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REVIEW

A Systematic Literature Survey on the Role of Artificial Intelligence Techniques in Industrial Revolution 4.0 Readiness

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Abstract: The service sector is a key focus of the Fourth Industrial Revolution (IR4.0), a digital revolution that affects all industries. A key component of IR4.0 is the introduction and uptake of new technologies by organizations, including artificial intelligence (AI), big data analytics, the Internet of Things (IoT), cloud computing, augmented reality, simulation, cybersecurity, systems integration, additive manufacturing, and robotics and autonomous systems. According to research, 59% of businesses with expertise in big data and IoT also employ AI technologies. Through the development, adoption, and integration of technology solutions into the workforce and industries, industry participants' readiness and their use of these technologies will be able to increase productivity growth. According to a survey of the literature, Malaysia in particular still has a low to medium degree of industry readiness for IR4.0. The purpose of this paper is to conduct a systematic literature review in order to comprehend the IR4.0 readiness models that have been discussed in the literature, the driving and impeding forces behind IR4.0 readiness, and the use of self-evaluation tools by industry participants to gauge their own IR4.0 readiness level. Six prominent internet databases, including Scopus, Emerald Insight, IEEE, Springer, Web of Science, and Science Direct, were used in the review. Finally, 55 out of the initially searched 10,428 articles were selected based on the inclusion and exclusion criteria set for the study after rigorous methods of screening the papers. According to the research, readiness models are frequently addressed and framed around a variety of theories and their theoretical constructs, including success models, information systems, acceptance theory, and pertinent maturity and readiness theories. The following factors frequently play a dual role, acting as both a driving and an inhibiting influence. These factors include funding, infrastructure, regulatory, skills and competency, technology, and commitment. This study suggests the IR4.0 Readiness and Implementation Framework for industry based on the synthesized literature. The framework seeks to help industry participants deploy IR4.0 in stages and gradually increase their IR4.0 readiness levels.

Keywords: Industrial Revolution 4.0, readiness, driving factors, inhibiting factors, self-evaluation, AI recommender system

1. Introduction

The evolution of Artificial Intelligence (AI) has dramatically impacted the approach to achieving readiness for Industrial Revolution 4.0 (IR4.0). As industries undergo digital transformation, AI's role in predictive analytics, machine learning (ML), robotics, and intelligent systems has become essential. AI technologies are seen not only as catalysts for enhancing operational efficiency but also as critical enablers of IR4.0 frameworks. AI can elevate economic growth by enhancing productivity, automating tasks, and enabling intelligent decision-making across industries, leading to increased efficiency and reliability (Dwivedi et al., 2021; Purdy & Daugherty, 2016).

IR4.0 integrates AI as a foundational technology alongside IoT, big data, and cloud computing to support smarter, autonomous operations across sectors (Ahmed et al., 2022; Schwab, 2016). This paradigm enables real-time monitoring, optimization, and autonomous decision-making in complex environments. As these technologies converge, readiness for IR4.0 increasingly relies on AI's potential to streamline processes, forecast trends, and handle large-scale data analytics efficiently, ultimately preparing industries for the digital demands of IR4.0 (Mahdi et al., 2022; Zhao et al., 2020). The industrial landscape, shaped by these developments, has transformed through distinct phases. The initial revolutions focused on mechanization and mass production, while the current phase emphasizes cyber-physical systems (CPS) and connectivity. As AI accelerates innovation within this framework, companies worldwide are compelled to assess their IR4.0 readiness (Pirola et al., 2019; Stentoft et al., 2021). This process often includes adopting AI-driven self-assessment tools that enable companies to evaluate and enhance their technological infrastructure and workforce competencies critical to IR4.0 objectives (Brozzi et al., 2018).

The role of Artificial Intelligence (AI) techniques in Industrial Revolution 4.0 (IR4.0) readiness is multifaceted, as AI serves as both a driver and enabler of the digital transformation that IR4.0 demands. Some of the identified key roles AI techniques play in

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IR4.0 readiness include enhanced decision-making and automation. This is because AI, especially through machine learning (ML) and predictive analytics, enables industries to automate complex decision-making processes. Manufacturers undergo a digital transformation that manages and uses their data sets by leveraging AI and ML for better quality control, standardization and maintenance (Javaid et al., 2022). Next is predictive maintenance, whereby AI techniques, such as deep learning and anomaly detection, predict potential failures in machinery before they occur. This predictive maintenance helps avoid costly downtimes and ensures continuous production, which is essential for high IR4.0 readiness in manufacturing environments (Cheung & Messom, 2018; Russell et al., 2003). Further, real-time monitoring and process optimization with AI-driven tools like computer vision and reinforcement learning, organizations can monitor and optimize production processes in real-time. AI-powered systems can dynamically adjust to changing conditions, ensuring continuous optimization and resource efficiency, which aligns with IR4.0 objectives (Carolis et al., 2017). In IR4.0, AI supports enhanced human-machine collaboration, which is new forms of human-machine interaction, such as collaborative robots (cobots) that work alongside human operators. AI-powered cobots enhance safety and productivity while allowing workers to focus on more complex tasks that require human insight (Tortora et al., 2021). Thus, AI techniques are integral to preparing industries for IR4.0, driving efficiency, scalability, and resilience while enabling continuous innovation and adaptability across digitalized and automated processes.

In the Malaysian context, the National Policy on Industry 4.0 (Industry4WRD) was introduced by the Ministry of International Trade and Industry in 2018 as a proactive strategy to enhance the Malaysian manufacturing sector and its related services, making them smarter, more systematic, and resilient through Industry 4.0 readiness initiatives. In 2021, the Malaysia 4IR Policy was introduced, extending beyond manufacturing to include various sectors, thus broadening the scope of IR4.0 and emphasizing AI-driven advancements and the role of digital transformation. To support these efforts, a readiness assessment (RA) tool was developed to evaluate the IR4.0 preparedness of Malaysian industries. The RA process includes seven stages: (i) public announcement, (ii) company registration, (iii) Industry4WRD – RA Technical/Steering Committee review, (iv) conducting the assessment, (v) full report preparation, (vi) readiness level presentation to the Industry4WRD – RA Committee, and (vii) informing companies of their RA results. This multi-step process has proven time-intensive, which has led some organizations to be reluctant participants in IR4.0 readiness assessments. Although various smart manufacturing assessment models exist, challenges in applicability remain, particularly for small- and medium-sized manufacturers (SMMs), as these models often require significant training and consulting resources, further straining the limited capacity of SMMs (Choi et al., 2018).

2. Literature Review

The potential of IR4.0 includes quicker decision-making, improved shop floor monitoring and control, more effective resource usage, and better demand forecasting (Hernandez-de-Menendez et al., 2020). Industry participants must keep up with the pace by having a high degree of IR 4.0 preparedness in order to achieve the potential. A number of research have been conducted in this context with focus on studying the driving factors, the barriers, and the impacts of IR4.0 technologies to business operations. Later, the investigation led to the creation of a new or enhanced readiness or maturity model. A maturity model that assesses the maturation process was developed by Schumacher et al. (2016), and a readiness model that assesses how prepared a company is for the development process. Initially, NASA's technology readiness model (TRL) introduced and used the model in 1974 (Eljasik-Swoboda et al., 2019). The TRL included nine stages and six dimensions: (1) fundamental technology research, (2) feasibility research, (3) technology development, (4) technology demonstration, (5) system/subsystem development, and (6) system, test, launch, and operations.

Analysts project that in 10 years (as in 2020), 3.5 million people will be required to fill specific manufacturing vacancies with high competencies on emerging technologies like IoT, digital twins, and smart factories (Hernandez-de-Menendez et al., 2020). This is in relation to the skills and competencies required to support IR4.0 readiness. The absence of experts with the necessary training, however, will result in fewer posts being filled (Turcu & Turcu, 2018). The management of complex industrial systems, as well as greater creativity, strategic thinking, and coordination abilities, is among the qualities reportedly required for the IR4.0 era (Hecklau et al., 2016). The Accreditation Board for Engineering and Technology, Inc. believes that effective professionals need to possess the following skills to deal with IR4.0, according to Hernandez et al. (2020): (1) to apply knowledge of mathematics, science, and engineering; (2) to plan and carry out experiments; (3) to analyze and interpret data; (4) to develop systems or processes taking into account economic, environmental, social, political, ethical, health and safety, manufacturing, and sustainability constraints; (5) to identify, formulate, and solve engineering problems; (6) to comprehend the impact of engineering solutions in global, economic, environmental, and societal contexts; and (7) to create systems or processes.

