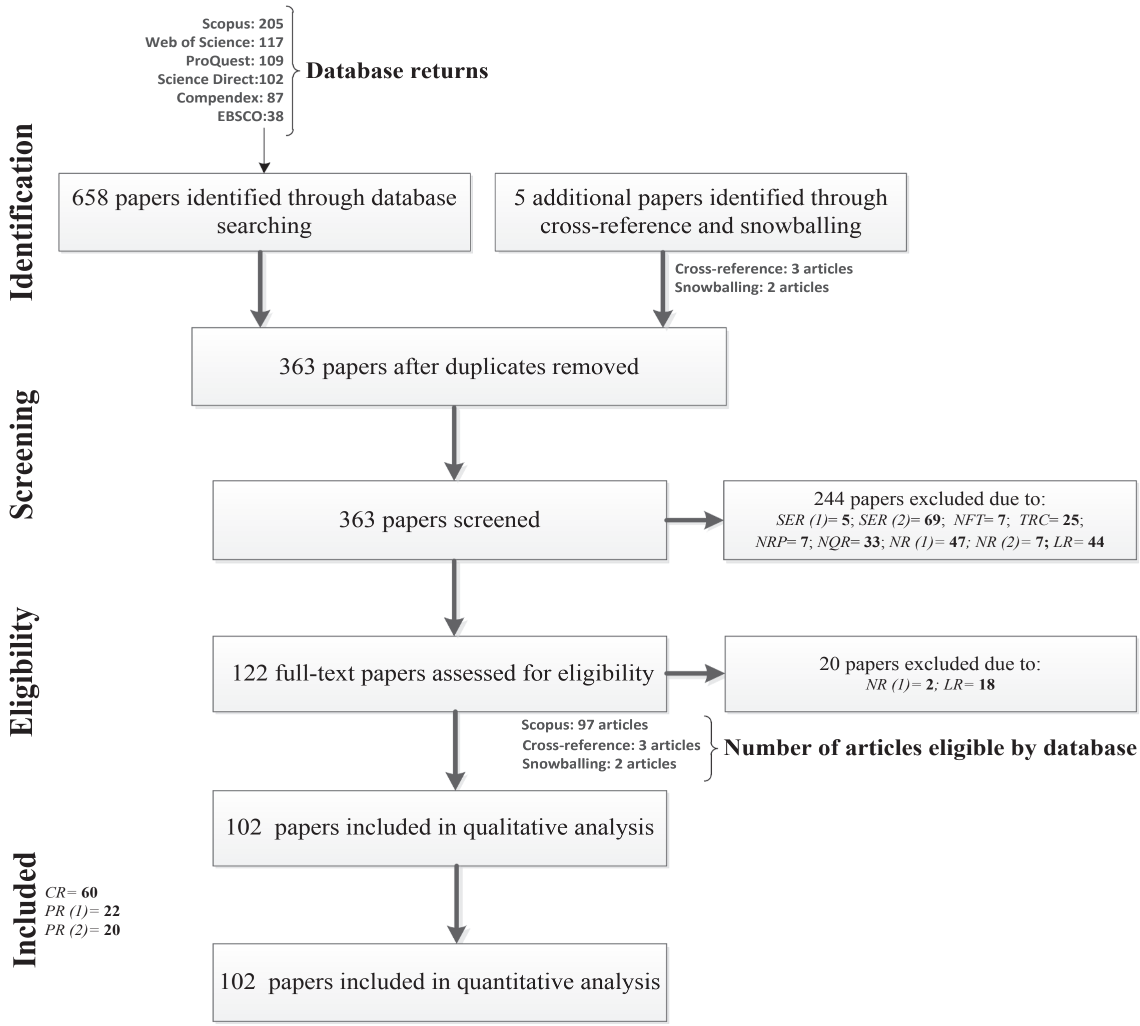


Fig. 3. PRISMA flowchart of the systematic review.

via planning and control. Our systematic review is based on environmental variables linked to product, demand, and manufacturing processes, as listed and explained by Jonsson and Mattsson (2003).

2.2. Stage 2: Conducting the review

Levy and Ellis (2006) argued that an SLR process should synthesize quality literature to provide a solid foundation for a field of research. Webster and Watson (2002) stated that the main contributions are likely to be found in leading journals. Thus, we adopted the same logic applied in the literature review of Ghadge, Dani, and Kalawsky (2012) and Kamalahmadi and Parast (2016), and also in the systematic review of Maestrini, Luzzini, Maccarrone, and Caniato (2017), i.e., using only journal articles in the study.

Our SLR focused on the analysis and scrutiny of a body of articles on the subject of Industry 4.0 combined with PPC and considered only articles from the year 2011 onward. Then, for consideration of the quality of a publication, a mutually contingent condition was adopted, in which a journal had to be classified in either the Academic Journal Guide 2018 (AJG) or one of the two highest quartiles (Q1 or Q2) of the Scimago Journal Ranking (SJR). The time range was set from January 2011 to October 2019. Kagermann et al. (2013) established the beginning of the Industry 4.0 era as the year 2011, as the Industry 4.0 concept was presented for the first time at the Hannover Fair in Germany (Hermann, Pentek, & Otto, 2016).

Concerning the SLR's operational steps, the Scopus, Web of Science, Science Direct, ProQuest, EBSCO, and Compendex databases were surveyed using two strings formulated from the keywords in Table 1. The search returned 658 documents. In general, the criteria guiding the selection of databases were based on the insertion of the most significant number of possible sources that traditionally hosted journals publishing works of high impact on the research subject.

We extracted the keywords related to Industry 4.0 from an exploratory survey of 50 recent scientific articles conducted in Stage 1 of this SLR. We also crosschecked the keywords with the recent systematic reviews of Liao, Deschamps, Loures, and Ramos (2017), Buer et al. (2018), and Moeuf et al. (2018). The search terms comprised keywords presented in the first column of Table 1.

PPC is a more well-established domain in the OM literature than Industry 4.0. Accordingly, the keywords presented in the second column of Table 1 for the PPC construct are assumed to be sufficient and comprehensive for the PPC domain. The first keyword in the second column, "planning and control," refers to a PPC function in a generalized manner, whereas the group of keywords below it encompasses the specification of traditional activities of the PPC function, according to Chapman (2006), Vollmann et al. (2005), and Jacobs et al. (2018). Thus, we clustered the PPC activities in the demand dimension: "demand forecasting," "inventory planning and control"; in the resources dimension: "capacity planning and control"; and also, in the planning and execution dimension: "S&OP," "aggregate planning," "materials

Table 2
Details of inclusion and exclusion criteria.

Criteria type	Criteria	Code	Criteria detail
Exclusion	Search engine reasons	SER	SER (1): The paper has a title and abstract in English, but does not have the full text SER (2): The article does not come from an academic journal, that is, it originates from a book, a book section, or a conference proceeding
	No full text	NFT	The paper does not have available text to be assessed
	Time range	TRC	The article was not published within the defined time range: as of 2011
	Not quality ranking	NRQ	The article does not have a Scimago Journal Ranking (SJR) at levels Q1 or Q2, and the article is not published in a journal that is indexed in the Academic Journal Guide 2018
	Not peer-reviewed	NRP	The article is not peer-reviewed academically
	Non-related	NR	NR (1): The article does not relate the relationships of the PPC function or its activities to the main means of realization for Industry 4.0 adopted in this review NR (2): The paper is not an academic article
	Loosely related	LR	The article is Loosely related to PPC integration with Industry 4.0, that is, the article does not express discussion or results regarding the constituent relationships of the research framework
Inclusion	Partially related	PR	PR (1): The article generically addresses the subject of Industry 4.0, focusing on integration with one or a few elements of the PPC function and its activities PR (2): Integration of PPC with Industry 4.0 frames only one of several research objectives, or some extracts of the article
	Closely related	CR	The research focus of a paper clearly and strictly addresses the integration of PPC with Industry 4.0 and its capabilities

requirement planning," "master production scheduling," and "production scheduling," as shown in Table 1.

The next procedure comprised applying the "Preferred Reporting Items for Systematic Review and Meta-Analysis" (PRISMA) (Moher, Liberati, Tetzlaff, & Altman, 2009) approach to the following activities (see Fig. 3): identification, screening, eligibility, and inclusion. These steps in PRISMA supported the operationalization of the activities 4 to 8 in the SLR, as shown in Fig. 1. We applied a preset to the databases' search engines in an attempt to guarantee accuracy in the return of the articles. We set up the search engines by inserting the two strings adopted in this process, and we recorded the files in a database. In the identification phase, we obtained a return of 658 documents. We added five documents obtained by cross-referencing and snowballing, and we excluded 300 duplicate documents, resulting in 363 documents remaining.

The first six exclusion criteria (SER, NFT, TRC, NRQ, NRP, and NR) presented in Table 2, were applied to the 363 identified articles in a first screening process. As a result, we excluded 244 documents. From a reading of the abstracts, keywords, titles, and conclusions, the remaining exclusion criteria in Table 2 (NR and LR) were applied, resulting in the additional exclusion of 20 articles. Accordingly, we obtained a final set of 102 articles. These articles were eligible for full reading and possible inclusion in the systematic review. The details regarding the number of articles excluded due to each criterion in Table 2 are shown in Fig. 3.

2.3. Stage 3: Reporting and dissemination

SLR's last stage considers the report and presentation of the theoretical and empirical findings regarding the three research questions. Besides, a "content analysis" showing an overview of the articles and the quantitative and qualitative analyses is presented in Section 3.

