

## A fuzzy rule-based industry 4.0 maturity model for operations and supply chain management

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### ABSTRACT

Industry 4.0 (I4.0) aims to link disruptive technologies to manufacturing systems, combining smart operations and supply chain management (OSCM). Maturity models (MMs) are valuable methodologies to assist manufacturing organizations to track the progress of their I4.0 initiatives and guide digitalization. However, there is a lack of empirical work on the development of I4.0 MMs with clear guidelines for OSCM digitalization. There is no I4.0 MM with an assessment tool that addresses the imprecision brought by human judgment and the uncertainty and ambiguity inherent to OSCM evaluation. Here we develop a fuzzy logic-based I4.0 MM for OSCM, through a transparent and rigorous procedure, built on a multi-method approach comprising a literature review, interviews, focus groups and case study, from model design to model evaluation. To provide a more realistic evaluation, fuzzy logic and Monte Carlo simulation are incorporated into an I4.0 self-assessment readiness-tool, which is connected with the model architecture. The proposed model has been validated through a real application in a multinational manufacturing organization. The results indicate that the approach provides a robust and practical diagnostic tool, based on a set of OSCM indicators to measure digital readiness of manufacturing industries. It supports the transition towards I4.0 in OSCM domain, by holistically analyzing gaps and prescribing actions that can be taken to increase their OSCM4.0 maturity level.

### 1. Introduction

Currently, there is a worldwide movement to improve productivity and efficiency in industrial manufacturing, which requires rethinking and changing the mindset of how products are manufactured and the services used in the supply chain (Koh et al., 2019). Industry 4.0 (I4.0) represents a new industrial stage of manufacturing systems, integrating a set of emerging and converging digital technologies that add value to the entire product life-cycle (Frank et al., 2019). The transition to I4.0 brought to the manufacturing industry new standards of decentralized and digitalized production (Koh et al., 2019), in which the production elements are highly autonomous (Tortorella et al., 2019). I4.0 increases

the connectivity and interaction between systems, people, and machines, leading to more interconnected manufacturing systems and more integrated supply chains (Mourtzis et al., 2019).

Thus, I4.0 has been driving a significant structural theoretical revolution for operations and supply chain management (OSCM) (Koh et al., 2019). OSCM is a vast domain that encompasses various knowledge areas of the operation management (OM) and supply chain management (SCM) fields (Coughlan et al., 2016), contemplating different and vital cogs in the context of I4.0, such as procurement, manufacturing and logistics (Lamba and Singh, 2017). Although there has recently been a growth in the recognition of the strategic importance of OSCM in creating shareholder value (Ding et al., 2018), Koh et al.

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(2019) have pointed out the lack of consideration of research on I4.0 technologies' disruption on OSCM. From a methodological point of view, there is a consensus that multiple research methods are critical to the development of the OSCM field, as they are less susceptible to systematically biased findings (Tangpong, 2011), which may be a way to address challenges in the context of I4.0.

Furthermore, a significant and difficult research challenge on I4.0 is related to the definition and validation of its constructs, such as I4.0 maturity and I4.0 readiness (Koh et al., 2019). I4.0 transformation requires a broad perspective on the company's strategy, organization, operations, and products, which makes maturity models (MMs) suitable (Aktil et al., 2018). Structural approaches as MMs aim to help organizations by providing comprehensive guidance and introducing a roadmap to assess and track the progress of improvement initiatives (Asdecker and Felch, 2018). This allows interested parties to measure the current and intended status of the company.

However, some authors point out problems in assessing the maturity of I4.0 (Aktil et al., 2018; Schumacher et al., 2016), as the perception about the highly complex I4.0 concept; uncertainty regarding the results of I4.0 projects in terms of benefits and costs; failure to assess the company's I4.0 capability, and lack of strategic guidance to I4.0 improvement. In this sense, there is a lack of empirical work on the development of MMs for I4.0 and a need for more prescriptive and non-descriptive models (Asdecker and Felch, 2018) and for clear guidelines to help leaders on understanding what stages and where supply chain digitalization should improve (Büyüközkan and Göçer, 2018). Most I4.0 MMs lack a self-assessment tool to support decision-makers in assessing the maturity of fragmented areas of OSCM, as Manufacturing or SCM, which include a readiness assessment tool (Mittal et al., 2018). In addition, most models do not have a well-defined structure with practices, inputs and outputs and do not support manufacturing enterprise architecture holistically (Gökalp et al., 2017). Therefore, a structured I4.0 assessment/MM for OSCM is required.

Moreover, imprecision and uncertainty are inherent in OSCM evaluation, since it is, in some cases, qualitative by nature or even because of a lack of data (Zanon et al., 2019), and causes the decision-making to be a complex process (Aqlan and Lam, 2015). Studies about I4.0 MMs generally do not address the inherent imprecision brought by the intangible aspects of the cognitive judgment of managers and decision-makers. In this sense, Mittal et al. (2018) highlight a need for a practical I4.0 MM that allows a more realistic representation of the real-world. These characteristics suggest that fuzzy logic theory (Zadeh, 1965) may be appropriate, as it addresses imprecision and incorporates the uncertainty of human decision-making behavior (Corrêa et al., 2014), when facing challenges related to manufacturing (Azadegan et al., 2011), reducing the gap between theory and reality. Although fuzzy inference system (FIS) has been widely applied to SCM problems to overcome the intrinsic imprecision in the criteria evaluation (Aqlan and Lam, 2015; Pourjavad and Shahin, 2018), to the best knowledge of the authors of this paper, there is no I4.0 MM with an assessment tool that deals with language imprecision and the ambiguity of human judgment in the OSCM area. To cope with the vagueness existing in the I4.0 maturity investigation and minimize rough assessments that lead to suboptimal assessments, a FIS approach is suggested in this study.

Therefore, within the I4.0 context associated to the limitations of the current MMs and the challenges regarding OSCM evaluation, this paper's goal is to propose a fuzzy logic-based I4.0 MM for OSCM following a transparent and rigorous procedure model design, including construction and application steps. The research is based on the stages offered in Becker et al. (2009) and applies a multiple research method approach, as recommended by Liebrecht et al. (2017), through the combination of content analysis, interviews, focus groups, and case study.

The paper aims to contribute in different ways: (i) it proposes a set of OSCM indicators to measure the digitalization score in manufacturing organizations and their supply chains; (ii) it proposes a MM connected

with a self-assessment readiness-tool to support the transition towards I4.0 in the OSCM domain; (iii) it uses multiple research methods to support the methodical rigor of I4.0 MM construction and application, combining FISs with indicators; and (iv) it pioneers the application of fuzzy rule-based MM with a probabilistic approach (Monte Carlo simulation) for evaluating the I4.0 maturity of companies in terms of OSCM criteria. Moreover, the proposed approach has several advantages including (i) the FIS application facilitates decision-making through approximate reasoning and linguistic terms through fuzzy if-then rules (Zanon et al., 2019); (ii) it helps in capturing knowledge-based expert judgments (Pourjavad and Shahin, 2018); (iii) provides an efficient tool to deal with the uncertainty of evaluation processes; and (iv) offers a useful and practical solution to understanding, quantifying and handling vague data (Aqlan and Lam, 2015).

The paper is organized into six sections. Section 2 provides the theoretical background, Section 3 describes the methodology, Section 4 presents the model and assessment development, Section 5 focusses on the model application, and the last section (Section 6) offers the paper's conclusions.

## 2. Theoretical background

### 2.1. Industry 4.0 and digitalization

The term Industry 4.0 (I4.0) was coined in 2011 by a German initiative to develop advanced production systems with the aim of increasing the productivity and efficiency of the national industry (Frank et al., 2019). There is no consensual definition of the term I4.0. It can be defined as the trend towards digitalization and automation of the manufacturing environment (Oesterreich and Teuteberg, 2016), as a confluence of technologies ranging from a variety of digital technologies (Koh et al., 2019), or as a new stage or paradigm for industrial production, focusing on the results of the transformation process (Weking et al., 2019). I4.0 brings innovation in three aspects: horizontal integration, vertical integration, and end-to-end integration (Meng et al., 2018). It also innovates business models in the manufacturing sector, mainly due to providing a transformational environment, knowledge management, and supply chain capacity building. I4.0 deployment has generated a new manufacturing working environment, changing traditional skills, and making employees survival depend on their degree of adaptability to new job requirements (e.g., non-technical skills, and data analytics) (Lichtblau et al., 2015; Sony, 2019). In this sense, learning factories, or islands of learning must be adapted to the new competencies required for I4.0 (Ras et al., 2017).

In the I4.0 era, digitalization is seen as the integration and optimization of information and the flow of goods along the supply chain (Bogner et al., 2016) and has a major impact on existing processes and capabilities (Bienhaus and Haddud, 2018). A central element of I4.0 is the complete digitalization that has a major impact on existing processes and capabilities (Erol et al., 2016). Geissbauer et al. (2016) state that I4.0 is driven by the digitalization and integration of vertical and horizontal value chains. Schuh et al. (2017) consider digitalization as a facilitator and a basic requirement to reach I4.0. Weking et al. (2019) claim that I4.0 describes the digitalization of manufacturing companies. In this sense, the degree of digitalization seems the appropriate measurement unit to determine its readiness for the digital transformation and the I4.0 maturity. Some recommended strategies for companies that have not yet defined their goals for I4.0 to achieve greater digital maturity are (i) lean management (LM) through lean processes, (ii) investment in digitalization in all areas of the company, and (iii) to promote knowledge in key components and motivate employees to exploit the potential of lean management and digitalization (Pessl et al., 2017).

### 2.2. I4.0 technologies in operations and supply chain management

Although Cyber-physical systems (CPS) and Internet of Things (IoT)

are well-known key technologies for this ongoing revolution, I4.0 encompasses numerous additional disruptive technologies that enable the digitalization of the manufacturing sector (Mourtzis et al., 2019). For example, 3D printing, Big Data and advanced algorithms, augmented reality/wearables and cloud computing (De Carolis et al., 2017). The literature does not have a consensus on what are the main technologies. Frank et al. (2019) state IoT, cloud services and Big Data Analytics (BDA) as the base technologies. Koh et al. (2019) state IoT, BDA, cloud, robotic systems, and 3D printing (also called - Additive manufacturing - AM) the five main digital technologies. Appendix A indicates a description of a set of technologies that are considered important for the digitalization of OSCM.

The expected benefits of using these technologies in the industry vary, as they can show synergies and interrelate to achieve better performance at I4.0 (Frank et al., 2019). For instance, there may be the interrelationship between IoT, BDA, virtual reality (VR)/augmented reality (AR) and cloud to integrate and analyze data between sources and companies, which are carried out mainly through the adoption of industrial communication protocols (e.g., OPC Unified Architecture). These synergies allow I4.0 to unlock a new value potential through new types of business models (Mourtzis et al., 2019), which are creating interesting opportunities in manufacturing. I4.0 also incorporates several unexplored dimensions, such as the integration of LM to materialize the power of I4.0 (Sony, 2019). In addition, the combination of embedded sensors, and artificial intelligence (AI), enable digital product service systems (PSS) - combination of tangible products and intangible services that jointly meet cert customer needs (Weking et al., 2019), since manufacturers can offer additional services with the product and even offer the product as a service (Frank et al., 2019).

From the point of view of SCM, a cognitive AI that mimics human thought, a combination of machine learning (ML) and natural language processing can be used for understanding individual customers' profiles (Ghobakhloo, 2018). Intelligent logistics models such as IoT-based Omni-Channel Logistics Service can maximize the synergies between manufacturers, retailers, and logistics providers (Lv et al., 2018), supporting real-time self-optimization. Moreover, integrated information systems and advanced forecasting methods determine supplier relationship management (SRM) (Skapinjecz et al., 2018). Blockchain solutions can contribute to real-time information sharing from the supply chain to multiple partners to achieve greater transparency, enabling the use of intermediate manufacturing resources and services between suppliers and customers in virtual marketplaces (Culot et al., 2019).

Regarding the OM view, there is a clear shift in the integration of CPS, MES for factory floor control and enterprise resource planning systems for BDA and cloud computing (Bendul and Blunck, 2019). Production, planning and control seek to combine well-established approaches such as Lean Six Sigma (LSS) (Gunasekaran et al., 2019) with I4.0 to create Lean 4.0 (Garza-Reyes, 2020; Sony, 2019). The combination of advanced sensors with BDA improves product forecasting and performance management across manufacturing and service units, ultimately achieving decentralized and autonomous decision-making. There is now a tendency to incorporate advanced robotics into industrial assembly processes, and potential for virtual quality management through modelling and simulation (Zaidin et al., 2018). In addition, the alignment of predictive maintenance based on ML algorithms with VR/AR accelerates worker training with an immersive simulation of maintenance routines (Scurati et al., 2018).

Therefore, as the I4.0 revolution consists of several digital technologies and associated paradigms and, in the literature, there is still no consensus on this, manufacturing companies should focus on the different needs they may have when prioritizing the implementation of the I4.0 technologies mentioned above (Frank et al., 2019) and should

systematically think about their implementation to reach a higher maturity level of I4.0 (Dalenogare et al., 2018).

### 2.3. Foundations of maturity models

MMs are an established means to support requirements as assessing the current situation, determining the desired situation, and obtaining possible evolution paths (Becker et al., 2009). MMs are positioned as a tool to compare the current level of an organization or process to the desired level in terms of maturity, conceptualizing and measuring (Schumacher et al., 2016), being used regularly for benchmarking and continuous improvement (Marx et al., 2012). Thus, the concept of maturity can be used for descriptive, prescriptive and/or for comparative purposes (Asdecker and Felch, 2018; Röglinger et al., 2012).

The terms 'readiness' and 'maturity' are relative and related (De Carolis et al., 2017). MMs aim to demonstrate the level of maturity of an individual or entity (Gökalp et al., 2017) and help them to reach a more sophisticated level of maturity after a step-by-step process of continuous improvement (Mittal et al., 2018). Readiness assessments are evaluation tools to analyze and determine the level of preparedness, attitudes, and resources, at all levels of a system (Mittal et al., 2018), where readiness models clarify whether the organization is ready to start the development process or not (Akdil et al., 2018).

Some of the common properties of MMs are (i) levels of maturity; (ii) "descriptor" with the name of each level (iii) generic description of each level; (iv) dimensions; (v) activities for each dimension; and (vi) description of each activity, for each maturity level (De Carolis et al., 2017; Fraser et al., 2002; Röglinger et al., 2012).

Regarding the MM design process, various procedure models have been proposed (e.g., Becker et al., 2009; De Bruin et al., 2005). Röglinger et al. (2012) claim that efforts are needed to develop ready-to-use instruments for evaluating and improving maturity and highlight that the usefulness and practical applicability of these instruments depend on following MMs design principles. For example, design principles for a prescriptive purpose, such as defined improvement measures, are quite useful, but the selection of these measures is often associated with a company's performance or business context (Röglinger et al., 2012). Thus, this prescriptive use of MMs requires the ability to adapt to the specific characteristics of the organization.