Employee competencies will be subject to new demands, as will the organizational framework conditions put in place to facilitate such development (Longo et al., 2017). Lassen & Waehrens (2021) summary of the competencies required for IR4.0 adoption includes: (1) Cyber-Physical Systems (CPS) skills to support operational working level; (2) higher de-centralization in decision-making and planning processes; (3) skills in process integration and cross-functional perspectives; (4) automation skills for quality and maintenance; (5) high complexity and dexterity to integrate and manage the automation; and (6) flexibility in working life and partner networks. Personal, social, action, and domain-related competences are currently being classified as future competencies (Erol et al., 2016). According to Erol et al. (2016), workers' mental states are correlated with market demands and environmental factors including flexibility in problem-solving and inventiveness, which are prerequisites for social competence. Future workers will need to possess strong analytical skills, and future engineers will need to possess the capacity to solve problems in a practical and domain-specific manner while maintaining focus on the big picture (Erol et al., 2016).

Focusing on the knowledge or abilities needed to complete a task, such as writing a software program, Lassen & Waehrens (2021) stressed that personnel must first be specialized in order to understand the intricate systems at play. For example, engineers will need to have a thorough understanding of the relationships between the electrical, mechanical, and computer components in order to create novel products and procedures (Erol et al., 2016). But critically, some business leaders stated in the interview by Lassen & Waehrens (2021) that they do not have time to change their organization. This contradicts the advice from Tortora et al. (2021) that businesses must make a difficult decision about whether to stick with the strategies and techniques that have been successful in the past or embrace the change by adopting new products and organizational paradigms on IR4.0. According to the study that has been done on the adoption of IR4.0, many have come to the conclusion that being ready for IR4.0 depends on having the necessary skills and competencies, as well as the business strategies, IR4.0 roadmap, and start-ups. The identified competencies that new entrants are need to possess in order to implement IR4.0 are listed in Table 1 (Hecklau et al., 2016).

The most promising technology solution is chosen and funded by investors, and most start-ups are anticipated to advance more quickly than existing businesses (Filieri et al., 2021). The decline in investment among European start-ups has been attributed, according to Guzman & Kacperczyk (2019), Thébaud (2015), and von Briel et al. (2018), to expectations of rapid development and industry disruption. According to Filieri et al. (2021), founders with prior job experience received the majority of investment from venture capitalists (VC), with educational background being unimportant and money proportionate to the traits of established businesses. However, education in the manufacturing industry had an impact on how well a firm performed. One example is the total predictive maintenance training that is frequently provided to engineers and technicians in Malaysia by a typical Japanese manufacturing company. With the improved human capital, higher performance and productivity levels are also possible (Schultz, 1961). Additionally, funding is taken into account for the purposes that will benefit the industry's key participants and be pertinent to how closely IR4.0 technologies interact with both people and the environment. For instance, Filieri et al. (2021) discovered that destination services and booking and preparation typically receive the majority of financing. In addition to investor funding, Filieri et al. (2021) came to the conclusion that the European travel and tourism industry is less interested in virtual reality, robotics, and automation, connected and automated objects, and resource allocation because they are receiving such small amounts of funding (Guzman & Kacperczyk, 2019; Thébaud, 2015).

Table 1
Type of competencies based on program in universities

Program name	Type of competencies
Makerlodge by The Massachusetts Institute of Technology (Hernandez-de-Menendez et al., 2020)	Circuit board manufacturing and 3D printers
MIT Leaders for Global Operations (MITLGO) by The Massachusetts Institute of Technology (Hernandez-de-Menendez et al., 2020)	Leadership
Smart Manufacturing Program by The Massachusetts Institute of Technology (Hernandez-de-Menendez et al., 2020)	Critical thinking and innovation
Workshop on Science, Technology, and Policy: The Future of Work by Singapore's National Research Foundation	Artificial intelligence, robotics, cybersecurity, and the management of disruptive changes
Master's Program in Automation Technology by RWTH Aachen University (RWTH AACHEN University, 2019)	System and automation, teamwork, problem-solving, leadership, and management
Master's in Data Analytics and Decision Science by RWTH Aachen University	Big data, decision-making, and problem-solving
Master's Program in Robotic Systems Engineering by RWTH Aachen University (Aachen International Academy, 2019; Aachen University and Robotic Systems Engineering, 2019)	Robotic, analytical, technological, and problem-solving

AI has recently emerged as a key component of the technology resources. AI-driven management can substitute for domain-fixed-functional-expertise (Schrettenbrunnner, 2020). Numerous modern AI technologies start out using common ML methods before becoming intelligent after being educated (Ransbotham et al., 2017). The development of the economies of nations like the United States (Makridakis, 2017), China (Li, 2017), and India (Acharya et al., 2019) will be significantly impacted by AI (Cheung & Messom, 2018). According to a recent PwC analysis, by 2030, AI might contribute 14% more ($15.7 trillion USD) to the global economy (Cheung & Messom, 2018). AI- and ML-based self-managing capabilities are becoming increasingly common in web services and data center management software, allowing these systems to automatically adapt to shifting workloads (Kettimuthu et al., 2018).

To increase competitiveness and preserve resources effectively, a number of electronic readiness (e-readiness) or readiness models have been put forth and implemented (Alshawi, 2007). E-readiness is a measure of the degree to which an organization may be ready, prepared or willing to obtain benefits which arises from the digital economy (Lou et al., 2020). This idea of e-readiness is used in a readiness evaluation that Choi et al. (2018) created. The recent explosion of AI technologies has increased the need for such research (strategies and means for selecting and implementing digital technologies that realize firms' goals in digital transformation), as they are being used more and more in a variety of organizational practices, creating both new opportunities for digital transformation and new challenges for managers of digital transformation processes (Holmström, 2022). ML, a branch of AI that enables a machine to automatically learn from the past without explicit programming, is a technique that enables a machine to replicate human behavior. As a result, Choi et al.'s (2018) model for the readiness of smart manufacturing uses ML to analyze data from a peer review system and adoption success stories from the past.

AI as an IR4.0 enabler is concurrently linked to plans such as the China State Council's Next Generation Artificial Intelligence Development Plan, which was launched in 2017 as the plans for the overall thinking, strategic goals, main tasks, and supporting measures for AI development before 2030, with seven keys of AI master plan such as medical imaging system, audio intelligence, connected vehicles, language translations, service robots, unmanned aerial vehicles, and image recognition. Furthermore, in line with John McCarthy's 1956 definition of AI as the "science and engineering" of creating intelligent machines, particularly intelligent computer programs (Rajaraman, 2014), the European Commission's (EC) (2020) master plan aims to develop and regulate the EU AI market while acknowledging the importance of striking a balance between common principles and the specific interests of the stakeholders (Borsci et al., 2022).

3. Methods

The systematic literature review was conducted to provide a comprehensive overview of existing terminology and customer journey approaches, addressing variations and key issues (Følstad et al., 2018). SLR is a thorough, transparent search of numerous databases and grey literature that may be duplicated and repeated by further researchers. Grant & Booth (2009) claimed that the expansion in evidence-based practice has led to an increasing variety of review types. Meantime, Tranfield et al. (2003) discuss the origins of the evidence-based approach to undertaking a literature review and its application to other disciplines including management and science. Hence, this study practiced this method of review to realize the RQs.

This SLR is made up of five distinct activities: define, searching, extraction, assess, and analyze and combine. Following that, the activities are divided into three major phases: planning the review, conducting the review, and reporting the review. Each step in the three phases ensures the validity and reliability of the systematic review process.