3. Findings

3.1. An overview of the included articles

As shown in Fig. 4, between the years 2011 and October 2019, there was a trend of accelerated growth in Industry 4.0 related articles that considered PPC as a term. Fifty-four articles comprise empirical research, and 48 articles comprise conceptual types of research. Regarding the methods employed, 25 are experimental studies with modeling and simulation, 21 are conceptual research studies (e.g., bibliographical surveys, review studies, and theoretical discussions), 20 are industrial cases with modeling and simulation, 17 are studies involving only modeling and simulation, 17 are case studies, one is a survey, and another study is a Delphi survey.

As for journals, the highest frequencies of articles are from the International Journal of Production Research (13 articles), International Journal of Computer Integrated Manufacturing (six articles), Journal of Intelligent Manufacturing (six articles), Computers & Industrial

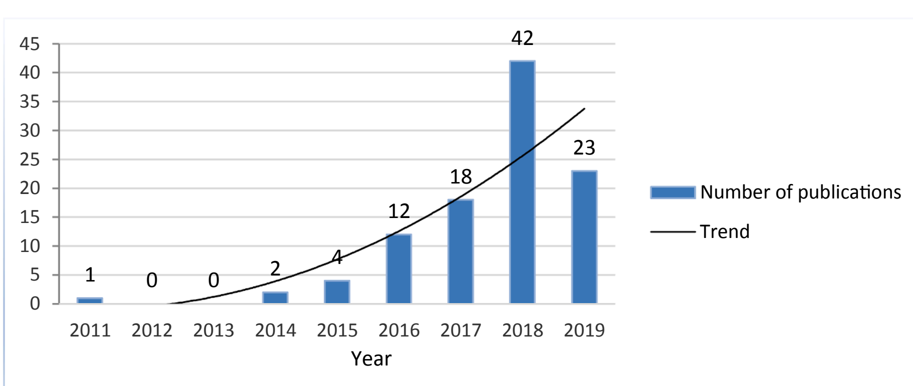


Fig. 4. Distribution of articles per year.

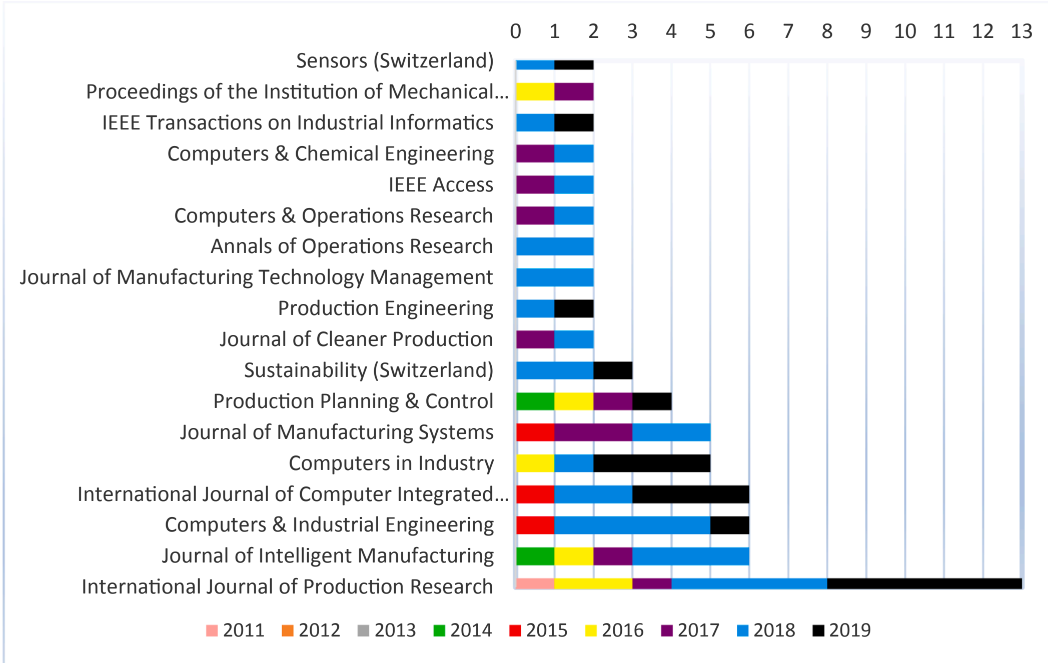
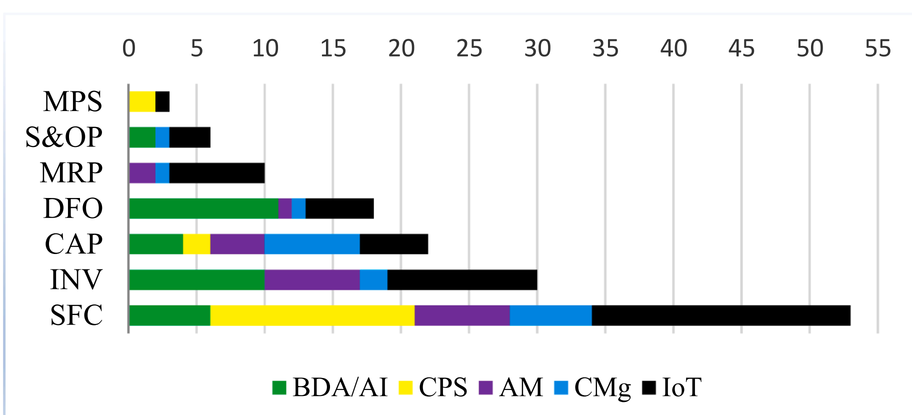


Fig. 5. Distribution of articles per journal and year.

Engineering (six articles), Computers in Industry (five articles), Journal of Manufacturing Systems (five articles), and Production Planning & Control (four articles) (see Fig. 5). Between one and two articles were extracted from the other journals. The 102 eligible articles (for both quantitative and qualitative analyses) were compared and can be found and extracted through the Scopus database. The Scopus database is one of the most significant databases for the subject searches addressed in this review.

The magnitude of harnessing of the industry 4.0 technologies by each PPC activity considered in this SLR is represented in Fig. 6. This association is regarding articles with codes of 1 to 87 (see codes in Fig. 7). The industry 4.0 technologies most explored are IoT (51 articles) and BDA/AI (33 articles) by shop floor control and scheduling activities (53 articles), and also inventory planning and control (30 articles). Note that some articles relate to PPC activities are exploring more than one technology. The red color numbers in columns and rows in Fig. 6 show the higher frequencies of each industry 4.0 technology on each PPC activity within the articles.



	CMg	CPS	AM	BDA/AI	IoT	Number of articles
MPS	0	2	0	0	1	3
S&OP	1	0	0	2	3	6
MRP	1	0	2	0	7	10
DFO	1	0	1	11	5	18
CAP	7	2	4	4	5	22
INV	2	0	7	10	11	30
SFC	6	15	7	6	19	53
Number of articles	18	19	21	33	51	

Fig. 6. Distribution of articles addressing PPC activities and Industry 4.0 technologies.

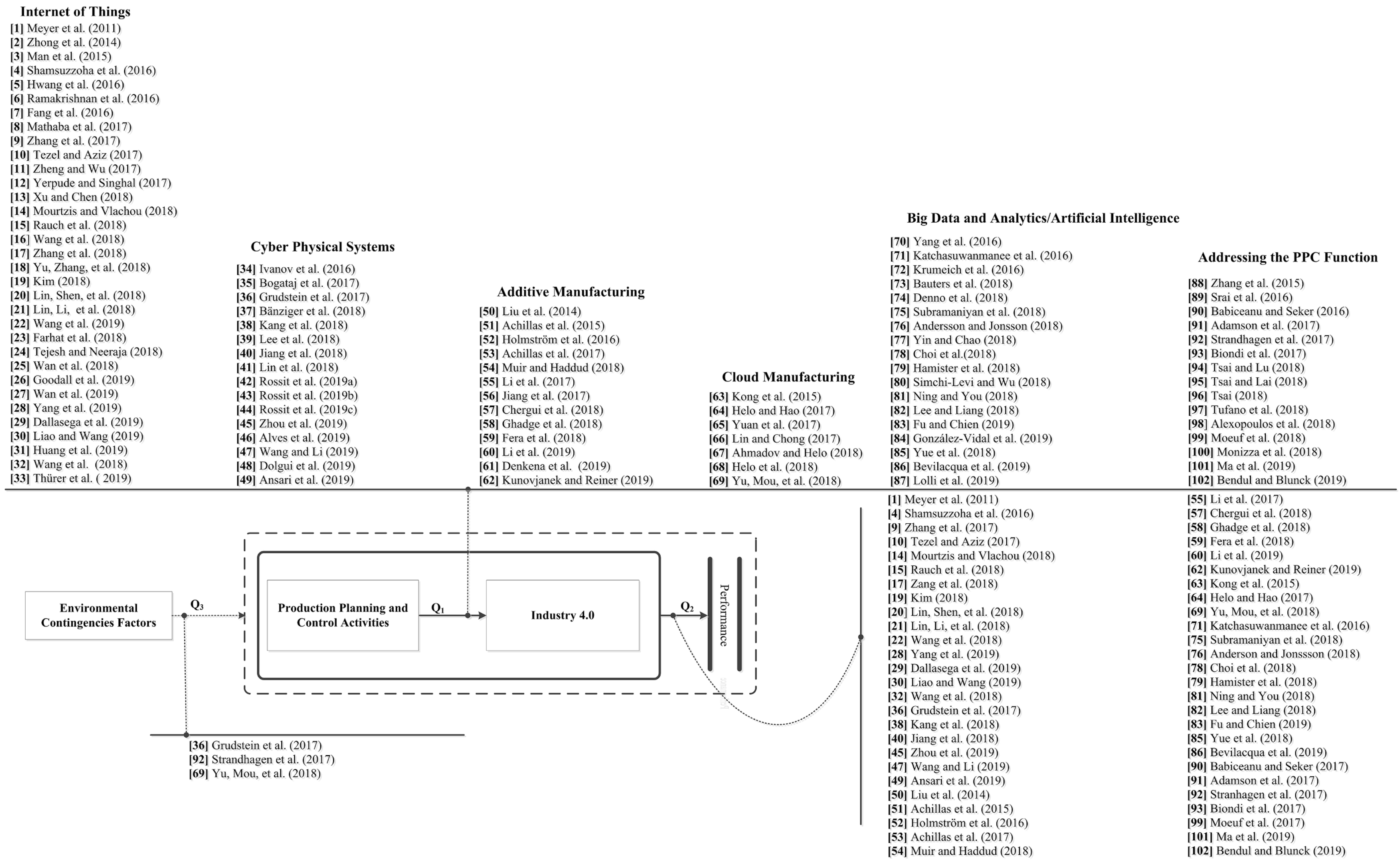


Fig. 7. Analytical framework of results– Authors, time range, and related Industry 4.0 technologies.

