Developing an Industry 4.0 Readiness Model Using Fuzzy Cognitive Maps Approach

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Abstract

Industry 4.0, or the fourth industrial revolution, is a new paradigm in manufacturing digitalization, which provides various opportunities for enterprises. Industry 4.0 readiness models are worthy methods to aid manufacturing organizations in tracking the development of their businesses and operations. Nevertheless, there are different Industry 4.0 readiness models; no work has yet analyzed Industry 4.0 readiness degree and causal effects relationships using fuzzy cognitive maps. This paper proposes an Industry 4.0 readiness model that consists of readiness requirements obtained from the literature and validated through a mixed-method approach, including literature reviews and questionnaires. To validate the proposed Industry 4.0 readiness model, the exploratory fmethods of exploratory and confirmatory factorsfuzzy Cognitive Map is utilized to assess readiness, identify relevant concepts to improve readiness degree, implement Industry 4.0, and analyze causal relationships among concepts and dimensions. Through this model and the FCM method, managers can recognize relevant concepts and predict complicated cause-effect relationships among concepts in two states of static and dynamic analyses to increase readiness degree. The paper concludes by emphasizing managerial implications for successful applications in practice as well as future research suggestions on developing the Industry 4.0 readiness model.

Keywords: Industry 4.0; Readiness Model; Fuzzy Cognitive Maps (FCM)

1. Introduction

Nowadays, emerging technologies make alterations in traditional manufacturing companies and shift them into Smart Factories, which move people, products, information, and technology-based machines towards digitalized and automated environments (B. Chen et al., 2017). New technologies also trigger new business models and changes in production systems, consumption, transportation, distribution and so on (Rajnai & Kocsis, 2018). The advent of a diversity of technologies such as the Internet of Things (IoT), Internet of Services (IoS), Big Data, Big Data Analytics, Cyber-Physical Systems (CPS), Autonomous Robots, and Cloud Computing introduce "the Fourth Industrial Revolution" (Rafael, Jaione, Cristina, & Ibon, 2020; Schumacher, Erol, & Sihn, 2016; Wagire, Joshi, Rathore, & Jain, 2020) and indicate the decentralization of information, flexibility, real-time data collection and create an interoperability connection (Murri, Streppa, Colla, Fornai, & Branca, 2019). Industry 4.0 has attracted significant consideration from academics, governmental officials, and politicians globally (Kagermann, Helbig, Hellinger, & Wahlster, 2013) and has been perceived by various authors (B. Chen et al., 2017; Mrugalska & Wyrwicka, 2017; Zhou, Liu, & Zhou, 2015) as a business model in which horizontal, vertical, and end-to-end integrations are necessary to be managed (Chiarini & Kumar, 2021). Horizontal integration indicates the integration among customer service processes, operations, and the supply chain (Chiarini & Kumar, 2021), which facilitates data sharing between the organization supply chains (Govender, Telukdarie, & Sishi, 2019); vertical integration indicates the integration of the production level with higher business levels (Chiarini & Kumar, 2021) which facilitate data flow from manufacturing systems to the ERP (Govender et al., 2019);

and end-to-end integration indicates the integration of the whole value chain, ranging from product design and development to customer experience and fulfillment (Chiarini & Kumar, 2021).

There is a lot of traction amongst leaders of organizations to implement Industry 4.0 technologies; however, they do not know how to adapt their manufacturing process to implement industry 4.0 (Rajnai & Kocsis, 2018). On the other hand, Industry 4.0 positively impacts business processes and makes them more productive and efficient (Murri et al., 2019). The implementation of Industry 4.0, thus, would be beneficial to meet critical objectives such as cost efficiency, flexibility, agility, and customer-centric production systems (Miśkiewicz & Wolniak, 2020).

Industry 4.0 transformation needs a comprehensive outlook on the firm's strategy, operations, technologies, organization, and products (Akdil, Ustundag, & Cevikcan, 2018). It requires prerequisites such as standardization (systems, protocols, communications), availability of smart products, emerging technologies such as Internet of Things, big data analysis, cloud computing, new business models, supporting and affording skilled workers, and so on (Gül T. Temur, Bolat, & Gözlü, 2019). Such prerequisites are the foundation for the successful implementation of Industry 4.0, as suggested by Hungarian Industry 4.0, National Technology Platform- "*The foundation is the real-time availability of all relevant information through the integration of all objects in the value chain and the capacity to determine the optimal value flow at any time from the data. The interconnection of people, objects, and systems produces dynamic, real-time-optimized, self-organizing, cross-enterprise value-adding networks that can be optimized according to various criteria such as cost, availability, and resource consumption"* (The term Industrie 4.0 (in Hungarian: Az Ipar 4.0 fogalma)., 2017, p. 1). It is, therefore, necessary to understand and assess the degree of readiness of the company to embrace Industry 4.0. To determine the readiness degree, we must begin by understanding and defining "readiness". Simpson and Winer explain readiness *as "the state of being fully ready or prepared for something" or "willing to do"* (Dictionary, 1989). Readiness also is described as the *"state in which an organization is ready to accomplish a task"* (Pacchini, Lucato, Facchini, & Mummolo, 2019, p. 1).

After introducing the Industry 4.0 paradigm, industry and academic researchers examined, developed, and introduced new concepts to assess the fourth industrial revolution's readiness to implement in organizations. As e result, various readiness models have been developed for a variety of purposes in different aspects, such as manufacturing systems (Vivares, Sarache, & Hurtado, 2018), ERP readiness assessment (Ahmadi, Papageorgiou, Yeh, & Martin, 2015; Razmi, Sangari, & Ghodsi, 2009), digital financial innovation (Hussain & Papastathopoulos, 2022), business process management (Tarhan, Turetken, & Reijers, 2016) and so forth. Similarly, different readiness models also have been developed for Industry 4.0 (Akdil et al., 2018; Pacchini et al., 2019; Rafael et al., 2020; Schumacher et al., 2016). However, the existing Industry 4.0 readiness models have certain limitations. Some models, on the one hand, were developed based on the technological aspects of the company and dimensions of these models were focused on assessing aspects like analyzing the amount of usage information technologies, Internet of Things and etc. On the other hnd, a few of them, were developed according to non-technological aspects to assess the readiness degree of dimensions such as strategy, culture and so forth. It is important to note that when it comes to developing an industry 4.0 readiness model, we need to develop a model which provides us with a comprehensive outlook of the company by analyzing various aspects ranging from technological perspectives (like using emerging technologies) to non-technological viewpoints (like employees' readiness degree, the culture of the company, and so on). Moreover, as mentioned earlier, Industry 4.0 interconnect people, objects, technologies and so on to each other to create an integrated physical and virtual world. Accordingly, to develop an Industry 4.0 readiness model, considering relationships among concepts and dimensions would be important. Consequently, the current contributions did not consider developing a holistic Industry 4.0 readiness model and evaluating the readiness degree and impact of both technological and non-technological concepts on each other which can be seen as the significant research gaps.

This paper aims to develop an Industry 4.0 readiness model and analyze relations among concepts. To do so, we utilize the Fuzzy Cognitive Maps method. Using this method provides an opportunity to distinguish the relationships among technological and non-technological aspects to assess the company's readiness to implement Industry 4.0. Peters (2017, p. 22) stated, "Industry 4.0 is more a paradigm or philosophy than a technology". This paradigm, therefore, affects industries extensively which has caused changing the relationships between organizations, products and services, organizations and value chains, and humans, from employees to customers (Sony & Naik, 2019). Furthermore, companies are dynamic systems, and an alteration in one concept can justify changes to the other concepts and the company's overall readiness. It is, thus, essential to use the assessment method regarding the causal relationships between concepts in the companies, such as relationships among smart products and customers. That is why we need to use a method such as Fuzzy Cognitive Maps (FCM) to model the relationships between concepts and dimensions. Here, we need to define concept and dimension. According to the Oxford English Dictionary (OED), the term "concept" is defined as *"an idea or a principle that is connected with something,"* and "Dimension" is defined as *"an aspect of something."* FCM methods have become an appealing way to successfully model real-world issues, revealing a solid capability to grab the dynamics of complicated environments (Christoforou & Andreou, 2017). In fuzzy cognitive maps, the concept is represented individually by its activation degree, which signifies to what extent this variable impacts other. The fuzzy approach permits us to have degrees of causality, defined relations between the concepts (Nápoles, Espinosa, Grau, & Vanhoof, 2018). In other words, using FCM, we can identify concepts that have the highest effect on the degree of readiness and focus on essential concepts to improve/increase readiness degree and predict all casual effects between concepts, dimensions, effects on each other, and overall readiness of company. For instance, using the FCM method, we can estimate the impact of concept number one on concept number two and vice versa and their effects on the overall readiness of the company.

To the best of our knowledge, this contribution is the first work to take advantage of FCM for analyzing cause-effect relationships and assessing the Industry4.0 readiness degree. The differences between this paper and previous contributions are substantial as stated below.

- Regarding developing the Industry 4.0 readiness model, some of the existing readiness models like Samaranayake, Ramanathan, and Laosirihongthong (2017), Pacchini et al. (2019), Tortora, Maria, Iannone, and Pianese (2021), and Castelo-Branco, Cruz-Jesus, and Oliveira (2019) have been developed considering technological points of view, and non-technological aspects are ignored. The rest of the models, such as M Ichsan and Dachyar (2019) only focused on non-technological factors. While to develop an Industry 4.0 readiness model, paying attention to all aspects of technological and non-technological would be important. Developing a holistic model, thus, is required.
- The other contribution is using a unique measurement method to assess readiness degree. Previous works used linear measurement to assess readiness degree while applying non-linear measures leads to significant outcomes for researchers and managers. Using the FCM method as a non-linear measurement, managers can identify concepts that have the highest effect on improving the company's readiness level, which would result in time-saving and cost-effectiveness activities for them.
- Managers can also examine static and dynamic analysis using FCM. They can analyze cause-effect relationships among concepts and dimensions. Through static analysis, managers can focus on essential concepts to improve the overall readiness of the company. Moreover, using dynamic analysis, they can predict various scenarios for the company's future which are close to the real-world.