### 2.4. Maturity and readiness models for industry 4.0

Many organizations define I4.0 as their evolution goal but do not know what it means or how to get there, or both (Ghobakhloo, 2018). Companies that actively seek to develop their I4.0 status should start by understanding their current maturity level (Bibby and Dehe, 2018), and the application of appropriate maturity assessment methodologies help them to understand their current capabilities given the maturity of their resources and technologies towards I4.0 (De Carolis et al., 2017).

Appendix B provides the 25 I4.0 MMs offered in the literature that is part of the sample of this research. The models are compared based on requirements suggested by Mettler (2009), Marx et al. (2012) and Nord et al. (2016). Section 3 describes the method adopted to generate the results of Appendix B. The comparison of these MMs with the problem definition (detailed in Section 1) was used to determine a design strategy, as also presented in the method section.

The comparison of the MMs reveals three publication streams. The first group of MMs is the largest and concentrates on manufacturing, specifically concerning smart manufacturing (Bibby and Dehe, 2018; Brandl, 2016; Canetta et al., 2018; De Carolis et al., 2017; Lichtblau et al., 2015; Ganzarain and Errasti, 2016; Gökalp et al., 2017; Jung et al., 2016; Pessl et al., 2017; Qin et al., 2016; Rockwell Automation, 2014;

Schumacher et al., 2016; Scremen et al., 2018; Stefan et al., 2018; Weber et al., 2017; Zheng and Ming, 2017). The second group focuses on SCM scope (Aktil et al., 2018; Asdecker and Felch, 2018; Geissbauer et al., 2016; Katsma et al., 2011; Oleskow-szlapka and Stachowiak, 2018; Rübel et al., 2018). The third group is focused on digital integration technologies (Asdecker and Felch, 2018; Leyh et al., 2016; Tolk and Muguira, 2003; Wang et al., 2016). Some works combine different scopes, as Bibby and Dehe (2018), Rockwell Automation (2014) and Weber et al. (2017) with manufacturing and digital integration technologies, and Asdecker and Felch (2018) and Katsma et al. (2011) with SCM and digital integration technologies. Thus, the MMs comparison indicates that I4.0 MMs that explicitly address OSCM in a generalized, comprehensive, and detailed manner are rare. Therefore, the design strategy is to propose a new I4.0 MM for OSCM structured by several dimensions, considering relevant contents of previous MMs, with appropriate documentation quality and to develop a MM architecture with a link to an assessment instrument to build a consistent basis for I4.0 OSCM.

It can also be observed that none of the MMs completely fulfill the analyzed criteria presented in Appendix B, as follows. Regarding the components criterion, most models have structures designed as the lightweight description of levels and dimensions (multidimensional grids) or questionnaires. Few models provide a self-assessment tool that can be applied independently by any company and most models do not show measurable results. The MMs offer a great variation in relation to the number of dimensions and levels of maturity and their content is quite heterogeneous. Few models present a formal architecture with links between the assessment instruments. Regarding the reliability/evaluation criterion, the development process of most models generally occurs only up to the verification stage, with a lack of validation through case studies, which limits a generalization by a means of the dissemination of the model. Moreover, most models lack transparency regarding their construction and do not offer documentation for their application. Regarding the Practicality criterion, few models consider the interests of companies to define improvement actions, being prescriptive and most do not consider the company profile or contextual aspects, considering specific guidelines of the evaluated company. The MMs do not address, directly in their components and practicability<sub>2</sub>, the inherent uncertainty brought by the intangible aspects of human judgment and imprecision, field research and complex decision-making processes related to manufacturing and supply chain, which are required for the OSCM evaluation (Aqlan and Lam, 2015; Zanon et al., 2019) and for a practical I4.0 MM (Mittal et al., 2018). This challenging view for uncertainties in OSCM can be addressed through fuzzy logic (Azadegan et al., 2011; Corrêa et al., 2014). Therefore, fuzzy logic seems a useful and practical solution that can represent a viable way of measuring the digitalization of OSCM through a self-assessment readiness-tool towards I4.0 in the OSCM domain. Hence, the next section introduces fuzzy logic.

## 2.5. Fuzzy logic in maturity models

Fuzzy set theory (Zadeh, 1965) is currently used to develop formalized tools to deal with imprecision intrinsic to a wide variety of manufacturing and SCM problems (Aqlan and Lam, 2015), including the maturity assessment of a company (Pedroso et al., 2017). Fuzzy logic allows a more realistic representation of the real-world with simplicity (Azadegan et al., 2011). Fuzzy inference system (FIS), a non-linear system that applies fuzzy if-then rules to model the qualitative aspects of human knowledge (Zanon et al., 2019), is considered one of the most practical tools (Pourjavad and Shahin, 2018). The rule-based approach is powerful, as it can interpret linguistic variables that normally cannot be explicitly analyzed or expressed statistically (Wong and Lai, 2011).

A FIS consists of input and output variables, membership functions and rules, and contains three fundamental elements: Fuzzification unit, Knowledgebase (database and rulebase) and Reasoning mechanism, and

Defuzzification (Kar et al., 2014). FIS converts crisp inputs into fuzzy (continuous) variables - fuzzification - that enter into the inference engine, which evaluates fuzzy variables based on decision-makers' set of if-then rules. Each decision rule generates an implication relationship through an implication operator used to relate the degree of association of input set and output set elements. After applying the "max-min" implication operator, a composition between a singleton set and the implication relation is obtained as an output of each rule. FIS ends with defuzzification, where an operator takes the values of one or more fuzzy output variables to crisp values (Pedrycz and Gomide, 2007). Thus, the result of each FIS is a set of infinite points that compose a solution region that represents a linguistic variable. The knowledge base, which is composed of the rule base with a reasonable and careful procedure of mapping fuzzy rules and by the database that defines the membership function of input and output elements is the core of a FIS (Rahmanifard and Plaksina, 2019). Osiro et al. (2014) state that fuzzy rule-based classification methods are very suitable for categorizing sets of alternatives according to their similarity.

Fuzzy logic is adopted as a more precise solution for the construction of a tool that assesses the maturity of an organization, as it allows considering all the variables used in the problem. In a fuzzy-based MM, fuzzy sets represent ambiguity, uncertainty and inaccurate information and the result of qualitative judgments and quantitative data are summarized in a general index (Corrêa et al., 2014). The effort to develop a fuzzy rule-based MM is justified by the desire to build a formal quantitative structure, capable of capturing the inaccuracies of human knowledge, that is, how this knowledge is formulated in natural language. Thus, a FIS-based MM has the following advantages: it provides a useful solution for understanding, quantifying and manipulating vague and uncertain data and estimates the total maturity score based on the maturity level of the dimensions (Aqlan and Lam, 2015); it is an analysis method developed purposely to incorporate uncertainty and imprecision in a decision model (Zadeh, 1965), allowing to include imperfect information in the subject of the cause; and it opens the possibility of including inaccurate entries and limits (Azadegan et al., 2011).

Therefore, the application of FIS for MM is appropriate due to its potential to deal with non-linear relationships between input and output variables (Zanon et al., 2019) and to be able to support the decision-making process with the robustness of the fuzzy sets and the flexibility of fuzzy rules. Despite the benefits of this approach, Corrêa et al. (2014) claim that there is still a lack of works in this direction due to the subjective aspect of the assessment process, which is a problem that fuzzy logic aims to help. Thus, the proposal of a tool based on fuzzy logic to assess an organization's I4.0 maturity is still a fertile area of study that deserves to be properly explored.

## 3. Methodology

In general, most of the existing MMs lack a solid theoretical foundation and/or are derived based on an arbitrary design method (Marx et al., 2012). Due to the lack of documentation of the model development method and the absence of empirical validation, Information Systems researchers have suggested several procedures models for MM design (Cuylen et al., 2016). A systematic approach to MM development based on a procedure allows the generalization and standardization of the model (De Bruin et al., 2005); leads to improved documentation and more profitable results than an intuitive procedure (Becker et al., 2009); and it is useful when the MM is practically relevant (Cuylen et al., 2016). Therefore, to provide a rigorous instrument for evaluation of OSCM digitalization, this research aims to develop a theoretically solid, empirically grounded, and methodologically sound I4.0 MM for OSCM, based on Becker et al. (2009) procedure model.

### 3.1. Research steps

The proposed MM was constructed and applied based on the problem

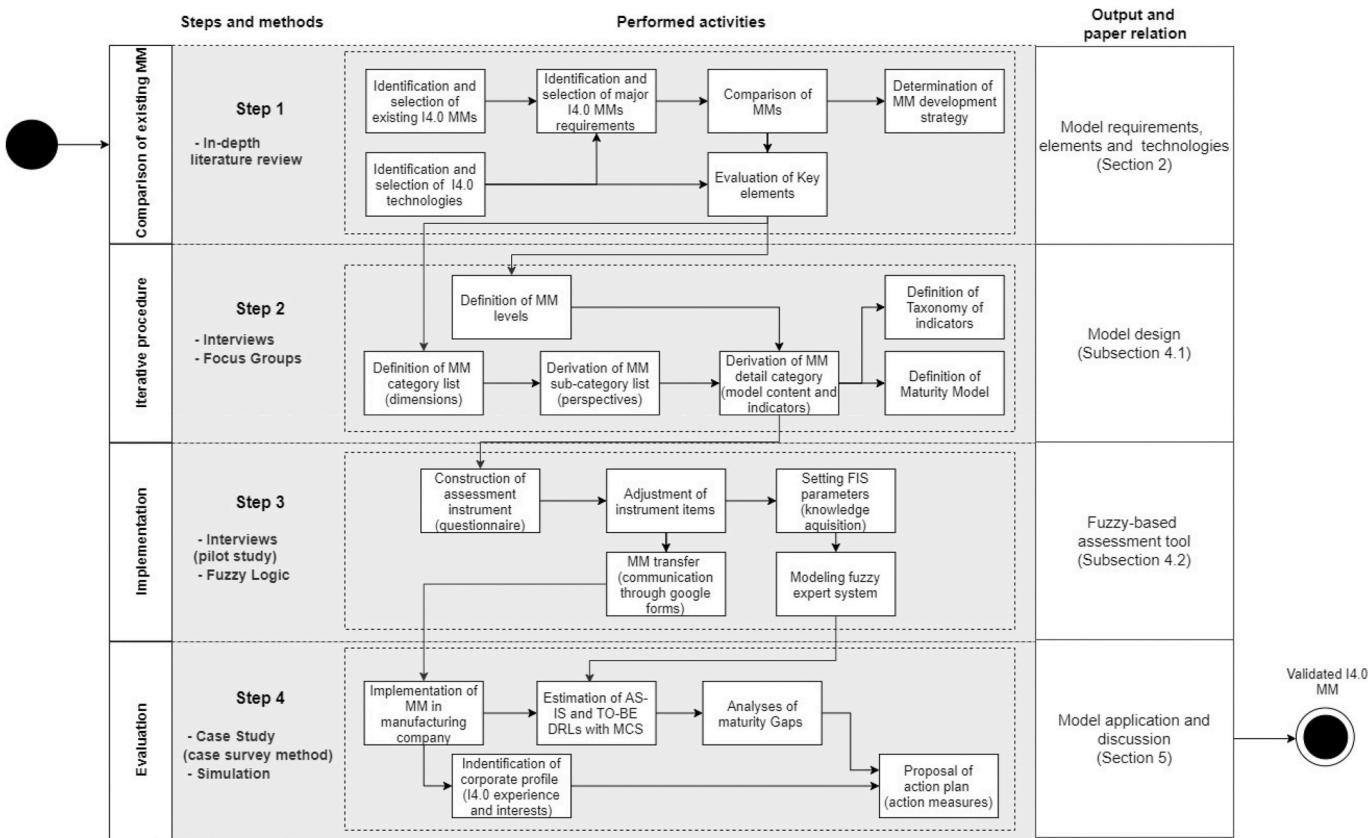


Fig. 1. Methodology steps (Adapted from Becker et al., 2009).

definition offered in the introduction section of this paper following four steps, as displayed in Fig. 1:

- comparison of existing I4.0 MMs, which aimed at identifying the major requirement of an I4.0 MM and identifying MM elements and I4.0 technologies;
- iterative procedure that aimed to define the MM design and determine a set of critical indicators to holistically assess I4.0 in OSCM in a systematic manner;
- MM implementation, which consisted of the model development and assessment, through the improvement and adjustment of the assessment tool (questionnaire) and the modeling of a set of fuzzy inferential systems; and
- MM evaluation, in which there was a case study in a manufacturing company, and results were discussed, with the maturity gap analysis and the proposal of action measures for manufacturing 4.0 continuous improvement.

Thus, a mixed-method study was adopted, by combining multiple methods (qualitative and quantitative), which is less susceptible to systematically biased findings (Tangpong, 2011), leading at the end to the model validation.

Becker et al. (2009) procedure model consists of the following stages: (i) problem definition and requirements; (ii) analysis and comparison with existing MMs; (iii) strategy development; (iv) iterative development and validation; (v) design of the transfer and evaluation of the model; (vi) implementation; and (vii) model evaluation in an organizational context (Mendes et al., 2016). The four initial stages of Becker et al. (2009) were applied in the first and second steps of our research, to design the OSCM I4.0 MM (detailed in Section 4.1). The fifth stage (transfer and evaluation of the model) occurs in our third step (detailed in section 4.2), in which there is also the modeling of the expert fuzzy system. Finally, the final two stages take place in the fourth step (detailed in Section 5). To demonstrate methodological rigor, the chronological iterations of research are described in Appendix C, including the procedures from model design and to model evaluation. Each of the four steps is presented next.

### 3.2. Step 1: Comparison of existing MMs

The first step consisted of a literature review to identify I4.0 MMs and I4.0 technologies following the guidelines given by Mendes et al. (2016). The search is limited to the string presented below. A keyword search in the article's title, abstract and keywords was conducted on the Scopus,

"Industry 4.0" OR ("Smart Manufacturing" OR "smart factory" OR "cyber-physical systems" OR "cloud manufacturing" OR "internet of things" OR "interoperability" OR "additive manufacturing" OR "Big Data" OR "augmented reality" OR "smart logistics" OR "digital supply chain" OR "supply chain 4.0" OR "SCM4.0") AND "maturity model" OR ("readiness assessment").

Emerald, Springer, Taylor and Francis, and ISI Web of Science databases.

The conducted research was limited to papers published in peer-reviewed journals and conference papers in English up to July 2018, resulting in 184 records. As inclusion criteria, the article should contain a proposition for a MM for I4.0 in the OM or SCM fields. Then, they were refined by analysing and screening the titles, keywords, and abstract, excluding 137 records. The remaining articles were analyzed in-depth in an iterative process. 'Snowball' backward and forward searches were performed for additional papers (8 articles and 15 white papers), as recommended by Thomé et al. (2016). Based on the full-text analysis, a total of 57 articles were retrieved for the study, all with explicit contents to the I4.0 MMs for OSCM purposes.