3.1. Planning the review

(i) Defining RQs

The conducted literature review, according to (Ali & Xie, 2021), served the purpose of developing the problem statement, stating RQs, defining the variables relevant to the problem being investigated by this research work, proposing hypotheses for this research work, and developing a comprehensive research model for the study to be carried out. The introduction section stated the need to investigate the readiness model and the factors driving and impeding IR4.0 adoption. As a result, four RQs were created to aid in the literature review process.

- RQ1. What are the different readiness models of IR4.0 in existence today?
- RQ2. What are the factors driving IR4.0 readiness?
- RQ3. What are the factors inhibiting IR4.0 readiness?
- RQ4. How are the self-evaluation instruments be developed for IR4.0 readiness?

(ii) Searching for relevant data sources

To answer the RQs, six scientific databases (Emerald Insight, IEEE, Science Direct, Scopus, Springer, and Web of Science (WoS)) were chosen to source relevant journals only, not books. Similarly, Peres et al. (2020) utilized Web of Science, Scopus, and Science Direct to conduct SLR on the application of industrial AI in real manufacturing environments. The development of the electronic age has resulted in the creation of numerous medical databases on the World Wide Web, each with search capabilities and the ability to perform citation analysis (Falagas et al., 2008).

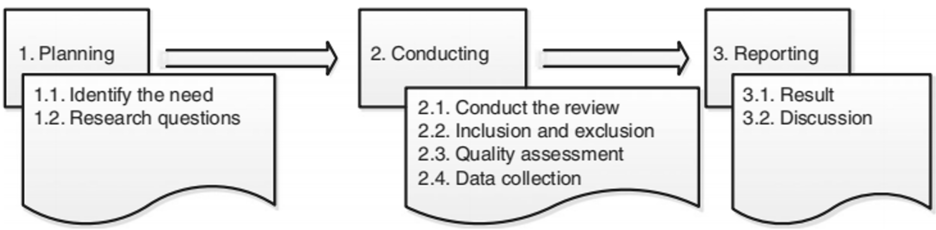
Elsevier created the Scopus database by combining the characteristics of both PubMed and WoS, whereas Thomson Scientific, a division of Thomson Corporation, another private company, created WoS and has dominated the field of academic reference, primarily through the annual release of the journal impact factor, a tool for evaluating the importance and influence of specific publications (Falagas et al., 2008). Studies indicate that researchers' relative rankings remain largely consistent between Scopus and WoS (Budimir et al., 2021). However, integrating bibliometric data from WoS and Scopus for inter-firm relationship analysis requires extensive data wrangling for unification and correction (Kumpulainen et al., 2022). According to Falagas et al. (2008), Scopus includes a broader range of journals than PubMed and WoS, and its citation analysis is faster and includes more articles than WoS's citation analysis. Meanwhile, the citation analysis presented by WoS has better graphics and is more detailed than the citation analysis presented by Scopus, most likely because WoS was designed with the intention of satisfying users in citation analysis, a field discussed and debated by scientists for decades.

Four databases were employed in the SLR investigation by Deshayes et al. (2016) up until April 2015: MEDLINE, SciELO, ScienceDirect, and Google Scholar. ScienceDirect, WoS, Scopus, PubMed, and Springer databases were cited by Ramon et al. in their study to evaluate the outcomes of the application of Business Process Management methodology on clinical processes, analyzing whether it can become a useful tool to improve the effectiveness and quality of processes. ACM, IEEE, Science Direct, Sage, Emerald, and Springer were the six databases chosen by Thuan et al. (2016) for their investigation to identify the elements influencing the decision to crowdsource. In the meantime, Hamid et al. (2016) have chosen four databases (WoS, Science Direct, Scopus, and IEEE) to undertake the SLR approach in order to investigate the information-seeking behavior of international students in terms of their information demands and to highlight the importance of social media. Figure 1 summarizes the SLR procedure used in this study.

3.2. Conducting the review

In order to clarify and validate the eligibility of the SLR process, the review is conducted by involving data inclusion and exclusion criteria, quality assessment, collection of the data, and data analysis.

Figure 1
Activities in systematic literature review adopted from Esfahani et al. (2015)



(i) Assess the eligibility of data inclusion and exclusion criteria

The inclusion and exclusion criteria were used to ensure that only the relevant articles were included in the SLR process (Hamid et al., 2016). The aim for this selection is definitely to assess the eligibility of the journals which to match the objectives of the SLR. As the keywords are not expected to return the papers with the related topic, inclusion and exclusion criteria are needed to refine the result through the databases. The inclusion and exclusion criteria were used to ensure that only the relevant articles were included in the SLR process, as per Table 2 (Hamid et al., 2016).

Table 2
Inclusion/exclusion criteria (Hamid et al., 2016)

Inclusion criteria	Indirectly or directly answer any one or more research question Focus on the role of social media in information-seeking behavior and problems of international students. Published in years: 2000–2015
Exclusion criteria	Exclude irrelevant books or overhead presentations Exclude which is not related to the research field Papers when only abstract and no full text were available Articles that did not match the inclusion criteria

(ii) Quality assessment

In the quality assessment, all the papers resulted through the databases till the final selection of papers are shown in Figure 2. This stage is to ensure that the selected papers are valuable to be analyzed and discussed.

(iii) Data collection and analysis

A data collection form was designed to collect the most relevant information from the selected papers in order to facilitate the process of analyzing the compiled data (Hamid et al., 2016). Table 3 shows categories of information and specific information needs during the data analysis.

3.3. Reporting the review

In this phase, analysis and combination of data are conducted which then be furthered in the next section of results and discussion.

4. Findings

This section discusses the findings framed around the four RQs posed earlier in Section 3.

4.1. RQ1: What are the different readiness models of IR4.0 in existence?

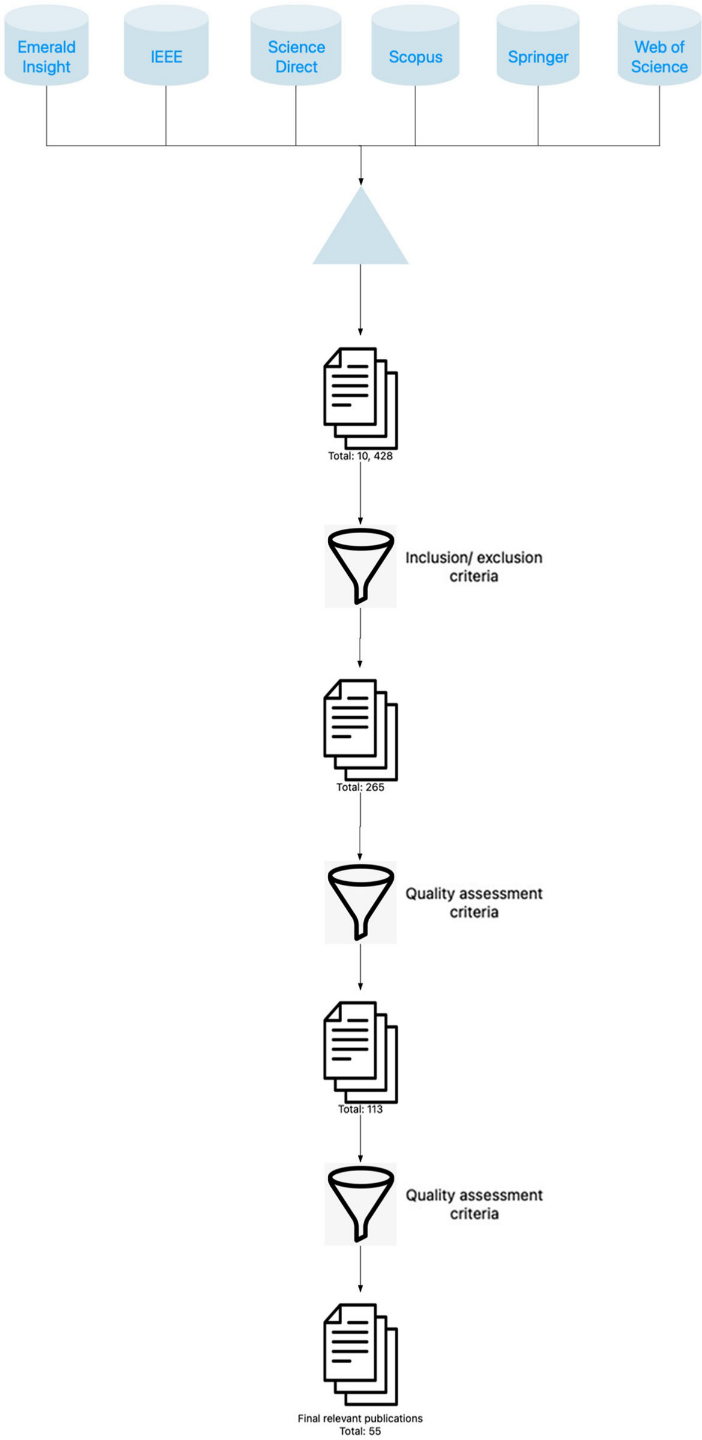
Academics have devised and studied a variety of maturity models so that both preparedness and maturity simultaneously addressed the same focus issue (Mushref & Ahmad, 2011). According to Schumacher et al. (2016), the distinction between readiness and maturity is that the former takes place before to engaging in the maturing process, while the latter tries to capture the state as-it-is while the latter is taking place. Although the properties and levels of complexity of these models vary (Carolis et al., 2017), basic structures, like dimensions and items, are common (Brozzi et al., 2018).

