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Establishment of a maturity model to assess the development of industrial AI in smart manufacturing

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Abstract

Purpose – The benefits of artificial intelligence (AI) related technologies for manufacturing firms are well recognized, however, there is a lack of industrial AI (I-AI) maturity models to enable companies to understand where they are and plan where they should go. The purpose of this study is to propose a comprehensive maturity model in order to help manufacturing firms assess their performance in the I-AI journey, shed lights on future improvement, and eventually realize their smart manufacturing visions.

Design/methodology/approach – This study is based on (1) a systematic review of literature on assessing I-AI-related technologies to identify relevant measured indicators in the maturity model, and (2) semi-structured interviews with domain experts to determine maturity levels of the established model.

Findings – The I-AI maturity model developed in this study includes two main dimensions, namely “Industry” and “Artificial Intelligence”, together with 12 first-level indicators and 35 second-level indicators under these dimensions. The maturity levels are divided into five types: planning level, specification level, integration level, optimization level, and leading level.

Originality/value – The maturity model integrates indicators that can be used to assess AI-related technologies and extend the existing maturity models of smart manufacturing by adding specific technical and nontechnical capabilities of these technologies applied in the industrial context. The integration of the industry and artificial intelligence dimensions with the maturity levels shows a road map to improve the capability of applying AI-related technologies throughout the product lifecycle for achieving smart manufacturing.

Keywords Industrial artificial intelligence, Smart manufacturing, Industrial processes, Maturity model

Paper type Research paper

1. Introduction

The increased demands of high-quality products and intensive competition have driven enterprises to utilize advanced technologies to achieve smart manufacturing (SM) (Sharma *et al.*, 2020). SM is an important force facilitating the industrial revolution that influences the pattern of international competition. Governments worldwide have proposed strategies to increase industrial competitiveness, such as Germany’s “Industrie 4.0” development strategy, “Strategy for American Innovation,” and “Made in China 2025 Plan” (Min *et al.*, 2019). All these strategies highlight the role of core technologies of the industrial revolution (including artificial intelligence (AI) and related technologies such as cyber-physical systems (CPSs), cloud and Big Data) in optimizing manufacturing operations, contributing to improving the effectiveness and efficiency of enterprises and promoting the economic growth. It was reported that economic gains from the productivity improved by AI-related

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technologies have achieved $1 trillion of additional GDP in 2017 and will reach more than $9 trillion of additional GDP in 2030 (PWC, 2017). There are examples showing that without SM, a few enterprises still maintain growth and profitability in the market (e.g. Dacia) (Sigal, 2018). Furthermore, in the context of SM, because machines and production processes are connected in the manufacturing systems, the risk of a cyberattack accumulates that could affect normal manufacturing operations and significantly outweigh any potential benefits, which has led to increased attention in addressing cybersecurity (Hao *et al.*, 2019). While in the background of constant development of AI-related technologies, SM is the trend in the manufacturing industry. Enterprises, therefore, should embrace this revolution and incorporate SM into the strategic planning of the company's long-term development.

The use of AI-related technologies for SM provides opportunities to (1) gain insights into the collected data for understanding customers, suppliers and competitors (Soroka *et al.*, 2017); and (2) address elasticity in resource allocation and access in internal industrial processes (Ding *et al.*, 2019). The benefits of AI-related technologies for manufacturing are well recognized (Mikalef and Gupta, 2021; Yu *et al.*, 2016). However, lack of capability to apply AI-related technologies was identified as the most significant barrier to achieve SM (Khan *et al.*, 2020). In light of this, there is a scarcity of theoretical lenses and tools to help enterprises understand their current state and gain insights to guide the achievement of their AI-enabled SM visions step by step.

Maturity models in relation to technologies are usually utilized in enterprises to appreciate the capabilities of technologies and improve enterprises' capability to apply technologies (Comuzzi and Patel, 2016). A maturity model has two common components: the measured objects (refer to dimensions or criteria such as application targets of technology, within specific measured indicators) and maturity levels (can be defined as a set of sequential development stages/degrees for the examined object) (Wendler, 2012). It can be used to assess and monitor the as-it situation of technology application or the concerned capabilities in an enterprise, as well as to shed lights on step-by-step improvements (Wendler, 2012). There has been an increasing number of maturity models developed to guild enterprises on leveraging technologies for SM (e.g. Gökalp *et al.*, 2017; Schumacher *et al.*, 2016). However, two main limitations exist in the literature. First, these existing maturity models have paid much attention to the integration of technologies and activities of production and management in general, rather than more extensive investigations of how the use of AI-related technologies supports SM. In other words, limited attention has been directed toward more nuanced understandings of specific capabilities on AI-related technologies used in industry. Second, existing maturity models include duplicate (but also different) dimensions with diverse measured indicators for these dimensions. This creates confusions and challenges for enterprises in selecting and using related maturity models. More systematic synthesis is thus needed to bring out the most important dimensions and indicators, especially with an AI lens, to assess and improve the AI capabilities of enterprises during their SM journey.

The aim of this study is to develop a maturity model of industrial AI (I-AI) related technologies, helping enterprises perform self-assessment to better understand the capabilities of these technologies applied in industrial processes and leverage them for SM. Over the recent years, the number of published maturity models has increased considerably (e.g. Tarhan *et al.*, 2016); however, Felch and Asdecker (2020) have shown that the methodological rigor regarding model development is weak and flawed, resulting in the quality of the maturity models that does not match the current publication quantity. In this study, to develop a maturity model, we first conducted a systematic review of empirical studies and existing maturity models involving assessments of AI-related technologies used in industry to identify the measured indicators. The present study thus is drawn upon the existing literature in relation to assessing AI-related technologies in the industry supported to establish the indicators of the maturity models. This then was followed by establishing the maturity levels through expert interviews, determining the characteristics related to different development stages of I-AI-related technologies.

The contributions of this study are twofold. First, our study proposes a theoretical maturity model of I-AI-related technologies, which integrates the indicators that can be used to assess I-AI-related technologies and extends the existing SM maturity models by adding specific technical and nontechnical capabilities of AI-related technologies applied in the industry. Second, the findings of our study provide the foundation to help enterprises (1) assess the development level of I-AI-related technologies to identify the strengths and weaknesses of the enterprises and (2) develop strategies of improving the capability of applying these technologies for SM. To specify, enterprises take advantages of the maturity model to evaluate the capabilities of AI-related technologies used in industrial processes based on the measured indicators identified from this study and determine the development level of these capabilities based on the characteristics of different maturity levels for the measured indicators described in the study. This helps enterprises understand the as-it situation of AI-related technologies applied in industrial processes and formulate measures on step-by-step improvement according to the characteristics of the next higher level of the capabilities to realize SM.

The rest of this paper is structured as follows. Section 2 reviews the literature of SM, I-AI and the existing relevant maturity models to give a background of the present study. Section 3 elaborates the research methods used to conduct this study. Section 4 presents the I-AI-related technologies maturity model proposed in this study. Sections 5 discusses our findings derived from the systematic review and expert interviews and outlines the implications and limitations of our work. Section 6 concludes the paper.

2. Background and related studies

This section reviews the literature of SM and I-AI in order to contextualize our maturity model. Furthermore, related studies are analyzed, revealing the limitations of the existing maturity models that also lead to the current research.

2.1 Literature on smart manufacturing

Smart Manufacturing is a term coined in the USA (Masse *et al.*, 2019). A few researchers developed definitions of SM, and they all highlighted the use of data analytics and information and communication technologies to govern and optimize manufacturing operations (Mittal *et al.*, 2019; Thoben *et al.*, 2017). Traditional manufacturing focusses on a process of converting raw materials into finished products to meet the requirements of customers (Zheng *et al.*, 2020), while manufacturing nowadays is a data-driven paradigm that facilitates manufacturing intelligence based on devices communication and sharing of real-time information where every aspect of the factory can be monitored and optimized (O'Donovan *et al.*, 2015). Based on CPSs, cloud and Big Data technologies, SM can self-optimize the performance of manufacturing systems, self-adapt to and learn from the context of manufacturing operations, and generate insights either for human or autonomous decision-making (Mittal *et al.*, 2019). In this light, SM improves products to meet customer demands and reduce material and time consumption that enhance manufacturing capability and cost-effectiveness, playing an essential role in improving the market competitiveness of manufacturing enterprises (Lin *et al.*, 2020). It was reported that the global market of SM was valued at $194.63 billion in 2020 and will achieve $314.39 billion by 2026 (Grand View Research, 2020). Undoubtfully, a higher maturity level of SM promises better improved competitiveness. Because CPSs, cloud and Big Data are the core enabling technologies for the smartness of manufacturing systems, these three technologies are reviewed as presented below.