The rest of the paper is structured as follows. In section 2, the research background has been reviewed in three areas: Industry 4.0 overview, Industry 4.0 readiness models, and fuzzy cognitive maps. In section 3, research processes are described, and in section 4 Industry 4.0 readiness model's concepts and dimensions are extracted, and confirmatory factor analysis and exploratory factor analysis are used to categorize the readiness model and propose it. The Fuzzy Cognitive Map, then, is applied to predict all casual relationships between concepts, dimensions, and their effects on each other. The results of FCM examine in section 5.

2. Literature review

2.1. Industry 4.0 overview

The first industrial revolution spanned from 1760 to 1840 and caused essential Industry changes by using steam and hydropower. This revolution was followed by the second industrial revolution, around the turn of the twentieth century, which saw the introduction of mass production by promoting and developing electricity and assembly methods. One of the most significant achievements is Ford's company (Lom, Pribyl, & Svitek, 2016). In the third industrial revolution, which started around 1969, computers and information technologies combined manufacturing processes. The fourth industrial revolution, also known as "Industry 4.0," emerged from a project initiated by the German government's high-tech strategy in 2011 to extend production computerization (Kagermann et al., 2013; TRADE, 2014).

To develop Industry 4.0, main features are identified that help the evolution of intelligent production systems in the future (Europe, ins, & Initiative; M. Y. Santos, J. O. e Sá, et al., 2017); including:

- Interoperability, integrity, and awareness: consider the degree of systems collaboration in utilizing capabilities, sharing information, and intelligent decision making (Akdil et al., 2018; D. Chen, Doumeingts, & Vernadat, 2008).
- Virtualization: permitting remote traceability and monitoring of all processes using different sensors, making smart factories;
- Service orientation: utilizing service-oriented software along with the internet of things;
- Real-time operation capability: ability of real-time decision making, instant data gathering and processing;
- Modularity: production processes based on the order, coupling, and decoupling of modules in production;
- Decentralization: it refers to the capability of cyber-physical systems to make decisions independently and produce locally, taking advantage of technologies like 3D printing.

There are also key technologies that enable implementing Industry 4.0. In table 1, technologies and their definition are gathered.

Table 1: Industry 4.0 technologies

Technology	Explanation
Internet of Things	IoT contains networking physical gadgets, internet of services (IoS), Industrial Internet of Things (IIoT), internet manufacturing services, internet of people (IoP), machines, vehicles, and environments by using embedded electronic tools and allowing the collection and exchanging of information (M. Y. Santos, J. Oliveira e Sá, et al., 2017).
Cyber-Physical Systems (CPS)	CPS describes the combination of embedded systems and the Internet to connect physical things (Broy, 2013; Matana, Simon, Godinho Filho, & Helleno, 2020).
Cloud Computing	Cloud explains the platform and infrastructure delivered as services on private or public networks on a pay-per-use basis. CPS produces an enormous volume of information required to be collected and processed. Cloud technology provides analysis results to be available anywhere around the world, at any time, as an essential technology of Industry 4.0 (Santos, Loures, Piechnicki, & Canciglieri, 2017).
Additive Manufacturing	Additive manufacturing, also called 3D-Printing, refers to three-dimensional manufacturing objects directly from virtual models. This technology provides localized, dispensed, and reconfigurable manufacturing that will alter supply chains entirely. Additionally, additive manufacturing is crucial for mass customization by decreasing production time and costs to establish individual products (M. Y. Santos, J. Oliveira e Sá, et al., 2017).
Artificial Intelligence	Using machines that perform a human-like cognitive function like understanding, learning, reasoning, and so on (Europe et al.).
Industrial Internet of Things	Describing the connection of devices to the Internet's network of networks utilizing sensors connected with big data analytics and cloud computing (Culot, Nassimbeni, Orzes, & Sartor, 2020; Europe et al.).
Autonomous Robot	Autonomous robots are used to accomplish independent manufacturing procedures more precisely and work in locations where workers are limited. Robots are also becoming increasingly autonomous, flexible, and collaborative day by day and will undoubtedly interact with each other and work safely alongside humans and learn from them (Vaidya, Ambad, & Bhosle, 2018).

Big Data and Analytics	Big data contains four dimensions: Volume, Variety, Velocity, and Value. Big Data connected with analytics permits to development of robust pattern recognition and automated functions (Europe et al.).
Augmented Reality	Supplies employees with real-time information to improve decision making and work procedures, therefore, supporting the production processes (Europe et al.).
Machine to Machine	Utilizing an enormous number of autonomous machines, communication technologies are swiftly rising. According to protocols, this communication method permits the independent managing of industrial organizations (Moeuf, Pellerin, Lamouri, Tamayo-Giraldo, & Barbaray, 2018).
Cyber Security	One of the main challenges to Industry 4.0 lies in the security and sustainability of Information Systems. Therefore, secure and trustworthy communications, complex identity, access management of machines and users are crucial (Vaidya et al., 2018)

It is essential to point out that Industry 4.0 is about more than just using cutting-edge technologies (Bai, Dallasega, Orzes, & Sarkis, 2020); it is about how those technologies are connected and how organizations can harness them to conduct operations and growth. As far as organizations are concerned, they struggle with various issues such as talent challenges, rising supply chain complexity, increasing competitive pressures, rapidly developing technological powers, and so on (Dieste, Sauer, & Orzes, 2022). Industry 4.0 technologies and principles address such issues. Industry 4.0 technologies can alter the creation and development of products and services. Analyzing and learning from data in real-time cause organizations to be proactive, predictive, and capable. Connected technologies can also guide completely new products and services. Using sensors and wearables, machine learning and analytics, as well as state-of-the-art manufacturing in the shape of robotics and additive manufacturing, can stimulate product improvements in manifold ways, which ultimately lead to new business models (Bai et al., 2020). Customer experience in Industry 4.0 would be driven not only through physical objects but also via information, analytics, and customization, which cause the customer′s interaction (Deloitte, 2017).

Using data gathered via smart products and services and information from connected systems enriches the customer experience. Marketing strategies offer customer post-sales support and heighten the customer relationship (Deloitte, 2017). Culture of the organization and employees are fundamental parts of implementing Industry 4.0, owing to their power and value (Schwab, 2017). Companies also use intelligent technologies and smart media, so employees′ competency and skill demands would be higher. An alternation in the current processes is also accentuated. A new strategic approach to include human resources management, therefore, cause to allow more straightforward implementation of new technologies and qualifications (Hecklau, Galeitzke, Flachs, & Kohl, 2016). Nonetheless, Industry 4.0 provides benefits and potentials for organizations, the majority of organizations are confused and unsure where to start the implementation journey. In other words, Industry 4.0 leaders need to focus their endeavors while they are not clear about in which areas to focus their Industry 4.0 initiatives.

2.2. Industry 4.0 readiness models

This study contributes to the debate on existing Industry 4.0 readiness models. To analyze critical points from the current contributions, we did a literature review according to (Andriolo, Battini, Grubbström, Persona, & Sgarbossa, 2014) and (Wolfswinkel, Furtmueller, & Wilderom, 2013) guidelines and conduct four steps (Table 2). To do so, keywords including “Industry 4.0 readiness model”, “Industry 4.0 readiness assessment” and “Industry 4.0 readiness framework” are searched from 2010 to 2022 in Web of Science, Scopus, and Google Scholar as a database.

We found 379 articles from the used database, of which the number of 12 papers and 263 were respectively removed based on exclusion criteria 1 (EC1) and 2 (EC2). Therefore, 91 papers were removed according to (EC3) which include industry 4.0 readiness models have been developed by consulting firms such as some web-based self-assessments like PwC (Industry 4.0 Self-Assessment), IMPULS – Industrie 4.0 Readiness (Foundation of the German Engineering Federation), BMWi (Federal Ministry for Economic Affairs and Energy Germany), Roland Berger Industry 4.0 Readiness Index, Industry 4.0 readiness assessment tool (The University of WARWICK) and IHK (Deutscher Industrie). It is worth to mention these tools analyze five Industry 4.0 dimensions: culture, strategic, organizational, and technical aspects

(products and processes), and employees' dimensions. Although these models attract practitioners considerably, they do not reveal background data for benchmarking. Furthermore, existing models utilize maturity and readiness interchangeably, while some studies differentiate between readiness (preparing for an initial implementation) and maturity (following development) (Akdil et al., 2018; Botha, 2018).
Generally, readiness assessment purposes recognizing opportunities, risks, obstacles to success, and potential challenges (Pirola, Cimini, & Pinto, 2019). Becker et al. (2009) stated that the readiness assessment models aim to evaluate a company's position concerning the current readiness of concepts of a company. Since we intend to assess the readiness degree and analyze cause-effect relationships between concepts and their impact on overall readiness, we discuss Industry 4.0 readiness models in the literature review. Two papers were also removed because they reviewed Industry 4.0 readiness models and did not develop a conceptual model. Finally, a total of 11 papers remained acceptable for examination.