This step embraced the comparison of existing MMs and the determination of the design strategy (Cuylen et al., 2016). To gain deeper insights for the decision of a development strategy, the authors conducted a MM analysis and comparison focusing on criteria adapted from Mettler (2009), Marx et al. (2012), and Nord et al. (2016), namely: scope, origin (academy or practice), components (lightweight description, questionnaire or architecture), reliability (untested, verified, validated or not transparent) and practicality (general recommendations or specific improvement measures). Additionally, the I4.0 technologies were selected, considering the purpose of identifying a set of factors that are critical to improving I4.0, comprising manufacturing operations and supply chains systematically. Based on the comparison of the existing I4.0 MMs (see Subsection 2.3), the authors decided, as a development strategy, to consider heterogeneous and relevant contents from existing MMs in a new model structured by multiple dimensions, linked with a fuzzy-based assessment instrument for OSCM 4.0.

Thus, this first iteration was conceptual-to-empirical and derived dimensions and characteristics of antecedent I4.0 MMs from literature. The authors used the findings of I4.0 MMs and I4.0 technologies for conceptual development, which the theoretical background section outlines. Content analysis (Seuring and Gold, 2012) was applied and an inductive approach (Eisenhardt, 1989) was used to categorize knowledge from the literature, iteratively, testing and revising by constant MM comparison and the information collected. One of the most important results was the description and analysis of a set of elements (levels and dimensions) and key I4.0 technologies linked to different perspectives of the manufacturing sector. This iteration provided a theoretical basis for the empirical study. Then, the category list (dimensions) was derived.

### 3.3. Step 2: Iterative procedure

This step dealt with the model design, which was based on a hierarchical structure of categories and subcategories, as different levels must be considered when implementing OSCM (Cuylen et al., 2016). Thus, iterative development comprised the procedures used to define an architecture and structure (e.g., content, dimensions) for I4.0 MM for OSCM, as well as the type of assessment instrument. These iterations were empirical-to-conceptual, applying the MM elements proposed from the first iteration to empirical methods with academics and professionals to collect relevant insightful and practical information (Weking et al., 2019). Semi-structured interviews and focus groups (FGs) were conducted for data collection, the two methods were considered effective to capture the interviewees' explicit understanding of a phenomenon (Bokrantz et al., 2019). In addition, empirical exploratory methodologies as focus groups were applied to bring insights to I4.0 research, given the interdisciplinary and revolutionary nature of the topic (Koh et al., 2019).

Firstly, semi-structured interviews were conducted with a sample of six academics (one mechanical engineer, one computer engineer, two

OM full-Professors and two production engineers), from August 2018 to September 2018, all experienced in the digitalization and automation of the manufacturing industry for more than five years. The interviews lasted from 30 min to 1.5 h and sought to survey potential enhancements in previous I4.0 MMs and to increase the value of existing models. These scholars provided important considerations and directions for the proposal of maturity levels and dimensions of the OSCM I4.0 model.

Then, six FGs were conducted, consisting of 5–6 specialists in computational modeling, digital technologies, and optimization and logistics, since smaller focus groups require greater participation from each member (Tremblay et al., 2010). The meetings were held between December 2018 and January 2019 with a total group of fifteen specialists with at least 10 years of experience in the areas of IT and OSCM. All of them held top positions in a well-known technical-scientific software development institute. Experts who had different responsibilities to represent a variety of points of view were deliberately chosen (Wang et al., 2019). In addition, in each group, one of the authors was the moderator and another author was an observer, responsible for avoiding personal points-of-view (Tremblay et al., 2010). All focus groups were carried out until reaching the saturation of ideas (Cuylen et al., 2016). One pilot FG, four exploratory FGs and one confirmatory FG were applied. Until the fifth focus group (FG1 – FG5), individual perspectives from I4.0 MM for OSCM were sought to be covered, while new categories (dimensions), subcategories (perspectives), details of categories (descriptors associated with the content of MM) and metrics (indicators) could emerge from the group discussion (Cuylen et al., 2016). The duration of each session was between 60 and 90 min and consisted of four parts for data collection: (1) overview of I4.0 MMs, intended to share basic knowledge among participants; (2) brainstorming with experts about adjustments and improvements in the proposed model, discussing key methods and technologies for its implementation; (3) zoom and filter session - workshop presenting the proposed model and discussing its elements, (4) details on-demand session, which was a description of the workflow of each dimension for application in future studies (Nascimento et al., 2018).

In addition, the confirmatory focus group (FG6) (Tremblay et al., 2010) had the purpose of verifying the integrity of the model, consistency, and adequacy of the problem (Nord et al., 2016). It aimed to adjust the content of the conceptual model and validate the taxonomy of the indicators derived from the proposed MM. To adjust the structure of the MM, the following qualification criteria were considered (Gökalp et al., 2017): aptitude for the purpose; completion of aspects; the granularity of dimensions; definition of measurement attributes; description of the evaluation method; and the objectivity of the evaluation method. Additionally, the indicators should satisfy taxonomy criteria, such as: concise, robust, comprehensive, extensible and explanatory (Weking et al., 2019). This led to small changes in the elements of the taxonomy, as reorganizing the elements of a dimension into existing ones and renaming and removing some elements. Finally, the MM subcategories were tested through a deductive literature review, reassessing their internal homogeneity and external heterogeneity (Cuylen et al., 2016). The theoretical and empirical data collected were checked again and assigned to the subcategories. Three authors codified the transcriptions in two processes: in deductive coding, existing categories and subcategories were enriched, while in inductive coding, new categories, subcategories, categories of details and indicators were extracted.

### 3.4. Step 3: Implementation

Regarding the MM development, the third step involved the following activities: construction of the research instrument

(questionnaire), pilot study (interviews) to test the instrument items and to set FISs, their membership functions and rules. First, a draft of the questionnaire was built based on the conceptual MM, with one question (item) per digital indicator. Prior to sending out the questionnaire survey, interviews with practitioners in engineering automation were undertaken to eliminate potential problems in the content and to offer a better refinement of the questions, ensuring that professionals from a manufacturing company would have no difficulty in answering the questions. The adjusted questionnaire consisted of seven questions concerning the demographic profile of the respondents, two questions concerning their perception of I4.0 technologies and fifteen questions divided into seven maturity dimensions: 1) consumer; 2) logistic; 3) supplier; 4) integration; 5) production, planning, and control; 6) quality; and 7) maintenance. The estimated time to complete it ranged from 30 min to 1 h. The questionnaire was available at <https://forms.gle/DimpQnhAvTypeFzP6>. Moreover, to model the experts' perception in decision-making judgments, considering the uncertainty and imprecision, an expert system composed of fuzzy inferential systems (FISs) with two key elements was designed: fuzzy rules and membership functions (Zadeh, 1965). To process the results, the construction of FISs relied on Mamdani-style fuzzy inference (Mamdani and Assilian, 1975), and its setting is segmented into four stages: fuzzification, rule evaluation, aggregation and defuzzification (Corrêa et al., 2014). Section 4.2 describes the FISs modeling and its elements.

### 3.5. Step 4: Evaluation

The fourth step embraced a case study (Voss, 2010) comprising the combination of two data collection methods including unstructured interviews and a questionnaire survey with four managers and four supervisors from a Brazilian manufacturing company. To increase the reliability of the analysis, the perception of senior management professionals from different departments were considered (Lins et al., 2019). The questionnaire aimed to verify which of the digital technologies individualized in the literature review were considered more relevant to their company (Lins et al., 2019), as well as to understand the current (AS-IS) and expected/targeted (TO-BE) levels of maturity of OSCM4.0, considering the corporate profile. Thus, the combination of mixed methods embedded within the case-study logic through both qualitative and quantitative data helped to test and validate the model (Bibby and Dehe, 2018). Section 5.1 presents a detailed description of the unit of analysis and the profile of the sample of respondents who participated in the survey.

Finally, an analysis of the current and expected maturity levels (given the digital readiness level of each measured indicator) was conducted, considering the present corporate experience and knowledge about I4.0 disruptive technologies, along with its strategic interests regarding possible investments in digital technologies. Based on the maturity level of a manufacturing company, guidelines were also proposed to address technological and methodological weaknesses and increase value-added across the seven dimensions of OSCM4.0, structured in a set of goals aligned with the organization's profile.

## 4. Model and assessment development

### 4.1. Model design

This section offers the results of the first iterations shown in Appendix C associated with the design of the model. During these iterations, there was the MM construction, including basic elements (number of levels, a descriptor for each level, generic description of each level, number of dimensions, number of perspectives, a descriptor for each

perspective) (Röglinger et al., 2012), a group of I4.0 indicators for evaluating OSCM perspectives as well as the combination of technologies and managerial practices that best represent each level of a conceptual MM. In the second iteration, the data collected from the comparison of I4.0 MMs (iteration 1) were reassessed and improved through interviews in which MM levels and categories (dimensions) were proposed. The third iteration involved six focus groups to discuss the categories, develop sub-categories (perspectives), detail categories for the sub-categories (description of the conceptual model), and indicators. The detailed categories described issues relevant to OSCM perspectives. With respect to the appropriate set of syntactic to measure the maturity of I4.0, one of the participants stated that it would be more feasible to evaluate manufacturing in terms of operational, tactical and strategic levels.

Some experts also assumed that four maturity levels would be adequate to help companies assess the maturity of their operations and supply chains as it avoids the central tendency and brings greater differentiation between levels. A consensus was reached that it would be more appropriate to use as a reference to the number of levels of some well-known model. Thus, some participants suggested following the CMM, which is composed of five levels and was used as a reference for various other models in the literature. However, this model started from level 1 and the aim was to propose an evolutionary model that departed from the level of the non-existence of digital technologies (level 0). As for the definition of the name of the levels, after the discussions, a consensus was reached that would be: nonexistent, conceptual, managed, advanced and self-optimized (Table 1). The results of the maturity evaluation could be easily interpreted, becoming thus a powerful and user-friendly artefact. The maturity levels represent the current state of I4.0 maturity, and the higher the level, the more mature the OSCM. In this way, these levels seemed to be sufficient for discrimination, providing a target-oriented evaluation and indicating improvement potentials. Table 1 presents a general description of each maturity level and the MM used as a background (see Appendix B).

Regarding the essential dimensions to assess I4.0 maturity, it was realized that processes, people, and technologies were key factors in manufacturing. Although there were several other dimensions such as organization, monitoring and control, strategy, products and services, integration, customer, channels, key partners, logistics, quality, maintenance, asset management, design and engineering, the participants pointed as key dimensions to assess the evolution of supply chains and operations: SCM, POM and technologies. Some respondents also pointed out that skills and knowledge management were critical attributes. However, after a few rounds of discussions, participants reached a consensus that technologies and processes, as well as managerial methodologies and good practices, should be evaluated transversally in the three major OSCM dimensions: SCM, SCM & POM (common), and POM. According to experts, the common dimension shows a wider view of external and internal operations and to measure OSCM companies should consider the perspectives: Customer, Logistics, Supplier, Integration, Production, Planning and Control (PPC), Quality and Maintenance.

The measurement of each maturity level by subcategory (perspective) occurred in the fifth focus group in which indicators were derived from perspective. Then, the sixth focus group (confirmatory) evaluated and improved the taxonomy of indicators and there was a final comparison of the elements proposed in a deductive way with the I4.0 MM literature. Thus, the relation between the previously reviewed MMs and the taxonomy of indicators proposed to evaluate the digital readiness level of OSCM are presented in Table 2.

Besides that, the measures that make up the model's assessment tool were derived with the development of a taxonomy of digital readiness

**Table 1**  
OSCM4.0 Maturity levels.

Level name	Description	MM background
0 Nonexistent	The process has not been implemented, it is based on experience and generated without standards, being implemented informally, and with little control. Process management is reactive and does not have the appropriate technologies to build an infrastructure that supports the digital revolution. The organization does not address I4.0 and the available enterprise IT-system supports only its field of application, generating data islands along the process.	16; 17; 23
1 Conceptual	A formal deployment process has been initiated and there is more exclusive knowledge about the process advancement. Process management is weak due to a lack of organization and/or enabling technologies. A partial maturity in the management of infrastructure development. The organization begins to address the problems of I4.0 within departments and connects existing technology applications to create data flow, data is fully integrated into a single enterprise system, but data exchange is not automated.	19; 23
2 Managed	Standardization can be achieved and I4.0 technologies and requirements can be implemented to detect improvement potentials as well as establish computer-assisted approaches and create automated data flows and processes. The process was formally documented and defined thanks to the planning and implementation of good management practices and procedures, but the planning and implementation of the process highlight some gaps/lack of integration and interoperability in the applications, despite the collection and sharing of structured data.	5; 8; 19
3 Advanced	The process is built on integration and interoperability, based on a common and shared standardization within the company; this has been completely implemented in an area or several areas, with established indicators and optimized management, evaluating opportunities, and applying benchmarking. The principles and technologies of I4.0 are reached beyond corporate boundaries and actively followed by all business partners; there is planning and control forecasting, the service-oriented and cloud-based platform is available throughout the supply chain, appropriate encryption techniques and authentication are in place to ensure secure access to data and simulation systems are used for testing, prototyping and factory optimization. The use of data prediction is required since there is pragmatic interoperability and automatic actions are promoted before a problem or bottleneck appears.	9; 15; 21; 24
4 Self-optimized	The process is digital oriented, relying on solid technology infrastructure and an organization with high growth potential. Available data allow for real-time simulation, which can be used in collaborative diagnostics and decision-making. This level consists of the complete digitalization of internal and inter-company processes, together with strong collaboration, integration of AI and self-learning skills in information systems, and creation of proactive processes for forecasting and planning future production, integrating data visualization and systems external partners to enable supply chain predictability and intelligent manufacturing.	16; 17; 24

level (DRL) indicators. Like the technology readiness levels (TRLs) proposed by the National Aeronautics and Space Administration (NASA) (Mankins, 2002), DRLs seek to be a valuable tool in digital technology management, indicating the current and desired level of digitalization in a specific area to serve as a guideline for continuous improvement OSCM compared to I4.0. Iteration 3 resulted in the final model, presented in Table 3, consisting of five levels of maturity and three dimensions within seven perspectives combining technological and methodological

characteristics, providing more detailed assessment information and a set of indicators. Therefore, the theoretical and empirical qualitative methods showed that a multi-perspective view allows for a holistic assessment of I4.0 maturity of operations and the supply chain.