CPSs integrate calculation and physical processes to monitor and control physical entities via embedded computers and networks. The feedback loops between calculation and physical processes create opportunities for real-time and flexible interactions within and across CPSs (Liu *et al.*, 2017). Based on CPSs, a manufacturing system has the potential to optimize a wide range of operations through improved interactions (Yao *et al.*, 2019).

Cloud technology is a type of hosting technology that unifies the use of hardware, software and networks to deal with the allocation and usage of virtual resources (e.g. servers, storage and services) (Wang *et al.*, 2018). It enables users to access the dynamically scalable and virtual resources over the networks (NIST, 2015). These capabilities of cloud technology allow for smart management and sharing of resources while maximizing environmental sustainability and economic efficiency and minimising the usage of energy and resources for enterprises (Fisher *et al.*, 2018).

Big Data concerns the capability of acquiring valuable information from a large amount of data (Zhang *et al.*, 2020). The massive datasets constantly generated in the industrial processes have a large, diverse and complex structure with difficulties of acquisition, storage and analysis using conventional ways. The value of this data is unlocked only when the data is turned into meaningful insights to drive decision-making (Gandomi and Haider, 2015). Enterprises have to rely on processes and technologies to manage data (e.g. acquire, store and process data) and obtain intelligence from data by analytics to realize data-driven SM (Inamdar *et al.*, 2020).

In contrast to this large body of literature emphasizing the technical perspective of CPSs, cloud and Big Data, limited attention has been paid to management and people issues on applying them in SM from a nontechnical perspective. Although a few SM maturity models were developed to integrate technologies and activities of production and management in general, none of them focused on the integration of CPSs, cloud and Big Data by specifying their capabilities when applying for SM. As mentioned, these technologies are the essential enablers to achieve SM; however, enterprises failed to apply them in industrial practices. Hence, this calls for developments of theoretical lenses and tools to appreciate the capabilities of these technologies and improve enterprises' capability to apply them. Furthermore, as noted in Li *et al.* (2019), technology is not the only critical factor that influences the success of SM. They showed the "intersection and interrelation" of technology, organization and people as the foundation of SM success. Hence, when studying the capabilities of applying CPSs, cloud and Big Data in SM, both technical and nontechnical perspectives are needed to be taken into account.

2.2 Literature on industrial artificial intelligence

In this study, we refer to Zhang *et al.* (2019)'s study to understand I-AI, as the concept they developed is well accepted in this field, covering the most comprehensive connotations in I-AI. These researchers defined I-AI as the deep integration of AI-related technologies and industrial processes to achieve intelligent functions, including "self-perception, self-cognition, self-control, self-adaptive, self-feedback, self-organization, self-learning, self-decision, and autonomy" (Zhang *et al.*, 2019, p. 2371). From the maturity level of AI, they further divided I-AI into three main groups: narrow, general and super I-AI. To specify, from a narrow level, I-AI can complete a given industrial task and harness a single intelligent function (Zhang *et al.*, 2019). From a general level, I-AI can think and do manufacturing operations independently as a human being (Zhang *et al.*, 2019). As to a super level, I-AI has the ability of innovation and knowledge to optimize manufacturing operations and create business values (Zhang *et al.*, 2019). The technical architecture of I-AI is established based on CPSs, cloud and Big Data technologies that are the key elements in I-AI to realize SM (Lee *et al.*, 2018, 2020). With this architecture, the AI technology system integrates multiple techniques such as speech recognition, machine vision and natural language processing to achieve intelligent functions in industrial processes that is the goal of SM (Zhang *et al.*, 2019).

As mentioned, the economic gains can be improved through increased productivity and consumer demands on high-quality products and services enhanced by AI (PWC, 2017). The importance of I-AI has motivated us to conduct a survey of literature to understand this phenomenon. Our review of the literature on I-AI reveals three main research themes. The first research theme of current I-AI studies focuses on defining I-AI and identifying opportunities, challenges and characteristics of I-AI (e.g. Dagnaw (2020)). The second research theme looks at the development of technical solutions to address the challenges of I-AI, especially for its cybersecurity (Hao *et al.*, 2019). The third research theme aims to provide reference frameworks of development and deployment of I-AI (Lee *et al.*, 2018; Zhang *et al.*, 2019) to help enterprises implement and apply AI-related technologies for SM from a technical perspective. These studies have made substantial contributions to improve our understanding of the field of I-AI. However, this rich amount of literature tended to limit their study scope to addressing technical issues of I-AI. According to Peng *et al.* (2017), applying technology involves more than simply finding solutions to solve a technical problem, and there is a nontechnical side (e.g. regulations of using technology) needed to be managed for its landing. Additionally, previous frameworks on I-IA failed to develop a road map for enterprises to apply I-AI-related technologies in a progressive way (from initial, when enterprises understand the potential capabilities and benefits of AI-related technologies used in industry, to optimizing when a concerned capability is harnessed in enterprises). Enterprises might still have confusion and difficulties in implementing and applying these technologies for SM. This study thus aims to develop a maturity model of I-AI-related technologies, looking at both technical and nontechnical perspectives, assisting in appreciating the capabilities of I-AI-related technologies and formulating measures for improvement.

2.3 Maturity model

As mentioned in the Introduction, maturity models serve as the tool/technique to (1) understand the current situation of technology applied in enterprises or the development level of concerned capabilities of an enterprise and (2) strategize steps for improvement in the near future. This helps enterprises quickly gain insights into the capabilities of technology and react to the assessment. Maturity models have been proposed for guiding enterprises on the journey of applying AI-related technologies (CESI, 2016 [1]; Mattoon *et al.*, 2011), managing data (CESI, 2018; Halper and Krishnan, 2013) and realizing SM (e.g. CESI (2016) and Schumacher *et al.* (2016)) that are related to I-AI. Table 1 lists relevant maturity models in our study context.

Several observations can be derived from Table 1. First, these maturity models include duplicate dimensions. For example, the data management capability maturity assessment model and TDWI Big Data maturity model both contain data governance dimension; however, the two maturity models utilize different indicators to measure data governance in enterprises. Second, dimensions included in a maturity model could be missing in another maturity model. For instance, as shown in Table 1, intelligent manufacturing capability maturity mode and Industry 4.0 maturity model have totally different dimensions. This could challenge the selection and usage of maturity models to assess enterprises' capability of applying AI-related technologies in the industry. Third, although these maturity models have studied the integration of technology and management activities in general, none of them investigated specific capabilities of I-AI-related

Reference	Name of model	Dimensions and/or measured indicators
CESI (2016)	Intelligent manufacturing capability maturity model	2 dimensions: Intelligence and Manufacturing 10 classes: Design, Production, Logistics, Sales, Service, Resource elements, System integration, Interconnection, Information integration, and New business pattern with 27 specific fields
CESI (2018)	Data management capability maturity assessment model	8 fields: Data strategy, Data governance, Data architecture, Data application, Data security, Data quality, Data standards, and Data lifecycle management, with 29 specific capabilities
Halper and Krishnan (2013)	TDWI Big Data maturity model	5 dimensions: Infrastructure, Data management, Analytics, Governance, and Organisation
Mattoon *et al.* (2011)	Cloud computing maturity model	8 domains: Architecture, Infrastructure, Information, "Operations, Administration and Management", Business and Strategy, Organization, Governance, and "Projects, Portfolios and Services", with 60 specific capabilities
Schumacher *et al.* (2016)	Industry 4.0 maturity model	9 dimensions: Strategy, Leadership, Customers, Products, Operations, Culture, People, Governance, and Technology, with 62 exemplary maturity items

Table 1.
Relevant maturity models in the context of this study

technologies integrated. Enterprises may not fully understand the capabilities of these technologies for SM that could have an impact on their application. Furthermore, they gave limited details on how the indicators and maturity levels were identified to the design of the models. In this study, we tend to address this by documenting research methods applied for constructing the maturity model. This also aligns with the eighth requirements of a procedure model for model development: "*The design process of the maturity model needs to be documented in detail, considering each step of the process, the parties involved, the applied methods, and the results*" (Becker *et al.*, 2009, pp. 216). According to Felch and Asdecker (2020), explorative research methods (e.g. focus groups and Delphi studies) are suggested in addition to literature reviews for model development. Hence, we conducted a systematic review to integrate all possibly relevant studies to identify the measured indicators for understanding the capabilities of I-AI-related technologies and develop the dimensions. Thereafter, we interviewed the experts in the area to determine the maturity levels of the proposed model.