Table 2: Reviewing methodology

Step	Inclusion criteria (IC)	Exclusion criteria (EC)	Papers found
1. Defining the scope of the review: Using Web of Science, Scopus, and Google Scholar as a database.	---	---	---
2. Searching for a preliminary list of papers: Keywords including Industry 4.0 Readiness Model, Industry 4.0 Readiness Framework, and Industry 4.0 Readiness Assessment are used.	---	---	379
3. Selecting relevant papers	Papers are in English (IC1)		367
	---	Papers are not in English (EC1)	12
	---	Papers are duplicate (EC2)	263
	---	Papers are about developing an Industry 4.0 maturity model/ using readiness and maturity interchangeably/ used selected keywords in the section of keywords and etc. (EC3)	91
	---	Papers reviewed Industry 4.0 readiness models and did not develop a readiness model (EC4)	2
	Papers developed an Industry 4.0 readiness model (IC2)	---	11
4. Investigate data from the included papers	---	---	11

Analyzing 11 remaining papers, various readiness models considering specific criteria and dimensions have been developed in different industries and companies, from SMEs to manufacturing industries. Schumacher et al. (2016) have designed the Industry 4.0 readiness and maturity model consisting of nine dimensions "Customers," "Strategy," "Culture," "Leadership," "People," "Products," "Operations," "Technology" and "Governance." This model is implemented in an Austrian manufacturing company producing physical goods in-house with their manufacturing machinery. Authors used linear measurement to analyze the degree of maturity and ignored relationships between dimensions and items, their impact on each other, and, more importantly, overall maturity. Samaranayake et al. (2017) identified important and relevant factors for implementing Industry 4.0 from a technological readiness aspect. The authors developed a readiness model into six categories of technological readiness. However, this contribution did not consider non-technological aspects of the readiness model and the relation between technological elements. Pacchini et al. (2019) developed an Industry 4.0 readiness model, which is comprised of eight technologies, including the Internet of things, Big data, Cloud computing, Cyber-physical system, Collaborative robots, Additive manufacturing, Augmented reality, and Artificial intelligence. This model was implemented in an engine manufacturing company in Brazil, concentrated on the technology dimension, and ignored the other essential dimensions that considerably affect readiness degree.

Moreover, a linear measurement method is used to analyze the degree of readiness. To assess Industry 4.0 readiness, Temur et al. (2019) applied the IMPULS self-assessment readiness model in Turkish construction, textile, and wire production. Using a self-assessment model has some drawbacks; because this kind of model dose not concern particular Industry conditions. Furthermore, linear measurement was used, and relationships between dimensions and their effects on each other and total readiness were not considered in their analysis. Ichsan et al. (2019) have presented the current manufacturing state of Indonesia's food and beverage industry using a Technology Organizational Environment (TOE) model. Analytical Network Process (ANP), then, is introduced to reflect the correlation among criteria based on readiness perspective; however, this model ignored relationships among dimensions, for instance, the effects of technology on the organization dimension and vice versa, and their effects on each other and overall readiness.

Table 3: Analyzing existing Industry 4.0 readiness models

	Readiness Model	Model focus		Assessment method		Source
		Technological	Non-technological	Linear	Non-linear	
1	Industry 4.0 readiness and maturity model	*	*	*		(Schumacher et al., 2016)
2	Implementing Industry 4.0 - A Technological Readiness Perspective	*			*	(Samaranayake et al., 2017)
3	Industry 4.0 readiness model	*		*		(Pacchini et al., 2019)
4	Evaluation of Industry 4.0 Readiness Level	*	*	*		(Gül T Temur, Bolat, & Gözlü, 2018)
5	Readiness for Implementing Industry 4.0 in Food and Beverage Manufacturer in Indonesia	*	*	*		(M Ichsan & Dachyar, 2019)
6	Industry 4.0 readiness in manufacturing companies: challenges and enablers towards increased digitalization	*	*	*		(Machado et al., 2019)
7	Worker readiness for Industry 4.0	*	*	*		(Blayone & VanOostveen, 2021)
8	A survey study on Industry 4.0 readiness level of Italian small and medium enterprises	*		*		(Tortora et al., 2021)
9	Assessing Industry 4.0 readiness in	*		*		(Castelo-Branco et al., 2019)

	manufacturing: Evidence for the European Union					
10	Industry 4.0 readiness in Hungary: model, and the first results in connection to data application		*	*		(Nick, Szaller, Bergmann, & Várgedő, 2019)
11	Industry 4.0 readiness in manufacturing: Company Compass 2.0, a renewed framework and solution for Industry 4.0 maturity assessment	*	*	*		(Nick, Kovács, Kő, & Kádár, 2021)

Regarding models analyzed (Table 3), there are two exciting research gaps to be explored in this study. First and foremost, former readiness models are either technology-focused and ignore other organizational dimensions or focus on non-technology aspects. Some readiness models included technological points of view, such as models were developed by Samaranayake et al. (2017), Pacchini et al. (2019), Tortora et al. (2021), and Castelo-Branco et al. (2019). Although Schumacher et al. (2016) and (M Ichsan & Dachyar, 2019) and (Machado et al., 2019) have considered both technological and non-technological concepts, all-important Industry 4.0 technologies were not included. They also used readiness and maturity interchangeably, while there is a difference between them. Though Nick et al. (2021) considered the digital twin in the readiness model, vital technologies were ignored. Nick et al. (2019) developed a readiness model in which important concepts from technological and non-technological points of view did not consider concepts like culture and leadership and management from a non-technological viewpoint and Industry 4.0 technologies from a technological perspectives. Blayone and VanOostveen (2021) developed the readiness model, which is appropriate to assess employees' readiness, not for evaluating the readiness of companies.

Secondly, existing readiness models used linear calculation to assess the readiness degree. None of them has considered relationships between dimensions and concepts and their impacts on the overall readiness of a company. With regard to the analyzed model, it can be concluded that existing readiness models do not meet our perspectives to assess the readiness degree from various points of view – technological and non-technological concepts. We, hence, develop an Industry 4.0 readiness model in which both technological and non-technological aspects of Industry 4.0 are included. Using the fuzzy cognitive map, we can consider all existing relationships and, more importantly, vital relationships that significantly impact readiness degrees.

2.3. Fuzzy cognitive maps

Political scientist Robert Axelrod (1976) introduced cognitive maps in the 1970s for modeling causal connections between concepts, in which concepts and their causal relationships are depicted in a graph. CMs cannot represent the power of causal relations, and direct deduction using CMs sometimes leads to baffling conclusions (Kosko, 1986; Yuan, Zhi-Qiang, Chee Kheong, & Chun Yan, 2001). For specific reasons, in 1986, Kosko introduced fuzzy cognitive maps (FCMs) as a tool to model and examine causality in qualitative systems and reveal relationships among variables as well as to comprehend and communicate system dynamics (Gray et al., 2015) in a variety of disciplines like political sciences (Andreou, Mateou, & Zombanakis, 2005), business (Xirogiannis & Glykas, 2004), engineering (Stylios & Groumpos, 2004), soft engineering (Salmeron & Lopez, 2011), and environmental sciences (Elpiniki I. Papageorgiou, 2011).

Modeling via FCMs proposes several benefits such as flexibility in representation, effortless construction, short time performing, handling complicated problems relevant to knowledge elicitation and management, addressing dynamic effects due to the modeled system's feedback structure, and so forth (Elpiniki I Papageorgiou & Salmeron, 2014).

FCMs is a modeling methodology for elaborate systems emerging from a combination of fuzzy logic and neural networks (Kosko, 1986). It can combine experts' knowledge and existing knowledge from data in the form of rules (Elpiniki I Papageorgiou & Salmeron, 2014).

Generally, concepts of an FCM indicate key components and features of the illustrated complex system and include goals, inputs, outputs, events, states, variables, and trends of the complex system (P. Groumpos, 2010). FCMs are directed diagrams capable of modeling connections or causalities between concepts. Each concept is identified by a number A_i that shows its value and outcomes from altering the real value of the system's variable. Therefore, concepts grab the values in the range among [0.1], and the weights of the arcs are in the interval [-1, 1] (León, Rodriguez, García, Bello, & Vanhoof, 2010; P. Groumpos, 2010). Every relationship between two concepts has a weight, which shows the power of the relationship between them. This weight is achieved by transforming the fuzzy values defined by experts into numerical quantities. Connections between concepts have three feasible kinds; (1) Positive causality between two concepts (W_{ij}>0), (2) Negative causality between two concepts (W_{ij}<0), (3) No connections between two concepts (W_{ij}=0). Each concept's value is affected by the values of the related concepts with suitable weights and by its preceding value. So, value A_i for each concept C_i is calculated by the following rule demonstrated in (Equation 1).

$$A_i^t = f(\sum_{\substack{j=1 \\ j\neq 1}}^{n} A_j^{t-1}\, W_{ij} + A_j^{t-1}) \text{ (Equation 1).}$$

Regarding Equation 1, where A_i^t is the value of concept C_i at time t, A_i^t the value of concept C_i at time t-1, A_i^{t-1} the value of concept C_j at time t-1 and the weight W_{ji} of the interconnection from concept C_j to concept C_i. The function f is a threshold function and the results are in the interval [0, 1]. This value implies at which level this concept will be activated. This activation level can be analyzed as a relative abundance (Hobbs et al., 2002). Precisely, the activation level can define membership in a fuzzy set representing linguistic calculations of relative abundance (e.g., low, average, and high) (Kosko, 1986). In this contribution, to overcome the limitation shown by the sigmoid function, we employed the transformed version of Equation (1) as follow (Elpiniki I. Papageorgiou, 2011).

$$A_i^t = f(\sum_{\substack{j=1 \\ j\neq 1}}^{n} (2A_j^{t-1}\text{-}1)\, W_{ij} + 2A_j^{t-1} - 1) \text{ (Equation 2)}$$

Moreover, the uni-polar sigmoid function is utilized to activate any concept’s value, where w > 0 specifies the steepness of the continuous function f as follows:

$$f\ (x) = \frac{1}{1+ e^{-w(x)}} \text{ (Equation 3)}$$

To construct FCMs, experts in a specific field create a mental model manually according to their knowledge in the related areas. Firstly, they identify key domain issues or concepts. Secondly, they identify the casual relationship among these concepts, and finally, they estimate causal relationships strength (Elpiniki I Papageorgiou, 2010). All the proposed values by experts are regarded as linguistic variables, and overall linguistic weight is acquired, which is converted to a numerical weight with the defuzzification procedure of Centre of Gravity (Elpiniki I Papageorgiou, 2010). A casual path from some concept node C_i to concept node C_j, display C_i –~ Ck1, Ck1–~… Ckn, Ckn–~C_j can be shown by sequence (i, k, …, $K_{n,j}$).