Furthermore, the MM architecture presented in Table 3 is linked to an assessment instrument. Section 4.2 describes the modeling of the assessment tool, which represents the results of iteration 5 (Appendix C). As in Asdecker and Felch (2018), the I4.0 readiness score was converted

**Table 2**  
OSCM4.0 Maturity dimensions and indicators.

Dimension	Perspectives	Description	MM background	Taxonomy of indicators
SCM	Customer	Refers to advances in customer' relationship, segmentation, and satisfaction, as well as, marketing and sales strategies through different channels (e.g., social media); as the organization increases its maturity, it increases the level of digital interaction/participation between the clients and the products/services offered. The organization also improves the accuracy and readiness in relation to the fulfillment of all the customer's requirements.	4; 6; 12; 13; 15; 21; 23; 24 3; 4; 6; 7; 8; 12; 17; 20; 21	Sales/Service digitalization (I1) Customer Data Usage (I2)
	Logistics	Refers to advances in delivery, transportation, distribution, asset, and inventory management; as maturity increases, processes become more structured and standardized, while logistical models become more autonomous and optimized.	4; 7; 14; 15; 16; 19; 21; 23; 24 2; 4; 7; 13; 14; 16; 17; 19; 20; 23	Logistics systems and model automation (I3) Optimization of material flows and logistics information (I4)
	Supplier	Refers to advances in supply network coordination, supplier(s) relationship management, and flexibility; with increasing maturity, there is greater cooperation and collaboration between partners, technologies and processes, enabling greater flexibility and decentralization.	3; 7; 15; 21; 23 2; 7; 13; 17; 20; 24	Relationship with suppliers (I5) Purchase and order digitalization (I6)
	Integration	Refers to advances in the level of integration of physical and computational processes, communication between actors, the connection between technologies, and interoperability; it identifies how processes and systems evolve from isolated silos to fully-connected ecosystems that support the remaining SCM and POM domains.	1-4; 6-13; 15; 17-25 3; 4; 7; 15; 18; 23 1-4; 6-11; 13; 16-25	Integration of internal and external processes (I7) Communication/collaboration between SC actors (I8) Interoperability between systems (I9)
	PPC	Refers to advances in the planning and control of production systems and the value chain of OM; the evolution of more intelligent systems follows the adoption of increasingly sophisticated Lean methods, exploring the synergies between technologies and methodologies.	2-6; 10; 11; 14-16; 22; 23; 25 2; 4; 5; 10; 11; 14; 16; 20-22; 25	OM Automation (I10)
	Quality	Refers to advances in quality control systems, the performance of quality management tools; it describes a combination of technological and methodological evolutions working together to improve efficiency and accuracy.	4; 5; 14; 15; 23; 25 3; 5; 8; 9; 14; 17; 20; 25	Digitalization of planning and control processes (I11) Quality control automation/virtualization (I12) Information quality (data collection and analysis (I13)
POM	Maintenance	Refers to advances in reliability, repair and maintenance plans, strategies and techniques; the increase in maturity leads to increasing automation in diagnostics combined with remotely-operated machines that gradually replace humans in specialized or high-risk activities.	4; 5; 14-16; 22; 23 5; 14; 16; 21	Maintenance and repair automation/virtualization (I14) Maintenance information and data logging digitalization (I15)

into a maturity level, in which the five levels of the conceptual model describe the path to the continuous improvement of digitalization. The score is represented by a scale from 0 to 100 percent, proportionally distributed among the five levels. Thus, for example, the second level corresponds to a score between 20 and 40 percent (Asdecker and Felch, 2018).

Finally, model implementation and evaluation is described in Section 5, which represents the results of iteration 6 (Appendix C). To guarantee the validity and reliability of the model, a case study was conducted, following the procedures of De Bruin et al. (2005), with a test application (pilot) with specialists involved in adjusting the assessment tool and, later on, a model application in a manufacturing organization. This case organization did not participate in the development and testing of the model. Tangpong (2011) corroborates the idea of validating the study with an independent sample to achieve greater replication and generalization.

To define recommendations to improve the performance and thus achieve greater maturity, the triangulation technique was used - combining insights related to the evaluated company (knowledge and interests of I4.0 technologies) and the actions detailed in each quadrant of the model (Table 3). In this sense, the proposed recommendations seek to consider specific characteristics of the company (Röglinger et al., 2012), for improving the digitalization of individual dimensions of OSCM, and thus boost the company's I4.0 maturity.

#### 4.2. Fuzzy based assessment tool

In the present research, data acquisition followed the knowledge engineering guidelines described by Klir and Yuan (1995). This consisted of seven interviews with professionals of the Reference Center in Technological Innovation (CERTI) in Brazil, who had more than five years of experience with industrial digitalization and I4.0 technologies. These professionals also provided rules. The fuzzy rule configuration proposed by Combs and Andrews (1998) was adopted, using the union rule configuration (URC) system. As the URC avoids rule explosion (Weinschenk et al., 2003), the number of inference rules was significantly reduced and 75 rules were elaborated for the 10 FISs. The membership functions were parameterized according to the judgments of the practitioners and experts who work with engineering digitalization. Each input/output has an amplitude in the range [0; 100] and five values that follow a triangular membership function, as shown in Table 4.

In total, the expert system has 15 inputs (indicators) and a final output that determines the I4.0 readiness level of the evaluated organization. The indicators' values were collected based on a questionnaire survey. As shown in Fig. 2, the proposed fuzzy expert system is composed of 10 FISs. The structure of the evaluation system presented in Fig. 3 follows the hierarchical tree approach, where the outputs of the low-level fuzzy systems are used as inputs to the high-level fuzzy systems and are of the Cascaded or Combined type (Siddique and Adeli, 2013).

As Zimmermann (2010) suggests, the defuzzification method can be changed according to the best representation of decision-makers' opinions. The modeling of the FISs presented in Fig. 3 used the standard Min-Max Mamdani "inference" operators, with centroid (or center of area – CoA) "defuzzification". The CoA allows considering all membership values in a given region, admitting a centralized position (Pedrycz and Gomide, 2007).

Furthermore, to reflect the inaccuracy and variance of the information, input data collected - from the perception of a group of key professionals in the organization under analysis - were adjusted to a probability distribution. This process is often used in risk analysis, and

Beta PERT or triangular distribution is commonly used (Vose, 2008). By collecting their perception about the current (index) and expected maturity for each indicator, the minimum, maximum, and modal values of expert group estimates are used as parameters for modeling the Beta PERT distribution, where the "shape" parameter indicates the degree of accuracy of the data mode. Monte Carlo simulation was then used to generate 100 random values for each digital readiness indicator that was used as input at the fuzzy tree. The modeling of the probabilistic fuzzy system, which steps are evidenced in Fig. 3, were implemented using the R software (R Core Team, 2019), in which there was the compilation of indicators aggregation algorithm. These analyses sought to support the suitability of the proposed methodology and the parameterization performed during implementation.

The gap analysis was made qualitatively based on the proposed conceptual model and quantitatively by comparing the expected and current mean maturity level ( $\bar{ML}$ ) according to Equation (1). In addition, the percentage of the level of target achievement was also calculated according to Equation (2), which was adapted from (Maasouman and Demirli, 2016).

$$\text{Gap} = \bar{ML}_{\text{expected}} - \bar{ML}_{\text{index}} \quad (1)$$

$$\text{Level of target achievement} = \frac{\text{Gap}}{\bar{ML}_{\text{expected}}} \times 100 \quad (2)$$

In addition to adjusting fuzzy sets (rules and parameters), the interviews with professionals from the CERTI also helped to validate the questionnaire items, eliminating potential conceptual divergences or particularities related to the manufacturing sector. These interactions with an innovative technology reference center provided important feedbacks, thus refining and improving the assessment tool accordingly (Bibby and Dehe, 2018).

## 5. Model application and discussion

### 5.1. Evaluation through a case study

Eight practitioners from the Brazilian site of a multinational manufacturing organization (named as XYZ) with extensive knowledge of the firm's manufacturing processes and strategies, and whose profile are detailed in Table 5, were asked to complete the maturity assessment items on behalf of the organization. As criteria to select the respondents, the research considered the level of knowledge of internal processes, the access to external organizations within the supply chain (Bibby and Dehe, 2018), and the area of expertise in the organization. The case organization has operated in Brazil for forty years and employs around 200 staff. Overall, XYZ has a revenue of over 100 million US Dollars in the commercial and military aviation industry.

Company XYZ is an essential industrial and technological partner for many industries and the Brazilian government/military. It is also a partner of helicopter operators in the civil sphere. Today, of every two helicopters operating in Brazil, one is equipped with components produced by XYZ and more than 60% of the air taxi fleet of the main airline company in the Brazilian aviation market uses its sophisticated parts.

### 5.2. General findings

Firstly, by analyzing the corporate profile, it can be noticed that although all OSCM perspectives are considered important, the organization's focus is on quality, maintenance, and supplier perspectives. Despite being from the aeronautical manufacturing industry, XYZ also stands out for providing repair and maintenance parts services, which

**Table 3**

OSCM 4.0 maturity model for manufacturing.

Domain	Perspectives	0 - Nonexistent	1 - Conceptual	2 - Managed	3 - Advanced	4 - Self-Optimized
SCM	Customer	- No customer post-transaction channel, just physical interaction with products/services; - Manual marketing through CRM surveys	- Feedbacks through CRM with structured processes, technologies, and trained collaborators; - Automated client data collection through sales	- Matched care-customer care automation; - BDA for pattern analysis	- Virtually guided self-service - BDA for demand forecast and data-driven design	- Customer engagement with product design towards co-creation and open innovation - Cognitive AI for understanding individual customers' profiles.
		- Unstructured logistics practices - Unstructured processes based on manual analysis	- Single-source logistics model; - Structured processes - Heterogeneous IT systems that support only some logistics management activities	- Hybrid logistics models; - Unequivocal processes with strategical intent; - Integrated IT systems;	- Advanced logistics models; - Digital processes for optimization; - IT systems forecast routes, rhythms, and movement routines;	- Smart logistics models (e.g., IoT-based Omni-Channel Logistics Service) for real-time self-optimization
		- Supplier relations follow defined processes and technologies, but present standards inconsistencies	- Application of SRM processes and technologies are followed through single-vendor sourcing	- Standardized and digitalized SRM processes and technologies are followed through multiple-vendor sourcing along the value chain	- Advanced integration between partners, technologies and process management; - Collaborative forecasting and planning take shape within the SRM	- Decentralized and real-time SRM take shape for autonomous decision-making actions
	Integration	- Isolated functional silos with undefined processes; - Manual communication processes among actors; - Point-to-point data integration and lack of interoperability.	- Standardizing of processes within departments; - Digital cooperation within isolated teams; - Basic data integration with syntactic interoperability through SOA and basic IoT limited to sensors.	- Vertical digitalization and integration of processes and data flows; - Digital cooperation between intra-company functions and actors, but still reactive; - Semantic interoperability through SSOA for the enterprise.	- Horizontal integration of processes and data flows among all actors; - Actors take digital cooperation to the process level and there is a proactive encouragement of sharing; - Common IT architecture creates a Partner Service Bus based on Cybersecurity and Blockchain technologies.	- Fully integrated ecosystem with self-optimized and virtualized processes; - Digital collaborative culture deeply rooted throughout the company; - Dynamic interoperability permeating OSCM.
		- Push-intensive inventory	- Pull system based on basic Lean Automation practices	- Integrated production systems with statistical tools focused on root-cause analysis	- BDA focused on predictability in planning and control	- Real-time systems with Total Lean Automation for manufacturing planning and control focused on decentralized autonomous decision-making
	POM	PPC	- Sampling-based inspections	- Integrated quality control with Six Sigma tools	- Automatic quality diagnostics based on advanced LSS automation	- Smart recommendations towards TQM
			- Corrective and preventive maintenance; - Manual (human) onsite inspections	- Indicators for performance and failure analysis; - Integrity data collection through sensors;	- Data mining for CBM and root cause analysis; - Remote inspections in inhospitable areas (e.g., drones)	- Intelligent and self-optimizing TQM  - Predictive analytics for reliability-based maintenance; - Remotely-guided repair robots
	Quality	Maintenance	I1 – I15 (indicators)	Input	0–100	Very low Low Medium High Very high
C, L, S, PPC, Q, M (perspectives)	POM, I and SCM (dimensions)					
I4.0 Readiness Level (maturity)				Output	0–100	(0, 0, 25) (0, 25, 50) (25, 50, 75) (50, 75, 100) (75, 100, 100)
					Very low Low Medium High Very high	(0, 0, 25) (0, 25, 50) (25, 50, 75) (50, 75, 100) (75, 100, 100)
					Nonexistent Conceptual Managed Advanced Self-optimized	(0, 0, 25) (0, 25, 50) (25, 50, 75) (50, 75, 100) (75, 100, 100)

**Table 4**

Inputs and outputs parameters.

Linguistic variable	Type	Universe of discourse	Value	Triangular fuzzy numbers
I1 – I15 (indicators)	Input	0–100	Very low	(0, 0, 25)
			Low	(0, 25, 50)
			Medium	(25, 50, 75)
			High	(50, 75, 100)
			Very high	(75, 100, 100)
C, L, S, PPC, Q, M (perspectives)	Input/ Output	0–100	Very low	(0, 0, 25)
			Low	(0, 25, 50)
			Medium	(25, 50, 75)
			High	(50, 75, 100)
			Very high	(75, 100, 100)
POM, I and SCM (dimensions)	Output	0–100	Nonexistent	(0, 0, 25)
			Conceptual	(0, 25, 50)
			Managed	(25, 50, 75)
			Advanced	(50, 75, 100)
			Self-optimized	(75, 100, 100)

are related to supplier and customer views or can be considered a new perspective in the case of a service industry. This finding corroborates the service-oriented manufacturing paradigm, which is a common I4.0 principle (De Carolis et al., 2017). Moreover, by analyzing the corporate experiences and strategic interests in I4.0 digital technologies, the level of diffusion of disruptive technologies in XYZ revealed that it possesses limited knowledge of virtual/augmented reality, cloud computing, intelligent manufacturing systems and BDA. Conversely, the organization has experience in IoT, AM and cybersecurity. Therefore, the results suggest that cybersecurity is the only technology that the organization is deeply familiar with, which may be related to the strict policy of controlling the use of systems and the network, following the standards of an international high technology group. Paradoxically, the organization is yet to consider Blockchain and its possible benefits for information security, regarding it as an emerging technology, without specific legislation and not yet well understood. Although XYZ has a 3D printer, it has not yet explored all its technological potential, using it for the manufacturing of simple parts and tools (low-value-added activities).