Note that a procedure model for model development defines standardized methodological steps to prevent arbitrariness in the design process and provide theoretical sound models (e.g. Becker *et al.* (2009) and Solli-Sæther and Gottschalk (2010)). As our focus of the study is on identifying the indicators and maturity levels to construct the maturity model, we did not use all requirements outlined in procedure models (e.g. Becker *et al.* (2009)'s requirements on evaluation). Furthermore, Felch and Asdecker (2020) recently developed the guidelines and literature-based criteria for maturity model development that contributes to methodological rigor in model development. Although we do not claim that our development of the maturity model utilized all these criteria, we applied as many criteria as possible to improve our study, such as multiple research methods employed for development and basic components of the maturity model (e.g. the number of levels, the title and a description for each maturity level, the number of dimensions and indicators and a description for each indicator), and the characteristics of different maturity level described for the integration of industry and AI dimensions that also address an activity as it might be performed for different maturity levels (see Appendix 6 and Appendix 7).

3. Research methods

The aim of this study is to develop a maturity model of I-AI-related technologies. As mentioned, a maturity model has two common components, including measured objects (dimensions with measured indicators) and maturity levels. For achieving the aim of this study, the present research followed the evidenced-based paradigm (Wolfswinkel *et al.*, 2013) to perform a systematic review in order to identify the measured indicators for the capabilities of I-AI-related technologies. We then conducted expert interviews to gain further empirical evidence for determining the maturity levels that also helps improve the maturity model. Both SLR and expert interviews support the development of the maturity model. Our study thus aligns with the guidelines of Felch and Asdecker (2020) that utilizes other research methods (i.e. expert interviews in the present study) in addition to literature reviews for maturity model development. The processes of data collection and analysis about our systematic review and expert interviews are explained below.

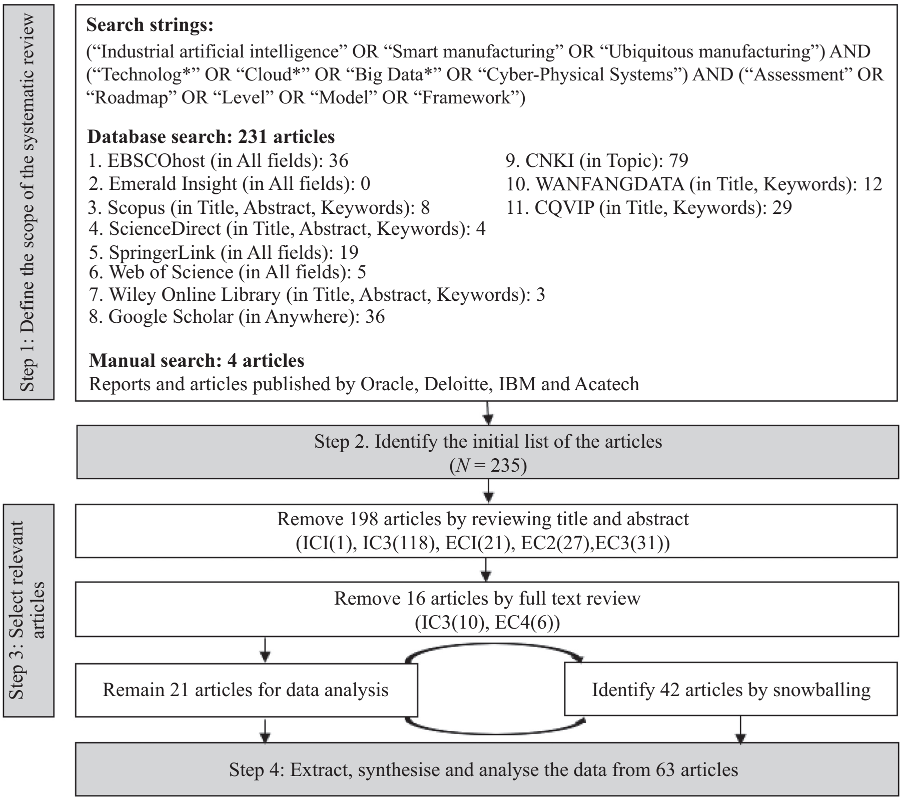
3.1 Data collection and analysis for systematic review

Due to the lack of a comprehensive analysis of the literature on assessing AI-related technologies used in industry, this study adopted the systematic literature review (SLR) method. An SLR follows a rigorous procedure for the search and selection of the sample studies in the review. It is a methodical process of collecting and collating the published empirical studies with systematic criteria for selection to reduce bias. The SLR method is suitable to provide a comprehensive overview of existing empirical research on the assessment of I-AI-related technologies undertaken within the field for identifying the indicators of the maturity model. The processes of SLR in this study are shown in Figure 1.

This study aims to develop a maturity model used to assess I-AI-related technologies, which is the main topic of interest. By conducting a systematic review, we tended to identify the indicators for the maturity model from the literature involving the assessment of AI-related technologies in the industry. Referring to the ways of determining the keywords (Kitchenham *et al.*, 2016), we identified three important concepts used in the aim of the study: "industrial artificial intelligence," "technologies," and "assessment" as the major search terms to develop the alternative terms for search (see Appendix 1). In light of this, we are most likely to address a more comprehensive perspective on the available literature. Appendix 1 presents the keywords generated in our search. Accordingly, our search began with those keywords by using the Boolean operators as the search strings, as shown in Figure 1.

Thereafter, we customized the search in the specific 11 online databases as advised by related studies on SM (e.g. Felch *et al.* (2019)) to identify an initial list of articles ($n = 235$) for selection. Based on our developed inclusion and exclusion criteria (see Figure 1), we remained 21 articles and then conducted the forward (finding citations to the papers) and backward (using the reference list to identify new papers) search to further include 42 articles. Finally, we had a total of 63 suitable articles retrieved.

Subsequently, we reviewed each of the 63 included studies thoroughly and identified a list of indicators for assessing AI-related technologies used in the industry. To specify, the main coder identified the keywords (e.g. nouns and gerundial phrases) utilized in the sentences to describe the application aspects of AI-related technologies accessed in industrial processes, including the processes from the reviewed studies. One member of the research group randomly selected and coded 17 articles from the data sample and compared them with the results generated from the main coder for achieving a consensus by discussion. This process contributes to minimizing coding bias. After removing duplicates, we had a flat list of the keywords and then arranged a group meeting to discuss and group the keywords into several clusters based on their similarity and gave each group an appropriate name based on our expertise and experience in the domain and referring to the terms explicitly mentioned in the included studies. The demographics of the group meeting is presented in Appendix 2.



Note(s): The inclusion criteria include: (1) the articles selected are published in English or Chinese (IC1); (2) the articles selected are published without time limitation (IC2); and (3) the articles selected have empirical studies on assessing AI related technologies (IC3). The exclusion criteria are: (1) the articles are duplicate (EC1); (2) the articles are not available online (EC2); (3) the articles are not peer reviewed nor formal industrial/government reports (EC3); (4) the articles do not mention the use of the technologies in the industry context (EC4)

Figure 1.
The SLR processes in this study

We thus had the 35 second-level indicators for the maturity model. Thereafter, based on our understanding from the description in the literature, as well as our knowledge and experience for the identified indicators, we assigned these indicators to two main groups (namely, industry and artificial intelligence dimensions) at first, as inspired by CESI (2016). Under each dimension, we further divided the indicators into several groups to improve the understanding of these detailed measured indicators and gave a proper name for each group based on their similarity through thematic analysis, generating the 12 first-level indicators. In this way, we proposed a maturity model of I-AI-related technologies with three levels. Further explanation and discussion of this proposed I-AI maturity model are given in the finding section.