According to one method of survey questions, Nick et al. (2019) readiness's model on the industrial area of Hungary was carried out. It is based on 99 questions, which were broken down into three sources: 16% from National Technology Platform (NTP) Workgroups, which introduced aspects of education, training, employment, and access to financial resources; 18% from Verband Deutscher Maschinen- und Anlagenbau and is the Germany's equipment manufacturing association (VDMA) Framework, which includes company level; and 66% from the author's interviews with industrial people. In terms of the evaluation stage, the author entered the survey responses into a relational database. Each response was then automatically, repeatedly, and manually changed until the statistical properties of the evaluated answers with regard to the question seemed satisfactory (the empirical distribution of the points has fitted the theoretical distribution).

The readiness model created by Lucato et al. (2019) is one way that a certified entity might relate to a standard structure that is based on a Society of Automotive Engineers (SAE) J4000 basis structure, with the author supposing that the model behaves like a linear parameter. The SAE J4000 standard is a guideline for finding and using best practices when putting a lean operation into place. The standard then establishes a set of components for each of the six aspects that make up lean manufacturing and reflect areas of the business to be examined in the firm. There are 52 elements and statements that will be reviewed, and each statement will have four potential responses: Level 0 (L0): The component is absent or its implementation has significant discrepancies; Level 1 (L1): The component is there, although its implementation has a few small errors; Level 2 (L2) refers to a component that is entirely present and successfully implemented, and Level 3 (L3) refers to a component that is fully present, successfully implemented, and demonstrates advances in its execution over the previous 12 months. In order to determine the maturity level of IR4.0 in various databases, the author first conducted a review of the relevant literature.

Academics like Schumacher et al. (2016) and Mrugalska & Stasiuk-Piekarska (2020) have presented the readiness model or maturity model, which is based on the maturity index. The problem of the statistical technique not guaranteeing the objectivity of the evaluation when the determinants are both subjective and objective is being solved in the following steps. In order to increase the precision of the judgment, the assessment in that continuation is based on rough set theory and involved an algorithm of indiscernibility relation. Six dimensions were selected as their study model for the IR4.0 digital transformation by Hamidi et al. (2018) using the IMPULS maturity assessment approach. One of the most well-known models of ready is "IMPULS – Industrie 4.0 Readiness" from 2015. Each of the six dimensions in the research model had a six-level model, and the formula to gauge readiness included weighing the dimension scores out of a possible 100 points. The average of each dimension for SMEs is then examined using a statistical comparison of the score and average for each dimension. The author created survey questionnaires that were given to Malaysian SMEs via email and in-person contact and were stored in Google Documents. The IMPULS model is an illustration of how to measure IR4.0 readiness with six dimensions (strategy and organization, smart factory, smart operations, smart products, data-driven services, and employees) (Alcácer et al., 2021), with each dimension having several sub-dimensions that describe the measurement in detail. As a result, the organizational readiness can be explained by six levels, ranging from level 0 (beginner level) to level 5 (high performance level).

Figure 2
Publication collection method flow



While many have alluded to the six dimensions in the IMPULS model, studies over the years have also discussed whether dimension is accurately to be employed in IR4.0 or Industry 4.0 (I4.0) preparedness before the development stage. Meanwhile, Sony & Naik (2019) recommended six dimensions: organizational strategy, organizational digitization level, supply chain digitization expansion, smart products and services, employee Industry 4.0 suitability, and top management engagement and commitment. Six dimensions of IR4.0 readiness were put forth by Soomro et al. (2021), namely technology, people, strategy, leadership, process, and innovation. Alcácer et al. (2021) new self-method in the IR4.0/I4.0 readiness model made it possible to identify the major obstacles as seen from the perspective of the companies. According to Brozzi et al. (2018), the IR4.0 readiness self-assessment tool should take into account the following factors: (1) the use of straightforward language in describing dimensions and items; (2) the ability to

Table 3
Information needs of IR4.0 readiness

Categories of information needs	Specific information needs	Authors
IR4.0 readiness model related	Empirical data, method, readiness insight, factors	(Alcácer et al., 2021; Horvat et al., 2018; Lucato et al., 2019; Mrugalska & Stasiuk-Piekarska, 2020; Nick et al., 2019; Schumacher et al., 2016; Soomro et al., 2021; Trstenjak et al., 2020; Wijewardhana et al., 2020)
Funding related	Policy, requirements	(Bosman et al., 2019 ; Filieri et al., 2021; Nick et al., 2019; Tortora et al., 2021)
Self-assessment related	Reason, method, benefit	(Alcácer et al., 2021; Brozzi et al., 2018; Choi et al., 2018; Hamidi et al., 2018; Horvat et al., 2018; Lucato et al., 2019)
Training related	Demand skills, benefit, barrier	(Ali & Xie, 2021; Hernandez-de-Menendez et al., 2020; Lassen & Waehrens, 2021; Matt et al., 2021; Müller & Voigt, 2018; Schinner et al., 2017; Smuts et al., 2021; Tortora et al., 2021; Wolf et al., 2018)

visualize the definition of specific topics or technologies; (3) assistance with the metrics proposed to measure readiness; and (4) concrete examples related to the achieved level of readiness, including the description of real-world technological implementation for a potential advancement, as insights on future actions. The self-assessment tool is intended to demonstrate a selective orientation, and the structure geared toward SME craftsmanship companies consists of three dimensions: production and operations, digitalization, and ecosystem. A total of 23 items are included in each dimension, and they are all scored using a Likert scale that ranges from 1 to 5, just like other tools (Brozzi et al., 2018). After an episode of an online survey based on the IMPULS model was sent, the responses to the survey have been translated into a company's self-assessment using the IR4.0 readiness self-assessment model (Alcácer et al., 2021).

The amount of preparedness of circumstances, attitudes, and resources at all levels can be analyzed and determined through RA (Wijewardhana et al., 2020). Additionally, maturity models are positioned as instruments to analyze the existing condition of the companies and a way to pursue implementation of IR4.0 initiatives, whereas readiness models are mostly beneficial to capture beginning point for initializing the development process (Schumacher et al., 2016). As noted above, the approach is often used questions as a survey instrument for the assessment over the existing readiness models on IR4.0. The main distinction between them is the source from which the questions were derived, the theories that were employed, and the analysis of the survey or assessment results.