From the strategic view, the analysis demonstrates that the I4.0 technologies considered most important in the short term were BDA and

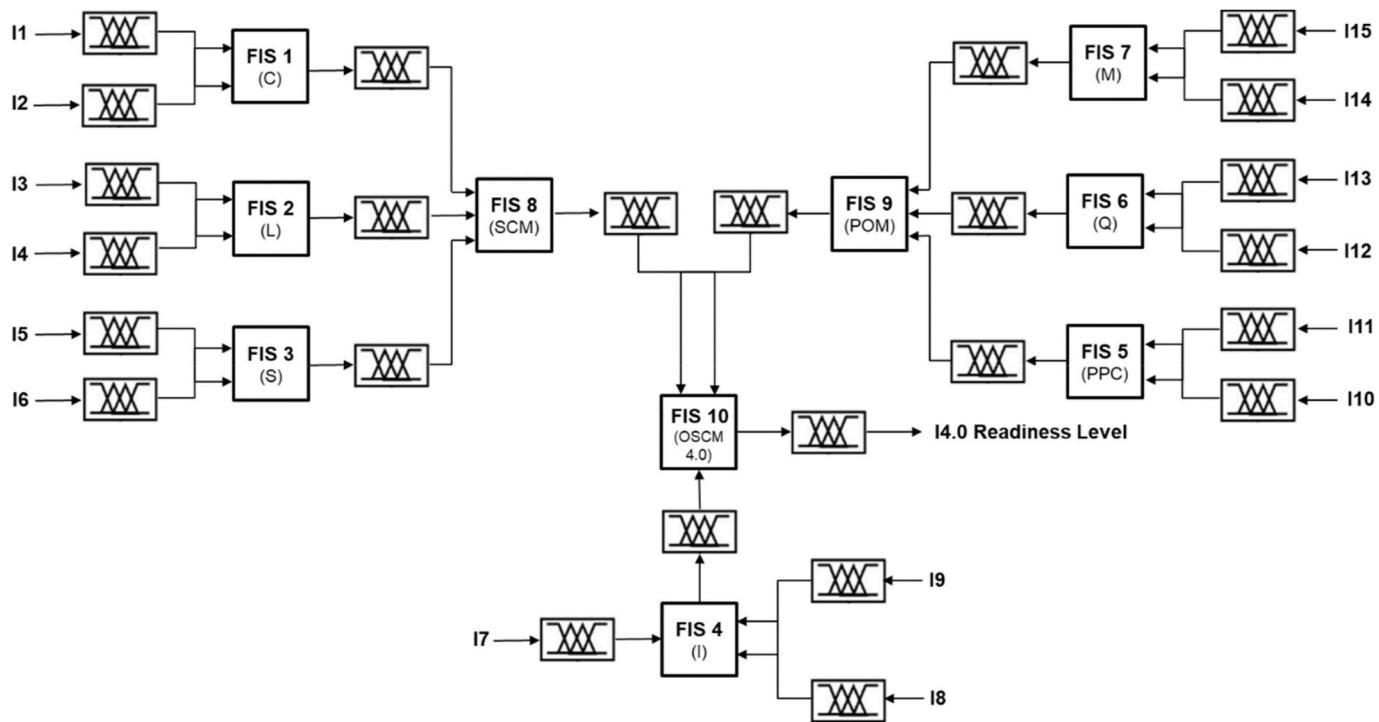


Fig. 2. Cascaded hierarchical fuzzy tree (adapted from Gaviao and Lima, 2015).

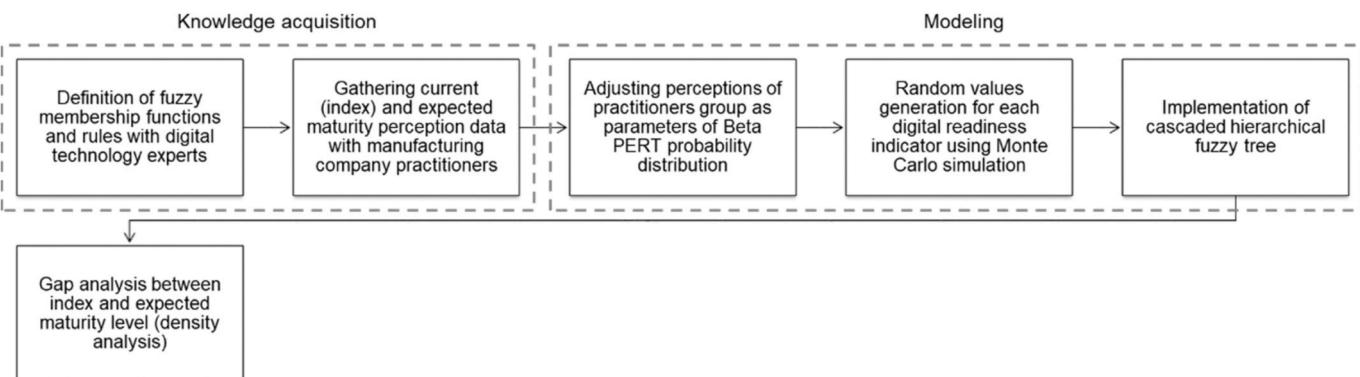


Fig. 3. Probabilistic Fuzzy modeling and knowledge acquisition.

virtual/augmented reality. Besides, cloud computing and AM were mentioned as a focus for later implementation. Lastly, some professionals highlighted the need for advanced robotics, IoT, and intelligent manufacturing systems. With regard to data-driven techniques, these findings portray that at first, the organization wanted to gain autonomy in the use of advanced AI algorithms and the integration of unstructured databases to extract knowledge for business intelligence. Then the firm will be concerned with the cloud platform, to use BDA effectively for very fast analytics with increased business scalability, elasticity on-demand, and financial viability. From this BDA and cloud manufacturing-based infrastructure, the organization will prioritize the use of IoT as it can consume massive volumes of data from different real-time analytics equipment connected to intelligent manufacturing systems. Regarding the automation of manufacturing and maintenance activities, XYZ will initially place greater emphasis on the use of virtual or augmented reality technologies that can be used for training and simulation and then will currently deploy 3D printers for the fabrication of custom parts used for replacement.

**Table 5**  
Profile of the respondents.

Respondents	Level of education	Level of experience	Role	Field
1	Complete college education	Over 10 years	Manager	Information technology
2	Specialization	Over 10 years	Manager	Finance
3	Specialization	Over 10 years	Manager	Production
4	Specialization	5–10 years	Supervisor	Quality
5	Specialization	5–10 years	Supervisor	Receiving
6	Complete college education	Over 10 years	Supervisor	Information technology
7	Specialization	5–10 years	Supervisor	Inspection
8	Master's degree	Over 10 years	Director	Board

### 5.3. Gap analysis

The next step consisted of measuring the DRL of each indicator to compare AS-IS and TO-BE performances. As mentioned previously, the current (index) and expected results by the digital readiness indicator (inputs of fuzzy-based OSCM4.0 MM) considered random values generated through Monte Carlo simulation based on Beta PERT distribution, which took into account the perception of the top management employees of XYZ. Fig. 4 presents the density chart of the index and the expected results for each MM input.

Fig. 4 illustrates that all fifteen indicators presented a gap between the index and the expected readiness level. The results also clarify the firm's technical strengths and weaknesses related to its digital readiness measures. For instance, there is a larger discrepancy in Information quality (data collection and analysis) (I13) input, considering that the median and the mean of the answers demonstrate a low score, via semi-automatic data collection from mobile devices for inferential analysis. However, the expected mean of the responses indicates that, in fact, the organization should be at the top level, with automatic and dynamic data collection through self-diagnosis of the products themselves, using ML algorithms and decision-making optimization models. Similarly, there are major divergences in the indicators: Customer Data Usage (I2), Interoperability between systems (I9), Digitalization of planning and control processes (I11), Quality control automation/virtualization (I12) and Maintenance and repair automation/virtualization (I14). These divergences may be associated with the deviation of about two readiness levels between those indicators, which indicate that in the present state (AS-IS) the organization uses sensors, advanced LSS multivariate analysis (e.g., multiple regression), KPIs, cloud for basic applications, but in the future state (TO-BE) it should use BDA, Blockchain, IoT-based cloud and Lean 4.0.

On the other hand, there is less variation in Sales/Service digitalization (I1), Purchase and order digitalization (I6), and Integration of internal and external processes (I7). It is noteworthy that I7 is the input with the least variation, considering that the organization has an average performance above 50% in this indicator since by management's perception there is already vertical integration of processes and data flows and horizontal integration is sought (among all actors in the chain), which is the next step in the transition to I4.0 (Leyh et al., 2016). The I1 analysis points to the need to transition from customer relationship management (CRM) with customer care automation to a virtually customer-driven self-service. From the I6 analysis, although now there is a digitally supported purchase order processing, XYZ intends to have a cloud-based IoT operating system and access via mobile devices.

Furthermore, there was an analysis and discussion of fuzzy probabilistic results, pointing out some important opportunities and emerging gaps. Fig. 5 shows a density chart with the expected and index overall corporate maturity.

The comparison of Fig. 5 results and the conceptual MM implies that the OSCM4.0 maturity of the organization is located at a mean index maturity of Level 1 (Conceptual) and that the company seeks an expected mean maturity of Level 3 (Advanced). Comparing the mean of current and expected performances quantitatively, it is observed that the Gap is 32.4 (71.25–38.85) and the level of target achievement is 45.47% (32.4/71.25). This indicates that the organization must go through two cycles of improvement, i.e., two transition levels in the conceptual model, to reach the expected level. Regarding the performance of the perspectives and dimensions, considering the average evaluation of the indicators set (e.g., I1 and I2 compose the customer perspective that is part of the SCM dimension), it is clear that the quality perspective was the one that presented the highest gap, which may be related to the

performance of I13, increasing the gap of the POM dimension, while the logistics perspective presented the smallest gap, which implied a lower gap in the SCM dimension.

Considering the organization I4.0 priorities and performance gaps, some major improvements in POM dimension include making the transition:

- From quality management based on LSS tools to intelligent total quality management based on Lean 4.0;
- From key performance indicators and failure analysis to the implementation of reliability-centered maintenance with AI algorithms for predictive analysis;
- From planning and control focused on good management practices with integrated engineering systems to use BDA to forecast planning and control of production processes.

Complementarily, the SCM dimension needs to evolve:

- From feedbacks through CRM to virtually guided self-service;
- From single-source logistic models to advanced AI-based logistics and process mining models; and
- From the application of SRM processes and technologies followed through single-vendor sourcing to advanced integration between partners, technologies, and process management.

Finally, from an integration perspective, there is a need to move from a basic data integration with syntactic interoperability (e.g., through service-oriented architecture – SOA) and basic IoT limited to sensors to common IT architecture, through a 'Partner Service Bus' based on cybersecurity and blockchain technologies. It should also be noted that although by the managers' perception the organization aims to reach an 'Advanced' maturity level, in certain areas there would be no need to reach such level. This happens, for example, in the case of Maintenance information and data logging digitalization (I15) since according to respondents, repairs could be directed by a remote data collection system using field protocol transmitters. After this technical improvement, XYZ could explore the use of image and video processing techniques integrated with AI algorithms to predict the maintenance and lifetime of assets. Similarly, in the Integration perspective, the organization could aim to achieve a 'Self-optimized' level. Possible drivers for this include technologies such as cloud computing to store/retrieve data in massive scale and Web 2.0, in which software work from the Internet and is under continuous and collaborative development, which ensures the interactivity between nodes through a collaborative, digitally rooted corporate culture throughout the chain; and greater interoperability between digital systems and processes.

### 5.4. Action plan

Finally, to bridge the previously observed gaps, an action plan was proposed composed of seven guidelines, each associated with an OSCM 4.0 perspective as follows (their details are offered in Appendix D).

- (1) **Guideline-1 (Customer)** – Provide a virtual and collaborative sales communicate on environment with integrated after-sales assistance.
- (2) **Guideline-2 (Logistics)** – Build an Omni-Channel platform for logistics optimization.
- (3) **Guideline-3 (Supplier)** - Standardize and digitalize SRM processes and technologies.
- (4) **Guideline-4 (Integration)** - Provide semantic integration with a standard automation architecture.

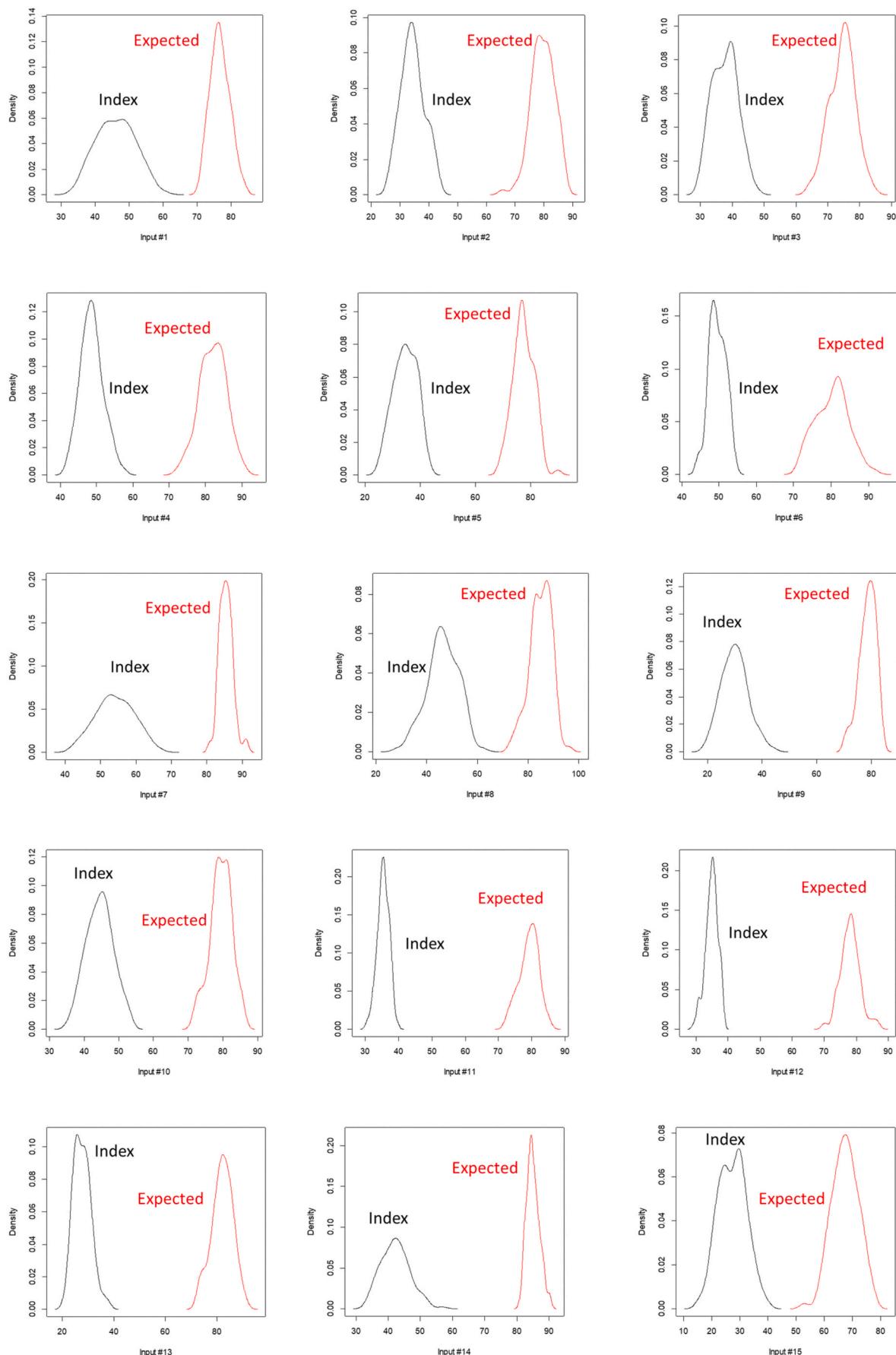
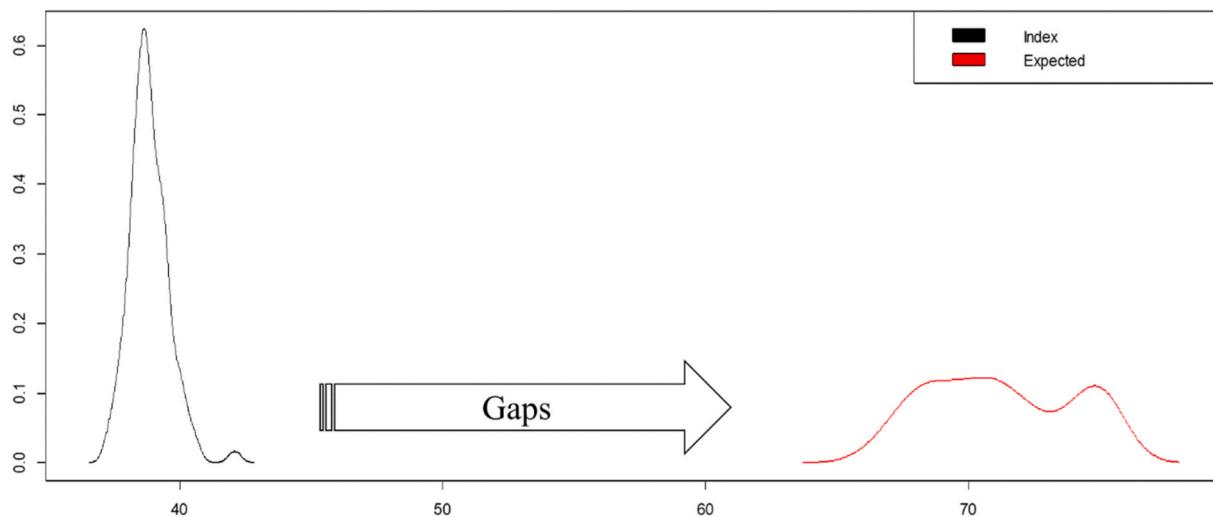


Fig. 4. PERT Beta Distributions of Inputs (Current Index vs. Expected Index).