3.2 Data collection and analysis for expert interviews

The present study used the method of the semi-structured expert interview to establish the maturity levels for the proposed maturity model for two reasons. First, the application of AI-related technologies is complex, and the development level is inconsistent in different enterprises. Second, as the majority of enterprises are still in the infancy of I-AI, normal staff members in manufacturing firms may not have sufficient knowledge about the maturity levels of I-AI-related technologies investigated in this study. Accordingly, we invited experts who have in-depth understanding and expertise in I-AI as our interview subjects expected to give insights on the topic of interests leading to meaningful findings of the study. Based on the results of the systematic review, we included the relevant studies on the topic of interest and identified the author names and their affiliation from the studies. Since these selected studies also include a few industrial reports, this has a great potential to identify the experts who have expertise in I-AI and work experience in dealing with I-AI. We first conducted the search by typing the author names and their affiliation in the Microsoft Bing search engine. Then we browsed and clicked the links shown on the first page on the Microsoft Bing search to identify their biography. The participants invited in our interviews were selected based on our inclusion and exclusion criteria (see Appendix 3). By using these criteria, we ultimately identified 15 experts from 246 authors as the interview subjects in this study. We first distributed the invitation letter to 15 experts by email with an indication of a reward (USD 50) and a research report for participation. A total of 12 subjects agreed to participate in this study. The profiles of the subjects interviewed are shown in Table 2. Among the 12 participants (see Table 2), 8 were involved in SM as consultants and 4 as product managers. All participants have a minimum job experience in SM and AI of 5 years and 3 years, respectively.

The guideline of the interview was developed from the literature review and the objective of obtaining the knowledge and experience of the experts about the application of AI-related technologies in the industrial context for SM and was structured into three parts: start-up, trigger and follow-up questions. See Appendix 4. The purpose of the first part was to introduce the purpose of the interview to the subjects and understand their job position, background and related experience. In the second part of the interview, the description of the identified and collated indicators from our systematic review was given to the subjects, and the subjects were asked to give the number of maturity levels and their description to each level and provide the characteristics of I-AI based on the indicators identified from the systematic review. When the subjects came up with new ideas, they were asked to further describe and explain these ideas that were the third part of the interview. Each interview was conducted in the office of the interview subjects and lasted for 50 minutes–90 minutes. After interviewing the subjects, their demographic information was collected. In the interviews, since we asked the interviewees' opinions on the number of maturity levels, ten participants answered five levels and only two gave six levels (the eighth and the ten participants). In the process of the interviews, the communication between researchers and interviewees was interactive. When the eighth and the tenth participants were interviewed, they first proposed six maturity levels for I-AI, while it was difficult for them to distinguish nuances and describe refined levels that may impact the interview completion. Then the researchers mentioned that previous SM maturity models normally have five levels, and the majority of the participants in the present study considered that I-AI maturity has five levels. These two participants then gave five levels of the I-IA maturity and found it easier to describe these levels.

Moreover, the interviews conducted were recorded with the approval of the subjects. After the interviews, all voice records of the interviews were transcribed for further analysis. The qualitative content analysis was employed to analyze the transcribed interviews because of its potential to provide a systematic and objective method for describing and classifying text material that helps fully use the knowledge and experience of the experts to establish the

Table 2.
The profile of the subjects interviewed in this study

Profession	Pseudonym	Gender	Geographic location	Experience in SM (No. of years)	Experience in AI (No. of years)	Research field	Type of industry
Smart manufacturing product manager	PM A	Male	Jiangsu	5–10	3–4	Industrial Internet	Mechanical equipment industry
	PM B	Male	Guangdong	>10	5–10	Industrial Internet	Tobacco manufacturing industry
	PM C	Male	Fujian	5–10	3–4	SM	Power equipment industry
	PM D	Male	Guangdong	>10	5–10	SM	Mechanical equipment industry
Smart manufacturing consultant	Consultant A	Female	Beijing	5–10	3–4	AI	New energy automotive industry
	Consultant B	Male	Beijing	5–10	5–10	AI	Multiple industrial fields
	Consultant C	Male	Beijing	>10	>10	SM	Aircraft industry
	Consultant D	Male	Beijing	>10	5–10	SM	Multiple industrial fields
	Consultant E	Male	Beijing	5–10	5–10	Industrial Internet	Steelmaking industry
	Consultant F	Male	Beijing	5–10	3–4	Industrial Internet	Motor industry
	Consultant G	Female	Beijing	5–10	5–10	Industrial Internet	Mechanical equipment industry
	Consultant H	Male	Guangdong	5–10	3–4	Industrial Internet	Multiple industrial fields

characteristics of the I-AI indicators toward the maturity levels. As the participants provided the number of maturity levels and their description for each level, we first identified similarities for each level (from the first level to the fifth level) through content analysis based on the participants' description and then developed the definition for each level. Since the indicators were developed in our systematic review and given to the subjects as a set of consistent interview questions, in the data analysis of the transcribed interviews, we did not modify the categories of the indicators and only focused on the characteristics of the indicators related to I-AI described by the experts and summarized them as phrases (namely, coding). Here we screened the phrases referring to the word frequency in the interview transcripts and merged the phrases based on their similarity to establish a coding table. By using the coding table, all interview transcripts were analyzed and coded. The characteristics of maturity emerged from this section of the study and were grouped into the corresponding levels based on the definition of the five levels. We then gave each level an appropriate name.

4. The proposed maturity model of industrial AI

This section presents the results of our systematic review on the dimensions and indicators developed for the maturity model of I-AI-related technologies and the maturity levels established based on the analysis of the interview transcripts. The maturity model has two dimensions, including "Industry" and "Artificial intelligence," with 12 first-level indicators and 35 second-level indicators that explain the concepts and components in I-AI. The maturity model has five levels covering from planning level to leading level that describe the planning objectives and implementation path of I-AI for SM.

4.1 Dimensions in the proposed maturity model

By analyzing the included literature, this study identified a set of indicators for assessing AI-related technologies in the industry. Table 3 presents the dimensions and indicators of the maturity model proposed in this study.

Dimension	First-level indicator	Second-level indicator
Industry	Research and development	Product design, Technological process design
	Manufacturing	Production, Quality inspection, Warehousing and distribution, Safety, energy consumption and environment protection
	Supply chain	Purchase, Logistics
	Marketing	Marketing management, Customer management, After-sales service
	Project support	Project management, Risk control
Artificial intelligence	Smart data acquisition	Data collection, Data transmission, Data prepossessing
	Big Data quality	Volume, Variety, Veracity, Velocity
	Smart data analysis	Artificial intelligence algorithm, Smart data visualization, Data analyst
	Smart decision-making	Machine-automated decision-making, Computer-assisted decision-making
	Big Data security	Data security management mechanism, Implementation of nontechnical data security provisions, Application of data security technology
	Big Data management	Data management strategy, Data integration and sharing, Data lifecycle management, Application of data quality management technology
	Smart cloud storage	Storage capacity, Calculation capacity, Network

Table 3. Dimensions and indicators in the proposed maturity model of I-AI-related technologies

4.1.1 Industry dimension. The industry dimension describes multiple aspects of the entire lifecycle of products, including five first-level indicators: research and development, manufacturing, supply chain, marketing and project support.

Research and development focused on the development of appearance and functions of products and the technological process by analyzing customer requirements and the optimization of products and technological process (Henning, 2013; Li *et al.*, 2017; Monostori *et al.*, 2016). Manufacturing concerns the process of converting materials into finished products through production (Henning, 2013; Schumacher *et al.*, 2016), quality inspection (Dagnaw, 2020; Henning, 2013), warehousing and distribution (Henning, 2013) and safety, energy consumption and environment protection (Henning, 2013; Li *et al.*, 2017). The supply chain focuses on the flow of both information and materials within suppliers, manufacturers, distributors and retailers, to deliver products to customers, including purchasing (Davis *et al.*, 2012) and logistics (Henning, 2013) indicators. Marketing emphasizes the planning and implementation of product sales and after-sales service to meet the customer requirements and at the same time achieve the expected organizational, including marketing management (Henning, 2013), customer management (Henning, 2013) and after-sales service (Shrouf *et al.*, 2014) indicators. Project support highlights using both managerial and technical methods for project management and risk control (Henning, 2013) to realize the plans set by the project.

