Evaluating readiness degree for Industrial Internet of Things adoption in manufacturing enterprises under interval-valued Pythagorean fuzzy approach

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ABSTRACT
The emergence of Industrial Internet of Things (IIoT) technology has caused a paradigm shift in the global manufacturing sector, despite its adoption remains costly, complex, and high risk. Therefore, the assessment of manufacturers’ readiness prior to IIoT adoption has become very important. This study proposes the evaluation framework for IIoT adoption using the interval-valued Pythagorean fuzzy set (IVPFS) method to reduce the uncertainty and ambiguity in human decision-making process. Through the extensive literature review and experts, twelve readiness criteria have been identified and validated. The relative importance weights of readiness criteria were determined by IVPF-AHP and the IIoT adoption readiness degree is calculated by IVPFS. The proposed approach enables manufacturers to make a rational decision on whether they are ready to initiate IIoT or take early remedial actions to increase the success rate of the adoption possibility. A leading Thai agro-food processing manufacturere is applied as an empirical case study.

1. Introduction

Internet of Things (IoT) technology is considered as a disruptive technological innovation. It is a growing technological platform and widely spread especially in an embedded network of various types of intelligent devices, autonomous vehicles, IoT automation, robots, and other connected devices (Majeed & Rupasinghe, 2017; Kamble et al., 2018). With its capability in predictive analysis and big data analytics, IoT can create the opportunities to increase an efficiency, the enhancement of traceability and productivity, incremental revenues, flexibility, and profitability (Khan & Salah, 2018). Data from IoT systems will help decision-makers easier to gain new insights for generating and delivering values, virtualizing across the supply chain, enhancing customers’ engagements, and implementing more effective policies and practices (Khan & Salah, 2018; Kamble et al., 2019). One of the most popular smart technologies of manufacturers is the Industrial Internet of Things (IIoT). IIoT then refers to IoT technology applied in the manufacturing process, which is believed to affect the future integration and optimization of...
information technology (IT) (Kiel et al., 2017). Many manufacturing firms are driven by different strategies in different technologies (Kiel et al., 2017). IIoT also provides an interactive platform for real-time interactions among the involved stakeholders.

With the overall emergence of IIoT technology movement, all industries, both large corporate firms and small-medium enterprise companies, are affected in unavoidable circumstances. Currently, the industrial players acknowledge the IIoT benefits in the supply chain process and require to be in the state of readiness to adopt the technology. Despite the remarkable potentials of IIoT, many firms have not been successful in IIoT implementation due mainly to encounters with the complexity, numerous risk and obstacles, and high cost of IIoT adoption (Hsu & Yeh, 2017). Hence, the assessment of readiness for IIoT adoption or emerging technological innovations becomes highly important for manufactures in order to reduce unexpected risks (Lokuge et al., 2019). However, they also encounter the challenges in lacking of the evaluation frameworks to guide IIoT implementation.

1.1. Research motivations

There are four reasons that motivated the proposal of this study, which are as follows: First, after a thorough analysis of the published literature, it is found that the research that identified and evaluated the readiness to IIoT adoption in the manufacturing sector is very scarce. In addition, the IIoT adoption in developing countries such as Thailand has not been broadly explored as much as compared to developed countries. To address this knowledge gap, this research proposes a comprehensive framework for evaluating the readiness degree for IIoT adoption in manufacturing enterprises. A case study in Thai leading agro-food processing manufacturer is performed to demonstrate the application of the proposed framework. Under the program of the Thai government, this industry is one of the ten key industries that will be transformed into a modern industry using new advanced manufacturing technologies. The Thai agro-food processing industry accounts for approximately 23% of the country’s GDP. With a large labor force and high investment in research and development, this industry has become an important growth engine for the national economy.