Subsequently, the indirect effect of C_i on C_j is the causality C ~ I impart to C_j via the path (i, K_I, …, $K_{n,j}$). The total effect of C_i on C_j is the composite of all indirect effect causalities C~ imparts to C_j (Kosko, 1986). A simple fuzzy causal algebra is constructed by analyzing the indirect effect operator I as the minimum operator, (or t-norm) and the total effect operator T as the maximum operator (or s-norm) on the partially ordered set P of causal values (Peláez & Bowles, 1996; Zare Ravasan & Mansouri, 2016). Formally let ~ be a causal concept space, and let e: ~ x ~ P be a fuzzy causal edge function, and suppose that there are m-many causal paths from C_i to C_j: (i, k~…k~, j) for 1 ~< r ~< m. Then, let Ir (C_i, C_j) indicate the indirect effect of concept $C_i$on concept C_j through the rth causal path, and let T (i, C_j) indicate the total effect of C_i on C_j over all m causal path. Then:

I ~ (C_i, C_j) = min (w (C_p, C_{p+}): (p, p+1) ~ (i, k~…k, ~j)) (Equation 4)

T (C_i, C_j) = max (Ir (C_i, C_j)), where I < ~ r < ~ m (Equation 5)

Where p and p + 1 are contiguous left to right path indices (Elpiniki I Papageorgiou, 2010). In FCM, two kinds of analysis are utilized. The static analysis is used to depict the effect of each concept on target concepts which aims to use the above algorithm. The dynamic analysis permits investigating 'what-if' scenarios by conducting simulations of a given model from various initial state vectors. Simulations present a description of the dynamic behavior of the system that can be used to support decision-making or projections about its future states (Stach, Kurgan, & Pedrycz, 2010).
Different expansions of the classic fuzzy cognitive maps can be used to solve complicated issues. An expanded FCM involves the organization of the models improved by variant experts and compounded concepts and weights determined by them (Dickerson & Kosko, 1994; Poczeta, Kubuś, & Yastrebov, 2019).

Table 4: Applications of FCM in various studies

Application of FCM	Benefits	Source
Assessing readiness and managing approach to implement blockchain in the supply chain.	Identifying readiness relevant activities to implement blockchain, modeling causal relationships among the identified activities	(Irannezhad, Shokouhyar, Ahmadi, & Papageorgiou, 2021)
Assessing readiness in legality of supply chains	Improving the readiness of Legality of the supply chain and developing functional areas of Business using static and dynamic analysis of FCM.	(Kalantari & Khoshalhan, 2018)
To estimate organizational readiness to implement ERP	Predict complex causal relationship between factors concerning organizational dimension including factors such as culture, process and etc.	(Ahmadi, Yeh, Martin, & Papageorgiou, 2015)
To estimate total readiness of a company for implementing ERP	To evaluate total readiness which is affected by the readiness degree of three dimensions entailing technical, organizational and social readiness.	(Ahmadi, Papageorgiou, et al., 2015)
Providing new approach for readiness-relevant activities for ERP implementation	To identify readiness relevant activities.	(Ahmadi, Yeh, Papageorgiou, & Martin, 2015)

As it is explained in table 4, there are several contributions in which to assess readiness degree, fuzzy cognitive maps are used. Studying an FCM aims to get a weight matrix capable of making practical forecasts and catering reliable decisions following guidelines and problem restrictions (Amirkhani, Papageorgiou, Mohseni, & Mosavi, 2017).

3. Research methodology

This study adopted a quantitative analysis in two stages; (1) designing a questionnaire and analyzing it using Exploratory Factor Analysis and Confirmatory Factor analysis to develop an Industry 4.0 readiness model; (2) examining cause-effect relationships among concepts and dimensions of the readiness model through fuzzy cognitive maps. The research structure is illustrated in figure 1. Several steps to develop the proposed readiness model are described in the following.

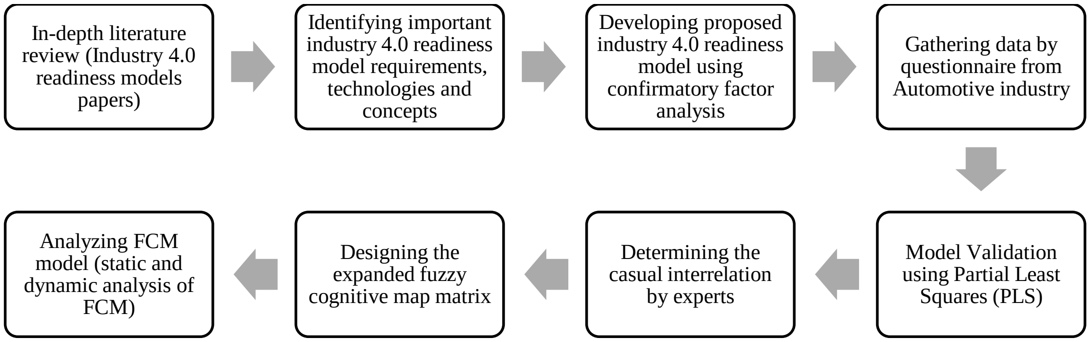

Figure 1: Schematic for the methodology used in the paper

Articles about Industry 4.0 readiness models are examined and principles, concepts, and technologies are extracted based on their importance and frequency in developing a readiness model (table 14 in Appendix). According to tables 1 and 2, 17 concepts are gathered. Concepts have been collected based on Industry 4.0 technologies, principles and existing Industry 4.0 readiness models which are shown in table 5. It is worth mentioning that some readiness items such as big data, cloud computing and similar items are comprised among readiness items of digitalization which is true for all concepts. Although some concepts such as customers, cyber-physical systems, modularization and smart supply chain have not the highest frequency in comparison with other concepts like digitalization and employees, they are selected owing to their importance in implementing Industry 4.0 and this is the difference between our model and the existing models. To develop a comprehensive Industry 4.0 readiness model, all principles and important technologies were included. Taking modularization as an example, this concept is used in one readiness model while it is among important principles of Industry 4.0 according to section 2.1 which should be comprised in developing readiness model.

Table 5: Extracting concepts to develop an Industry 4.0 readiness model

Concepts	Readiness items	Sources
Process	Product design processes Product planning Manufacturing Engineering and Services	Nick et al., 2021; Nick et al., 2019; Schumacher et al.,) (2016
Customers	Integrating Customers in design and production processes Involving customers in decision making	Caiado et al., 2021; Nick et al., 2021; Schumacher et al.,) (2016
Smart products and smart services	Data analysis Product personalization Product integration Product digitalization	Blayone & VanOostveen, 2021; Lichtblau, 2015; Nick et) al., 2021; Nick et al., 2019; Schumacher et al., 2016; Gül T (Temur et al., 2018
Finance	Allocate financial resources	(M Ichsan & Dachyar, 2019)
Culture	Open-innovation Cross-company cooperation Knowledge sharing	Bibby & Dehe, 2018; Blayone & VanOostveen, 2021;) (Nick et al., 2021; Schumacher et al., 2016
Employees	Knowledge-based skills Knowledge-based workers	Bibby & Dehe, 2018; Blayone & VanOostveen, 2021; M) Ichsan & Dachyar, 2019; Lichtblau, 2015; Machado et al., 2019; Nick et al., 2021; Nick et al., 2019; Schumacher et (al., 2016; Gül T Temur et al., 2018
Strategy	Designing strategies and policies based on Industry 4.0	Bibby & Dehe, 2018; M Ichsan & Dachyar, 2019;) Machado et al., 2019; Nick et al., 2021; Nick et al., 2019; (Schumacher et al., 2016; Gül T Temur et al., 2018

Management and Leadership	Intelligence Organization Management Management competencies and commitments Willingness	(M Ichsan & Dachyar, 2019; Schumacher et al., 2016)
Digitalization	Real-Time Analytics Big Data Machin to Machin Mobile & Augmented Reality Augmented/Virtual/Mixed Reality Automation Cloud Computing Mobile Computing Virtualization	(Bibby & Dehe, 2018; Blayone & VanOostveen, 2021; Caiado et al., 2021; Castelo-Branco et al., 2019; M Ichsan & Dachyar, 2019; Machado et al., 2019; Pacchini et al., 2019; Samaranayake et al., 2017; Schumacher et al., 2016; Gül T Temur et al., 2018; Tortora et al., 2021)
Cyber Security	Security and stability of information systems	(M Ichsan & Dachyar, 2019; Samaranayake et al., 2017; Tortora et al., 2021)
Robotics	Artificial Intelligence Deep Learning	(Bibby & Dehe, 2018; Blayone & VanOostveen, 2021; Pacchini et al., 2019; Tortora et al., 2021)
Cyber-Physical Systems (CPS)	Embedded System Embedded Sensors Ability to Identify Information and communication processing	(Bibby & Dehe, 2018; Blayone & VanOostveen, 2021; Pacchini et al., 2019)
Additive Manufacturing	3D Printing	(Bibby & Dehe, 2018; Pacchini et al., 2019; Tortora et al., 2021)
Modularization	Decentralized structure Prefabrication	(Meissner, Ilsen, & Aurich, 2017)
Internet of Things	Embedded Sensors Internet of People Internet of Services Industrial Internet of Things Embedded Internet System Web-Based Applications Business Intelligence Radio Frequency Identification (RFID)	(Bibby & Dehe, 2018; Blayone & VanOostveen, 2021; Tortora et al., 2021)
Smart Supply Chain	Accessing supply chain Flexible supply chain	(Blayone & VanOostveen, 2021)
Interoperability, integrity, and awareness	Collaboration systems Exchanging information Sharing data	(Caiado et al., 2021; Castelo-Branco et al., 2019; Samaranayake et al., 2017; Tortora et al., 2021)

Based on the number of concepts, a questionnaire is designed. Due to collect data, a survey is carried out using a designed questionnaire consisting of one closed-ended question per item in the Automotive Manufacturing Company in Iran. It is essential to note that we selected the Automotive industry to conduct our survey for two critical reasons. Firstly, the automotive industry is a significant industry that contains a vast range of activities, including design, manufacturing, supply, selling, after-sale services, and so forth. Furthermore, this industry has approximately 80 sub-industries and is considered propulsion for other sectors such as steel, petrochemical, electronic, etc. In the case of improving the readiness degree of the Automotive industry, other connected industries mentioned earlier can be affected and enhance their ability and get ready somehow to implement Industry 4.0.