4.1.2 Artificial intelligence dimension. The artificial intelligence dimension depicting technical and nontechnical capabilities of I-AI-related technologies applied in enterprises contains seven first-level indicators, as explained in Table 4.

4.1.3 Integration of the "industry" and "artificial intelligence" dimensions. As inspired by previous studies (e.g. CESI, 2016), the above "Industry" and "Artificial intelligence" dimensions and related indicators are not independent of each other. In particular, the capabilities of smart data acquisition, big data quality, smart data analysis and smart decision-making in the AI dimension can vary significantly according to specific industrial aspects (e.g. research and development, sales and marketing, manufacturing and logistics). Nonetheless, the capabilities of big data security, big data management and smart cloud storage should be consistently established enterprise-wide.

Based on these considerations and results of the SLR process, we established and proposed the integration of "Industry" and "Artificial intelligence" dimensions, as shown in Figure 2. This figure, in fact, also provides a conceptual view of intelligent transformation for an enterprise when AI-related technologies are integrated into the industrial processes. For example, the capabilities of big data security, big data management and smart cloud storage should be holistically planned and applied thoroughly across the entire enterprise. On top of these, and in the process of research and development (R&D), if an enterprise can use AI-related technologies to address smart data acquisition, big data quality, smart data analysis and smart decision-making, this enterprise is more likely to realize intelligent research and development. The intelligent development of other industrial processes (i.e. manufacturing, supply chain, marketing and project support) can also be analyzed in a similar way, based on the measured indicators of the artificial intelligence dimension in the maturity model.

4.2 Maturity levels in the proposed maturity model

As discussed earlier, in the second component of this study, the researchers sought expert opinions by using semi-structured interviews to shed lights on the characteristics of maturity levels of the various indicators included in the proposed model. Based on the data analysis of expert interviews, this study extracts the performance of enterprises on AI-related technologies used in industrial practices at different maturity levels, ranging from level 1 (i.e. planning level) to level 5 (i.e. leading level), as shown in Table 5. The relevant quotations extracted from the interviews to support these developed concepts are given in Appendix 5.

First level indicator	Description	Second level indicator	Description (references)
Smart data acquisition	The use of AI-related technologies in providing required data for enterprises to achieve intelligent functions in industrial processes	Data collection	The use of AI-related technologies to collect data from multiple sources (Li *et al.*, 2017)
		Data transmission	The collected data transmitted from the transmitter to the receiver via networks (Jatzkowski and Kleinjohann, 2014)
		Data preprocessing	To prepare required data for achieving user's requirements (Lee *et al.*, 2014)
Big data quality	Concern whether the collected data meets the needs toward SM	Volume	The capability of dealing with massive datasets generated in the industrial processes (Li *et al.*, 2017)
		Variety	The capability of dealing with the large amount of data in multiple structures from various sources (Li *et al.*, 2017)
		Veracity	The capability of providing accurate data that represents the real world (Li *et al.*, 2017)
		Velocity	The capability of dealing with the data at a fast rate to align with the speed of its production (Li *et al.*, 2017)
Smart data analysis	The use of AI-related technologies in mining values and discovering knowledge from industrial Big Data	Artificial intelligence algorithm	The capability of applying AI algorithms to analyze industrial Big Data for SM (Henning, 2013)
		Smart data visualization	Visually interpret industrial Big Data and simulate the physical world (Brettel *et al.*, 2014)
		Data analyst	The professional who deals with data collection, processing and analysis to provide related reports and recommendations for decision-makers (Hortonworks, 2016)
Smart decision-making	The use of AI-related technologies to generate insights from data for either autonomous or human decision-making	Machine-automated decision-making	The capability of the system on determining or predicting the situation of production and operations for an enterprise and performing independent decision-making (Monostori *et al.*, 2016)
		Computer-assisted decision-making	The capability of the system on developing recommendations to support human decision-making (Henning, 2013)
Big data security	The use of technical and managerial methods for ensuring the security of industrial Big Data	Data security management mechanism	Enterprises establish a clear plan with technical and nontechnical provisions to ensure data security and backup, such as designing the hierarchical structure and job responsibilities for data security professionals, assigning data access authorities, and formulating (1) use of hardware and software to protect data security and (2) requirements and methods of data backup (Li *et al.*, 2017)
		Implementation of nontechnical data security provisions	Actual implementation of nontechnical data security provisions established in an enterprise, including improving staff members' awareness of data security and their ability to protect data security, checking data access authorities, and continuous formulation and modification of data security regulations (China National Standardisation Management Committee, 2019)
		Application of data security technology	The use of cyber security technology such as firewall software that also involves dealing with cyber security, encryption technology, and backup technology to prevent unexpected or malicious access to data and/or data manipulation (Li *et al.*, 2017)

(continued)

Table 4. The description of the indicators of artificial intelligence dimension

First level indicator	Description	Second level indicator	Description (references)
Big data management	Enterprises formulate management strategies for industrial Big Data, and realize data integration and sharing, data lifecycle management and data quality management	Data management strategy	An enterprise formulates the strategies for data management such as data governance, data standards and metadata management, and continuously optimizes data management systems and processes through monitoring and analyzing the data management process. Meanwhile, the enterprise implements the performance assessment based on different job positions to standardize and enhance data management (Halper and Krishnan, 2013)
		Data integration and sharing	The integration of all data generated inside and outside of an enterprise and throughout the product lifecycle to realize data sharing cross departments (Halper and Krishnan, 2013)
		Data lifecycle management	The process of data lifecycle such as data planning, acquisition, storage, analysis, maintenance, application and extinction integrated with enterprises' demands (Halper and Krishnan, 2013)
		Application of data quality management technology	The use of data quality management system to assess and monitor the quality of data, identify and address data quality issues (Halper and Krishnan, 2013)
Smart cloud storage	The cooperation of various devices to provide services for data storage and access	Storage capacity	The storage power of cloud data center in an enterprise to meet the needs of realizing I-AI (Mezgár and Rauschecker, 2014)
		Calculation capacity	The computing power of cloud data center in an enterprise to guide the intelligent production and operations (Mezgár and Rauschecker, 2014)
		Network	Deal with (1) data transmission from sensors to local servers and then to the cloud, and (2) instructions delivery from the cloud to machines and devices (Mezgár and Rauschecker, 2014)

Table 4.

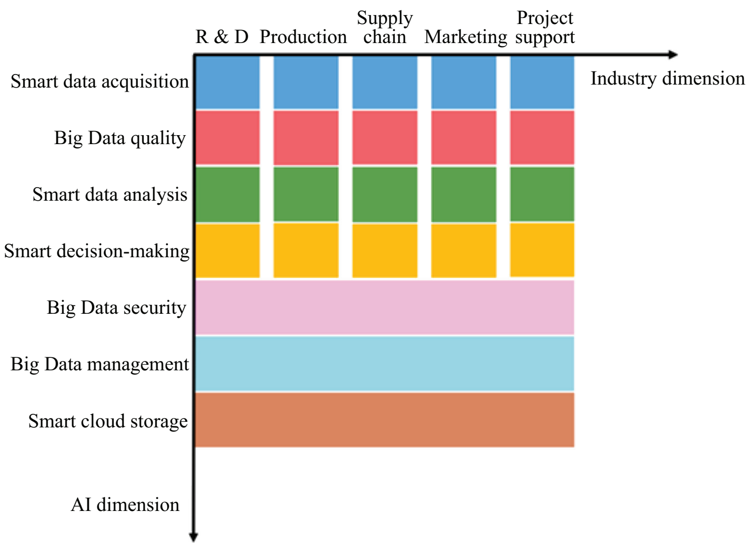


Figure 2.
The integration of the industry and AI dimensions

Name of level		Concept of level
Level 1	Planning level	The enterprise has paid attention to use of I-AI-related technologies, made a preliminary plan and configurated hardware for the production process
Level 2	Specification level	The enterprise has made a comprehensive plan for the application of I-AI-related technologies and invested on smart equipment and systems for core business units
Level 3	Integration level	The enterprise has changed the focus of I-AI from physical equipment configuration and information system optimization to integration of systems across different departments of the enterprise
Level 4	Optimization level	The enterprise has fully applied and integrated the production system, the management system and other information systems to realize the digitalization of the enterprise and a few intelligent functions such as intelligent production scheduling and risk evaluation
Level 5	Leading level	The enterprise is able to collect, filter, transmit, and analyze real-time data, and realizes the automatic decision-making and optimization across all industrial processes within departments of the enterprise

Table 5. The maturity level identified from this study and their concepts

Further to the above general description of the five maturity levels, Figure 3 shows a roadmap of achieving SM by using AI-related technologies in industrial processes, from a planning level to a leading level, through integrating the maturity levels with both industry and artificial intelligence dimensions.