The remaining articles with code of 88 to 102 associate the entire PPC function to industry 4.0 technologies. These papers explore with the highest frequency CPS (8 articles) and BDA/AI (6 articles) (see Fig. A1 in Appendix A).

Universities and research centers studying the combination of PPC and Industry 4.0 are spreading across all continents, emphasizing research conducted in Asia, especially in China (responsible for approximately ¼ of the articles analyzed in this review). The rest of the articles originated from research institutions in countries such as Germany, the United Kingdom, the USA, Finland, Italy, France, Norway, Sweden, India, Canada, and Greece. For researchers, the main departments/areas origin is Industrial/Mechanical Engineering (37%), Business, Management, and Economics (17%), Information Systems and Computer Science (11%), Electric/Electronic, Robotics/Automation (5%), other areas (30% - statistics, mathematics, and other related fields).

3.2. *Key findings: Analytical framework*

Next, we discuss the results concerning the three research questions presented in the analytical framework section. The results were extracted by using the content analysis technique for each of the 102 articles.

3.2.1. *What are the smart capabilities for production planning and control (PPC) provided by Industry 4.0?*

i. **Analyzing the Smart Capabilities Explored for Demand Forecasting, Capacity Planning and Control, and Inventory Planning and Control**

Demand Forecasting: According to Fig. A1 (Appendix A) and related articles/authors in Fig. 7, the leading smart capabilities explored in the demand dimension and reported in the literature are based on the IoT, and concern real-time data collection and integration with aggregate planning and inventory management (Man, Na, & Kit, 2015; Yerpude & Singhal, 2017; Yu, Zhang et al., 2018). The forecasting processing and data analytics portion are strongly focused on BDA/AI tools for supporting smart capabilities concerning the predictability of resources, improving the accuracy and performance of forecasting, processing sets of big data and analytics using machine learning methods, automatic selection of demand predictors, real-time data collection, and monitoring and diagnosis with data analytics tools for the integration of demand forecasting with capacity and inventory management (Andersson & Jonsson, 2018; Choi, Wallace, & Wang, 2018; Fu & Chien, 2019; González-Vidal, Jiménez, & Gómez-Skarmeta, 2019; Hamister, Magazine, & Polak, 2018; Lee & Liang, 2018; Lolli et al., 2019; P. Yin & Chao, 2018; Yue, Liu, Diao, & Liu, 2018). Other capabilities explored by forecasting include accurate fulfillment of seasonal demands for spare parts (Muir & Haddud, 2017) based on AM and real-time data collection, and processing for auctions with demand forecasting based on cloud services (Kong et al., 2015).

Capacity Planning and Control: The main smart capabilities for capacity planning and control are explored in the digital environments of the IoT and CMg with BDA/AI, and support integration of forecasting and inventory activities (for more details, see Fig. A1 in Appendix A, and related articles/authors in Fig. 7). The core capabilities explored for capacity management are the digitalization of capacity resources with real-time data collection and monitoring through products with product-embedded intelligent devices (PEID) (Meyer, (Hans) Wortmann, & Szirbik, 2011), synchronization of a PPC plan module (MPS, MRP, capacity and production scheduling) (Rauch, Dallasega, & Matt, 2018; Yu, Zhang et al., 2018), data-driven-predictive capacity planning (Wan et al., 2018), and traceability and/or processing of machine and real-time monitoring status products (Liao & Wang, 2019). AI applications in CPS support the integration of control tasks (order releasing, sequencing, and capacity control) (Grundstein, Freitag, & Scholz-Reiter, 2017) and predictive maintenance planning into PPC (Ansari, Glawar, & Nemeth, 2019). CMg and BDA/AI support capabilities such as scalability, reconfiguration, and flexibility in production capacity management (Helo & Hao, 2017; Kong et al., 2015; Yuan, Deng, Chaovalitwongse, & Cheng, 2017), production resource monitoring with information and material flow optimization, integration and synchronization of capacity with other systems and operations, and predictive and robust capacity management (Ahmadov & Helo, 2018; Katchasuwanmanee, Bateman, & Cheng, 2016; Lee & Liang, 2018; Lin & Chong, 2017; Ning & You, 2018; Subramaniyan, Skoogh, Salomonsson, Bangalore, & Bokrantz, 2018; Yu, Mou, et al., 2018). AM has been explored to optimize and manage a distributed, flexible, and available capacity of 3D-printers (Achillas, Tzetzis, & Raimondo, 2017; Li, Kucukkoc, & Zhang, 2017; Liu, Huang, Mokasdar, Zhou, & Hou, 2014; Muir & Haddud, 2017).

Inventory Planning and Control: In this dimension of PPC activity, the smart capabilities provided by Industry 4.0 technologies are actively explored, as highlighted by the IoT and AM (for more details, see Fig. A1 in Appendix A, and related articles/authors in Fig. 7). The main capabilities observed in the literature are real-time monitoring and control with PEID (Meyer et al., 2011), integration between forecasting, customer service, and aggregate planning (Hwang, Kim, & Rho, 2016; Mathaba, Adigun, Oladosu, & Oki, 2017; Ramakrishnan, Gaur, & Singh, 2016), smart inventory system concepts (sensor data, analytics, CPS integration, and green attributes) (Zheng & Wu, 2017), automatic inventory management, continuous monitoring and optimization (Tejesh & Neeraja, 2018), IoT-driven-e-Kanban, and smart vendor managed inventory systems (Thürer et al., 2019; Yerpude & Singhal, 2017).

The smart capabilities reported in the literature in AM environments include flexibility of choice between decentralized and centralized safety inventories, mass customization/direct digital manufacturing for low-volume production, and improvements in the real-time traceability and decentralized control of parts, kits, and available spare parts stocks (Achillas, Aidonis, Iakovou, Thymianidis, & Tzetzis, 2015; Achillas et al., 2017; Ghadge, Karantoni, Chaudhuri, & Srinivasan, 2018; Holmström, Holweg, Khajavi, & Partanen, 2016; Jiang, Kleer, & Piller, 2017; Kunovjanek & Reiner, 2019; Li, Kucukkoc, & Zhang, 2017; Liu, Huang, Mokasdar, Zhou, & Hou, 2014; Muir & Haddud, 2017).

Concerning CMg with BDA/AI, the smart capabilities concern the integration of inventory systems with enterprise and execution manufacturing systems, PPC activities and tasks, optimization, automated storage and retrieval systems, and real-time traceability based on AI methods (Andersson & Jonsson, 2018; Bevilacqua, Ciarapica, & Antomarioni, 2019; Choi et al., 2018; Hamister et al., 2018; Helo & Hao, 2017; Kong et al., 2015; Lee & Liang, 2018; Lolli et al., 2019; Simchi-Levi & Wu, 2018; Yang, Zhang, & Chen, 2016; Yu, Mou, et al., 2018; Yue et al., 2018).

ii. **Analyzing the Smart Capabilities Explored for Sales and Operations Planning (S&OP)/Aggregate Planning, Master Production Scheduling (MPS), and Material Requirements Planning (MRP)**

S&OP/Aggregate Planning: For these activities, the smart capabilities exploration concerns real-time data collection (IoT) for information sharing and collaboration, aggregate planning based on CMg, and applying BDA/AI and analytics technologies for enterprise and control systems integration (Fang, Liu, Pardalos, & Pei, 2016; Shamsuzzoha et al., 2016) (for more details see Fig. A1 in Appendix A, and related articles/authors in Fig. 7). Aggregate planning is found in searched articles exploring IoT digital capabilities for multi-level data sharing, traceable data flows, and integration with demand forecasting, inventory control, and manufacturing execution system (MES)/ERP systems (Yu, Zhang et al., 2018). In a CMg environment, the S&OP employs real-time integration to feed PPC operational tasks and adaptive real-time pricing integrated with sales data, adequate level capacity data, production scheduling, and S&OP desegregation (Kong et al., 2015). The smart capabilities explored for BDA/AI include real-time optimization prices combined with big data processing, information cost and inventory level monitoring integrated for S&OP processes (Simchi-Levi & Wu, 2018), and spare parts demand planning integrated with S&OP (Andersson & Jonsson, 2018).

MPS: Only three articles were identified for MPS based on IoT and CPS (Rauch et al., 2018; Rossit et al., 2019b, 2019c). IoT supports demand-driven and real-time capabilities for the PPC function, providing synchronization of the IoT with the capacity, scheduling, MPS, and MRP (Rauch et al., 2018). The CPS support capabilities concerning real-time production scheduling, enterprise, and control systems, with distributed and collaborative decision-making through MES, MPS/ERP, and CPS integration (Rossit et al., 2019b, 2019c). More details can be found in Fig. A1 and from the related articles/authors shown in Fig. 7.