4.2. RQ2: What are the factors driving the IR4.0 readiness?

The firm-level and industry-level perspectives both present factors that help to confirm the amount of IR4.0 readiness in a company. This concept's basic tenet is that value cannot be created by a stand-alone enterprise and that numerous diverse entities, such as businesses, universities, research institutions, regulators, and governmental bodies, must each contribute (Reynolds & Uygun, 2018). The innovation ecosystem idea is an example of the perspective (firm-level perspective), according to Matt et al. (2021). The emergence of an IoT-based business ecosystem may be described by six structural aspects, and Chen et al.'s (2015) research demonstrates that this leads to a complex network supported by various stakeholders.

The incorporation of new internal processes, such as the restructuring of flows to promote flexibility and training, characterizes the implementation of IR4.0 in SMEs (Luco et al., 2019). New training courses that relate to the staff's flexible emotions management, can be introduced such as stated that one of the means by which we can "control" these parameters (high performance, good interrelation, and high professional self-development potential) is psychological evaluation of candidates as part of the selection process, we consider that we have to define and build a standard profile to match training needs, identification, and development of soft skills (Cotet et al., 2017). Whereas, Galati & Bigliardi (2019) stated in their review such that government's support, training programs, and the organizational structures required to give insights to the IR4.0 success. Ahmad et al. (2020) agreed that the staff's hard and soft skills need to be rectified through a program such as training program. According to Luco et al. (2019), training employees is a significant barrier for both businesses and the government. This indicates that training is a vital role in the success of IR4.0 technology.

While highly skilled workers are only required for installing the system, implementing modifications within the system, or for maintenance purposes in the automation scenario (Schinner et al., 2017), the technology directs the personnel. AI is crucial for IR4.0, enabling advanced self-capabilities such as self-optimization, self-awareness, and self-monitoring, and reshaping manufacturing processes and business models (Peres et al., 2020). Finally, as a result of the training programmes and government and organisation support, skilled employees are produced that are proportional to the IR4.0 technology and environment of the training programs and support by government and organization, skilled employees are produced which proportional to the IR4.0 technology and environment. According to Ahmad et al. (2020), the opportunity from IR4.0 implementations is to increase industry efficiency, productivity, and flexibility, as well as the presence of direct customer interaction and better connectivity and fast information flow are to increase efficiency, productivity and flexibility of the industries, existence of direct interaction of the customer, and better connectivity and fast information flow. Hard and soft skills are believed to be needed in IR4.0. The relevant soft competencies required in manufacturing, however, such as interpersonal skills, assertiveness, respect, self-strength, empathy, will, a spirit of perfection, self-discipline, intellectual curiosity, refinement, independence, and creativity (Cotet et al., 2017), are not always taken into account by such a soft skill of psychology test. However, when SMEs are taken into account, concerns with the skills gap are exponentially worse (Bosman et al., 2019).

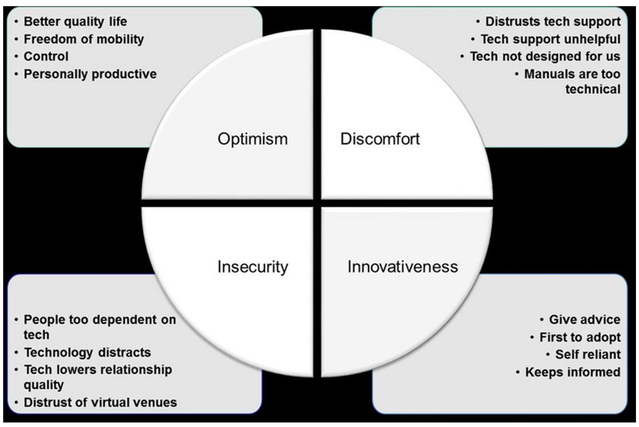
To educate their personnel for the digital age, businesses must create competences for their workforce that place a larger emphasis on technological transformation than ever before (Schinner et al., 2017). According to Lassen & Waehrens (2021), new knowledge and abilities are frequently taken for granted when new technologies are used. For this reason, competency strategies are broken down into three levels of learning journeys: individual, technological, and organizational. As a result, Trstenjak et al. (2020) discovered that process planning in IR4.0 necessitates a high degree of task automation, the application of predictive analytics, and sophisticated computer-aided process planning (CAPP) systems. Process planning is positioned in the value chain between physical manufacturing and building, so it too requires digital transformation, while managing the transition to the new digital framework represents one of the most difficult difficulties (Trstenjak et al., 2020) and, simultaneously, contributions.

Knowledge is a component of training and competences which is also a driving factor, according to Wolf et al. (2018), who noted that knowledge is a crucial factor and the element that binds the firm together. Because of this, older workers' knowledge, expertise, and experience are increasingly valued by businesses, according to Schinner et al. (2017). As a result, businesses will be forced to find ways to keep older workers on staff for longer periods of time as well as to retrain them to handle future challenges using new technological advancements. Knowledge-sharing technologies, according to studies by Argote et al. (2003), Reagans & McEvily (2003), and Sambamurthy & Subramani (2005), could be a potent tool for resolving organizational issues because their use is essential for preserving industrial competitiveness when knowledge is lost due to employee retirement. Technologies that promote knowledge sharing enable employees to learn both implicit and explicit information from one another. Trstenjak et al. (2020) claimed in the discussion that Croatia's IR4.0 process planning is still significantly influenced by the conventional approach, which is founded on a single person's subjectivity, intuition, and knowledge. Since their familiarity with IR4.0 or even the CAPP idea is still not at a satisfactory level, which is the first step to start to design the digitization strategy, education of the workforce played a significant role in the adoption of IR4.0 (Trstenjak et al., 2020). Higher education engineers will need to combine diverse technologies and be knowledgeable about mobile technology, embedded systems, and sensors, which is supported by Hernandez-de-Menendez et al. (2020). IR4.0 engineers require automation expertise, including bionics, robotics, and AI (Benbya et al., 2020), network technology, machine-to-machine communication, and safety-related skills (Hernandez-de-Menendez et al., 2020). Contrary to Filieri et al.'s (2021) assertion that founders with prior job experience obtained the greatest amount of funding from VC, educational background is not a deciding factor.

Another factor is acceptance on technologies and digitalization. Because Wolf et al. (2018) observed that innovation demands flat structure, short path, and free space to materialize ideas while highly regulated structures impede digitization, a sudden substitution of technologies and surroundings in the organization can be a high-risk strategy. This is a theory that start-ups or SMEs can use to project new technologies when adoption of technology and process improvements is possible (Wolf et al., 2018). The adoption of IR4.0 will succeed if people are informed of new technology roadmaps, adapt existing procedures, and upgrade old technology, according to Rachinger et al. (2018). All participants in the sector must take note of the importance of acceptance of technological advances. Many researchers have reported the benefits of IR4.0 adoption in industry, including Ali & Xie (2021) who came to the conclusion that there is a proportionate relationship between the organizational performance of Pakistan's retail industry and the five core pillars of IR4.0 (3D printing, big data analytics, cloud computing, IoT, and robotics). Although Pakistan's retail industry lags behind other nearby countries like India, China, and Malaysia, proportionality has been shown to improve performance in the country's retail sector. Therefore, the acceptance to adopt these technologies must begin with awareness, knowledge and time by the employers, and all level of employee. There is no shortcut to the acceptance before one realization which is sourced from the knowledge. Future workers will have more complex roles, requiring both technical and knowledge-based skills, such as modifying machine programs via mobile devices and controlling machines in real-time using advanced software systems (Matt et al., 2020) and competencies, such that in any industry or organizational although the introduction of smart factory may affect efficiency of the workers, the business model of a company, and employment.