**Fig. 5.** Density chart with index and expected results.

- (5) **Guideline-5 (PPC)** – Deploy smart planning and control and flexible customized production.
- (6) **Guideline-6 (Quality)** - Use advanced LSS tools to automatic diagnostics and problem-solving.
- (7) **Guideline-7 (Maintenance)** - Develop a reliability-centered maintenance strategy based on virtualization.

Therefore, in each perspective, there is a set of I4.0 technologies that can be deployed and combined under different dimensions as enablers to boost digitalization. For example, there may be an interrelation between cobots (advanced robots) and 3D printers to automate the production of customized parts, as well as the combination of embedded sensors for data acquisition and ML or deep learning algorithms for data processing in the cloud, that would allow efficient data exchange and sharing and could stimulate new approaches like PSS. Moreover, the cloud could be combined with cybersecurity for the safety of advanced systems, or be integrated with IoT, facilitating the combination of multiple devices and machines, which allows remote operations. In addition, CPS can take advantage of cloud and IoT and can be combined with VR/AR through 3D models for simulation, and thereby systems could adapt to adverse events.

##### 5.5. Discussions and implications

This research contributes in different ways to both academics and practitioners, as follows. First, it employs a quantitative model based on fuzzy sets that allow quantifying qualitative, inaccurate, and vague information. This is a valuable way to analyze process evolution, as the opinions of decision-makers can be captured more accurately and the knowledge of the problem domain is maintained in the system. The use of FIS is not new to the OSCM literature (Aqlan and Lam, 2015; Pourjavad and Shahin, 2018), as its addresses many of the challenges associated to the nature of research in OM and SCM (Aqlan and Lam, 2015; Azadegan et al., 2011; Corrêa et al., 2014; Pourjavad and Shahin, 2018; Zanon et al., 2019). However, to the best of the authors' knowledge, this is the first time the fuzzy logic is applied in the construction of an I4.0 MM for OSCM.

Second, the proposed MM is developed in a transparent and rigorous procedure based on the stages offered in Becker et al. (2009). This is relevant, as this research revealed a lack of transparency regarding MMs

construction and application. The model development is built upon a multiple research method approach, as recommended by Liebrecht et al. (2017). Its development goes beyond the verification stage, reaching the validation through a case study, which is rare in the literature, as revealed in the existing I4.0 MMs comparison offered in this research.

Third, this study presents a real application in a multinational manufacturing organization to illustrate how this approach can be applied in different scenarios. Empirical applications are limited in the I4.0 maturity literature (Bibby and Dehe, 2018) and are needed to allow more realistic representations of the real-world environment, corroborating the need for more practical I4.0 MM (Mittal et al., 2018). This also makes the model easier to be understood and used, providing a well documentation of its application, which was also revealed as being rare in existing I4.0 MMs.

Fourth, the use of Monte Carlo simulation to generate random values based on the top management perception of the evaluated focal company, concerning the digital readiness indicators, makes it possible to make statistical inferences with a higher degree of significance, allowing an easier and more visual understanding of the gaps in relation to index and expected states and, thus propose a set of guidelines for their transition towards manufacturing 4.0. This also addresses a lack in the literature identified in this research regarding prescriptive MMs. The proposed model could prescribe actions towards increasing the maturity level of the evaluated company in the last stage of its development.

Finally, still regarding practicality, the model could assess the OSCM digitalization of a company in a real-life setting providing a self-assessment readiness tool easily applied to provide measurable results, another gap identified in existing I4.0 models.

## 6. Conclusions and recommendations

This study proposes a novel model to assess the I4.0 maturity of manufacturing companies based on a fuzzy probabilistic expert system to overcome the inaccuracy and uncertainty of previous MMs, addressing the complexity of digitalization level perception across OSCM. The study centers on addressing the question of how to measure readiness digitalization in manufacturing organizations.

Both academic and practical contributions are offered herein. This paper fills a research gap by providing a theoretically grounded and methodologically rigorous development of a MM for OSCM4.0

manufacturing companies. The value of the model presented lies in the combination of scientific rigor, practical relevance and direct applicability. OSCM4.0 is evaluated using FIS to eradicate the human ambiguity in a decision-making scenario. The use of fuzzy logic eliminates the ambiguity in the allocation of the degree of compatibility of a sample with a semantic concept in human judgment. In addition, the probabilistic distributions of the Monte Carlo simulation can deal with statistical uncertainty. The paper provides a different quantitative model for analyzing I4.0 maturity, which can handle inaccurate information. This research can also help to define important Research and development – R&D - directions by defining a set of guidelines in an action plan that can guide future research.

From an industrial perspective, this paper presents a robust diagnostic tool intended to assist companies in their digitalization by providing insight through guidance that enables them to discover the true level of maturity in OSCM4.0. One relevant practical contribution is the prescription of guidelines for improving the OSCM4.0 maturity level based on the conceptual MM. In general, companies struggle to identify their actual I4.0 maturity level, and it is unclear to them what actions they should take to improve maturity. Thus, with the proposed model, organizations can investigate gaps that hinder the maturity of their OSCM and implement actions (guidelines) to bridge those gaps to develop the maturity of the organization.

Moreover, with regard to business practice, this work provides detailed knowledge to support the transition towards OSCM4.0 maturity of manufacturing organizations. Just like DPMM 4.0 (Asdecker and Felch, 2018), OSCM 4.0 is a good starting point for practitioners who seek to ensure the competitiveness of their processes in the digital age ahead. The developed model allows an organization to determine its current and expected maturity level in each digital readiness indicator, compare its current maturity level with other sites, business units and/or companies, develop a corporate vision for manufacturing excellence, identify possible improvement measures and provide guidance on the development path. Moreover, the organization can use fuzzy probabilistic concepts to help managers achieve business excellence through better decision models.

## Appendix A. I4.0 technologies

Technology	Description	References
CPS	It represents a set of physical devices that interact with virtual cyberspace through a communication network, in which each physical device will have its cyber part as a digital representation of the real device, culminating in 'digital twin' models.	Lu (2017); Frank et al. (2019)
IoT	It is called "the world of widespread connectivity" in which the Internet is the connectivity center of all smart devices, and can create an intelligent network along the value chain to which machines, products, and systems can be autonomously connected and controlled.	Katsma et al. (2011); Bibby and Dehe (2018); Fatorachian and Kazemi (2018)
BDA	It involves the use of advanced AI data analysis techniques that use machine learning algorithms and deep learning, an endeavor to extract valuable knowledge from large amounts of data, facilitating data-driven decision making.	Babiceanu and Seker (2016); Lamba and Singh (2017); Frank et al. (2019)
Cloud	It is a set of technologies that provides organizations with IT infrastructure resources as a service over the Internet; it covers the entire extended life cycle of a product. It is considered as a parallel, networked and intelligent manufacturing system (the "Cloud-manufacturing"), as it receives support from cloud computing, IoT, virtualization, and service-oriented technologies.	Frank et al. (2019)
Cybersecurity	It is a field dedicated to safeguarding the privacy, confidentiality, and integrity of data stored and/or transmitted in any format, given the huge and unstructured amount of data generated by IoT technologies within the organization.	Babiceanu and Seker (2016); Ghobakhloo (2018)
Blockchain	It is known as "the trust protocol" because it is a distributed registration technology that aims at decentralization as a security measure. It is a distributed database with a peer-to-peer network, a consensus engine, and cryptographic methods.	Wang et al. (2016)
Additive manufacturing	It reflects the set of technologies for developing three-dimensional, layer-by-layer manufacturing objects under computer control, enabling the fabrication of an often geometrically complex component composed of a series of layers of material. The most representative technologies in this field are 3D printing.	De Carolis et al. (2017); Nascimento et al. (2018)
VR/AR	In VR the creation of the immersive experience makes the user feel like being somewhere else or living things that do not really exist, while in AR the concept of reality is in its purest state, that is, brings to real-world elements that do not exist.	Ras et al. (2017)
Advanced robotics	Advanced robots (adaptive or collaborative robots) allow systems to mimic human actions and work autonomously. The modern robotics systems are able to have learning ability.	Bibby and Dehe (2018); Ghobakhloo (2018)

Like every study, this paper has some limitations, which can be used as new avenues for further research. Although this research was based on all the steps of the procedure model design offered in Becker et al. (2009), from construction to application, the model can take advantage of further work on its evaluation. The evaluation step considers the multifunctional corporate process, due to the participation of a wide range of functional areas, however; only one company from a specific industrial sector with its own characteristics was evaluated. In the future, several case studies should be carried out in different countries and/or sectors (as Health Care, Petrochemical and Construction, through an intersectoral investigation), to analyze whether there are significant discrepancies regarding the maturity in different contexts. Another research suggestion is to conduct a longitudinal survey and evaluate maturity at different times by applying a roadmap with periodic goals. It is also suggested to conduct a study that considers group decision-making with multi-criteria decision aid methods for I4.0-related problems to solve conflicting views of decision-makers. Finally, it is suggested to create a strategic expert system for addressing maturity gaps (between current and expected states), combined with the business intelligence of the organization, and displaying the results in a dashboard for real-time management of the organization.

## Declaration of competing interest

No potential conflict of interest was reported by the authors.

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## Appendix B: Comparison of I4.0 MMs based on requirements

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Reference	MM	Name of the model	Scope			Components			Reliability/evaluation				Practicality	
			Manufacturing	SCM	Technology	Lightweight descript.	Questionnaire	Architecture	Untested	Verified	Validated	Not transparent	General recommendations	Specific improvement measures
Tolk and Mugirra (2003)	1	Levels of Conceptual Interoperability Maturity – LCIM		●	●			●				●		
Katsma et al. (2011)	2	IoT maturity framework for supply chain systems		●	●	●					●			
Rockwell Automation (2014)	3	The Connected Enterprise Maturity Model	●		●		●			●		●		
Lichtblau et al. (2015)	4	Industrie 4.0 Readiness - IMPULS	●				●		●			●		●
Brandl (2016)	5	MESA Manufacturing Operations Management – MOM/CMM	●					●		●		●		●
Schumacher et al. (2016)	6	MM for I4.0 Readiness	●	●			●			●		●		
Geissbauer et al. (2016)	7	I4.0/Digital Operations-Self Assessment		●				●		●		●		●
Wang et al. (2016)	8	Blockchain MM – BCMM		●	●				●			●		
Leyh et al. (2016)	9	System Integration MM I4.0 - SIMMI 4.0		●	●				●					
Qin et al. (2016)	10	A Categorical Framework of Manufacturing for I4.0 and Beyond	●		●				●			●		
Jung et al. (2016)	11	Smart Manufacturing Readiness Level - SMSRL	●					●		●		●		
Ganzarain and Errasti (2016)	12	Stage process Maturity Model for I4.0	●		●				●					
Gökalp et al. (2017)	13	SPICE-based I4.0 – MM	●		●				●			●		
De Carolis et al. (2017)	14	Digital Readiness Assessment MaturitY model - DREAMY	●				●			●		●		
Pessl et al. (2017)	15	Capability Maturity Model Human	●				●			●		●		
Zheng and Ming (2017)	16	A maturity model for smart	●				●			●		●		●

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Reference	MM	Name of the model	Scope			Components			Reliability/evaluation				Practicality	
			Manufacturing	SCM	Technology	Lightweight descript.	Questionnaire	Architecture	Untested	Verified	Validated	Not transparent	General recommendations	Specific improvement measures
Weber et al. (2017)	17	manufacturing workshop Maturity Model for Data-Driven Manufacturing - M2DDM	●		●				●					
Canetta et al. (2018)	18	A Digitalization Maturity Model	●				●		●			●		
Oleskow-szlapka and Stachowiak (2018)	19	The Logistics 4.0 Maturity Model		●		●			●					
Scremin et al. (2018)	20	Adoption Maturity Model - AMM	●					●		●	●	●	●	
Rübel et al. (2018)	21	Maturity Model for Business Model Management in I4.0		●		●			●					
Stefan et al. (2018)	22	Evolutionary Maturity Based I4.0 Migration Model	●			●			●			●		
Akdil et al. (2018)	23	Maturity and Readiness Model for I4.0 Strategy		●				●		●				
Asdecker and Felch (2018)	24	Delivery Process Maturity Model - DPMM 4.0		●	●			●		●				
Bibby and Dehe (2018)	25	I4.0 maturity assessment framework	●		●			●		●		●		