Second, research on IIoT adoption is still in the early stage of development (Kamble et al., 2019). Most of the relevant studies were carried out with normative and theoretical contribution (Gretzel et al., 2015), qualitative case studies (Nolich et al., 2019), and conventional statistical methods (Bogicevic et al., 2017). Nevertheless, the evaluation of an emerging technologies adoption such as IIoT is a complex strategic decision and involves many decision criteria. Hence, the Multi-Criteria Decision-Making (MCDM) approach is selected to deal with such problems. It is also widely used as the best alternative to compute, with various decision criteria being simultaneously considered (Bakioglu and Atahan, 2021). In addition, human decision-making processes are often inherited with uncertainty, ambiguity, and inaccurate information caused by decision-makers. The combination of MCDM and fuzzy set theory, namely, ‘Fuzzy Multi-Criteria Decision-Making’ (FMCDM) is an effective tool to deal with such issues (Seiti et al., 2019; Zadeh, 1975). Until recently, there have been few studies using FMCDM approaches to evaluate IIoT adoption.
Next, there are many different types of fuzzy sets such as triangular fuzzy set (TFS), interval two-type fuzzy set (IT2FS), intuitionistic fuzzy set (IFS), and Pythagorean fuzzy set (PFS) (Yager, 2014). The principle of PFS and IFS is similarity in which both of them can be presented in terms of membership, non-membership function, and hesitancy degree. The advantage of PFS over IFS is that it allows the sum of degrees of membership and non-membership values to be greater than 1, but the sum of squares of two values does not exceed 1 (Perez-Dominguez et al., 2018a). For example, if a decision-maker (DM) provides the membership degree and the non-membership to be 0.7 and 0.4, respectively, then it will not be able to operate under IFS. The interval-valued Pythagorean fuzzy set (IVPFS) is a new extension of PFS in forms of authorizing the membership and non-membership levels of the set with the interval value. Therefore, IVPFS has more flexibility and ability than PFS so as to handle strong fuzziness, ambiguity, and imprecision during the decision-making process (Yu et al., 2019). Recently, IVPFS has been extensively applied in various real-world decision-making problems, i.e. sustainability for supplier selection (Yu et al., 2019), evaluation for large, high-technology project portfolios (Mohagheghi et al., 2020), and supplier selection for sustainable e-bike sharing recycling (Tang & Yang, 2021). Due to its superior benefits, this study used the IVPFS method as one of the useful tools in FMCDM approaches to evaluate the readiness degree for IIoT adoption based on its dealing with vagueness of decision-makers. IVPFS has also not previously been employed to evaluate the adoption of emerging technologies in manufacturing.

Finally, one of the essential parts in MCDM is to accurately determine the relative importance of each criterion. Among MCDM techniques, the Analytic Hierarchy Process (AHP) is the most popular technique used for analyzing the relative importance weights of the evaluation criteria. AHP provides many advantages such as (i) the pairwise comparison allows users to easily define the weight criteria and alternatives comparison and (ii) AHP’s measurement scale can easily accommodate decision-making problems in various sizes of the hierarchical structure (Bakioglu & Atahan, 2021). In this study, Interval-valued Pythagorean fuzzy AHP (IVPF-AHP) was utilized to handle vagueness and the imprecision in determining the relative importance weights of the readiness criteria for IIoT adoption.

1.2. Research contributions

Based on the above discussions, this study makes four unique contributions to the body of knowledge in the IIoT adoption domain, which are as follows:

(i) This study is the first attempt to propose an evaluation framework of readiness degree for IIoT adoption in manufacturing, which has never been addressed in any previous studies.

(ii) The proposed evaluation framework is conceptualized as a FMCDM problem, which can provide more insights into the uncertainty and imprecise information in decision-making processes.

(iii) In this study, IVPF-AHP is employed to calculate the relative importance weights of readiness criteria and IVPFS is used for evaluating the readiness degree. The application of IVPFS can effectively reflect the uncertainty of inaccurate information of decision-makers compared to IFS.
(iv) This study contributes to the literature on the evaluation of IIoT readiness adoption in developing countries, which has been scarce in previous studies. Although the focus is on the agricultural food processing industry of Thailand, this proposed framework can be considered as a reference for other industries in all developing countries as they share similar characteristics.

The remainder of this article is structured as follows: Section 2 presents literature review. The research methodology is described in Section 3. The empirical case study is presented in Section 4. Section 5 provides the discussions of findings, the readiness degree evaluation of overall and case company, and a benchmarking study. Managerial implications are provided in Section 6. The conclusion is presented in Section 7. Finally, future research is given in Section 8.