Discussions around readiness in accepting new technologies are commonly scaffolded or guided by understanding the theories behind. For instance, acceptance theory is frequently used in information systems (IS) research to examine how well societies, companies, or people are accepting of changes brought about by the use of new technologies. It is crucial to recognize the significance of acceptance theory at the outset since knowledge can help foresee its applications more accurately. One well-known metric for assessing readiness to embrace and employ cutting-edge technology is the Technology Readiness Index (TRI) model (Figure 3). According to four personality traits – optimism, inventiveness, discomfort, and insecurity – technology readiness can be seen as a belief (Figure 3) (Ijab et al., 2019). Turcu & Turcu (2018) claim that these personality traits have an impact on people's inclination to adopt and use new technology. The TRI model, according to Shonhe & Jain (2017), comprises a total of 36 operational statements that may be used to determine users' readiness to utilize technology, making it straightforward yet

Figure 3
Technology readiness index model (Parasuraman, 2015)



comprehensive enough to be used by information providers to evaluate user readiness for using mobile technology. Meanwhile, a number of theories, like the Technology Acceptance Model (TAM) and the IS DeLone Success Model and McLean (DeLone and McLean IS Success Model), are used in the field of e-government. The Technology Acceptance Model (TAM), developed by Davis in 1989, has received the most citations and empirical replications (Soomro et al., 2021).

The implementation of IR4.0 in a corporation depends on resources or funding. There are sufficient resources, including money and workers from many fields of employment, to project the adoption of new technology (Wolf et al., 2018) that includes the IR4.0. Manufacturing companies that want to stay competitive in the global economy must invest in IR4.0, but many of them struggle with the complexity and ambiguity of where to concentrate their technological expenditures (Bosman et al., 2019). AI investment has a negative impact on the firms' market value (Lui et al., 2022) due to factors such as high implementation costs, uncertainty about returns, workforce displacement concerns, or regulatory issues. Contrarily, Smuts et al. (2021) discussed how, even though some businesses and their stakeholders are helping to drive the adoption of IR4.0 enabling technologies in a particular way, the general public's perception of the world as it relates to the reality of the digital environment scenario is very different. Bosman et al. (2019) found that larger enterprises felt better prepared to adopt IR4.0 compared to smaller enterprises SMEs that had probability to become victims in IR4.0 technology. Whence, this study found that firm actions, training, skills, competencies, knowledge, education, acceptance, and funding are lists of factors driving the IR4.0 readiness.

4.3. What are the factors inhibiting IR4.0 readiness?

SMEs still need more information and training to increase their knowledge for successful adoption of IR4.0 technologies in Malaysia (Zaidi et al., 2019). According to Balvin (2019), just 15–20% of Malaysian commercial organizations adopt IR4.0, which presents a relatively low usage rate for the industry. Even if several key participants in the business are aware of IR4.0's significance, they are still not entirely sure that it will be good for their company. This is because of a number of obstacles, such as a lack of strategy and leadership, a lack of resources, a talent shortage, and a lack of understanding regarding the implementation of IR4.0 (Jayashree et al., 2020). Based on the current situation with the low degree of industry preparation for IR4.0, it is argued that Malaysia will take about 12 years to catch up to industrialized nations like Japan and Germany, even if it adheres to every guideline in the Industry4WRD strategy framework. In order to improve the industry's readiness for IR4.0, it is necessary for them to become more aware of and cognizant of its advantages.

According to Sony & Naik (2019) and Soomro et al. (2021), there is currently no universally accepted consensus regarding how to gauge the industry's readiness for IR4.0. Therefore, it is crucial that a study be carried out to identify the crucial variables that determine whether an industry is prepared for IR4.0 and to further evaluate the relationship that exists between these readiness variables. Although IR4.0 is seen as significant by the government, Sony & Naik (2019) continued that only a small number of organizations fully comprehend its concept. Since obtaining IR4.0 readiness is crucial for the industry right now (Soomro et al., 2021), it is crucial to develop a readiness model for IR4.0 because it will enable stakeholders in the industry to recognize precedents and antecedents in the process of digital transformation toward IR4.0.

The deployment of IR4.0 technologies faces distinct obstacles in developing nations than they do in wealthy nations (Balvin, 2019). Adopting IR4.0 is a significant strategic choice, thus firms must evaluate their readiness (Sony & Naik, 2019). Alcácer et al. (2021) online self-assessment came to the conclusion from the survey results that both small and large organizations with a lower readiness level viewed a lack of top management support as one of the most significant obstacles. This proves that a company's size has no bearing on IR4.0 preparedness, but rather on the response and activity of the management division, which paves the road. However, it is important to keep in mind that major service organizations are more advanced in their strategy for adopting IR4.0 since small- and medium-sized businesses frequently focus on the most urgent and immediate business investments, making strategic planning look like a burden to them (Soomro et al., 2021). While this is going on, Lassen & Waehrens (2021) claimed that one of the main barriers to IR4.0 is that many businesses lack sufficient understanding of how new technologies might support greater growth and productivity.

Müller & Voigt (2018) discussed on their empirical evidence such that the German SME might claimed that large enterprises are more designed to be in IR4.0 compared to the Chinese SMEs which do not contained any bias. This indicates that the innovation also begins with the action and reaction from the utmost top level in the industry instead of only the technologies substitution. When it comes to "Industrie 4.0," German SMEs prefer to see the benefits from an operational perspective, whereas Chinese SMEs place an emphasis on both strategic and operational economic gains (Müller & Voigt, 2018). The lack of economic benefit clarification, a lack of interoperability and compatibility standards, and immature IT infrastructures are all considered to be barriers to IR4.0 readiness from the firm level during the online survey among industry players.

Businesses must take into account the requirement for employees to constantly acquire new competencies by implementing training programs that actively encourage this development (Hernandez-de-Menendez et al., 2020). The digitalization is impeded by employees' insufficient knowledge and skills. Future employees are therefore expected to meet the following requirements: (1) use, combine, and reflect on at least one set of tools and technologies within the company; (2) imagine and predict the relationship between these various tools and technologies both within and outside of their primary domain; (3) describe the implications for the overall company systems, both with respect to finance and IT; and (4) identify where technology can improve operations or support innovation (Lassen & Waehrens, 2021). According to Vaduva-Sahhanoglu et al. (2016), the main obstacles to the adoption of IR4.0 technologies include the high cost of research and development (R&D) innovation, the cost of updating technology to the most recent state of the art, the cost of training employees, incompatibilities with current practices and operations, difficulties in locating the necessary technologies, and psychological barriers relating to the acceptance of the new technologies. In the meantime, investments in new technologies were frequently hampered in regard to the cost issued by a lack of technical expertise among middle managers and managers (Lassen & Waehrens, 2021). In their study on the South African Construction Industry, Akinradewo et al. (2018) agreed that the lack of standards adoption, inadequate professional and skilled labor training in the use of digital tools at the institutional level, and the high cost of such training prevent the construction industry from adopting IR4.0 concepts. Alcácer et al.'s (2021) online survey of small businesses found that a lack of personnel skills prevents the projection of

IR4.0. While the IT manager in the case study claimed that they mostly relied on consultants for assistance in deploying new solutions and making any necessary changes, external dependencies frequently become dominant when working with new capabilities (Lassen & Waehrens, 2021). Power restrictions (such as limited electricity supply or energy constraints) slow down the shift to IR4.0. This is because, in the past, industrialization led to increased power usage, large-scale production, and advanced machinery (as noted by Weightman in 2007). Briefly, general factors that inhibit the IR4.0 readiness are continuously about cost, training, skills and competencies, and management, which can be scoped down into two essentials: (1) money source and (2) people management.

4.4. How are the self-evaluation instruments be developed for IR4.0 readiness?

Self-evaluation tool is a method of evaluation that can be done by the respondent independently. In this context of IR4.0 self-RA tool, studies were discussing to aim the SMEs for reasons of better transition of new technology significantly during the first stage in the smart manufacturing journey (Choi et al., 2018), add new knowledge or understanding to the readiness, acceptance, or maturity theories pertaining to IR4.0 readiness topic, and measure their own IR4.0 readiness status.

There are companies unable to relate the industry 4.0 with their business models, leading to a lack of a correct self-assess in order to understand the reached readiness level (Alcácer et al., 2021). According to the IR4.0 Readiness Assessment created to date, concerns with scarcity mean that SMEs or SMMs need training and outside consultants to conduct internal assessments, which proposed risk because the financial resources owned by the firms themselves are insufficient to fund their IR4.0 investment (Choi et al., 2018) the SMEs or SMMs need training, external consultants to conduct the assessments internally, which proposed risk as the resources owned is lacked (Choi et al., 2018). These factors, according to Choi et al. (2018), make it necessary to create an assessment platform that enables manufacturers to either conduct a self-assessment with a very intuitive, step-by-step user interface or provide access to assessment models and community-evaluated consulting services. SMEs are said to need a clear value proposition and a mechanism to evaluate the reliability of consulting services.