## Appendix C: Iterations of research

	Iteration 1	Iteration 2				
<b>Process</b>	Model requirements and elements	Category level of initial model				
<b>Method</b>	Literature review	Interviews				
<b>Model element</b>	Category list (dimensions)	Category list (dimensions)				
<b>Test results</b>	Qualitative expert interviews	Evaluation and enhancement with FG1				
<b>Outputs (Model structure)</b>	Comparison of I4.0 MMs (based on requirements) Identification of key elements (levels and dimensions) and key technologies	<u>Maturity level:</u> 1 through 4 <u>Dimensions:</u> 4 SCM, Technology, Sales & Operations Management, and Knowledge, Skills & Attitude				
<b>Changes</b>	-	-				
<b>Data collection</b>	<u>Time frame:</u> until July 2018 <u>Search terms:</u> 'Industry 4.0' AND "maturity models" and synonyms <u>Databases:</u> Scopus, Emerald, Springer, Taylor and Francis, and ISI Web of Science <u>Selection criteria:</u> explicit references to the I4.0 MM for manufacturing operations and supply chains	<u>Time frame:</u> August through September 2018 Interview length: ~30–90 min <u>Demographics:</u> 6 experts who research and has experience in manufacturing digitalization for more than 5 years (one mechanical engineer, one computer engineer, two professors of operations management and two production engineers)				
	Iteration 3					
<b>Process</b>	Revised model (category level)	Sub-category level of initial model	Revised model (Sub-category level)	Model with detailed categories	Revised model (with detailed categories) and initial indicators	Proposed Model and revised indicators
<b>Method</b>	Focus groups (FGs)					
<b>Model element</b>	Sub-category list (perspectives)	Category and sub-category list	Category and sub-category list	Detail category list	Detail category list	Detail category list
<b>Test results</b>	FGI2	FGI3	FGI4	FGI5	FGI6	Deductive literature review
<b>Outputs (Model structure)</b>	<u>Maturity level:</u> 1 through 5 <u>Dimensions:</u> 2 SCM and POM	<u>Maturity level:</u> 0 through 4 <u>Dimensions:</u> 2 SCM and POM <u>Perspectives:</u> 6	<u>Maturity level:</u> 0 through 4 <u>Dimensions:</u> 3 SCM, integration and POM <u>Perspectives:</u> 6	<u>Maturity level:</u> 0 through 4 <u>Dimensions:</u> 3 SCM, SCM & POM and POM <u>Perspectives:</u> 9	<u>Maturity level:</u> 0 through 4 <u>Dimensions:</u> 3 SCM, SCM & POM and POM <u>Perspectives:</u> 7	<u>Maturity level:</u> 0 through 4 <u>Dimensions:</u> 3 SCM, SCM & POM and POM <u>Perspectives:</u> 7 <u>Indicators:</u> 13
<b>Maturity levels:</b> 0 through 4	<u>Dimensions:</u> 3 <u>Perspectives:</u> 7 <u>Indicators:</u> 15					
	<u>Results of this iteration are presented in Tables 1, 2 and 3.</u>					
<b>Changes</b>	- Maturity levels: adoption of concepts from CMM Dimensions were revised.  - Sales was added to SCM while Operations Management was added to POM. - 'Technology' and 'Knowledge, skills & Attitude' became part of the two new dimensions.	- Maturity levels renamed to reflect the level 0 (non-existent) - Dimensions: derived SCM dimension to four perspectives and derived POM dimension to two perspectives. - Perspectives: Suppliers relations, Logistics, Customer relations, Integration, Production management and Planning & Control	- Dimensions: SCM dimension has been adapted without integration - Perspective Integration has been transformed into a dimension, considering three new perspectives: people, processes and technologies. - Perspectives Quality and Maintenance added to POM dimension	- Dimension Integration has changed to SCM & POM to show a wider view of external and internal operations - Perspectives people, processes and technologies were considered one holistic perspective also named Integration - Perspectives from SCM dimension were revised - Detailed perspectives developed	- Perspectives extended significantly - Detailed categories adjusted with focus on technologies and processes - Indicators derived from technologies/ processes associated to each perspective	- Detailed perspectives extended - Indicators revised. Perspective integration derived into three indicators associated to people, process and technologies respectively
<b>Data collection</b>	Time frame: ~90 min, December 2018 <u>FGI1 demographics:</u> Chief Technology Officer (R1), o Industrial engineer with experience with maturity models (R2) , Project Manager with experience in computer modeling (R5) , Electrical engineer with experience in maintenance (R6) , Industrial engineer with experience in logistics (R7) , Mechanical engineer with experience with robotics (R8)	Time frame: ~75 min, December 2018 <u>FGI2 demographics:</u> Industrial engineer with experience with maturity models (R2) , Project Manager with experience in computer modeling (R5) , Electrical engineer with experience in maintenance (R6) , Industrial engineer with experience in logistics (R7) , Mechanical engineer with experience with robotics (R8)	Time frame: ~60 min, January 2019 <u>FGI3 demographics:</u> Industrial engineer with experience with maturity models (R2) , Senior researcher with experience in data integration (R4) , Electrical engineer with experience in maintenance (R6) , Industrial engineer with experience in logistics (R7) , Mechanical engineer with experience with robotics (R8)	Time frame: ~80 min, January 2019 <u>FGI4 demographics:</u> Chief Technology Officer (R1) o Industrial engineer with experience with maturity models (R2) , Senior researcher with experience in data integration (R4) , R&D Consultant with experience in engineering automation (R10) , Artificial Intelligence Engineer (R11) , Civil engineer with experience with construction digitalization (R12)	Time frame: ~60 min, January 2019 <u>FGI5 demographics:</u> Industrial engineer with experience with maturity models (R2) , Project manager with experience in agile projects and lean manufacturing (R3) , Industrial engineer with experience in logistics (R7) , Quality and maintenance specialist (R9) , Front-end developer with web viewing experience (R13)	

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<b>Iteration 3</b>	
<u>Time frame:</u> ~90 min, January 2019 <u>FG16</u>	<u>demographics:</u> Chief Technology Officer (R1), Industrial engineer with experience with maturity models (R2), Mechanical engineer with experience with robots (R8), Civil engineer with experience with construction digitalization (R12) o Data Scientist with experience in machine learning algorithms (R14), Project Manager with experience in business intelligence (R15)
<b>Iteration 4</b>	
<b>Process</b>	Model with assessment instrument
<b>Method</b>	Interviews
<b>Model element</b>	Test assessment tool (questionnaire adjustment)
<b>Test results</b>	Case study
<b>Outputs (Model structure)</b>	Results of this iteration are presented in section 4
<b>Changes</b>	- Instrument: Improvements and better refinement of items/questions - Fuzzy system: knowledge acquisition (rules and membership functions) to fuzzy modeling
<b>Data collection</b>	<u>Time frame:</u> ~60–90 min, July 2019 through August 2019 <u>Demographics:</u> 7 professionals of a Reference Center in Technological Innovation: o Director of a manufacturing SME company, o Technology consultant >10 years of experience with industry automation, o Two mechanical engineers with experience in automation and control of production systems, o Two industrial engineers with experience in digitalization in SCM o Automation engineer with experience with robotic systems
<b>Iteration 5</b>	
<b>Process</b>	Model application
<b>Method</b>	Case survey method
<b>Model element</b>	Implementation of model (empirical validation)
<b>Test results</b>	Multiple case study (future studies)
<b>Outputs (Model structure)</b>	Results of this iteration are presented in section 5
<b>Changes</b>	- Fuzzy system: Simulation to probabilistic analysis of gaps (AS-IS x TO-BE) - Action measures (guidelines) proposed based on key technologies associated to MM level and the corporate profile.
<b>Data collection</b>	<u>Time frame:</u> October 2019. Length: ~30–60 min each respondent <u>Demographics:</u> 8 practitioners from the Brazilian site of a multinational manufacturing organization (three managers, four supervisors and the director)

#### Appendix D. Action plan – Guidelines

Dimension	Perspective	Guideline	Actions
SCM	Customer	1	Initially, this could occur through an interface for sales, in which there would be the possibility of selecting pre-configured models (greater interaction), integrated with after sales with the option of suggestions and assistance services. Then, the sales environment would receive a co-creation module where the customer could propose new products (customization) based on existing parts and modules, and the choices and suggestions made initially would serve as input to advanced AI models, combining ML and sentiment analysis for understanding individual customers' profiles.
	Logistics	2	First, full and secure supply chain integration (process integration) is required with a logistics-ready team and WMS solutions that can integrate storage and inventory. Next, the seamless link generated between the nodes in the chain enables data sharing that could be analyzed with BDA models, optimizing decision-making, improving communication and coordination efficiency, and predicting routes, rhythms, and movement routines.
	Supplier	3	Initially, there should be an e-sourcing SRM platform to create one-to-one communication between buyer and supplier and the use of RFID technology, as well as smart sensors to support transparency and traceability from the supply chain. Next, to achieve a complete exchange of data and information in real-time, cybersecurity with a multifunctional approach is required and must be developed and enforced by everyone involved in the supply chain. One alternative to this would be the development of proprietary Blockchain solutions for sharing information from the supply chain to multiple partners. In addition, to achieve IoT by supporting the creation of full transparency in the supply chain ecosystem, an SRM 4.0 system based on mobile applications and cloud-based ERP solutions that will enable your organization to work with complete remote access and control.
SCM & POM	Integration	4	In principle, there is a need to follow a common IT architecture, setting an interoperability standard for safe and reliable data exchange in the industrial automation space (e.g., through Open Platform Communications Unified Architecture - OPC UA) to ensure the connection between the various devices on the shop floor. Then, to solve strategic problems of interoperability with regard to semantic heterogeneity, the organization may propose the construction of ontologies that can provide information exchange between systems, and even between people, solving communication problems. Given this new infrastructure, it should be possible then to develop and implement dynamic interoperability through a fully integrated ecosystem with self-optimized and virtualized processes, possibly achieving a higher maturity level, which would further contribute to the integration of OSCM domains in the company.
POM	PPC	5	First, there should be the integration of manufacturing systems, the use of advanced data collection sensors, and the start of intelligent decision-making BDA that can guide operations planning and process monitoring automatically through connected dashboards, decreasing waste along the value chain. Then, based on the insights gained from a cloud-based BDA structure, 3D printers, used to

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Dimension	Perspective	Guideline	Actions
Quality	6	generate on-demand customized products, and collaborative robots and drones that seek to reduce downtimes and human risks will be allocated to key processes.	
		First, the organization must have a rooted lean culture with continuous use of advanced quality statistical tools. From this, the organization can virtualize Lean tools and integrate them with digital technologies such as BDA and Learning Factories to achieve Lean 4.0.	
Maintenance	7	Firstly, mobile robots (e.g., drones) can be used in maintenance and operations rooms or used in inventory levels and spare parts deliveries, and the company may focus on the use of virtual reality/augmented reality with 3D models to accelerate training. Subsequently, based on data generated by various connected devices and robots, the organization will be able to use BDA algorithms to automatically monitor and predict asset maintenance in a smart RCM, and can also improve data logging, by making use of wearables and immersive technologies (e.g., thermal cameras 360 and interactive navigation).	