2. Literature review

This section provides an overview of the existing literature on IIoT, followed by the readiness factors/criteria of IIoT adoption.

2.1. Industrial Internet of Things (IIoT)

Industrial Internet of Things, also known as IIoT, stands for the Internet of Things (IoT) technology in manufacturing processes. IIoT is characterized by the integration of Cyber-Physical Systems (CPS), which connects the physical and digital worlds to manage industrial processes. With the CPS concept, manufacturers can create interactions between the real and virtual worlds along the core manufacturing value chain. IIoT is a widely spread technology platform of autonomous and intelligent devices (Kiel et al., 2017).

The primary objective of IIoT adoption is to achieve increased productivity, operational efficiency, and enhanced management of the manufacturing process and assets through product customization, intelligent inspection in the production shop floors, and predictive and preventive maintenance of production equipment. There are several technologies that are embedded under the IIoT umbrella, including cloud computing, machine-to-machine (M2M) communication, machine learning, artificial intelligence (AI), and distributed computing. IIoT results in not only a shift in technical manufacturing but also broader corporate impact and opportunities (Kiel et al., 2017). Implementing IIoT in supply chains and operations provides tangible commercial benefits such as low risk and cost, increased transparency, visibility, flexibility, operational flow, and virtualization (Khan & Salah, 2018; Trappey et al., 2017). Manufacturing enterprises have realized the impacts of IIoT in five key perspectives such as design and innovation, asset utilization and revenue planning, supply chain and logistics design, resource productivity optimization, and extension of stakeholder experience. Notwithstanding, the IIoT adoption remains costly, complex, and high risk for manufacturers. Therefore, the assessment of manufacturers’ readiness prior to IIoT adoption has become very important.


2.2. Readiness factors/criteria for IIoT adoption

2.2.1. Top management commitment and support

A large and growing literature investigated how the level of commitment and support of top management positively influence the introduction of new technologies in manufacturing organizations (Oliveira et al., 2019; Yang et al., 2015). Conversely, the managerial obstacles negatively impact the decision to adopt advanced manufacturing technologies. According to Gangwar et al. (2015), the innovative technology adoption has been shifted from top to bottom. Sony and Naik (2019) emphasized that top management should understand the contribution of IoT adoption to the future of competitive advantage and organizational performance. It is supported that the commitment and support from top management played a key role in keeping up with strategic news, resource commitment, resolving resistance to change, and assessing an organization’s ability to implement new technologies (Oliveira et al., 2019).

2.2.2. Financial capability

The adoption of IIoT requires a long-term investment and high acquisition costs in enabling technologies such as identification and tracking technologies, wired and wireless sensors, and actuator, enhanced communication protocols, and distributed intelligence for smart objects (Kache & Seuring, 2017; Kovács, 2018). Consequently, IoT adoption of manufacturers will incur additional costs for repair and maintenance of IoT infrastructure technology (Ryan & Watson, 2017). In a study conducted by Kamble et al. (2018), the adoption cost is a major obstacle for IIoT adoption among manufacturers. Only manufacturers with sufficient financial resources can adopt IIoT technology.

2.2.3. Managing cyber security and privacy

Due to the high volumes of data transmission and exchange between devices in the IoT system, it is vulnerable to cyber attacks. Reaidy et al. (2015) and Bruijn & Janssen (2017) investigated that IoT security is not only about accountability, authorization, validity, and authenticity but also related to business continuity, disaster recovery, and data protection. According to Lee and Lee (2015), Insecured or inadequately authorized data encryption or web interfaces make the IoT more vulnerable to cyberattacks. Therefore, manufacturers are aware of cyber threats and invest in cyber-security (Hughes et al., 2017). Díaz et al. (2016) and Ouaddah et al. (2017) suggested that the establishment of special protocols, authentication, and authorization for supporting large volumes of data transmission and exchange among a wide variety of devices in IoT system is vulnerable to cyber attacks (Bruijn & Janssen, 2017; Reaidy et al., 2015).