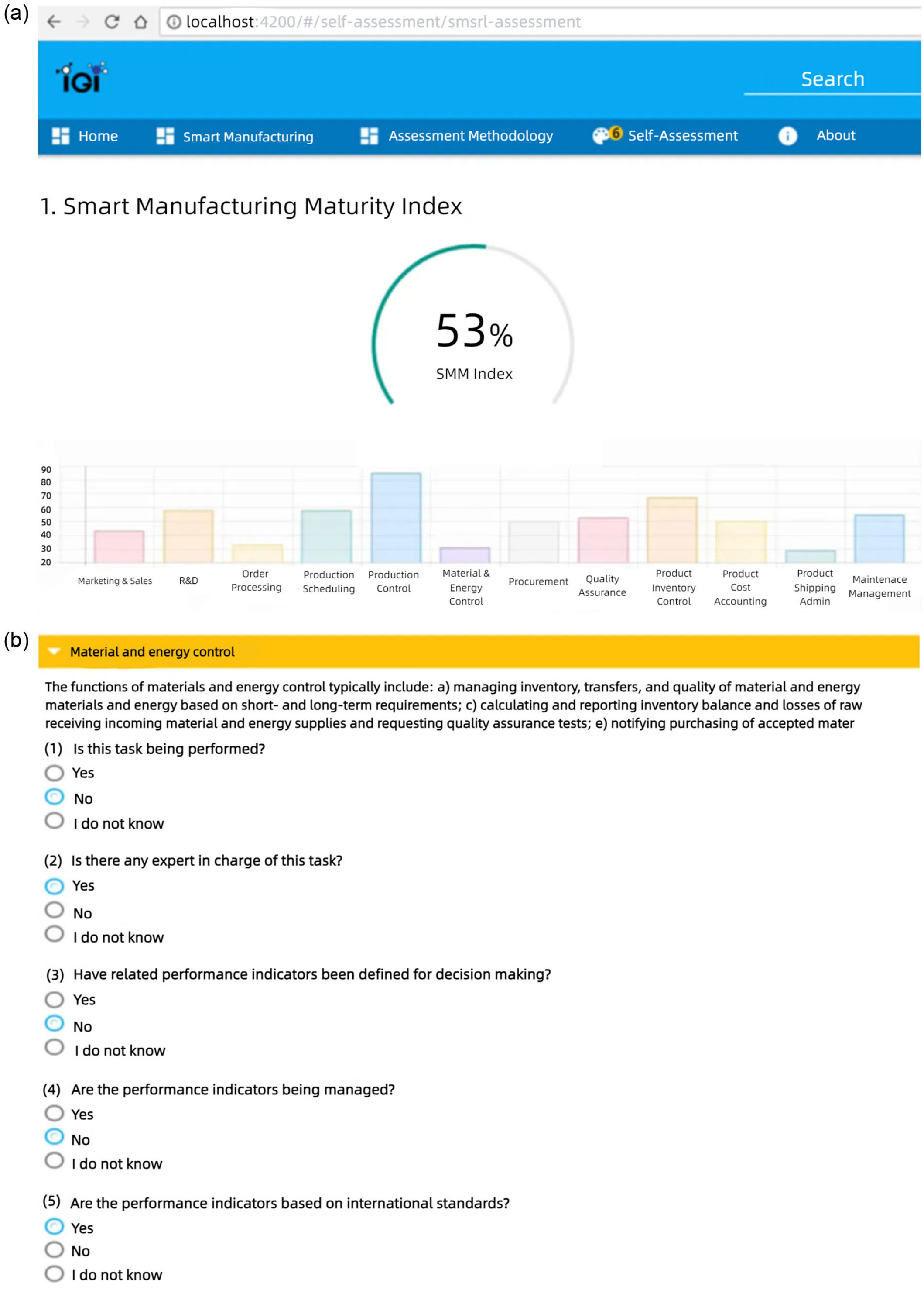
Table 4 shows list of existed IR4.0/I4.0 RA that has features or claimed to be as a “self-tool.” Ideally, discussions among academia in RQ1 are commonly on the developed I4.0 readiness/maturity model while this study is propelling the IR4.0 principle which differs the sectors to involve in not only manufacturers but indeed agriculture and services. Figure 4(a) and (b) demonstrates how the Smart Manufacturing Assessment System (SMAS) was created by Choi et al. (2018) based on two assessment techniques: the West Virginia University (WVU) approach and Smart Manufacturing Systems Readiness Level (SMSRL) (Jung et al., 2016) method, which are appropriate to more advanced manufacturers that are typically medium to large in size (applicable to a less mature typically of a small size manufacturer).

In order to increase prediction accuracy and address data sparsity and cold start issues, the recommender system has naturally incorporated AI, notably computational intelligence and ML methodologies and algorithms (Zhang et al., 2021). According to Zhang et al. (2021), AI can significantly advance the technological advancement and use of recommender systems. Recommender systems were primarily developed to help people who lack experience or understanding navigate the enormous number of options that are available to them (Shapira et al., 2011). Recommender systems were initially utilized in e-commerce to address the issue of information overload brought on by Web 2.0, and they were swiftly expanded to personalize e-government,

Table 4
List of existed “self-tool” IR4.0/I4.0 readiness assessment

Model name	Context	Features of “self-tool”	Methodology	Studies gap
Smart Manufacturing Assessment System (SMAS) (Choi et al., 2018)	IR4.0	1. Based on MEAN stack (MongoDB, Express.js, Angular 4, and Node.js) 2. An open source, web-based, free for manufacturing companies 3. Provide a platform to host various SMS assessment methodologies 4. Reflecting the diversity of manufacturing companies and their individual (often domain-specific requirements) 5. Consists of a detailed description (Figure 4(a)), questionnaires (Figure 4(b)), computation logics, and charts are defined using a standard XML schema	1. SMSRL 2. WVU by WVU’s Smart Manufacturing Lab	Only at prototype stage and not released yet as an open-source platform
SME Craftsmanship Self-Assessment tool (Brozzi et al., 2018)	I4.0	1. Simple wording in describing dimensions and items 2. Visualize the definition of certain topics or technology 3. Aided guidance on metrics proposed to measure readiness 4. Description of real case technological implementation for a potential advancement	1. Comprehensive literature review 2. Online survey	Lack of analysis on additional aspects indicating internal and external readiness level, such as the willingness to share information and awarenessof data security protocols

Figure 4
(a): Charts in Smart Manufacturing Assessment System (SMAS) and (b): Questionnaires in SMAS



e-business, e-learning, and e-tourism (Lu et al., 2015). Choi et al. (2018) readiness model can be classified as a recommender system and includes AI, but it contains fewer details about ML's technique, such as its kind. Many recommender systems emphasize techniques and accuracy but fall short of providing acceptable justification (Zhang et al., 2021). According to Zhang et al. (2021), deep neural networks, transfer learning, active learning, reinforcement learning, fuzzy approaches, evolutionary algorithms, natural language processing, computer vision, and six other AI techniques have all improved recommender systems.