With regard to the questionnaire, each question requires an answer based on the evolution path, which undergoes ten readiness levels ranging from level 0 "not ready" to level 10 "completely ready". It is important to stress that all of the questionnaire's items have been fully explained for all respondents to generate an identical understanding of Industry 4.0 concepts and technologies. First of all, the pilot test of

the questionnaire is done in-person, and 10 people among senior experts and managers in the Automotive industry have participated. As stated by (Halpin, 1957), increasing the number of 10 participants in the pilot study will not positively affect a significant score. Analyzing the result of the pilot test of the questionnaire showed the value of 0.811 of the Cronbach Alpha. In the actual survey, the questionnaire is administered in-person and online to employees, including senior managers, process and systems experts, software experts, web application experts, and employees who have other specialities in the Automotive industry. In-person distribution of 190 questionnaires to employees in the Automotive industry resulted in 172 responses. The questionnaire's online link is also sent to 200 employees in Automotive industry to participate online in a survey, which resulted in 118 valid responses. Some of the questionnaires did not fill out completely. Overall, a number of 257 questionnaires are filled out. Among participants, 35% are associated with senior managers, 52% and 13% are related to senior experts and junior experts respectively from various departments in the Automotive industry. A summarized example of questionnaire is illustrated in table 15 in Appendix.
The reliability of the research instrument can be confirmed by the Cronbach Alpha coefficient, α, which reveals the value of 0.922. Assessing and analyzing questionnaire items to develop the readiness model follows a three-step procedure; exploratory factor analysis, confirmatory factor analysis, and developing an Industry 4.0 readiness model. Finally, the fuzzy cognitive map analyzes cause-effect relationships among concepts and dimensions.

4. Findings

4.1. Exploratory factor analysis (Principal component analysis)

Various conditions must be performed prior to testing whether the items are appropriate to conduct the analysis; thus, we did the Kaiser-Meyer-Olkin Test (KMO) and Bartlett's Test of Sphericity tests.

Table 6: KMO Test and Bartlett’s Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.807
Bartlett’s test of Sphericity	Approx. Chi Square	560.4980
	Df	136
	Sig	.000

As it is evident from table 6, Bartlett's Test of Sphericity revealed a significant value of 0.000, showing $p < 0.05$. It, therefore, reveals the correlation between items is adequate to run the factor analysis. In Kaiser-Meyer-Olkin Test (KMO), the value is 0.807, and the KMO is more significant than 0.50. This indicates that these items are appropriate for the factor analysis conducted and revealed no issues of serious multicollinearity data (Alias, Ismail, & Sahiddan, 2015). After the Kaiser-Meyer-Olkin Test (KMO) and Bartlett's Test of Sphericity are conducted, the following Rotating Matrix Component Table is employed to test the construct validity of each questionnaire item. Concerning Rotating Matrix Component Table constructed (Table 7), the concept of finance is removed since this concept has two dimensions. According to Akdil et al. (2018), we considered finance as a readiness item among items in the concept of strategy. We can, therefore, sort the things that evaluate each component built. It is found that three dimensions exist after Varimax rotation.

Table 7: Rotating Component Matrix Table

Concepts	Dimension 1	Dimension 2	Dimension 3
Strategy	0.840		
Culture	0.808		
Customers		0.755	
Process		0.751	
Management & leadership	0.748		
Employees	0.635		
Smart products & services		0.857	
Finance	0.482	0.394	
Cyber security		0.592	0.796

Robotics			0.784
Modularization			0.690
Digitalization		0.485	0.674
Cyber-physical systems			0.619
Additive manufacturing			0.615
Interoperability			0.817
Internet of Things		0.761	0.842
Smart supply chain			0.773

4.2. Confirmatory factor analysis

To test the confirmatory factor of components, we utilized PLS-SEM (partial least squares structural equation modeling) research technique (Hair Jr, Sarstedt, Matthews, & Ringle, 2016). The external loadings of concepts should be evaluated, including appraising the reliability of individual indicators (Hair, Ringle, & Sarstedt, 2011; Hair, Sarstedt, Ringle, & Mena, 2012). According to Hair et al. (2016), 0.70 is the threshold for maintaining a model's components. Table 6 illustrates ample outer loadings up to 0.70 or higher. It, therefore, met the criteria of the reliability of individuals. As stated by (Hair et al., 2011), reliability should be higher than 0.70. Table 8 illustrates the CR factor ranging from 0.880 to 0.933. It, thus, has sufficient Internal consistency reliability. As specified by (Fornell & Larcker, 1981), CV assessment should be done along with AVE assessment. Table 6 shows AVE scores ranging from 0.708 to 0.755, concluding that the readiness model has sufficient CV.

Table 8: Model validation

Readiness model	Components	Loadings	Cronbach Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
Dimension 1 (D1)	Customers	0.860	0.794	0.880	0.710
	Smart products and services	0.789			
	Processes	0.877			
Dimension 2 (D2)	Employees	0.836	0.891	0.925	0.755
	Culture	0.877			
	Management and leadership	0.835			
	Strategy	0.926			
Dimension 3 (D3)	Digitalization	0.731	0.919	0.933	0.708
	Cyber-security	0.717			
	Robotics	0.772			
	Cyber-physical systems	0.848			
	Additive manufacturing	0.783			
	Modularization	0.795			
	Internet of things	0.763			
	Smart supply chain	0.706			
	Interoperability, integrity, and awareness	0.884			

4.3. Proposed Industry 4.0 readiness model

Considering all available literature and analyzing existing models from consulting frameworks to all readiness models, we analyzed results from exploratory factor analysis and confirmatory factor analysis. As it is obvious from table 8, all 16 concepts have the sufficient amount of reliability and validity. All concepts, therefore, remain in table 7 to develop a readiness model. We, then, categorized concepts into three perspectives; concepts at the operational level, the organization level, and the technology level. It should be noted that we named each category according to its concepts and their definitions. Finally, we proposed an Industry 4.0 readiness model consisting of three prime dimensions,16 sub-dimensions, and readiness items associated with concepts (table 9).

Table 9: Proposed Industry 4.0 readiness model

Dimensions	Concepts	Readiness items	Sources
D1: Operational Readiness	C1: Process	Product design processes Product planning Manufacturing Engineering and Services	Nick et al., 2021; Nick et al., 2019;) (Schumacher et al., 2016
	C2: Customers	Integrating Customers in design and production processes Involving customers in decision making	Caiado et al., 2021; Nick et al., 2021;) (Schumacher et al., 2016
	C3: Smart products and smart services	Data analysis Product personalization Product integration Product digitalization	Blayone & VanOostveen, 2021;) Lichtblau, 2015; Nick et al., 2021; Nick et al., 2019; Schumacher et al., (2016; Gül T Temur et al., 2018
D2: Organizational Readiness	C4: Culture	Open-innovation Cross-company cooperation Knowledge sharing	Bibby & Dehe, 2018; Blayone &) VanOostveen, 2021; Nick et al., 2021; (Schumacher et al., 2016
	C5: Employees	Knowledge-based skills Knowledge-based workers	Bibby & Dehe, 2018; Blayone &) VanOostveen, 2021; M Ichsan & Dachyar, 2019; Lichtblau, 2015; Machado et al., 2019; Nick et al., 2021; Nick et al., 2019; Schumacher et al., (2016; Gül T Temur et al., 2018
	C6: Strategy	Designing strategies and policies based on industry 4.0 Allocate financial resources	Bibby & Dehe, 2018; M Ichsan &) Dachyar, 2019; Machado et al., 2019; Nick et al., 2021; Nick et al., 2019; Schumacher et al., 2016; Gül T Temur (et al., 2018
	C7: Management and Leadership	Intelligence Organization Management Management competencies, commitments and willingness	M Ichsan & Dachyar, 2019;) (Schumacher et al., 2016
D3: Technological Readiness	C8: Digitalization	Real-Time Analytics Big Data Machin to Machin Mobile & Augmented Reality Augmented/Virtual/Mixed Reality Automation Cloud Computing Mobile Computing Virtualization	(Bibby & Dehe, 2018; Blayone & VanOostveen, 2021; Caiado et al., 2021; Castelo-Branco et al., 2019; M Ichsan & Dachyar, 2019; Machado et al., 2019; Pacchini et al., 2019; Samaranayake et al., 2017; Schumacher et al., 2016; Gül T Temur et al., 2018; Tortora et al., 2021)
	C9: Cyber Security	Security and stability of information systems	(M Ichsan & Dachyar, 2019; Samaranayake et al., 2017; Tortora et al., 2021)
	C10: Robotics	Artificial Intelligence Deep Learning	(Bibby & Dehe, 2018; Blayone & VanOostveen, 2021; Pacchini et al., 2019; Tortora et al., 2021)
	C11: Cyber-Physical Systems (CPS)	Cyber Physical Production Systems (CPPS) Embedded System	(Bibby & Dehe, 2018; Blayone & VanOostveen, 2021; Pacchini et al., 2019)

		Embedded Sensors Ability to Identify Information and communication processing	
	C12: Additive Manufacturing	3D Printing	(Bibby & Dehe, 2018; Pacchini et al., 2019; Tortora et al., 2021)
	C13: Modularization	Decentralized structure Prefabrication	(Meissner et al., 2017)
	C14: Internet of Things	Embedded Sensors Internet of People Internet of Services Industrial Internet of Things Embedded Internet System Web-Based Applications Business Intelligence Radio Frequency Identification (RFID)	(Bibby & Dehe, 2018; Blayone & VanOostveen, 2021; Tortora et al., 2021)
	C15: Smart Supply Chain	Accessing supply chain Flexible supply chain	(Blayone & VanOostveen, 2021)
	C16: Interoperability, integrity, and awareness	Collaboration systems Exchanging information Sharing data	(Caiado et al., 2021; Castelo-Branco et al., 2019; Samaranayake et al., 2017; Tortora et al., 2021)

4.4. Construction of an FCM model

As stated by Kosko (1988) there is no limitation on the number of experts but in the case of the comparison model which is built according to experts' knowledge, selecting a large number of experts in the model will converge the results to the mean, which is incorrect. Therefore, we established our expert plan including eight experts from both academia and important industries such as the Automotive industry and so on to design a manual model.