MRP: MRP is mostly based on the IoT (for more details, see Fig. A1 in Appendix A, and related articles/authors in Fig. 7). The core capabilities provided by the IoT to MRP are: the integration of building information models, ERP/MRP systems with resources and data systems, and MRP element digitalization following context-awareness resources (Rauch et al., 2018; Tezel & Aziz, 2017), real-time resources status monitoring, responsive shop floor material management (Wang et al., 2018; Xu & Chen, 2018), automatic data collection from material controls integrated with ordering systems (P. Lin, Shen, et al., 2018), data-driven simulations to predict material flows and shop floor operations behavior (Goodall, Sharpe, & West, 2019), and real-time sensing and positioning using a data-driven optimization of materials, and intelligent automated guided vehicles (Huang, Guo, Zha, & Wang, 2019). In a CPS environment, the IoT supports capabilities related to extending MRP with real-time calculations, early reports, traceability, and visibility in the food chain (Bogataj, Bogataj, & Hudoklin, 2017), in addition to MRP automatic optimization, prediction, and re-scheduling based on the digital twin model (Lin, Wong, & Ge, 2018). AM technology provides smart capabilities, including direct digital manufacturing with minimization of the handling and processing of materials, and minimization of the MRP complexity with a reduction of logistics flow is smart (Achillas et al., 2015, 2017; Kunovjanek & Reiner, 2019). In CMg, the research has explored servitization's smart capability, which frames ERP/MRP systems as serviced by cloud platforms.

iii. Analyzing the Smart Capabilities Explored for Production Scheduling/Shop Floor Control

Production Scheduling/Shop Floor Control: The production scheduling and shop floor control activities are explored in greater detail for Industry 4.0 in all technologies considered for this study (the details can be seen in Fig. A1, and the related articles/authors in Fig. 7). The leading smart capabilities explored for the IoT are related to digitalization and networking integration in manufacturing execution, rather than planning and control systems. These smart capabilities at the level of manufacturing execution, scheduling, and control include real-time shop floor monitoring, resource traceability, data collection, data mining (Liao & Wang, 2019; Meyer et al., 2011; Thürer et al., 2019; Zhong, Huang, Dai, & Zhang, 2014), and real-time information sharing for collaborative production scheduling (Shamsuzzoha et al., 2016). The concept of smart scheduling is based on the integration of digital capabilities for real-time, data-driven, collaborative, green energy-aware, and automatic data collection, and can be used for, e.g., 3-D printer scheduling (Farhat, Iliev, Marriage, & Rolland, 2018; Goodall, Sharpe, & West, 2019; Kim, 2018; Liao & Wang, 2019. Lin, Shen, et al., 2018; Thürer et al., 2019; Wang, Ong, & Nee, 2018; Wang, Yew, Ong, & Nee, 2019; Zhang, Wang, & Liu, 2017). The remaining capabilities concerning the IoT concentrate on adaptive and distributed shop floor control, integrated scheduling of enterprise and control systems (Mourtzis & Vlachou, 2018; Wan et al., 2018), synchronization task scheduling, operations (vertical/horizontal synchronization) for real-time visibility of the shop floor on a mobile display (Goodall et al., 2019; Lin et al., 2018; Lin, Li, et al., 2018; Rauch et al., 2018), data-driven simulations to predict material flows and shop floor operations behavior (Wan et al., 2018), flexible and reconfigurable production scheduling (Wan et al., 2019), responsiveness (Dallasega, Rojas, Bruno, & Rauch, 2019) and real-time optimization (Kim, 2018; P. Lin, Shen, et al., 2018; Wang et al., 2019; Zhang et al., 2018).

CPS's main smart capabilities for production scheduling and control are related to smart scheduling and automation. Smart scheduling in the context of CPS is based on the smart capabilities of scalability, modularity, autonomous and decentralized data collection, data-driven operations, adaptiveness, flexibility, and collaboration, for scheduling and shop floor control systems (Alves, Varela, Rocha, Pereira, & Leitão, 2019; Dolgui, Ivanov, Sethi, & Sokolov, 2019; Ivanov et al., 2016; Jiang, Jin, & Li, 2018; Kang et al., 2018; Lin et al., 2018; Rossit et al., 2019a, 2019b, 2019c; Wang & Li, 2019). Other capabilities concern cooperative cyber-physical production systems integrated with the IoT-MES/APS (J. Lee, Noh, Kim, & Kang, 2018). Shop floor control predominates the smart capabilities regarding automation, such as autonomous production control and task integration based on CPS/AI (Bogataj, Bogataj, & Hudoklin, 2017; Grundstein, Freitag, & Scholz-Reiter, 2017), predictive maintenance integrated to production scheduling and based on CPS/AI (Ansari et al., 2019), intelligent planning and control algorithms for optimized and automatic human-robot task allocation (Bänziger, Kunz, & Wegener, 2018), manufacturing cells with autonomy (intelligent perception, optimization/simulation, awareness, prediction, and control), and self-optimization (self-thinking, self-decision-making, self-execution, and self-improvement) (Zhou, Zhang, Li, Ding, & Wang, 2019).

Concerning AM, the main capabilities explored are direct digital manufacturing, real-time traceability of parts and machines, decentralized control of individual parts and kits, scalability, synchronization operations, planning and control, dynamic order acceptance for on-demand production, optimum allocations of 3D-printers, mass customization control, 3-D printer production, inventory integration, and product model (Achillas et al., 2017; Denkena, Dittrich, & Jacob, 2019; Holmström et al., 2016; Li, Zhang, Wang, & Kucukkoc, 2019), optimization of 3D-printer scheduling (Chergui, Hadj-Hamou, & Vignat, 2018; Fera, Fruggiero, Lambiase, Macchiaroli, & Todisco, 2018; Li et al., 2019), integration of detailed adaptive process planning, and AM production planning and scheduling (Denkena et al., 2019).

In a CMg environment, the main capabilities explored are servitization, production scheduling-as-a-service for manufacturing-as-a-service (Helo, Phuong, & Hao, 2019; Helo & Hao, 2017), digitalization of production scheduling via real-time auction and performance analytics (Kong et al., 2015), optimization production scheduling, flexibility, and reconfigurable lines based on cloud services (Ahmadov & Helo, 2018; Lin & Chong, 2017; Yuan et al., 2017).

The core smart capabilities based on BDA/AI are real-time MES and object traceability for adaptive and optimized production scheduling (Katchasuwanmanee et al., 2016), smart scheduling based on big data collection, analysis, and optimization, energy-smart/green optimization (Krumeich, Werth, & Loos, 2016; Lee & Liang, 2018), predictability/event-driven scheduling (Bauters et al., 2018; Lee & Liang, 2018; Subramaniyan et al., 2018), and automated data analytics/embedded self-learning/AI (Denno, Dickerson, & Harding, 2018).

iv. Analyzing the Articles Addressing the Entire PPC function, Without Focusing on any Specific Activity

The SLR articles (codes 88-102) highlighted in Fig. A2 (Appendix A) discuss PPC as a function of management (see articles in Fig. 7); they do not address any PPC activity, but rather holistically approach the PPC function, facilitating the exploration of smart capabilities using Industry 4.0.

Table 3
Articles addressing the influence of the smart PPC on manufacturing system performance.

Articles	Performance Indicators												
Legend: C = conceptual research E = empirical/ field research ✓[d] = demonstrated indicator	Cost	Flexibility	Productivity	Agility	Reliability	Quality	Energy and Resources	Profitability	Lead Time	Robustness	Inventories	Complexity	Customer Satisfaction
[C]Meyer et al. (2011)		✓		✓						✓			
[E]Liu et al. (2014) [Case Study]	✓								✓		✓		
[E]Kong et al. (2015) [Case Study]	✓	✓		✓					✓				✓
[E]Achillas et al. (2015) [Case Study]	✓[d]	✓				✓	✓		✓[d]			✓	✓
[E]Shamsuzzoha et al. (2016) [Case Study]	✓	✓							✓				✓
[E]Katchasuwanmanee et al. (2016) [Experimental Research/Simulation]			✓				✓						
[C]Holmström et al. (2016)			✓										
[C]Babiceanu and Seker (2016)	✓	✓	✓	✓									
[E]Strandhagen et al. (2017) [Case Study]		✓		✓							✓		
[E]Helo and Hao (2017) [Case Study]	✓	✓		✓	✓	✓	✓	✓	✓				
[C]Tezel and Aziz (2017)			✓		✓								
[C]Adamson et al. (2017)		✓											
[E]Biondi et al. (2017) [Experimental Research/Simulation]	✓				✓								
[E]Grundstein et al. (2017) [Case Study/Simulation]	✓[d]		✓[d]		✓[d]					✓			
[E]Achillas et al. (2017)[Case Study]	✓[d]	✓							✓[d]				
[E]Muir and Haddud (2017) [Survey]					✓				✓[d]		✓[d]		
[C] Jiang et al. (2018)	✓	✓	✓	✓	✓	✓			✓				
[E] P. Lin, Shen, et al. (2018) [Case Study]									✓		✓		
[C;E]Li et al. (2017,2019) [Experimental research/Simulation]	✓	✓											
[E]Mourtzis and Vlachou (2018) [Case Study]		✓	✓						✓				
[C]Subramaniyan et al. (2018)			✓										
[E]Yu, Mou, et al. (2018) [Case Study/Simulation]		✓		✓					✓		✓		
[E] Lin, Li, et al. (2018) [Case Study/Simulation]			✓	✓	✓[d]				✓				
[C]Fera et al. (2018)	✓												
[E]Zhang et al. (2018) [Experimental research/Simulation]	✓						✓						
[C]Chergui et al. (2018)					✓								
[E]Ghadge et al. (2018) [Experimental Research/Simulation]		✓		✓									
[E]Hamister et al. (2018) [Case Study]	✓[d]										✓[d]		
[E]Kim (2018) [Experimental Research/Simulation]		✓			✓								
[E]Ning and You (2018) [Experimental Research/Simulation]								✓[d]					
[C]Moeuf et al. (2018)	✓	✓	✓	✓	✓	✓			✓				✓
[E]Yue et al. (2018) [Case Study/ Simulation]				✓	✓								
[E]Zhang et al. (2017) [Case Study/Simulation]		✓					✓					✓	
[E]Rauch et al. (2018) [Case Study]	✓[d]				✓							✓	
[E]Andersson and Jonsson (2018) [Case Study]					✓[d]								
[C]Choi et al. (2018)	✓							✓			✓		
[E]Lee and Liang (2018) [Case Study]	✓[d]				✓			✓[d]					
[C]Bendul and Blunck (2019)		✓	✓	✓			✓			✓		✓	
[C]Yang et al. (2019)	✓					✓					✓		
[C]Dallasega et al. (2019)	✓			✓				✓			✓	✓	
[C]Ma et al. (2019)		✓			✓					✓			
[C]Kang et al. (2018)		✓	✓						✓			✓	
[C]Zhou et al. (2019)	✓	✓		✓		✓						✓	
[E]Fu and Chien (2019) [Case Study/Simulation]	✓	✓			✓[d]						✓		
[E]Liao and Wang (2019) [Experimental Research/Simulation]	✓						✓						✓
[E].Wang et al. (2019) [Case Study/Simulation]			✓			✓				✓			
[E]Bevilacqua et al. (2019)	✓			✓	✓						✓		
[C]Ansari et al. (2019)					✓					✓			
[C]Kunovjanek and Reiner (2019)											✓		
[C] Wang and Li (2019)			✓			✓	✓						
[E]Wang et al. (2018)[Case Study]	✓[d]		✓[d]										