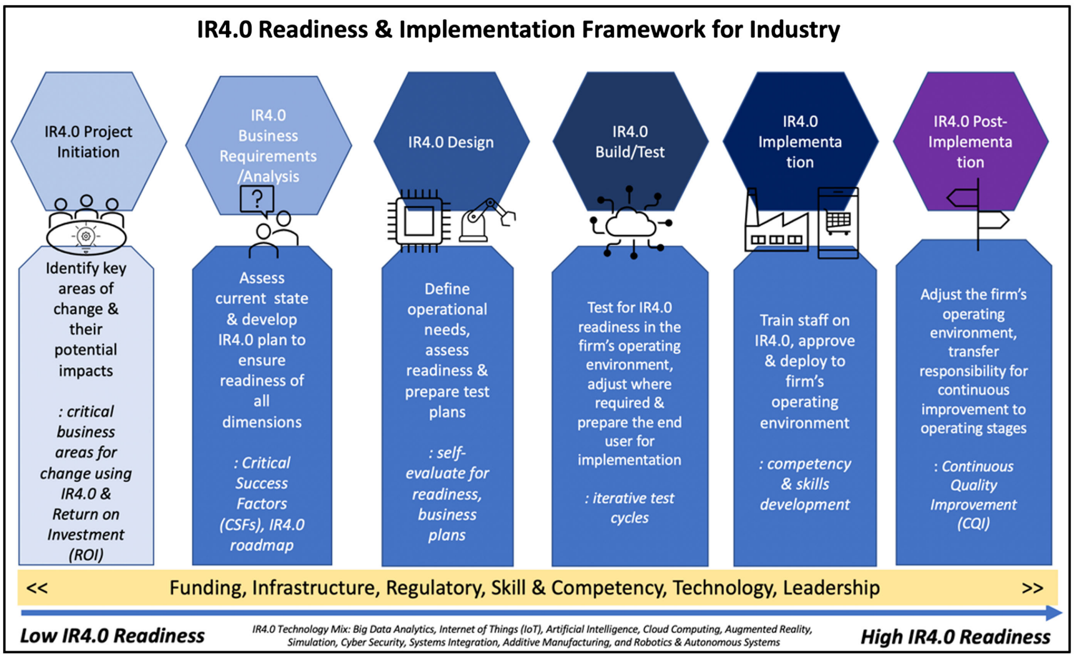
4.5. IR4.0 readiness and implementation framework for industry

This paper introduces a framework refined from the literature and analysis of the selected 55 papers. Figure 5 summarizes the six stages of readiness from low to high, providing insights into how firms can achieve IR4.0 readiness. The initial stage is on the IR4.0 project initiation followed by its business requirements or analysis, design, build or test, implementation, and post-implementation.

IR4.0 project initiation is aimed to identify key areas of change and their potential impacts. The top and bottom layers of organization are complementing each other in succeeding this stage. They are required to foresee the future of their company in the society and competitors, with the most crucial element of changes which is learning. According to the majority of literature in this field, many companies have completed the initial plan to adopt new technologies, but only the top layer of the organisation is involved and understands the reason for the substitution, while the bottom layer continues to believe in the routine only plan to adopt the new technologies but only the top layer of organization is involved and understand the reason of the substitution while the bottom layer is still continuously believe in the routine only. At this point, all staff need to be included in the strategy. The first step in making changes is to put aside the justifications for having a limited staff and amount of time. In the subsequent phase of IR4.0 business requirements or analysis, the goal is to evaluate the present situation and create an IR4.0 strategy, which is proportionate to the application of an IR4.0 readiness evaluation instrument. R&D team is in pivot in this stage when they need to analyze the current revolution of technology, situation, and phenomena across the globe to revert them into the company's size. For instance, delivery robots in the restaurants and logistics, vacuum robot by Xiaomi, and one of the biggest inventions of a kinetic energy launch system as a private space to orbit. Simultaneously, critical success factor and IR4.0 roadmap are expected to be the outputs or inputs during this stage. Moving to the IR4.0 design stage, the company is prescribed to seek external consultancy such as collaborating with academia to have own IR4.0 self-evaluation tool or applying an assessment to the government committee such as in Malaysia on the Industry4WRD RA. The result of the assessment is important to the business analyst to understand the company's size to fit in the IR4.0 and therefore plan forward such as defining operational needs, assess readiness, and prepare test plans. Significantly, the plan is built to test the IR4.0 readiness in the firm's operating environment and rectify requirements and preparation of the end user for implementation. To validate and verify the test, an iterative test cycle is compulsory.

During the IR4.0 implementation, training programs must be conducted beforehand on the employees and employers in a scheduled time, which initiated with the awareness and introduction of the fundamental of IR4.0. This SLR study proved that training is a control element during the transition of technology and culture in the company. Employees as well as employers are required to learn new analytical skills by broadening their perception and awareness of IR 4.0 skills of analyzing by broaden the perception and awareness. Meanwhile, industry players are required to adopt the subject matter expert to expand the performance of company. After the training, trainees are expected to execute the learned new skills such that engineers learned to build autonomous mobile robot in the logistics, analyst implements the big data to forecast the business growth, and real-time monitoring for the manager to inspect the defections or loss during the night shift of production. After numbers and continuous training, execution and assessment, competency, and skills development aid the company growth such that the productivity and output are proportionally high. Eventually, IR4.0 post-implementation stage that regulates the firm's operating environment and transfer responsibility for continuous improvement

Figure 5
IR4.0 Readiness and implementation framework



to operating stages can be monitored via Continuous Quality Improvement. These six stages are expected to be attained when the source such as funding and training is adequate as it complies the element of money and energy.

5. Conclusion and Future Works

Since 2020, a gathering of research and technology groups hosted by the EC has been the main forum for the discussion of Industry 5.0. Therefore, there exist discussions about the relevancy of the IR4.0. To regard their differences, IR4.0 is a machine-to-machine communication environment while Industry 5.0 is a human-to-machine communication. Industry 5.0 aims to capsize the IR4.0 in a way of more sustainable and human-centered. But in order to address the question of relevance, it is crucial to note that IR4.0 is a prerequisite for Industry 5.0 because this sector places a high priority on the interaction between human and AI (Saniuk et al., 2022). Therefore, Industry 5.0's main goal will be to use AI algorithms to create more sophisticated human–machine interfaces. In relevant to that, two main elements to project and focalized on to adopt IR4.0 are training and funding. Industry players can continuously improve and update the needs of IR4.0 in their organization when the readiness level has been well determined through the self-assessment.

New technologies mean to bring new perspective of live and new professions or skills and competencies are needed to accord the IR4.0 environment. For instance, AI technology in human robots requires employees to capable of developing algorithms, fluent in programming languages, and high patience during training and testing the model. Besides, they also need to have high creativity to solve the problems. IR4.0 is not only for manufacturing sector such that to invent new automation and communication between machines, indeed it can be applied in marketing sector, such as prediction of customers preferences on products. For instance, online shopping platform such as Shopee applications that features the tracking capability of the users across other platforms or applications. But, to take note of that, the feature of tracking also implies the security issues. Therefore, cybersecurity is improved and updated over time and periodically. To date, the developed self-RA tool that aims for a smart manufacturing or IR4.0 environment is not released yet to be as an open-source platform such as one by Choi et al. (2018). Apart from that, the existed RA commonly differs from each other in the dimensions used and or the methodology of development. The terms of self-evaluation in this readiness tool are getting recognized in the research and development due to the issue; during the tool's implementation in such way, external consultancy is needed to practice the subject. Meanwhile, previous studies are circling around the discussion on Industry 4.0 context or manufacturing sector only and less is found on the IR4.0 that includes sectors of agriculture and services, when developed the RA. It is understandable that covering all sectors and fitting them into the tool are challenging when many dimensions or factors need to be considered.

Therefore, future work is to study all sectors' size and requirements to be measured in the RA tool, and ML methods to be used in the self-evaluation readiness tool. Further and broad surveys with 25 companies from all sectors are contemplated to be stored in a database before data analysis, filtering, and classification. Additionally, to the best of this studies' knowledge, RA in IR4.0 that essentially uses the term of "self-evaluation" is still vague and in remote. The complementation of future IR4.0 RA is based on the ML capabilities and a type of either web-based or mobile-based. The features of ML implementation are model-based learning or model analytics type. In going to that, industry players can assess their performance from time to time independently to the time, cost, and external human consultancy.

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Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data available on request from the corresponding author upon reasonable request.

Author Contribution Statement

Nurul Izzati Saleh: Methodology, Software, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Mohamad Taha Ijab:** Conceptualization, Methodology, Validation, Resources, Writing – review & editing, Supervision, Project administration.

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