It is interesting to note that the standard method of developing FCM models is based on experts' knowledge. They are selected based on their industry work experiences, the best knowledge of Industry 4.0, and understanding of the industry modeled system. They define the number and type of concepts that contain an FCM and the relationships between them and recognize the principal concepts that define the behavior of the complex system. According to their experience implementing Industry 4.0 technologies and leading technological change in organizations, we planned to capture their perception of the interrelationship between concepts and how they impact each other. They, thus, determine the negative or positive effect of one concept on the others, with a fuzzy degree of causation. To construct the model, experts filled out an FCM weight matrix individually. They allocated a weight to every concept's interrelation with the other concept based on the values in table 10, as stated by (Zare Ravasan & Mansouri, 2016). Table 10 shows the connection between numbers and linguistic and triangular variables. The interdependencies, therefore, among model concepts are extracted (Zare Ravasan & Mansouri, 2016).

Table 10: Linguistic values and the mean of fuzzy numbers

Linguistic values	The mean of fuzzy numbers
Very high	1.00
High	0.70
Medium	0.50
Low	0.30
Very low	0.10

The relations are demonstrated with weights such as 1 = strong positive relation, -1 = strong negative relation, and other links remained between these two ranges. The final matrix is built as the average matrix of all experts' answers. Regarding equation 5, where $W_{A_i A_j}^{Aug}$ is the extended fuzzy weight of the causal relationship between activity A_i and A_j. m comprises the number of experts. k is associated with expert number k and $W_{A_i A_j}^{k}$ is the fuzzy weight allocated by expert number k to the causal relationship between activity A_i and A_j. This average matrix is the last model of Industry 4.0 readiness utilized for further analysis and assessment. Table 11 represents relations among numbers and semantic variables.

$$W_{A_i A_j}^{Aug} = \frac{\sum_{k=1}^{m} W_{A_i A_j}^{k}}{m} \text{ (Equation 5)}$$

A depiction of the FCM model of this research is illustrated in Figure 2, which shows the 16 concepts and the three dimensions of the Industry 4.0 readiness model.

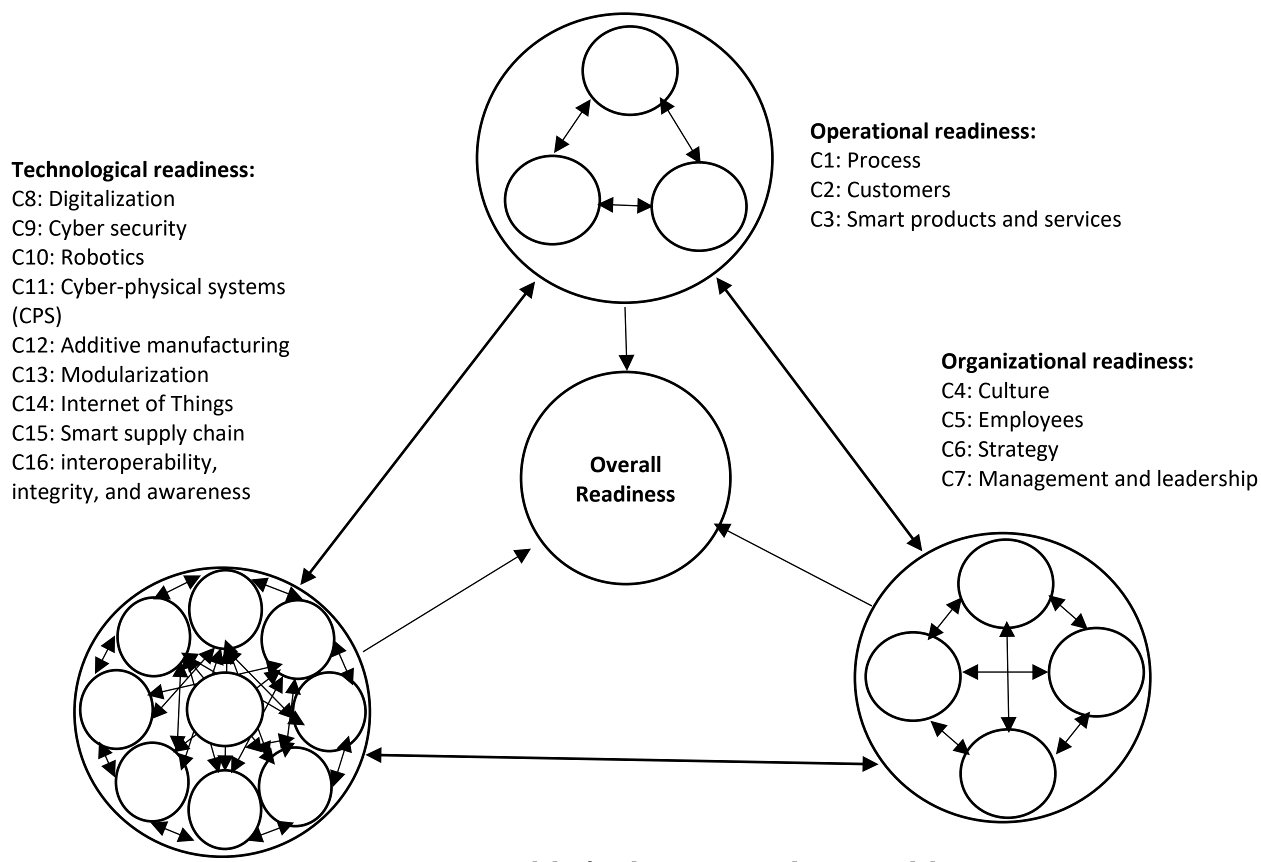

Figure 2: FCMs model of Industry 4.0 readiness model

Table 11: Extended FCM concepts weight matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	D1	D2	D3	OR4
C1	0	0.11	0.09	0.033	0.08	0.054	0.08	0.071	0.054	0.046	0.04	0.04	0.027	0.054	0.027	0.054	0.072	0.061	0.046	0.070
C2	0.01	0	0.027	0.006	0.006	0.046	0.033	0.022	0.027	0.01	0.01	0.01	0.01	0.013	0.01	0.062	0.012	0.023	0.019	0.054
C3	0.002	0.033	0	0.002	0.002	0.022	0.001	0.01	0.04	0.09	0.099	0.099	0.070	0.046	0.070	0.017	0.013	0.007	0.060	0.04
C4	0.054	0.04	0.002	0	0.054	0.054	0.08	0.01	0.017	0.013	0.006	0.002	0.002	0.002	0.002	0.022	0.026	0.047	0.008	0.062
C5	0.070	0.099	0.122	0.099	0	0.070	0.046	0.027	0.022	0.022	0.027	0.027	0.022	0.013	0.013	0.027	0.077	0.054	0.022	0.110
C6	0.110	0.122	0.11	0.062	0.07	0	0.017	0.006	0.01	0.01	0.006	0.013	0.01	0.01	0.006	0.017	0.129	0.037	0.01	0.071
C7	0.04	0.054	0.04	0.099	0.09	0.110	0	0.04	0.033	0.04	0.006	0.004	0.006	0.01	0.006	0.013	0.058	0.075	0.018	0.099
C8	0.187	0.046	0.046	0.033	0.054	0.033	0.033	0	0.017	0.054	0.070	0.062	0.022	0.022	0.04	0.04	0.075	0.038	0.036	0.04
C9	0.027	0.04	0.046	0.001	0.000	0.000	0.000	0.004	0	0.027	0.062	0.027	0.017	0.013	0.046	0.027	0.028	0.000	0.025	0.022
C10	0.099	0.004	0.006	0.001	0.01	0.002	0.004	0.01	0.013	0	0.027	0.046	0.09	0.04	0.022	0.01	0.028	0.004	0.028	0.04
C11	0.070	0.006	0.017	0.001	0.004	0.000	0.000	0.002	0.091	0.027	0	0.022	0.25	0.006	0.006	0.001	0.024	0.001	0.045	0.033
C12	0.09	0.000	0.013	0.001	0.002	0.001	0.001	0.000	0.017	0.027	0.025	0	0.022	0.013	0.04	0.001	0.026	0.001	0.016	0.046
C13	0.01	0.004	0.006	0.000	0.000	0.001	0.000	0.000	0.022	0.017	0.022	0.017	0	0.006	0.01	0.004	0.005	0.000	0.011	0.017
C14	0.002	0.004	0.017	0.001	0.000	0.000	0.000	0.000	0.006	0.006	0.013	0.017	0.01	0	0.017	0.013	0.006	0.000	0.009	0.046
C15	0.006	0.000	0.01	0.000	0.001	0.000	0.000	0.000	0.01	0.006	0.01	0.01	0.01	0.07	0	0.04	0.004	0.000	0.017	0.04
C16	0.002	0.004	0.017	0.002	0.004	0.002	0.004	0.002	0.022	0.017	0.006	0.006	0.006	0.080	0.04	0	0.006	0.003	0.020	0.08

5. Results

The final model can predict the effects of concepts on each dimension's readiness and overall readiness by the FCM method. This method can show direct and indirect concepts effects on readiness dimensions and overall readiness. Table 11 presents the outcomes of FCM analysis. It should be noted that concepts' relationships are positive, which means that alterations in the level of concepts lead to alterations in the outcome of other relevant concepts, readiness dimensions as well as overall readiness in the same direction. Similarly, an expansion in the concepts' level expands the readiness of each dimension and overall readiness. This way, we should use dynamic FCM to detect these relations more precisely. It is important to note that we measured readiness for each concept and dimension. Overall readiness is the sum of all dimensions readiness and are calculated using the FCM method and its software. To do so, the Mental Modeler are used to assess the readiness of each concept, dimension and overall readiness. Table 12 reveals the direct and indirect effects of FCM used to identify relationships. The first column shows the direct effects of concepts, and the second columns show the indirect impacts of concepts. Since Fuzzy Cognitive Maps are interpretable methods (Wang, Peng, Wang, Li, & Wu, 2020), static and dynamic analyses are available utilizing weight matrix to define the modeled system. By finding the maximum value among concepts, we can show the concepts' causal effects in static analysis (Ravasan & Mansouri, 2014).