In this way, the core smart capabilities explored for the PPC function in articles 88 to 102 are mostly based on IoT technologies concerning the interoperability and integration of different manufacturing execution and planning systems (e.g., for MES/ supervisory control and data acquisition, and MRP/ERP) (Zhang et al., 2015), digitalization, the real-time collection, visibility, traceability, and sharing of information from enterprise-level planning and control and operations monitoring (Moeuf et al., 2018; Srai et al., 2016; Strandhagen, Alfnes, Strandhagen, & Vallandingham, 2017; Zhang et al., 2015), and distributed manufacturing control (Bendul & Blunck, 2019). Concerning the CPS environment, the literature approximates the PPC function from an Industry 4.0 perspective as a cyber-physical production system (CPPS). Therefore, the smart capabilities reported in articles searched for this item address distributed and ubiquitous PPC control systems endowed with complex events processing and a predictive manufacturing CPS integrated with BDA and cloud services (Babiceanu & Seker, 2016), servitization (control-as-a-service), adaptive, collaborative, and distributed control for the CPPS (Adamson et al., 2017), green optimization models and status monitoring for shop floor control (Tsai, 2018; Tsai & Lai, 2018; Tsai & Lu, 2018), digitalization, optimization, and simulation using key performance indicator dashboards (Tufano, Accorsi, Garbellini, & Manzini, 2018), smart planning and control for

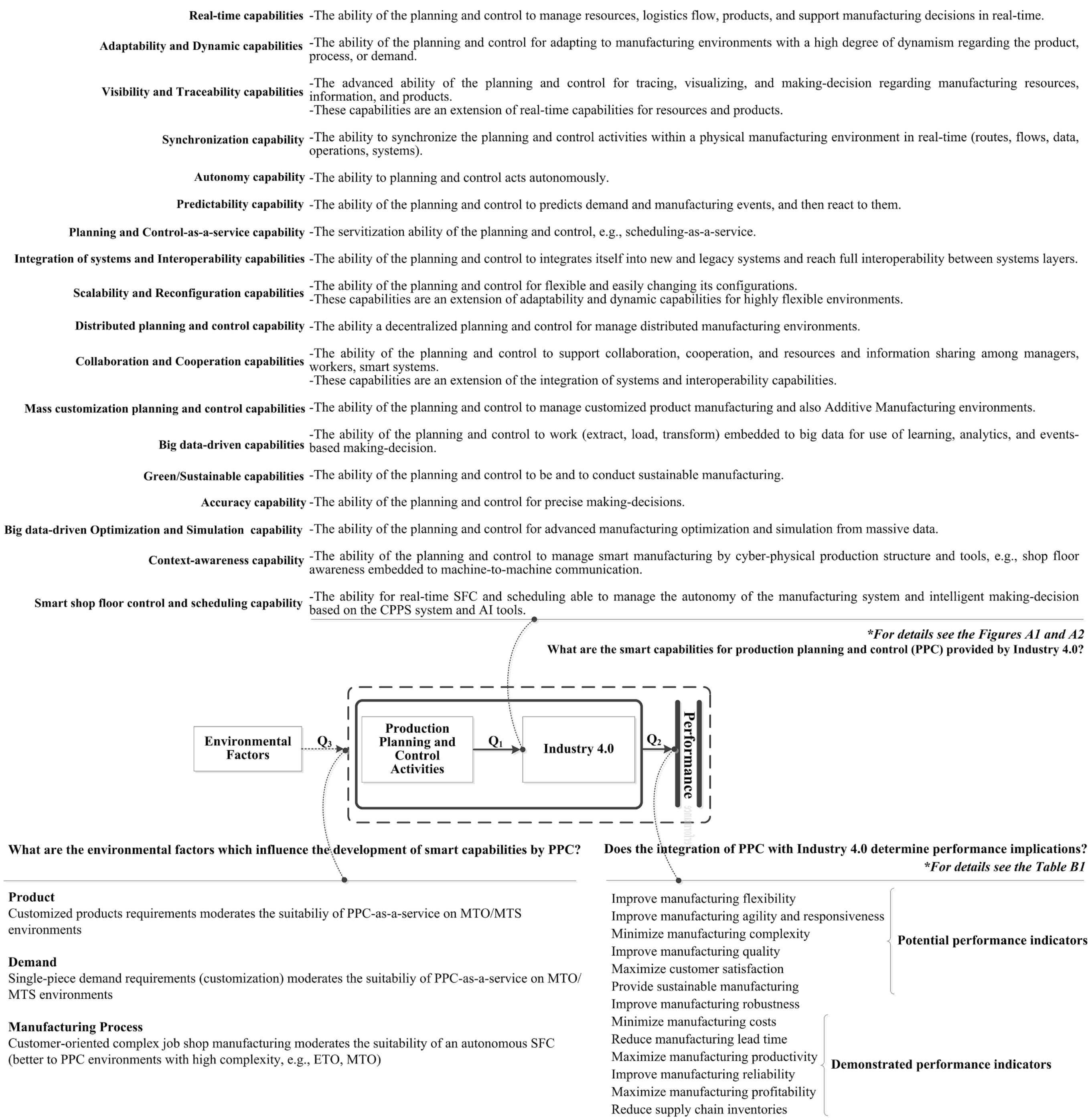


Fig. 8. Summary of smart capabilities provided by Industry 4.0 to PPC (Q_1); key performance indicators (Q_2), and; environmental variables (Q_3).

projects/shops with distributed information, context-aware information services, decision-making supported by a CPPS for improving machine-human interactions (Alexopoulos, Sipsas, Xanthakis, Makris, & Mourtzis, 2018), smart PPCs for SMEs, vertical/horizontal integration systems, automation with production reconfiguration (Moeuf et al., 2018), and self-organization and self-control, based on a CPPS constructed for mass customization planning and control (Monizza, Bendetti, & Matt, 2018).

In a CMg environment, the articles exploring the PPC function usually address servitization, such as in the context of PPC-as-a-service based on cloud computing and cloud services (Adamson et al., 2017; Babiceanu & Seker, 2016; Moeuf et al., 2018), in addition to feature-based manufacturing control for manufacturing-as-a-service (Adamson et al., 2017).

Finally, the BDA/AI technologies provide new organizational philosophies for the PPC function, including anarchic manufacturing, i.e., an extremely distributed PPC system with adaptability and self-optimization (autonomous and intelligent multi-agent systems) (Ma, Nassehi, & Snider, 2019), distributed manufacturing control, trade-offs regarding hierarchical, semi-hierarchical, and hierarchical manufacturing control systems (Bendul & Blunck, 2019), optimization multi-scale maintenance integrated with plant process scheduling (Biondi, Sand, & Harjunkoski, 2017), and data-driven decision-making for production control (Tufano et al., 2018).

3.2.2. Does the integration of PPC with Industry 4.0 determine manufacturing system performance implications?

Table 3 presents the articles addressing each performance dimension in a clustered manner. We identified 52 studies linking manufacturing systems performance to the various indicators; however, both flexibility and cost were the more prominent performance indicators obtained from the exploration of smart capabilities provided by Industry 4.0.

Table 3 provides some indicators, as demonstrated in the 30 empirical types of research analyzed. Cost reduction, reliability, and lead time improvements are the indicators demonstrated from the 13 empirical/ field types of research. Despite these findings, the reduced number of studies empirically demonstrating impacts on performance indicators from the exploration of Industry 4.0 is insufficient for any generalization, as these studies show sparingly different indicators (see Table 3).

Many of the studies shown in Table 3 discuss performance indicators as potential performance indicators, since the results are not empirically tested. Thus, we observed that most of the research analysis encompassing performance is based on theoretical studies or empirical studies that do not demonstrate the performance indicator acting in real cases. Thus, our analysis concerning the performance described below is based on the theoretical viewpoints provided by the 52 articles analyzed in our study. In the Table B1 (Appendix B) we built a comprehensive explanation regarding 13 performance indicators found in the SLR: operational manufacturing flexibility, manufacturing agility and responsiveness, manufacturing complexity, manufacturing quality, manufacturing customer satisfaction, sustainable manufacturing, manufacturing robustness, manufacturing costs, manufacturing lead time, manufacturing productivity, manufacturing reliability, manufacturing profitability, supply chain inventories.