For a better understanding of how to achieve a higher maturity level of I-AI-related technologies (see Figure 3), Table 6 provides more detailed exemplifications about the characteristics of maturity levels of the key AI indicators in the industrial context. As shown in Table 6, in order to grow from planning level to leading level in smart data acquisition, enterprises should put efforts into establishing data collection standards and ensuring real-

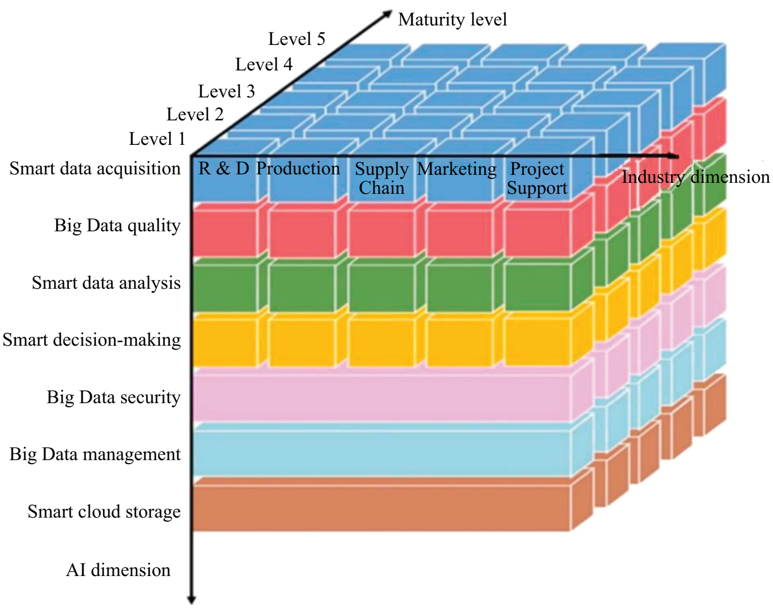


Figure 3. Integrated maturity model of I-AI-related technologies

First-level indicators of artificial intelligence dimension	Level 1	Level 2	Level 3	Level 4	Level 5
Smart data acquisition	Pay attention to data acquisition standards for production process	Propose data acquisition standards for core business units	Establish data acquisition standards across multiple departments	Realize smart data acquisition for the integrated systems	Optimize smart data acquisition across all industrial processes within departments of the enterprise
Big Data quality	Pay attention to dealing with data quality problems for production process	Make plans to deal with data quality problems for core business units	Deal with data quality problems across multiple departments	Address data quality problems for the integrated systems	Optimize data quality across all industrial processes within departments of the enterprise
Smart data analysis	Pay attention to using AI-related technologies in data analysis for production process	Make plans to use AI-related technologies in data analysis for core business units	Use AI-related technologies in data analysis across different departments	Realize smart data analysis for the integrated systems	Optimize smart data analysis across all industrial processes within departments of the enterprise
Smart decision-making	Pay attention to using AI-related technologies in decision-making for production process	Make plans to use AI-related technologies in decision-making for core business units	Decision-making is supported by data analysis across different departments	Smart decision-making is supported by data analysis from the integrated systems	Optimize smart decision-making across all industrial processes within departments of the enterprise
Big Data security	Pay general attention to data security management for IT environment	Make both technical and nontechnical plans to deal with data security management for core business units	Implement data security management tools and plans across different departments, and pay particular attention to IoT-based cyber security	Realize standardized data security management for the integrated system with diverse big data sources (e.g. IoT, MIS and Internet data)	Optimize data security management and practices across all industrial processes of the firm to eliminate any potential cyber risks in an SM environment
Big Data management	Pay attention to big data management and governance standards for production process	Propose big data management standards and data governance plans for core business units	Implement big data management and governance plans, standards and tools across multiple departments	Realize standardized big data management and governance to achieve efficient big data integration for the integrated system	Optimize big data management and governance across all industrial processes to maintain highest standard of data integration
Smart cloud storage	Pay attention to establish a cloud platform to deal with data for production process	Make plans of establishing a cloud platform to deal with data for core business units	Establish a cloud platform across multiple departments	Realize smart cloud storage for the integrated systems	Optimize smart cloud storage across all industrial processes within departments of the firm

Table 6.
Characteristics of maturity levels of the key AI indicators

time data transmission and preprocessing. To address the quality of big data, this large amount of data is collected from multiple sources and in various structures that should be dealt with at an expected time interval for ensuring its accuracy. When the collected data is prepared for analysis at a planning level, the system needs to address simple data analysis together with the corresponding visualization results. With the improvement of AI algorithms used in data practices, the system identifies the patterns and trends based on self-learning from the data to guide industrial practices. Meanwhile, the system provides the results of data visualization according to different users' requirements. This shows a higher level of smart data analysis. As to approaching a higher maturity level of smart decision-making, the system needs to realize automatic detection and analysis based on relevant data to determine and predict the concerned situations, performing self-decision for operations and planning and/or providing meaningful suggestions for different users. To achieve a higher level of big data security, enterprises need to establish a DSMS to ensure data security and defend against threats. Regarding big data management, data management systems and processes should be dealt with to address the integration and sharing of quality-assured data. In terms of smart cloud storage, the development of the cloud platform should receive more attention from enterprises to guarantee computing and storage power and transmission speed for data practices.

After a further thorough analysis of the interview transcripts, we developed a very detailed and holistic table that depicts the characteristics of maturity levels of all AI indicators against the various industrial processes. Due to word limitation, we do not present this table in full in the paper. In light of this, and in order to demonstrate the richness of our findings, we present (in Appendix 6) the characteristics of the highest maturity level of indicators in the proposed integrated model, with support of relevant quotations extracted from the interviews. This provides a future scenario that manufacturing firms should aim to achieve in relation to the use of AI-related technologies in SM. In Appendix 7, we give the activities in relation to the four maturity levels for the AI indicators integrated with the research and development stage as an example since these activities that might be performed at the different stages of the product lifecycle like manufacturing, supply chain, marketing and project support are similar.

5. Discussion

Our study is motivated by the need of improving the capability of enterprises to apply AI-related technologies for SM (Khan *et al.*, 2020). A maturity model can serve as a tool to understand how to integrate AI-related technologies with industrial practices, while such a model is lacking in the existing literature. This study, therefore, develops a maturity model of I-AI-related technologies to address this limitation. The indicators and maturity levels included in the I-AI maturity model are described in Section 4.

We further establish the links between the dimensions and the maturity levels of I-AI-related technologies (see Figure 3 above). The integration of industry and artificial intelligence dimensions presents how AI-related technologies are used in industrial processes to achieve SM (see Appendix 6 and Appendix 7). Moreover, we transform the I-AI maturity model from a matrix of dimensions to a tool enabling enterprises to benchmark their I-AI capabilities (see Appendix 8). This tool assists enterprises in identifying activities and opportunities on the path to achieving their SM goals. To develop the assessment tool, we took the characteristics identified for each level of maturity in each of the integrated industry and artificial intelligence indicators based on Appendix 6 and Appendix 7 and restated them as yes/no questions. This yes/no format eliminates any ambiguity in assessing the level of compliance for a specific activity. In other words, an enterprise is performing an activity or it is not. The integration of industry and artificial intelligence indicators is captured in a series of questions (see Appendix 8). Each question can have an assigned point value for a "yes" answer and “no” responses receive 0 points. The number of points assigned to a specific question can be determined by the I-AI assessment team based on the relative importance of the activity referenced by the question.