Table 12: FCM model

Concepts		Direct				Indirect			
		D1	D2	D3	Overall Readiness	D1	D2	D3	Overall Readiness
Processes	C1	0.0727	0.0619	0.0462	0.0707	0.0777	0.0751	0.09	0.09
Customers	C2	0.0127	0.0234	0.0195	0.0542	0.0466	0.0377	0.0275	0.0625
Smart products and Smart services	C3	0.0134	0.0071	0.0606	0.04	0.0289	0.0234	0.0606	0.0466
Culture	C4	0.0266	0.0471	0.0089	0.0625	0.0585	0.0751	0.0462	0.0800
Employees	C5	0.0777	0.0543	0.0227	0.1108	0.0777	0.0619	0.0606	0.1108
Strategy	C6	0.1293	0.0377	0.0102	0.0712	0.1293	0.0619	0.0911	0.1339
Leadership and Management	C7	0.0585	0.0751	0.0180	0.0998	0.1108	0.0751	0.0911	0.0998
Digitalization	C8	0.0758	0.0386	0.0366	0.04	0.0758	0.0619	0.0466	0.0707
Cyber Security	C9	0.0288	0.0004	0.0252	0.0225	0.0288	0.0275	0.0466	0.04
Robotics	C10	0.0289	0.0045	0.0289	0.04	0.0727	0.0619	0.0462	0.0707
Cyber Physical Systems	C11	0.0244	0.0014	0.0454	0.0335	0.0707	0.0619	0.0462	0.0707
Additive Manufacturing	C12	0.0262	0.0014	0.0164	0.0466	0.0727	0.0619	0.0462	0.0707
Modularization	C13	0.0055	0.0004	0.0113	0.0176	0.0225	0.01	0.0225	0.0225
Internet of Things	C14	0.0062	0.0004	0.0096	0.0466	0.017	0.0071	0.0176	0.0766
Smart Supply Chain	C15	0.0045	0.0004	0.0175	0.04	0.01	0.0071	0.0203	0.0466
Interoperability, integrity and awareness	C16	0.0067	0.0034	0.02	0.0800	0.0225	0.0071	0.0225	0.0800

5.1. Static analysis

Based on the weight matrix (table 11), concepts directly affect each other. Since Fuzzy Cognitive Maps are dynamic systems, concepts have interconnected effects on each other, on dimensions, and finally on overall readiness. Table 12 shows the direct and indirect effects conducted by the static analysis.

Based on the indirect results, the strategy has the highest effect on overall readiness and organizational readiness. The process has the highest impact on operational readiness. Moreover, interoperability has the highest effect on technology readiness.

5.2. Dynamic analysis of the FCM

So far, in light of the FCM's static analytics, the most crucial variables to improve readiness degree are identified. FCM is also able to perform what-if analysis via the dynamic analysis to examine more insight about behaviors of the readiness model in various situations. Dynamic analysis of the FCM requires explaining a primary scenario, representing a suggested primary status to be evaluated. In this study, a total of six scenarios are generated. These scenarios are determined as a collection of assumptive occasions created to explain a feasible chain of causal events and their decision spots in the future (Kahn & Wiener, 1967). The attention of scenarios can remarkably heighten the capability to deal with unreliability and the general decision-making process's functionality. Scenario designing, thus, has been selected for technological planning or strategic analysis. Various scenarios have been constructed to examine the different concepts and their effects on the readiness model's three dimensions and overall readiness. Six scenarios are planned based on the following. The scale of the effect is classified by the following range: very low: 0- 0.2, low: 0.2-0.5, medium: 0.5- 0.65, high: 0.65-0.8 and very high: 0.8-1 (Figure 3).

1. *Operational Type Scenarios***:** If all of the concepts in operational readiness are completely effective on overall readiness, the overall readiness will be 0.26. Also, operational readiness will be 0.12. On the other hand, if enterprises only focus on operational concepts, the readiness degree for Industry 4.0 would be 0.12. In this case, process has the highest effect on overall readiness.
2. *Organizational Type Scenario***:** When all of the concepts in organizational readiness are entirely effective, the overall readiness will be 0.41. Moreover, organizational readiness will be 0.20. In other words, if enterprises focus on organizational concepts, the readiness degree for Industry 4.0 will be 0.41. In this case, strategy has the highest effect on overall readiness.
3. *Technological Type Scenario***:** If all of the concepts in technology readiness are completely effective on overall readiness, the overall readiness will be 0.42. Also, technology readiness will be 0.67, indicating technology readiness has a more significant impact on overall readiness. In other words, enhancing readiness degree of IoT, robotics and CPS have a significant effect on overall readiness.
4. *Low Random Type Scenario***:** When all concepts have a low effect on overall readiness, it will be 0.29. on the other hand, if an enterprise has a low degree of readiness in all concepts, operational readiness will be 0.16, organizational readiness will be 0.11, and technology readiness will be 0.32.
5. *Medium Random Type Scenario***:** If all concepts have a medium effect on overall readiness, overall readiness will be 0.47. On the other hand, if the enterprises in all concepts have a medium degree of readiness, operational readiness will be 0.26, organizational readiness will be 0.19, and technology readiness will be 0.51.
6. *High Random Type Scenario***:** When all concepts increase overall readiness, overall readiness will be 0.60. On the other hand, if the enterprises in all concepts have a high degree of readiness, operational readiness will be 0.35, organizational readiness will be 0.25, and technology readiness will be 0.64. Table 13 shows the weight of each concept and the result for each dimension and overall readiness for low, medium and high random scenarios.

Table 13: The result for each dimension and overall readiness for low, medium and high random scenarios.

Concepts	Low random	Medium random	High random
C1	0.30	0.52	0.80
C2	0.35	0.63	0.67
C3	0.40	0.52	0.70
C4	0.50	0.52	0.80
C5	0.25	0.64	0.75
C6	0.45	0.51	0.80
C7	0.37	0.60	0.67
C8	0.49	0.51	0.78
C9	0.40	0.64	0.75
C10	0.50	0.51	0.80
C11	0.30	0.62	0.66
C12	0.20	0.55	0.80
C13	0.35	0.53	0.78
C14	0.25	0.60	0.67
C15	0.30	0.58	0.70
C16	0.40	0.65	0.74
Results			
D1	0.16	0.26	0.35
D2	0.11	0.19	0.25
D3	0.32	0.51	0.64
Overall Readiness	0.29	0.47	0.60