## References

- Akdil, K.Y., Ustundag, A., Cevikcan, E., 2018. Maturity and Readiness Model for Industry 4.0 Strategy. [https://doi.org/10.1007/978-3-319-57870-5\\_4](https://doi.org/10.1007/978-3-319-57870-5_4).
- Aqlan, F., Lam, S.S., 2015. A fuzzy-based integrated framework for supply chain risk assessment. *Int. J. Prod. Econ.* 161, 54–63.
- Asdecker, B., Felch, V., 2018. Development of an Industry 4.0 maturity model for the delivery process in supply chains. *J. Model. Manag.* <https://doi.org/10.1108/JM2-03-2018-0042>.
- Azadegan, A., Porobic, L., Ghazinoory, S., Samouei, P., Saman Kheirkhah, A., 2011. Fuzzy logic in manufacturing: a review of literature and a specialized application. *Int. J. Prod. Econ.* 132, 258–270.
- Babiceanu, R.F., Seker, R., 2016. Big Data and virtualization for manufacturing cyber-physical systems: a survey of the current status and future outlook. *Comput. Ind.* 81, 128–137.
- Becker, J., Knackstedt, R., Pöppelbuß, J., 2009. Developing maturity models for IT management. *Bus. Inf. Syst. Eng.* 1, 213–222.
- Bendul, J.C., Blunck, H., 2019. The design space of production planning and control for industry 4.0. *Comput. Ind.* 105, 260–272.
- Bibby, L., Dehe, B., 2018. Defining and assessing industry 4.0 maturity levels—case of the defence sector. *Prod. Plann. Contr.* 29, 1030–1043.
- Biernhaus, F., Haddud, A., 2018. Procurement 4.0: factors influencing the digitisation of procurement and supply chains. *Bus. Process Manag. J.* 24, 965–984.
- Bogner, E., Voelklein, T., Schroedel, O., Franke, J., 2016. Study based analysis on the current digitalization degree in the manufacturing industry in Germany. *Procedia CIRP* 57, 14–19.
- Bokrantz, J., Skoogh, A., Berlin, C., Wuest, T., Stahre, J., 2019. Smart Maintenance: an empirically grounded conceptualization. *Int. J. Prod. Econ.* 107534. <https://doi.org/10.1016/j.ijpe.2019.107534>.
- Brandl, D., 2016. MESA MOM capability maturity level. White paper. Version 1.0. *Manuf. Enterp. Solut. Assoc.*
- Büyüközkan, G., Göçer, F., 2018. Digital Supply Chain: literature review and a proposed framework for future research. *Comput. Ind.* 97, 157–177.
- Canetta, L., Barni, A., Montini, E., 2018. Development of a digitalization maturity model for the manufacturing sector. In: 2018 IEEE Int. Conf. Eng. Technol. Innov., pp. 1–7.
- Combs, W.E., Andrews, J., 1998. The Combs method for rapid inference. *Fuzzy Syst. Handb.* 659–680.
- Corrêa, A.S., de Assis Mota, A., Mota, L.T.M., Corrêa, P.L.P., 2014. A fuzzy rule-based system to assess e-government technical interoperability maturity level. *Transforming Gov. People, Process Policy* 8, 335–356.
- Coughlan, P., Draaijer, D., Godsell, J., Boer, H., 2016. Operations and supply chain management: the role of academics and practitioners in the development of research and practice. *Int. J. Oper. Prod. Manag.* 36, 1673–1695.
- Culot, G., Orzes, G., Sartor, M., 2019. Integration and scale in the context of Industry 4.0: the evolving shapes of manufacturing value chains. *IEEE Eng. Manag. Rev.* 1–1.
- Cuylen, A., Kosch, L., Breitner, M.H., 2016. Development of a maturity model for electronic invoice processes. *Electron. Mark.* 26, 115–127. <https://doi.org/10.1007/s12525-015-0206-x>.
- Dalenogare, L.S., Benítez, G.B., Ayala, N.F., Frank, A.G., 2018. The expected contribution of Industry 4.0 technologies for industrial performance. *Int. J. Prod. Econ.* 204, 383–394.
- De Bruin, T., Rosemann, M., Freeze, R., Kaulkarni, U., 2005. Understanding the main phases of developing a maturity assessment model. In: Australasian Conference on Information Systems (ACIS). Australasian Chapter of the Association for Information Systems, pp. 8–19.
- De Carolis, A., Macchi, M., Kulvatunyou, B., Brundage, M.P., Terzi, S., 2017. Maturity Models and tools for enabling smart manufacturing systems: comparison and reflections for future developments. *IFIP Adv. Inf. Commun. Technol.* 517, 23–35.
- Ding, L., Lam, H.K.S., Cheng, T.C.E., Zhou, H., 2018. A review of short-term event studies in operations and supply chain management. *Int. J. Prod. Econ.* 200, 329–342.
- Eisenhardt, K.M., 1989. Making fast strategic decisions in high-velocity environments. *Acad. Manag. J.* 32, 543–576.
- Erol, S., Jäger, A., Hold, P., Ott, K., Sihm, W., 2016. Tangible industry 4.0: a scenario-based approach to learning for the future of production. *Procedia CIRP* 54, 13–18.
- Fatorachian, H., Kazemi, H., 2018. A critical investigation of Industry 4.0 in manufacturing: theoretical operationalisation framework. *Prod. Plann. Contr.* 29, 633–644.
- Frank, A.G., Dalenogare, L.S., Ayala, N.F., 2019. Industry 4.0 technologies: implementation patterns in manufacturing companies. *Int. J. Prod. Econ.* 210, 15–26.
- Fraser, P., Moultrie, J., Gregory, M., 2002. The use of maturity models/grids as a tool in assessing product development capability. *IEEE Int. Eng. Manag. Conf.* 1, 244–249.
- Ganzarain, J., Errasti, N., 2016. Three stage maturity model in SME's towards industry 4.0. *J. Ind. Eng. Manag.* 9, 1119–1128.
- Garza-Reyes, J.A., 2020. The future of manufacturing: lean 4.0. The Future Factory. Available at: <https://www.thefuturefactory.com/blog/47>. (Accessed 15 July 2020). Accessed on.
- Gaviao, L.O., Lima, G.B.A., 2015. Indicadores de sustentabilidade para a educação básica por modelagem fuzzy. *Rev. Eletrônica em Gestão, Educ. e Tecnol. Ambient.* 19, 274–297.
- Geissbauer, R., Vedso, J., Schrauf, S., 2016. Industry 4.0: Building the Digital Enterprise, 2016 Glob. Ind. 4.0 Surv. Retrieved from PwC Website. <https://www.pwc.com/gx/en/industries/industries-4.0/landing-page/industry-4.0-building-your-digital-enterprise-april-2016.pdf-1-39>.
- Ghobakhloo, M., 2018. The future of manufacturing industry: a strategic roadmap toward Industry 4.0. *J. Manuf. Technol.* 29, 910–936.
- Gökalp, E., Sener, U., Eren, P.E., 2017. Development of an assessment model for industry 4.0: industry 4.0-MM. In: International Conference on Software Process Improvement and Capability Determination, 0–14.
- Gunasekaran, A., Subramanian, N., Ngai, W.T.E., 2019. Quality management in the 21st century enterprises: research pathway towards Industry 4.0. *Int. J. Prod. Econ.* 207, 125–129.
- Jung, K., Kulvatunyou, B., Choi, S., Brundage, M.P., 2016. An overview of a smart manufacturing system readiness assessment. In: IFIP International Conference on Advances in Production Management Systems. Springer.
- Kar, S., Das, S., Ghosh, P.K., 2014. Applications of neuro fuzzy systems: a brief review and future outline. *Appl. Soft Comput.* 15, 243–259.
- Katsma, C.P., Moonen, H.M., Van Hillegersberg, J., 2011. Supply chain systems maturing towards the internet-of-things: a framework. 24th Bled eConference - eFuture Creat. Solut. Individ. Organ. Soc. Proc. 478–494.
- Klir, G.J., Yuan, B., 1995. *Fuzzy Sets and Fuzzy Logic: Theory and Applications*, p. 563. Up. Saddle River.
- Koh, L., Orzes, G., Jia, F., 2019. The fourth industrial revolution (Industry 4.0): technologies disruption on operations and supply chain management. *Int. J. Oper. Prod. Manag.* 39, 817–828.
- Lamba, K., Singh, S.P., 2017. Big Data in operations and supply chain management: current trends and future perspectives. *Prod. Plann. Contr.* 28, 877–890.
- Leyh, C., Schäffer, T., Bley, K., Forstenhäusler, S., 2016. SIMMI 4.0 – a maturity model for classifying the enterprise-wide it and software landscape focusing on industry 4.0. In: Computer Science and Information Systems (FedCSIS), pp. 1297–1302.
- Lichtblau, K., Stich, V., Bertenrath, R., Blum, M., Bleider, M., Millack, A., Schmitt, K., Schmitz, E., Schröter, M., 2015. Impuls INDUSTRIE 4.0 READINESS. Vdma, pp. 1–76.
- Liebrecht, C., Jacob, A., Kuhnle, A., Lanza, G., 2017. Multi-criteria evaluation of manufacturing systems 4.0 under uncertainty. *Procedia CIRP* 63, 224–229.
- Lins, M.G., Zotes, L.P., Caiado, R., 2019. Critical factors for lean and innovation in services: from a systematic review to an empirical investigation. *Total Qual. Manag. Bus. Excel.* 1–26.
- Lu, Y., 2017. Industry 4.0: A survey on technologies, applications and open research issues. *J. Ind. Inf. Integr.* 6, 1–10.
- Lv, Y., Tu, L., Lee, C.K., Tang, X., 2018. IoT based Omni-Channel logistics service in industry 4.0. In: Proc. 2018 IEEE Int. Conf. Serv. Oper. Logist. Informatics, SOLI 2018, pp. 240–243.
- Maasouman, M.A., Demirli, K., 2016. Development of a lean maturity model for operational level planning. *Int. J. Adv. Manuf. Technol.* 83, 1171–1188.
- Mandani, E.H., Assilian, S., 1975. An experiment in linguistic synthesis with a fuzzy logic controller. *Int. J. Man Mach. Stud.* 7, 1–13.
- Mankins, J.C., 2002. Approaches to strategic research and technology (R&T) analysis and road mapping. *Acta Astronaut.* 51, 3–21.
- Marx, F., Wortmann, F., Mayer, J.H., 2012. A maturity model for management control systems: five evolutionary steps to guide development. *Bus. Inf. Syst. Eng.* 4, 193–207.
- Mendes, P., Leal, J.E., Thomé, A.M.T., 2016. A maturity model for demand-driven supply chains in the consumer product goods industry. *Int. J. Prod. Econ.* 179, 153–165.
- Meng, Y., Yang, Y., Chung, H., Lee, P.H., Shao, C., 2018. Enhancing sustainability and energy efficiency in smart factories: a review. *Sustain. Times* 10, 1–28.

- Mettler, T., 2009. A Design Science Research Perspective on Maturity Models in Information Systems, vol. 41.
- Mittal, S., Khan, M.A., Romero, D., Wuest, T., 2018. A critical review of smart manufacturing & Industry 4.0 maturity models: implications for small and medium-sized enterprises (SMEs). *J. Manuf. Syst.* 49, 194–214.
- Mourtzis, D., Fotia, S., Boli, N., Vlachou, E., 2019. Modelling and quantification of industry 4.0 manufacturing complexity based on information theory: a robotics case study. *Int. J. Prod. Res.* 1–14, 0.
- Nascimento, D.L.M., Alencastro, V., Quelhas, O.L.G., Caiado, R.G.G., Garza-Reyes, J.A., Lona, L.R., Tortorella, G., 2018. Exploring Industry 4.0 technologies to enable circular economy practices in a manufacturing context: a business model proposal. *J. Manuf. Technol.* 32, 942–954.
- Nord, F., Dorbecker, R., Bohmann, T., 2016. Structure, content and use of it service catalogs - empirical analysis and development of a maturity model. *Proc. Annu. Hawaii Int. Conf. Syst. Sci.* 2016-March 1642–1651.
- Oesterreich, T.D., Teuteberg, F., 2016. Understanding the implications of digitisation and automation in the context of Industry 4.0: a triangulation approach and elements of a research agenda for the construction industry. *Comput. Ind.* 83, 121–139.
- Oleskow-szapka, J., Stachowiak, A., 2018. The framework of logistics 4.0 maturity model. In: International Conference on Intelligent Systems in Production Engineering and Maintenance. [https://doi.org/10.1007/978-3-319-97490-3\\_0-11](https://doi.org/10.1007/978-3-319-97490-3_0-11).
- Osiro, L., Lima-Junior, F.R., Carpinetti, L.C.R., 2014. A fuzzy logic approach to supplier evaluation for development. *Int. J. Prod. Econ.* 153, 95–112.
- Pedroso, C.B., Calache, L.D.D.R., Lima Junior, F.R., Silva, A.L. da, Carpinetti, L.C.R., 2017. Proposal of a model for sales and operations planning (S&OP) maturity evaluation. *Production* 27, 1–17.
- Pedrycz, W., Gomide, F., 2007. Fuzzy Systems Engineering: toward Human-Centric Computing (New Jersey).
- Pessl, E., Romina Sorko, S., Mayer, B., 2017. Roadmap industry 4.0 – implementation guideline for enterprises. *Int. J. Sci. Technol. Soc.* 5, 193–202.
- Pourjavad, E., Shahin, A., 2018. The application of Mamdani fuzzy inference system in evaluating green supply chain management performance. *Int. J. Fuzzy Syst.* 20, 901–912.
- Qin, J., Liu, Y., Grosvenor, R., 2016. A categorical framework of manufacturing for industry 4.0 and beyond. *Procedia CIRP* 52, 173–178.
- R Core Team, 2019. R: A Language and Environment for Statistical Computing. Vienna R Found. Stat. Comput. <https://www.R-project.org/>.
- Rahmanifard, H., Plaksina, T., 2019. Application of artificial intelligence techniques in the petroleum industry: a review. *Artif. Intell. Rev.* 52, 2295–2318.
- Ras, E., Wild, F., Stahl, C., Baudet, A., 2017. Bridging the skills gap of workers in industry 4.0 by human performance augmentation tools. In: Proc. 10th Int. Conf. PErvasive Technol. Relat. To Assist. Environ. - PETRA '17, pp. 428–432.
- Rockwell Automation, 2014. The connected enterprise maturity model. *Ind. Conectada*, 4.0 1–12.
- Röglinger, M., Pöppelbuß, J., Becker, J., 2012. Maturity models in business process management. *Bus. Process Manag. J.* 18, 328–346.
- Rübel, S., Emrich, A., Klein, S., Loos, P., 2018. A maturity model for business model management in industry 4.0. Multikonferenz Wirtschaftsinformatik. In: MKWI 2018 - Multiconference Bus. Informatics, MKWI 2018 2018-March, pp. 2031–2042.
- Schuh, G., Anderl, R., Gausemeier, J., Hompel ten, M., Wahlster, W., 2017. Industrie 4.0 maturity index. Acatech Study 62.
- Schumacher, A., Erol, S., Sihm, W., 2016. A maturity model for assessing industry 4.0 readiness and maturity of manufacturing enterprises. *Procedia CIRP* 52, 161–166.
- Scremin, L., Armellini, F., Brun, A., Solar-Pelletier, L., Beaudry, C., 2018. Towards a Framework for Assessing the Maturity of Manufacturing Companies in Industry 4.0 Adoption. <https://doi.org/10.4018/978-1-5225-3468-6.ch012>.
- Scurati, G.W., Gattullo, M., Fiorentino, M., Ferrise, F., Bordegoni, M., Uva, A.E., 2018. Converting maintenance actions into standard symbols for Augmented Reality applications in Industry 4.0. *Comput. Ind.* 98, 68–79.
- Seuring, S., Gold, S., 2012. Conducting content-analysis based literature reviews in supply chain management. *Supply Chain Manag. An Int. J.* 17, 544–555.
- Siddique, N., Adeli, H., 2013. Computational Intelligence: Synergies of Fuzzy Logic, Neural Networks and Evolutionary Computing. NJ Wiley, Hoboken.
- Skapinycz, R., Illés, B., Bánya, I., 2018. Logistic aspects of industry 4.0. *IOP Conf. Ser. Mater. Sci. Eng.* 448, 0–11.
- Sony, M., 2019. Key ingredients for evaluating Industry readiness for organizations: a literature review. *Benchmark Int. J.* <https://doi.org/10.1108/BIJ-09-2018-0284>.
- Stefan, L., Thom, W., Dominik, L., Dieter, K., Bernd, K., 2018. Concept for an evolutionary maturity based Industrie 4.0 migration model. *Procedia CIRP* 72, 404–409.
- Tangpong, C., 2011. Content analytic approach to measuring constructs in operations and supply chain management. *J. Oper. Manag.* 29, 627–638.
- Thomé, A.M.T., Scavarda, L.F., Scavarda, A.J., 2016. Conducting systematic literature review in operations management. *Prod. Plann. Contr.* 27, 408–420.
- Tolk, A., Muguiria, J., 2003. The levels of conceptual interoperability model. *Fall Simul. Interoperability Work.* 1–9.
- Tortorella, G., Nascimento, D., Caiado, R., Posada, J.G.A., Sawhney, R., 2019. How do different generations contribute to the development of a learning organization in companies undergoing a lean production implementation? *Learn. Organ.*
- Tremblay, M.C., Hevner, A.R., Berndt, D.J., 2010. Focus groups for artifact refinement and evaluation in design research. *Commun. Assoc. Inf. Syst.* 26, 599–618.
- Vose, D., 2008. Risk Analysis: a Quantitative Guide. John Wiley Sons, New York.
- Voss, C., 2010. Case Research in Operations Management. *Res. Oper. Manag. Routledge*, pp. 176–209.
- Wang, H., Chen, K., Xu, D., 2016. A maturity model for blockchain adoption. *Financ. Innov.* 2.
- Wang, Y., Singgih, M., Wang, J., Rit, M., 2019. Making sense of blockchain technology: how will it transform supply chains? *Int. J. Prod. Econ.* 211, 221–236. <https://doi.org/10.1016/j.ijpe.2019.02.002>.
- Weber, C., Königsberger, J., Kassner, L., Mitschang, B., 2017. M2DDM - a maturity model for data-driven manufacturing. *Procedia CIRP* 63, 173–178.
- Weinschenk, J.J., Marks, R.J., Combs, W.E., 2003. Layered URC fuzzy systems: a novel link between fuzzy systems and neural networks. In: *Proc. Int. Jt. Conf. Neural Networks*, vol. 4, pp. 2995–3000.
- Weking, J., Stöcker, M., Kowalkiewicz, M., Böhm, M., Krcmar, H., 2019. Leveraging industry 4.0 – a business model pattern framework. *Int. J. Prod. Econ.* <https://doi.org/10.1016/j.ijpe.2019.107588>.
- Wong, B.K., Lai, V.S., 2011. A survey of the application of fuzzy set theory in production and operations management: 1998-2009. *Int. J. Prod. Econ.* 129, 157–168.
- Zadeh, L.A., 1965. Fuzzy sets. *Inf. Control* 8, 338–353.
- Zaidin, N.H.M., Diah, M.N.M., Po, H.Y., Sorooshian, S., 2018. Quality management in industry 4.0 era. *J. Manag. Sci.* 8, 82–91.
- Zanon, L.G., Munhoz Arantes, R.F., Calache, L.D.D.R., Carpinetti, L.C.R., 2019. A decision making model based on fuzzy inference to predict the impact of SCOR® indicators on customer perceived value. *Int. J. Prod. Econ.* 107520.
- Zheng, M., Ming, X., 2017. Construction of cyber-physical system-integrated smart manufacturing workshops: a case study in automobile industry. *Adv. Mech. Eng.* 9, 1–17.
- Zimmermann, H.J., 2010. Fuzzy set theory. *Wiley Interdiscip. Rev. Comput. Stat.* 2, 317–332.