As mentioned, taking advantages of the maturity model, enterprises could assess and determine their as-it situation of using AI-related technologies in industrial processes. However, they may find different evaluation results for these processes. For example, an enterprise realizes automatic data analysis and visualization in the manufacturing process by applying AI-related technologies, while it only carries out simple data analysis in the marketing process. The enterprise might need to put more efforts into smart data analysis for the marketing process. It is also worth mentioning here that when implementing AI-related technologies, enterprises should improve their capabilities step by step (e.g. from a planning level to a specification level or from an integration level to an optimization level) rather than blindly pursuing strategic goals. Enterprises thus need to select an appropriate level as the current target (this choice of the level may not be the highest maturity level that is an ideal status of I-AI), based on their current development situation, market position, customer demands and investment capability.

Note that the assessment tool developed aims to help perform the self-assessment of I-AI for an enterprise but not for comparison among enterprises. When different weighting strategies are used for the indicators, the results could be different. Here, we give a simplified example of the assessment strategies. We assume that the assessment is with no weighting of the indicators and only when an enterprise responds “yes” to all questions for specific integrated “industry” + “artificial intelligence” indicators selected toward a certain maturity level, the selected I-AI capabilities of the enterprise can be considered as at this level. When the actual situation of the enterprise meets the required characteristics of a certain level (e.g. level 1) but does not respond “yes” to all questions for a higher level (e.g. level 2), the enterprise is then determined as the lower level (namely, level 1). Only if the enterprise meets the requirements at a lower level, it has the opportunity to apply for the assessment for higher levels.

Regarding conducting the assessment of the I-AI maturity levels, first of all, an enterprise needs to select the whole I-AI maturity model or some indicators from the maturity model according to its specific actual situation and the SM development strategies, as inspirited by CESI (2016). For small and medium-sized enterprises or the enterprises that need to focus on improving certain I-AI capabilities for parts of industrial processes, it is appropriate to select one or a set of indicators of interest. For large-scale enterprises or the enterprises that can balance the AI development in many industrial processes, the overall maturity model can be applied. Then, by using the assessment tool, an enterprise can determine its as-it situation of the I-AI development. The results of the assessment are determined based on collected evidence from the enterprise, such as expert interview records, document records and system operation records. To better understand the application of the assessment tool, we explain a case as an example in Appendix 9. In the light of using the assessment tool, enterprises can acquire the current development level of using AI-related technologies in each industrial process and formulate specific measures according to the characteristics of the next higher level to improve the capabilities of AI-related technologies used in these processes.

5.1 Theoretical implications

Compared to other SM maturity models available in the literature, our maturity model integrates the indicators utilized to assess I-AI-related technologies from the empirical studies and extends extant maturity models by adding specific technical and nontechnical capabilities of AI-related technologies applied in industry. It defines five maturity levels for the integration of industry and AI dimensions, including their relevant indicators with detailed characteristics from expert interviews, addressing the gap about the theoretical lenses used to help enterprises understand their current state of I-AI and guide them to achieve the AI-enabled SM visions step by step.

The proposed I-AI maturity model appears to be understandable to domain experts, and they explained the characteristics for different maturity level for I-AI according to the indicators identified in the study. As noted in Felch and Asdecker (2020), following a procedure model and literature-based criteria for model development has a better chance to provide theoretical sound models. Since we focused on identifying the indicators of assessing AI-related technologies in industrial processes and defining maturity levels to construct the maturity model, an evaluation and demonstration of the maturity model used in real-world manufacturing enterprises go beyond the scope of this study. By comparing the study with the model development criteria, a few of these criteria are addressed in the present study as mentioned in Section 2.3, while our future work needs to take all requirements of a procedure model (e.g. Becker *et al.*, 2009) and criteria of model development into account to improve the maturity model. For example, the maturity model can be validated by a scoring system developed based on open expert interviews.

The characteristics of different maturity levels for the integrated indicators presented in this study (see Appendix 6 and Appendix 7) that essentially describe an activity as it might be performed at each level of maturity for I-AI at a high level can be served as a theoretical reference to develop an assessment tool (see Appendix 8) for as-is assessment of the development stage of I-AI in an enterprise (a descriptive purpose of maturity model (Pöppelbuß and Röglinger, 2011)) and to identify desired maturity level together with the direction and referenced activities of improvements (a prescriptive purpose of maturity model (Pöppelbuß and Röglinger, 2011)). Specific improvement measures toward expected maturity levels in the form of a detailed specification and operationalization within different industry context might not have been achieved in this study. The findings derived from the study reveal that the capabilities of AI-related technologies used in industrial processes mainly address the issues related to industrial data at different stages of the lifecycle of products for better leveraging data. This helps develop a hypothesis that a higher level of I-AI development is associated with more values created by the data addressed by AI-related technologies, which will be of interest to researchers on testing this hypothesis.

Although the maturity model includes big data security as an indicator for accessing I-AI derived from the data analysis based on the reviewed studies, security issues that are more about the security of big data and cyber appear as a critical concern in I-AI should be investigated in depth. For addressing this, a future improvement could isolate security issues as an individual indicator of I-AI maturity models.

5.2 Practical implications

The present work reveals that the industry dimension conceptually differentiates the artificial intelligence dimension while these two dimensions interact with each other. When AI-related technologies are seamlessly embedded into industrial processes, enterprises are more likely to make SM come true. Essentially, these technologies address industrial data issues from data collection to data use in operations and planning, aligning with the data-driven paradigm in a smart manufacturing context. More specifically, AI-related technologies can help automatically capture the required data from either sensors, local databases or external sources (such as market prices, social media data, Internet news and industrial reports) for further analysis. Then this collected data is processed and analyzed to identify hidden patterns and values of the data to gain intelligent manufacturing power characterized by machine-to-machine interactions, self-awareness, self-prediction, self-optimization and automated decision-making throughout the product life cycle (Lee *et al.*, 2018).

In light of this, the maturity model proposed in this study provides the foundation for enterprises to carry out self-assessment (and so gather holistic understanding) on their current capabilities of AI-related technologies developed and applied in different industrial processes. Based on the assessment results, business decision-makers and IT directors can generate step-by-step plans and set up appropriate targets to improve not just the overall situation in the firm but also specific AI-related aspects and capacities alongside diverse industrial processes. In this study, we only give a simplified example of the assessment strategies with no weighting for the indicators, as shown in Appendix 9. Other strategies of decision calculus also can be used. For example, the average principle is utilized to weight indicators. Each question can receive 1 point value for a "yes" answer and 0 point value for a "no" answer. An enterprise applies for assessing a certain I-AI maturity level (e.g. the first level), and the average score of the integrated indicators of industry and artificial intelligence toward the selected level achieves 0.8, being set as the basic requirement of reaching this level (i.e. the first level in this case). This also helps the enterprise identify the alternatives to satisfy the objectives best (Pöppelbuß and Röglinger, 2011). The I-AI maturity model developed in this study tends to provide reference paths and direction for enterprises in their SM journey from a qualitative perspective. We open specific strategies of decision calculus for an enterprise' self-assessment that can be defined and customized based on the specific industry context and development goals of the enterprise, referring to the guidelines of Pöppelbuß and Röglinger (2011).

Furthermore, the present study shows that establishment of standards and procedures for I-AI landing is an important aspect that enterprises cannot overlook. The focus of I-AI development merely on technical aspects will not be enough. In fact, I-AI evolution will need to be aligned with individual (e.g. recruiting and retaining high-quality data analysts) and managerial initiatives, covering all industrial processes across multiple departments.

Overall, we hope that the application of the established maturity model in practice can lead to useful and holistic improvement paths that eventually help enterprises to achieve manufacturing intelligence and realize their visions of SM.