We observed from the articles that both manufacturing operations and PPC could be made more flexible by harnessing the benefits provided by Industry 4.0. For example, Achillas et al. (2015) address the interconnections between mass customization, manufacturing flexibility, and production responsiveness on-demand. Kong et al. (2015) discuss the influence of manufacturing flexibility on adaptive PPC for an auction process. Shamsuzzoha et al. (2016) address collaborative and flexible production planning for product development through virtual enterprises.

Manufacturing agility, reliability, and robustness are likely to be improved in a smart manufacturing context by exploring smart capabilities. In general, the studies report improvements in reliability concerning the traceability and visibility of information, resources, and products, and real-time capabilities. The reliability of plans and operations increases customer satisfaction (Helo & Hao, 2017; Jiang et al., 2018; Kim, 2018; Lin et al., 2018; Moeuf et al., 2018; Tezel & Aziz, 2017).

Besides, the improvement of specific objectives in production scheduling is verified through the reduction of the total setup times, total tardiness, and makespan, and increases in the throughput time, due date reliability, work-in-process, and utilization (Grundstein et al., 2017; Helo & Hao, 2017; Kim, 2018; Lin et al., 2018). Mourtzis and Vlachou (2018) and Bendul and Blunck (2019) argue that the digitalization of manufacturing planning and control results in a manufacturing quicker response, improved flexibility, and an increase of productivity by approximately 30%.

Lastly, quality, profitability, and productivity of manufacturing are performance indicators less reported in the research, but positively related to Industry 4.0 adoption (Bendul & Blunck, 2019; Holmström et al., 2016; Jiang et al., 2018; Katchasuwanmanee et al., 2016; Kim, 2018; Moeuf et al., 2018; Muir & Haddud, 2017; Ning & You, 2018; Yang, Chi, Tang, Zhou, & Fan, 2019; Zhou et al., 2019). Performance indicators as energy-saving and resources constitute an emerging green indicator that is coupled to Industry 4.0 effects (Achillas et al., 2015; Bendul & Blunck, 2019; Helo & Hao, 2017; Katchasuwanmanee et al., 2016; X. Wang et al., 2019; Zhang et al., 2017). Moreover, the complexity minimization in networking manufacturing concerns of products, planning processes, operations, shop floor control, production scheduling, and management systems is another emerging indicator coupled to the structural aspects of smart manufacturing in smart factories (Achillas et al., 2015; Bendul & Blunck, 2019; Dallasega et al., 2019; Kang et al., 2018; Rauch et al., 2018; Wang et al., 2018; Zhang et al., 2017).

3.2.3. What are the environmental factors which influence the development of smart capabilities by PPC?

We found only three papers addressing the effects of environmental contingency factors as moderator for the integration between PPC and Industry 4.0, and the corresponding effects on manufacturing performance (Grundstein et al., 2017; Strandhagen et al., 2017; Yu, Mou, et al., 2018). These three articles show that some PPC smart capabilities are influenced by the following environmental factors: product, demand, and manufacturing process.

Regarding the product, PPC-as-a-service is an example of a PPC smart capability moderated for product requirements. These requirements are related to product design modularization and communality integrated to order release, inventory, and sourcing decisions based on cloud manufacturing (CMg). The product environmental variables found on (Yu, Mou, et al., 2018) moderate the PPC regarding scalable product variety and greater flexibility based on holding generic stocks before the customer order. Thus, product variables seem to positively influence the suitability of the PPC-as-a-service for integrated MTO and MTS environments.

PPC-as-a-service is also moderated for demand. The demand forecasting and inventory accuracy are especially important for manufacturing systems with high demand uncertainty, e.g., single-piece production for customized products, therefore, it influences the technology adoption (CMg) and its smart capabilities. These smart capabilities enable the PPC to manage to resources sharing pool to meet single-piece demand (by using the idle manufacturing in the customization stage for smoothing demand fluctuations). The demand environmental variables found on (Yu, Mou, et al., 2018) are, for example, reliable P/D ratio for customized production, procurement ordering of semi-finished items, and forecast for distributed independent demand for customized items on assembly, data inventory-demand accuracy, replenishment stock, and customer order synchronization for better release-order and sourcing decisions. Thus, customized demand seems to influence the suitability of the PPC-as-a-service for integrated MTO and MTS environments positively.

Regarding process manufacturing factors, shop floor control's autonomy is moderated by environmental variables related to complex manufacturing processes. Thus, the following environmental variables moderates the SFC autonomy for a complex manufacturing environment, according to Grundstein et al. (2017): a broad mix of products and operations in complex job shop manufacturing (batch processes with unrelated parallel machines), the throughput time of the order, and the setup times. Customer-oriented complex job shop manufacturing variables seem to positively moderate the suitability of the autonomous production control (SFC autonomy), mainly for complex manufacturing environments (ETO, MTO). Besides, Strandhagen et al. (2017) show by four case studies, which companies with a low degree of repeatability in production, low material flow complexity, and a high degree of engineering-to-order are less suitable for transition to Industry 4.0 in terms of logistical production flows.

4. Summary of results and future research directions

In this section, we summarize the results obtained through our systematic review (Fig. 8), which can be used to address research in the literature, thereby constructing a future research agenda for a subject. Our research gaps are based on the 102 articles presented in Fig. 7 and detailed in Fig. A1 (Appendix A). Future research and projects can focus on investigating these gaps and advancing the theories and practices supported by this emergent research field. In short, the main gaps were clustered. The first cluster concerned long-term gaps regarding tactical and strategic planning activities (PPC engine and front-end) in smart manufacturing PPC systems. The second cluster concerned PPC organizational issues and structural changes in the context of a new smart PPC. Besides, the drivers toward smart PPC can further cluster smart capabilities based on digitalization/real-time capabilities, automation/autonomy capabilities, and integration systems capabilities, along with their respective variants.

Briefly, our results have shown that IoT provides many attributes that can be used in PPC activities, through the exploration of new capabilities. According to Fig. A1, production scheduling/shop floor control is the activity that most incorporates the new capabilities provided by Industry 4.0, such as smart scheduling, real-time capabilities, distributed dynamic scheduling, CPS enablement, adaptive production scheduling, shop floor control synchronization, integration systems, and green production scheduling optimization.

In contrast, according to Fig. A1, in the context of S&OP/aggregate planning, MPS, and MRP, the new capabilities provided by Industry 4.0 are poorly explored. The central smart capabilities (explored jointly for engine and front-end PPC activities) include integration systems, digitalization/real-time capabilities, automation, traceability, context-aware objects, adaptiveness, servitization (ERP/MRP-as-a-service), data-driven optimization and simulation, synchronization processes and systems, MRP complexity minimizations, and distributed and collaborative aggregate planning for decision-making.

The results expressed in Fig. A1 also demonstrate that the shop floor PPC activities are those that have explored smart capabilities the most through the attributes provided by Industry 4.0, evidencing greater applicability and exploration for PPC activities linked in a short-range, and concentrated in shop floor planning and control and its interface activities (demand forecasting, inventory, and capacity management). For demand forecasting, we observed a concentration of studies regarding the exploration of BDA/AI tools for improving accuracy in forecasting and for integration with enterprise and control systems, data collection, and analytics methods.

Concerning the structure and organization of the traditional PPC, more distributed configurations are imposed on manufacturing by AM, CMg, and CPS. There is a trend of PPC design and manufacturing control taking on a central role, owing to the reduced need for redesigns for engine activities, greater autonomy, intelligence for shop floor control activities, and greater precision in the implementation of PPC system design (Bendul & Blunck, 2019; Liu et al., 2014; Ma et al., 2019). Studies regarding this topic were scarce in our review, leading to the research gaps 7 and 8.

New capabilities have emerged to support manufacturing planning and control in this scenario of smart manufacturing, such as anarchic manufacturing (Ma et al., 2019), manufacturing-as-a-service (Helo & Hao, 2017), AI tools for smart manufacturing (Ning & You, 2018), and CMg scalability/modularitý for PPC (Yu, Zhang et al., 2018). The latent capabilities (such as awareness-context PPC, adaptability, predictability, scalability, and integration systems and tasks provided by the attributes and new capabilities of Industry 4.0) mainly favor the flexibility and agility/responsiveness indicators. Adopting smart capabilities can help facilitate the emergence of new manufacturing performance indicators, such as resource-saving and green optimization scheduling (energy saving/smart energy grid/sustainability). These performance indicators appear to be already emerging for smart manufacturing.

Concerning the indicator performance, flexibility is the most impacted in the integration between PPC and Industry 4.0. Although operational flexibility is the most significant promise for Industry 4.0, its implementation is the hardest and a less achieved by enterprises (Dalenogare et al., 2018; Frank et al., 2019). Our premise is that industries need a profound change in both structure and PPC systems. There are lacking studies addressing this gap of research according to our findings.

Flexibility is a core performance advantage promised by Industry 4.0 (Table 3). However, this finding is not empirically demonstrated in articles. In contrast, cost minimization and the improvement of lead times are demonstrated but are not generalizable. Performance indicators such as quality and productivity are less addressed in the 52 studies analyzed, and still constitute potential research gaps.

Concerning environmental factors, three studies indicated that manufacturing process, product, and market factors could affect PPC integration with Industry 4.0, and could also affect performance. However, there remain too few contingencies studies to support conclusions regarding this research question.

The 18 smart capabilities explored for all PPC activities, the 13 performance indicators, and the three environmental factors were synthesized, and are presented as a summary of results in Fig. 8 (i.e., the answers to research questions 1, 2, and 3).