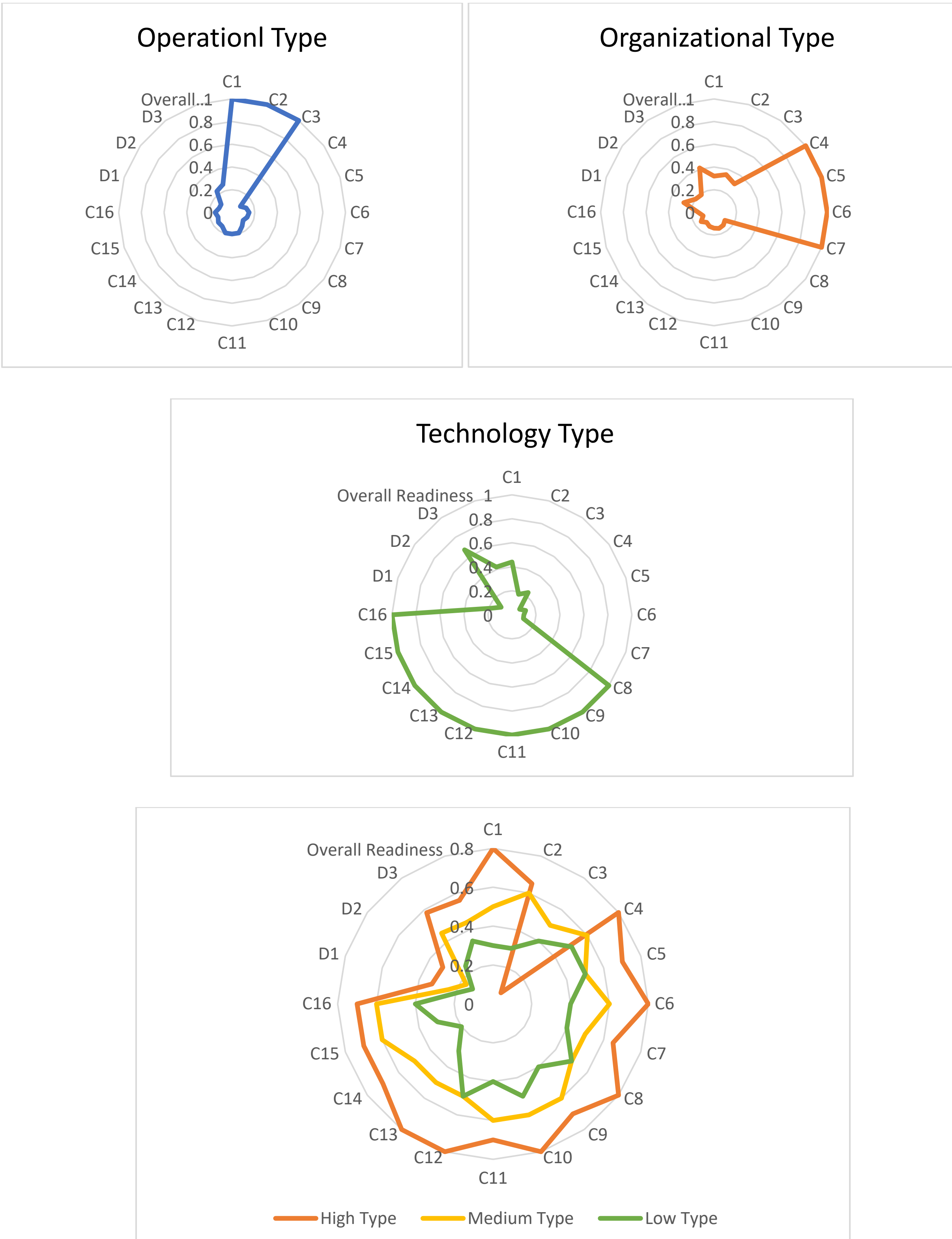

Figure 3: Dynamic FCM results of different type of scenarios

6. Discussion and conclusion

Due to digital technologies, we are witnessing a time of constant shifts leading to a transformation in business operations. This transformation causes a disruptive impact on traditional procedures concerning the method of producing products, carrying out business, and advantages are acquired for customers and producers (Culot et al., 2020; Fichman, Dos Santos, & Zheng, 2014). Therefore, analyzing the effect of digital technologies on companies, identifying their readiness degree, and finding important areas to focus on would be beneficial for managers. Hence, approaches such as readiness models have been developed to assess the readiness level of companies and implement Industry 4.0.

The present paper discusses Industry 4.0, its criteria, and technologies. As our first contribution, we developed a conceptual Industry 4.0 readiness model in which technological and non-technological concepts have been considered. The suggested model follows a holistic approach to Industry 4.0 readiness assessment by integrating Organizational, Operational and Technological dimensions, 16 concepts and 52 readiness items (table 9).

It is vital to note that consulting firms and various researchers have developed several Industry 4.0 readiness models. With regard to existing Industry 4.0 readiness models, we found some critical gaps and problems. Firstly, to develop an Industry 4.0 readiness model noticing all aspects would be necessary. In the extant literature, some Industry 4.0 readiness models were developed regarding technological aspects and did not include critical Industry 4.0 technologies. There are also models developed with respect to non-technological points of view. It should be noted that Industry 4.0 is a philosophy and is not related just to technological aspects. It is related to all important aspects of the companies from technological to non-technological perspectives. Although few studies paid attention to companies' technological and non-technological aspects, there are some issues which are important Industry 4.0 concepts that were ignored (table 3). According to the analysis of readiness models in terms of dimensions and criteria, it can be concluded that the assessment feature to assess Industry 4.0 readiness completely depends on researchers' points of view (Bibby & Dehe, 2018). We, therefore, have found that existing contributions do not meet our viewpoints and expectations from an extensive Industry 4.0 readiness model that includes all essential components from technological to non-technological aspects.

Moreover, most of the existing models have also been developed based on the authors' theoretical analysis, and few used statistical analysis to examine the readiness model. As another contribution, we used a mixed-method and analyzed our proposed model based on statistical analysis. To do so, we used exploratory factor analysis and confirmatory factor analysis to verify the concepts of the model and develop a conceptual Industry 4.0 readiness model.

In addition to developing a readiness model, as another contribution, we used fuzzy cognitive maps (FCM) which model the causal relationships among activities, create their contribution weights to the overall readiness and design an effective readiness improvement scheme by prioritizing those activities with the most impact on the overall readiness. It should be noted that the proposed FCM technique relies on the experts' knowledge to a great extent about the readiness-relevant activities and the power of their interrelationships. It is important to point out that the high level of dependence on experts' judgments puts at risk the reliability of the final model, particularly if experts have not been selected carefully. To do so, we have considered the vital actions to enhance the reliability of our readiness model. These actions are as follows: (1) considering experts' selection criteria, (2) the number of experts, (3) data gathering, as well as (4) the procedure employed for aggregating experts' judgments. Using FCM, we also can carry out Static and Dynamic analysis to evaluate readiness degrees. It is essential to note that no work has yet been presented assessing Industry 4.0 readiness degree using FCMs and extant models ignored using non-linear measurement method and examining cause-effect relationships among concepts and dimensions. To be more specific, they did not pay attention to indirect cause-effect relationships, while it is evident each concept not only has a direct impact on each other but also affect each concept indirectly. In this paper, by analyzing direct and indirect effects, we can recognize concepts with the highest impact on the overall readiness of the company and their effects on the other concepts and dimensions. Moreover, using FCM, we can use the experts' opinion, making the proposed model more accurate and closer to the real world.

Concerning the results of static and dynamic scenarios, it can be viewed that concepts like strategy, process, customers, IoT, CPS, robotics and interoperability and integrity are among important concepts and have the highest effect on the overall readiness. Noticing some vital concepts, therefore, would be beneficial to take advantage of the proposed model and practise it. Taking IoT as one of the important concepts as an example. As stated by (Karakuş, Karşıgil, & Polat, 2018) IoT has various applications in a variety of domains such as in supply chain, logistics, monitoring production lines, and so on. It is, therefore, evident that enhancing the readiness degree of IoT can impact various concepts, which lead to increasing the readiness degree of the company.

The proposed model permits managers to identify the readiness-relevant activities for Industry 4.0 implementation and would be beneficial for them for several important reasons. First and foremost, the model is easy to implement and use because data can be gathered by a verified questionnaire. The transformation of the model into a handy software tool also makes its application in practice. To assess companies' readiness and get aware of the company's current situation to become ready for implementing Industry 4.0, managers need a comprehensive outlook of the company concerning all aspects of that. To achieve this important point, managers require an Industry 4.0 readiness model, in which all aspects of the company, from technological to non-technological points of view, have been considered.

Furthermore, to take advantage of analyzing the results of this proposed model, managers can do various steps to increase overall readiness degree and implement Industry 4.0 in companies. Managers can develop or modify their strategy as a critical organizational concept to increase the readiness degree. It is necessary to improve processes as an important operational concept. As far as technological concepts are concerned, among emerging technologies to implement Industry 4.0, based on the type of industry, managers should select and invest on technologies like the Internet of Things, Robotics, Cyber-physical Systems, as well as Interoperability and Integrity and focus their efforts on enhancing the readiness degree of these theses concepts. Consequently, analyzing all mentioned concepts and doing endeavors to increase the readiness degree, managers will be able to offer a personalized products and services to its customers which will result in growing customer satisfaction as a critical aim of all companies. Utilizing FCM method, managers can identify dimensions and concepts that have the most critical effects on company′s readiness. Since it is evident from the FCM static analysis, managers can focus their endeavors on improving the readiness degree of concepts like strategy, process, and interoperability which cause improving readiness degree of a company to implement Industry 4.0. The dynamic analysis also implied that concepts could improve the readiness degree. Managers, therefore, can carry out a what-if analysis and check the effects of concepts and dimensions on overall readiness through this analysis. Compared to existing readiness models, using proposed model, managers can compare the current situation of the company and the ideal status applying dynamic scenarios and develop future plan according to requirement and so forth.

The proposed model has been developed based on gaps in existing models. The model's generalizability, therefore, is significant. We suggest implementing the proposed model in various industries, especially those connected to the Automotive industry, such as steel, petrochemical, or implementing on other Automotive industries in different contexts to improve the usability of this model. Implementing readiness model in service industries is another future research.

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Appendix:

Table 14: The industry 4.0 concepts according to the extant literature.

	Process	Customers	Smart products and smart services	Culture	Employees	Strategy	Management and Leadership	Digitalization	Cyber Security	Robotics	Cyber-physical Systems	Additive Manufacturing	Modularization	Internet of Things	Smart Supply Chain	Interoperability, integrity, and awareness
Industry 4.0 readiness and maturity model	*	*	*	*	*	*	*	*					*			
Implementing Industry 4.0 - A Technological Readiness Perspective								*	*							*
Industry 4.0 readiness model								*		*	*	*		*		
Evaluation of Industry 4.0 Readiness Level			*		*	*		*								
Readiness for Implementing Industry 4.0 in Food and Beverage					*	*	*	*	*							*

Manufacturers in Indonesia																
Industry 4.0 readiness in manufacturing companies: challenges and enablers towards increased digitalization			*		*	*		*								
Worker readiness for Industry 4.0				*	*			*		*	*			*		
A survey study on Industry 4.0 readiness level of Italian small and medium enterprises								*	*	*		*		*		*
Assessing Industry 4.0 readiness in manufacturing: Evidence for the European Union								*								*
Industry 4.0 readiness in Hungary: model, and the first results in connection to data application	*		*		*	*										
Industry 4.0 readiness in manufacturing: Company Compass 2.0, a renewed framework and solution for Industry 4.0 maturity assessment	*	*	*	*	*	*		*	*	*					*	

Table 15: The example of readiness questionnaire

	Question	0	1	2	3	4	5	6	7	8	9	10
1	To what extent are the processes of the company ready with regard to product design processes, production planning, production engineering, and services for compatibility and integration with each other and finally becoming smart to implement the fourth industrial revolution?											
2	To what extent is the culture of the organization ready regarding some important aspects such as open innovation, knowledge sharing, using creative ideas, as well as using creative people inside and outside the organization?											
3	To what extent does the company utilize the Internet of Things? The Internet of Things is defined as a network of physical objects, environments, vehicles, and machines that are equipped with sensors that collect and exchange data as well as use web-based applications.											

…	……….											