5.3 Limitations and future work

This study also presents several limitations. First, although we have consistently followed the guidelines of Wolfswinkel *et al.* (2013) to search and select articles, there may still be relevant studies that have not been included in our SLR. Our search was limited to the 11 specific online databases with our keywords, and the articles were included only in English and Chinese languages. There could be potential articles in other languages and other databases. However, these are the main sources on assessing I-AI-related technologies for investigation, addressing confidence that our SLR has identified the key literature. Second, the selection of articles was based on our inclusion and exclusion criteria, and the data analyzed from the included articles was subjective. The original authors of the selected studies may not agree with our interpretation. For ensuring the reliability of the research results, the included articles were coded and reviewed by multiple researchers. For example, one member of the research group randomly selected and coded 17 articles from the data sample and compared them with the results generated from the main coder. The results showed a high level of consistency (91%) in the data analysis between the two coders. Any inconsistent coding was solved by discussion within the research team. We also arranged a group meeting to group the identified indicators and name the groups in order to minimize the bias. Regarding the data analysis of the interview transcripts, the transcribed interviews were sent to each participant to confirm and make adjustments if necessary. All these subjects agreed with our transcription and confirmed that the I-AI maturity has five levels. Third, this study only designs a maturity model and gives a simplified example about the use of the assessment tool, while we did not apply all requirements of a procedure model for model development nor empirically apply the assessment tool to assess AI-related technologies used in industrial processes and to formulate strategies in order to improve the capability of applying the technologies that will be our future study. We also welcome researchers and practitioners to discuss different strategies of decision calculus and compare the findings derived from these strategies for the same enterprise. Fourthly, our maturity model developed may lack a stronger theory. In the present study, we constructed the maturity model based on the literature of assessing AI-related technologies in the industry and classified the indicators as inspired by the intelligent manufacturing capability maturity model (CESI, 2016). These studies reveal that in the SM context AI-related technologies applied in the industrial processes help realize various intelligent functions. Hence, the application aspects of AI-related technologies incarnated in these industrial processes drove us to identify the indicators and group them into the industry and artificial intelligence dimensions. Future studies are suggested to select a theoretical foundation before developing maturity models that helps improve scientific rigor and create a theoretically sound model. As noted in Sutton and Staw (1995), theory concerns the nature of causal relationships among phenomena, contributing to developing convincing and logically interconnected arguments. A missing theoretical foundation dismisses the logic stream on which researchers are drawing and to which they are contributing that makes a maturity model difficult to theoretically justify and achieve theoretical requirements of model development. Last, in this study, we did not consider making all the completely transcribed interviews available on an online repository for the transparency purposes; thus, we did not seek the copyright clearance from the interviewees at the time of the interview, while retrospective clearance is often time-consuming or impossible. Therefore, we failed to share the completely transcribed interviews in the present study in order to verify our research findings by triangulation outside of the research group. Future research should take this into account at the stage of the interview design for addressing required transparency in a qualitative study.

6. Conclusions

This study proposes a maturity model of I-AI-related technologies that contains industry and artificial intelligence dimensions within 12 first-level indicators (in Section 4.1) and five levels of maturity (in Section 4.2), based on an SLR and expert interviews. The maturity model contributes to understanding the capabilities of AI-related technologies used in industrial processes and assessing the capability of applying the technologies in practices. The findings of the study benefit decision-makers on strategizing measures for improvement to realize SM from both technical and nontechnical perspectives. Our work suggests a future direction for research on defining the indicators for assessing the use of I-AI-related technologies. In addition, the study raises the awareness for decision-makers about selecting appropriate targets and formulating measures based on the current development state to improve the capability of applying the technologies.

Note

1. CESI refers to China Electronics Standardization Institute.

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Appendix 1

Major search term	Industrial artificial intelligence	Technologies	Assessment
Synonyms and alternative terms	"Smart manufacturing" "Ubiquitous manufacturing"	"Technolog*" (e.g. technologies, technology, technical support)	"Roadmap"
		"Cloud*" (e.g. cloud platform, cloud support)	"Level"
		"Big Data*" (e.g. Big Data analytics, Big Data)	"Model"
		"Cyber-Physical Systems"	"Framework"

Note(s): Note that we used "industrial artificial intelligence" rather than "industrial" + "artificial intelligence" as the search term because we identified that prior studies on maturity models of SM adopted the keywords like "smart manufacturing" or "ubiquitous manufacturing" (e.g. Felch *et al.* (2019) and Gökalp *et al.* (2017)) rather than using "smart" + "manufacturing" or "ubiquitous" + "manufacturing" to conduct their literature review for the development of SM maturity models and these keywords also match the term "industrial artificial intelligence" used in our study. Similarly, previous literature on SM maturity models included "assessment" as an alternative term for "maturity model" (e.g. Unterhofer *et al.* (2018)) that the researchers have successfully identified extant relevant studies. And the search term "assessment" is used in the study to identify the indicators of assessing AI-related technologies, which has the great potential to help reveal the indicators that are not included in prior maturity models but appear in the empirical studies of assessing AI-related technologies in industrial processes. Finally, with a wildcard token, the articles covering numerous synonyms of "technologies" like technology, technical support and so on can be searched by using the search term "technolog*". At the same time, we included cloud, big data, and cyber-physical systems as alternative terms for "technologies" in the search because they are three essential AI-related technologies to support SM. In this study, we have also conducted a pilot search with the search strings using the term "assess" rather than using "assessment" for search in one of the selected databases (i.e. Wiley Online Library) and compared the results with the term "assessment." There are no differences in the identified articles. Hence, we selected the term "assessment" in our search strings that also matches the keywords frequently used in related studies

Table A1.
Keywords used in the systematic review

Appendix 2

Table A2.
Demographics of the group meeting in this study

Gender	Number	Education level	Number
Male	4	Master	2
Female	2	Doctor	4
Years of research experience in the subject area	Number	Years of working experience in the field	Number
3–5 years	2	<3 years	1
6–10 years	2	3–5 years	3
>10 years	2	6–10 years	2
Total	6	Total	6

Appendix 3

Table A3.
The inclusion and exclusion criteria on the participants selection

Criteria	Number	Description
Inclusion criteria	1	The biography of the authors is available online
	2	The authors are working in the manufacturing industry
	3	The authors are working in the same country of the researchers of this study (as we intended to visit the experts and conduct interviews in their workplace in which is closer to our workplace for saving the travel time and expenses)
	4	The authors have the research experience related to SM, AI or industrial Internet
	5	The authors deal with SM, smart factory or industrial Internet in the workplace
Exclusion criteria	1	The authors are duplicate
	2	The contact email address of the authors is not available online

Appendix 4

First part: start-up questions Hi, my name is XXX, from XXX. The purpose of our study is to develop a maturity model used to assess the development level of industrial artificial intelligence in smart manufacturing. This interview aims to collect your opinions about the maturity levels and their characteristics for the measured indicators identified from our systematic review I will ask you to answer interview questions and this would not take no more than 90 minutes of your time. You can change your mind at any time and stop completing the interview without consequences If you agree to be part of the research, please continue with answering the following interview questions Q1: Can you please tell me your profession, years of experience in smart manufacturing, years of experience in artificial intelligence, research field, and type of industry that you are working in?
Second part: trigger questions (Give a table (see Table 3) with the description on the indicators of the proposed I-IA-related technologies (as shown in Section 4.1.1 and Section 4.1.2) and a figure that presents the integration of "Industry" and "Artificial intelligence" dimensions (see Figure 2), to the participants.) These are our research findings from the systematic review. Our maturity model includes two main dimensions: industry and artificial intelligence. We identified 5 first-level indicators for the industry dimension and 7 first-level indicators for artificial intelligence with 22 second-level indicators Q2: According to your expertise and experience, what do you think the maturity levels should be when artificial intelligence is applied in industrial processes? Can you please describe these levels? Can you please give the characteristics for artificial intelligence applied in these industrial processes, based on the indicators of artificial intelligence? For example, what are the characteristics of smart data acquisition, including data collection, data transmission, and data prepossessing used in the research and development stage of products?
Third part: following-up questions (When the subjects come up with new ideas, ask the following question.) Q3: Can you please give further explanation or more details about this . . .? *End of the interview* Thanks for your participation in the study

Table A4.
Interview guideline used in this study

Appendix 5

Appendix 5 is available at the following link: https://www.dropbox.com/s/kllh1wz2dvh1spv/Appendix%20IV.docx?dl=0

Appendix 6

Appendix 6 is available at the following link: https://www.dropbox.com/s/v1vw9y85jv2qv79/Appendix%20V.docx?dl=0

Appendix 7

Appendix 7 is available at the following link: https://www.dropbox.com/s/3qqdc919x7oq9sm/Appendix%20VI.docx?dl=0

Appendix 8

Appendix 8 is available at the following link: https://www.dropbox.com/s/79y59js06bp08e8/Appendix%20VII.docx?dl=0

Appendix 9

Appendix 9 is available at the following link: https://www.dropbox.com/s/7akx8d2b68zstjk/Appendix%20VIII.docx?dl=0

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