Our SLR found some gaps concerning smart capabilities for PPC. From these gaps, we propose a future research agenda with ten research topics (RT). The first gap concerns the absence or a low number of studies investigating smart capabilities exploration by front-end and engine PPC activities (tactical planning). BDA has been explored significantly for demand forecasting, but CPS, AM, and CMg have been poorly explored (RT 1). Also, according to the gaps in the PPC planning activities, S&OP studies have not explored CPS, AM, and BDA/AI's smart capabilities. The MRP studies have not explored CPS and BDA/AI, and only one research study explored CMg. MPS is the PPC activity less impacted by the smart capabilities exploration provided by Industry 4.0 and appears only in three studies (one exploring IoT, and two for CPS) (RT 2).

Literature indicates the need for integration as a recurrent capability for PPC planning activities. We also observed a lack of studies regarding the effects and role of scalability/modularity for planning and control capacity and inventory planning and production scheduling through the exploration of CMg. This subject is addressed just in very few studies (RT 3) (Helo & Hao, 2017; Kong et al., 2015; Wan et al., 2019; Zhang et al., 2018). The reduction of complexity in planning (design, manufacturing, and inventory control) from AM's adoption was another observed gap (RT 4).

We observed end-to-end integration with BDA and CPS for demand management, and data feeding for S&OP/aggregate planning and other planning activities. These also constitute challenging research subjects once studies with such goals are scarce (RT 5). It is interesting to notice that gaps 1, 2 and 5 can be addressed together once we did not observe studies exploring AI, machine learning, data mining, or big data tools and methods with applicants for the integration of demand forecasting, S&OP, aggregate planning, MRP, or MPS with real-time capabilities (RT 1, 2, and 5).

Similarly, few empirical studies (Grundstein et al., 2017; Mourtzis & Vlachou, 2018) approach the effects of more distributed manufacturing (by adopting CPS, AM, CMg) causes on the traditional structures for planning, control, and operations performance. The exploration and implementation of the new management capabilities offered by Industry 4.0 (IoT, CPS, AM, CMg, BDA/AI) can change organizational aspects, such as the PPC responsibilities, PPC objects, and PPC process. Moreover, cultural factors and maturity levels in an industry, sector, or country can be vectors for transitions to smart factories. Research is absent regarding this aspect. Therefore, we propose research topics 6, 7, and 8.

Our review also shows that the research concerning the applicability and fit of the integration of PPC/Industry 4.0 in different environments is limited. (Grundstein et al., 2017; Muir & Haddud, 2017; Yu, Mou, et al., 2018). From this, arise research topic 9. Moreover, no studies were found regarding decision support systems for smart PPC systems, frameworks, or architectures in the context of moving toward PPC digitalization (RT 10). The ten proposed research topics are detailed as follows:

(RT 1) Research regarding how Industry 4.0 can support PPC activities for medium/long-term planning (strategic and tactical levels), such as smart S&OP/aggregate planning, MRP/ERP, and MPS;

(RT 2) Studies encompassing S&OP, MRP/ERP, and MPS/APS integration systems, frameworks, and models, based on BDA/AI, CPPS, and CMg ecosystems;

(RT 3) Research focusing on smart PPC as-a-service, and addressing capabilities such as scalability, collaboration, cooperation, modularity, and the trade-offs from adopting pay-as-you-go services based on CMg;

(RT 4) Research on the impact of AM on the reduction of overall smart PPC complexity;

(RT 5) Empirical research regarding end-to-end integration based on BDA/AI and CPPS, as applied to demand management and other PPC activities like smart shop floor scheduling and control;

(RT 6) Theoretical and empirical studies regarding the adoption level of Industry 4.0, maturity levels, and their influence on managers' awareness and their willingness to pay for the adoption of smart capabilities;

(RT 7) Studies on the effects of distributed manufacturing over the traditional PPC hierarchical structure discuss how new features of distributed manufacturing can affect the PPC configuration as to logistical objectives, degrees of autonomy, complexity, and effects on operations performance, like flexibility implementation;

(RT 8) Studies on how PPC design and autonomous manufacturing planning and control can be conceived periodicals with less expectation of re-planning or periodic planning at the tactical level (compression of front-end and engine PPC activities, owing to the more autonomous control on the shop floor and accurate PPC design afforded by Industry 4.0);

(RT 9) Approaches to grounded theory through in-depth organizational investigation, e.g., use of theoretical lenses such as contingency theories with dynamic capabilities to jointly investigate the roles of moderating environmental factors with intangible asset factors on the applicability or development of smart PPC (endowed with smart capabilities) in different manufacturing environments;

(RT 10) Development of intelligent decision support systems, frameworks, architectures, and models to advance and consolidate smart manufacturing planning and control.

5. Conclusions and limitations

The 102 articles analyzed in this SLR indicated that IoT is the technology that predominantly supports most PPC activities in exploring smart capabilities. IoT can be highly integrated with other means of realization for Industry 4.0, such as CMg, CPS, BDA/AI, and AM. The researchers for this new study area, PPC and Industry 4.0, are concentrate in Asian and European Universities, mainly from Industrial/Production and Mechanical Engineering departments. Furthermore, these researchers are focusing on investigating key capabilities offered by IoT, CPS, Big Data/AI for shop floor control, scheduling, inventory control, and capacity planning.

Important attributes were expressed in the analyzed studies. The three drivers of smart capability exploration for PPC are the digitalization that supports, for example, real-time capabilities, synchronization of manufacturing stages, visibility and traceability, servitization/PPC-as-service, collaboration/cooperation, big-data-driven PPC, context-aware PPC, accuracy, smart PPC, mass customization/direct digital manufacturing planning and control, and green/sustainable PPC. The second driver observed was the integration of systems and operational tasks for clustering smart capabilities for advantages in predictability, interoperability, servitization/PPC-as-service, distributed PPC, scalability/reconfiguration, cyber-physical production systems, and ubiquitous manufacturing. The third driver is automation for supporting adaptiveness, dynamic, responsiveness and robustness in PPC, automatic scalability, reconfiguration, distributed and ubiquitous PPC, big-data-driven optimization and simulation, big-data-driven PPC, AI, and data analytics tools for intelligent PPC.

Concerning the exploration of new smart capabilities for PPC, the activities with interfaces on the shop floor (scheduling, capacity, and inventory) can be integrated into the IoT, CPS, and CMg. Demand forecasting can explore the capabilities provided by BDA/AI tools. It is interesting to notice that studies regarding S&OP/aggregate planning based on the smart capabilities provided by Industry 4.0 are scarce.

Concerning performance measures, the digitalization of manufacturing planning and control positively impacts manufacturing flexibility. There is also a trend that the PPC smart capabilities be focused on green/sustainability performance indicators. Besides, our study also shows that three environmental factors (product, demand, and manufacturing process) influence the development of smart capabilities by PPC.

The limitations of our literature review are as follows. First, there is no consensus regarding the means of realization of Industry 4.0. Second, the systematic review processes are naturally subject to the researchers' biases in the steps of extracting and analyzing the results. Third, in our review, we dedicate the analysis exclusively to journals and adopt an objective quality criterion (AJG/SJR index) that excludes searches of non-indexed sources, conference proceedings, book chapters, and non-English language articles; all of these could contain relevant results. Finally, the number of studies addressing the propositions for moderating effects is insufficient for generalizing strong conclusions regarding this research question.

CRediT authorship contribution statement

Adauto Bueno: Conceptualization, Methodology, Software, Visualization. **Moacir Godinho Filho:** Resources, Methodology, Data curation, Validation, Supervision. **Alejandro G. Frank:** Validation, Supervision.

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.

Appendix A

See Figs. A1 and A2.

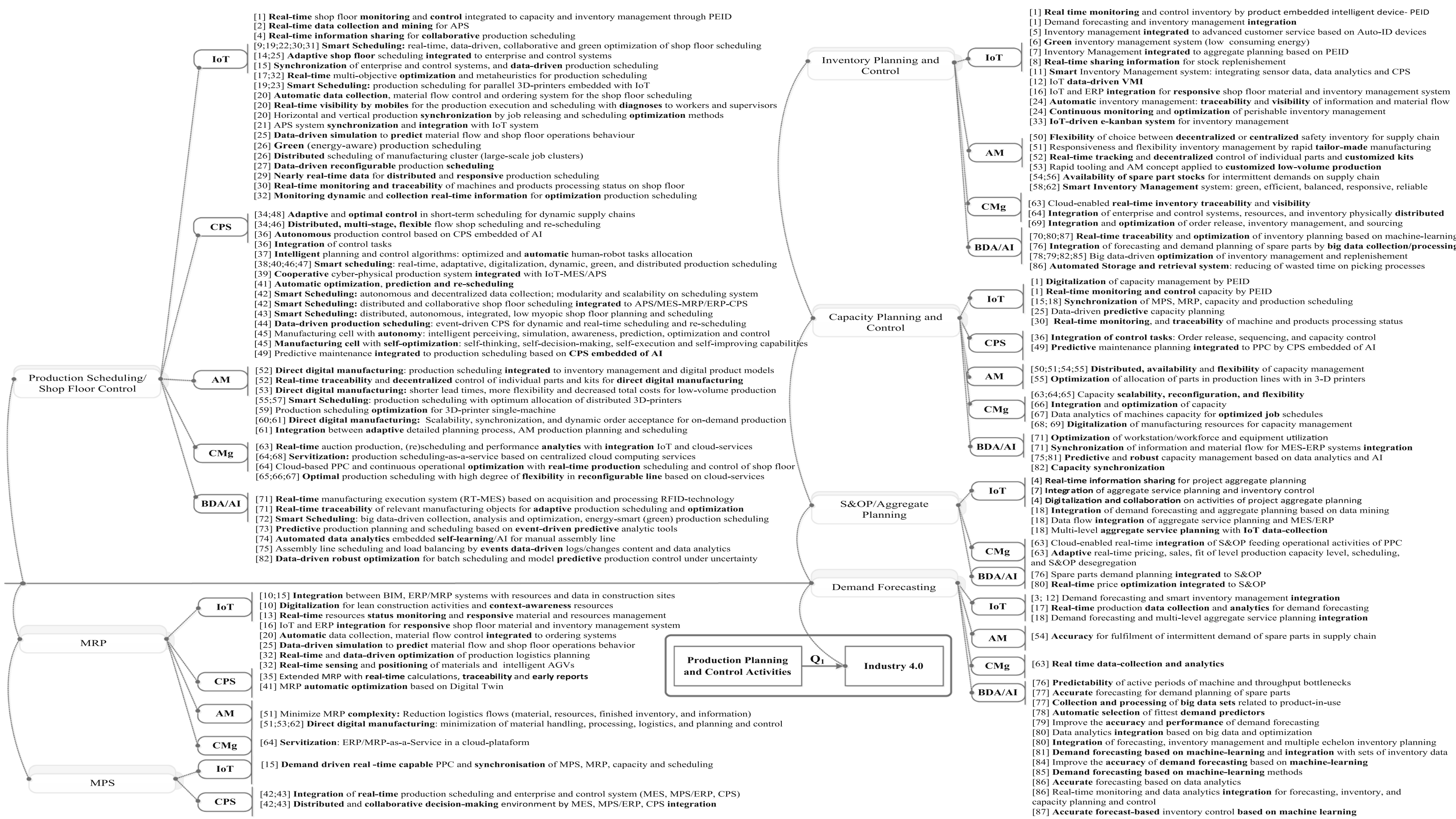


Fig. A1. Big picture for smart planning and control: smart capabilities, industry 4.0 technologies, and articles (by code).

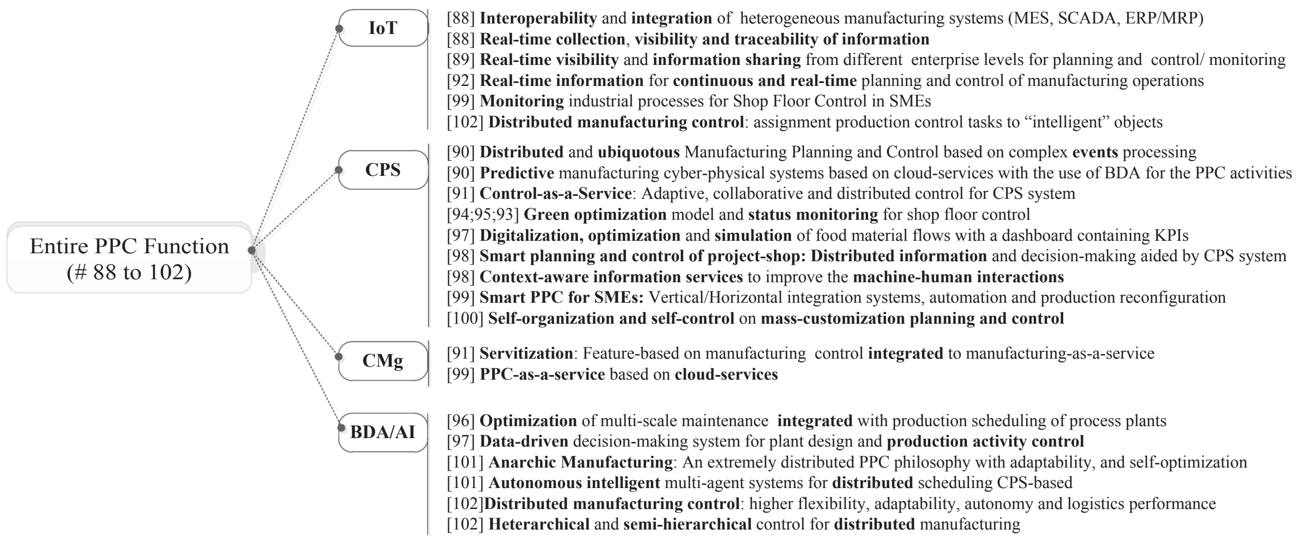


Fig. A2. Smart capabilities regarding entire PPC function.

Appendix B

See Table B1.

Table B1
Performance implications of a Smart PPC on manufacturing system performance.

Indicators Performance, and its Descriptions and Definitions * (see the source of example in the Literature column)	Literature
Indicator: Manufacturing flexibility (machines and resources, manufacturing systems, shop floor) **Definition:** Adaptation to operational manufacturing change requirements. **Description:** Smart PPC provides flexibility for adaptive manufacturing can be made and manage in real-time. *For example, data collection by IoT devices on shop floor allows real-time (re)-scheduling, orders progress monitoring, resources traceability and visibility that enable operational flexibility in environment manufacturing.	Bendul and Blunck (2019); Helo and Hao (2017); Zhang et al. (2017)*
Indicator: Manufacturing agility and responsiveness (machines and resources, manufacturing systems, shop floor) **Definition**: Quick response to manufacturing change requirement. **Description:** Smart PPC provides responsiveness for manufacturing to react quickly to changes. *For example, real-time data collection allows an automatic task pool assignment in an IoT-enabled APS system that reacts to a responsive manner to changing for small batch production.	Wan et al. (2019); Dallasega et al. (2019); Lin, Li, et al. (2018)*
Indicator: Manufacturing complexity (manufacturing systems, shop floor/layout, assembly, products) **Definition**: Simplified operations manufacturing, products, and installation. **Description:** Smart PPC provides the minimization of manufacturing complexity. *For example, IT-support allows real-time modeling, scheduling and monitoring in ETO environment that enable minimize the high degree of complexity in the planning and coordination between manufacturing shop and the installation of products and components.	Rauch et al. (2018)*; Achillas et al. (2015); Kang et al. (2018)
Indicator: Manufacturing quality (manufacturing systems, products, machines, and resources) **Definition:** Manufacturing accuracy and "make do right" for products, management, and assemblies. **Description:** Smart PPC provides accuracy, efficiency, and adaptability for manufacturing quality improvements. *For example, the use of CPPS affect the manufacturing quality and efficiency concerning scheduling activity positively.	Yang et al. (2019); Zhou et al. (2019); Jiang et al. (2018)*
Indicator: Manufacturing customer satisfaction (internal and external customers) **Definition:** Customer satisfaction integrated to manufacturing. **Description**: Smart PPC provides ways to the manufacturing maximizing customer satisfaction. *For example, the use of IoT, and modeling and simulation for integrated production-delivery scheduling, which considers low carbon emission and accurate delivery time (customer satisfaction criteria).	Liao and Wang (2019)*; Huang et al. (2019); Chergui et al. (2018)
Indicator: Sustainable manufacturing (manufacturing systems, energy management, assembly, products, machines, and resources) **Definition:** Manufacturing focused on saving resources and green operations. **Description:** Smart PPC provides ways to the manufacturing of saving energy, resources, and developing sustainable operations. *For example, the use of Big Data techniques, and modeling and simulation based on saving energy for a green production process scheduling.	Liao and Wang (2019); Zhang et al. (2018); Katchasuwanmanee et al. (2016)*
Indicator: Manufacturing robustness (machines and resources, manufacturing systems, shop floor) **Definition:** Manufacturing stability and reaction to unexpected changes. **Description:** Smart PPC provides robustness and stability for manufacturing to react against unforeseen changes or disruptions. *For example, the use of RFID/PEID, and modeling and simulation for the shop floor monitoring to react to disturbances, e.g., material shortage.	Ma et al. (2019); Ansari et al. (2019); Meyer et al. (2011)*
Indicator: Manufacturing costs and lead times (machines and resources, manufacturing systems, shop floor, operations logistic flow) **Definition:** Lead times and costs of manufacturing operations. **Description:** Smart PPC provides ways to improve both costs (operations manufacturing, machines, resources) and lead times (cycle time, setup time, wait time, working time, etc.) manufacturing reduction. *For example, the use of AM for customized small production volumes provides both cost and lead time reduction in the MTO environment.	Liu et al. (2014); Achillas et al. (2015)*; Li et al. (2017)
Indicator: Manufacturing productivity and profitability (machines and resources, manufacturing operations, manufacturing systems) **Definition:** Productivity of manufacturing operations and profitability of the entire manufacturing system. **Description:** Smart PPC affords an increase in productivity and profitability in manufacturing. *For example, CMg, ERP/TI tools, and optimization were used to increase the productivity and profitability in an IoT-based shop-floor material management system.	Helo and Hao (2017); Lee and Liang (2018); Wang et al. (2018)*
Indicator: Manufacturing reliability (machines and resources, operations manufacturing, manufacturing systems) **Definition:** Reliability in the manufacturing operations and systems performance. **Description:** Smart PPC affords more reliability for the performance of manufacturing. *For example, the use of the CPPS concept for autonomous production control (sequencing, order release, and capacity control integration) to meet due dates.	Grundstein et al. (2017); Andersson and Jonsson (2018); Fu and Chien (2019)
Indicator: Manufacturing and supply chain inventories (manufacturing system, supply chain, operations logistic flow) **Definition:** Amount of products, parts, resources, and materials streaming in the manufacturing chain. **Description:** A smart PPC provides a reduction of inventories in the manufacturing and supply chain. *For example, the use of AM affects positively the overall inventories performance in the supply chain (less buffer stock, less spare parts obsolescence, delivery time improvement).	Liu et al. (2014); Muir and Haddud (2017)*; Kunovjanek and Reiner (2019)

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