Raut et al. (2018) examined that IoT security is not only just about accountability, authorization, and authenticity but also related to business continuity, disaster recovery, and data protection. According to Karkouch et al., (2016), because of the lack of transportation encryption, insecure web interfaces or insufficient authorization causes IoT vulnerable to against cyber attacks. Thus, manufacturers are aware of cyber threats and invest in cyber security (Hughes et al., 2017). Díaz et al. (2016) and Ouaddah et al. (2017) suggested that the creation of special protocols, authentication and authorization for reliable access control and interaction, security through transparency, or hardware-
based security at the chipset level can reduce cyber security and privacy risks. Kamble et al., (2018) emphasized that the assurance of security and privacy in manufacturer’s IoT is essential for IoT adoption.

2.2.4. Digital business model development
Previous research identified that most of the business model innovations are derived from new technology opportunities (Ng et al., 2015; Parry et al., 2016; Rymaszewska et al., 2017). The transition to IoT adoption would spawn new capabilities and open up the new opportunities and challenges that lead to new sources of revenues for manufacturers (Lerch & Gotsch, 2015). IoT also provides a wide range of benefits for organizations, such as productivity enhancement, information exchange of both products and services, and real-time interaction improvement for the relevant stakeholders (Ghanbari et al., 2017). Ikävalko et al. (2018) viewed the process of IoT implementation to be very complicated, which could render traditional business model ineffective. Therefore, manufacturers need to develop a new digital business model to deal with technological complexity and enable high-level suppliers and consumer engagement (Ikävalko et al., 2018). The digital business model will guide organizations in achieving Interaction with IoT technology (Lee & Lee, 2015). Without proper digital business development, organizations cannot generate revenues and profits and leverage the real IIoT benefits (Frank et al., 2019; Sarvari et al., 2018).

2.2.5. Technology infrastructure
The adoption of IoT requires a strong backbone of IT infrastructure to facilitate data communication within a network, which includes sensors, internet coverage, high-bandwidth internet access, and high-speed network for transmission and exchange of data among different devices (Davis et al., 2015). Raut et al. (2018) claimed that the availability of the sufficient IT infrastructure is one of the critical factors for the readiness of IIoT adoption. This is also aligned with a study by Hasselblatt et al. (2018), manufacturing enterprises considering IoT adoption should have adequate technological infrastructure, as well as supporting solutions in place that digitize core business processes.

2.2.6. Change management capability
IoT advancements have resulted in tremendous changes in operations and technology, production, physical infrastructure, human resources, and implementation (Hasselblatt et al., 2018). To accommodate these changes, the culture and structure of manufacturing organizations must be changed, which may cause the organizational resistance (Vey et al., 2017). Kiel et al. (2017) stated that the increased use of production automation in IoT would remarkably reduce the workforces. Consequently, it will lead to unemployment and probably even make employees resist IoT adoption (Lee & Lee, 2015). Furthermore, Horváth & Szabó (2019) noted that many manufacturers operating in traditional business practices were often reluctant to give up their status quo and traditional practices. The organization’s ability to implement the appropriated change management would help to achieve cultural acceptance of innovation (Müller et al., 2018). Fischer and Pöhler (2018) emphasized that the success of change management requires all supports and participations from top executives and employees in an organization. A similar
2.2.7. Data management and analytics capabilities

Reaidy et al. (2015) viewed that it is difficult to measure data integrity and accuracy because large amounts of data are exchanged between devices and connected physical objects in IoT. However, the manufacturers’ ability to manage and analyze huge volumes of data generated from heterogeneous sensors on a real-time basis is one of the key success factors for IoT adoption (Horváth & Szabó, 2019). The ability to ingest data from IoT systems into a data lake would provide opportunities for predictive analytics, learning ability, self-efficacy, and decentralized decision-making (Ben-Daya et al., 2017). Also, Raj et al. (2020) emphasized that the ability to data analysis can transform sensor data into automated-enabled data. Lu (2017) supported that the effective data management would eliminate errors and damage caused by defective data.

2.2.8. Seamless value-chain integration

IoT can be characterized by a network of connected objects, enabling data and information sharing among different objects (Mital et al., 2018). Therefore, one of the key success factors for IoT adoption is the ability to integrate and collaborate between various technologies and networks systems that create information flows across the value chain (Majeed & Rupasinghe, 2017). In such a case, manufacturers need to build a close cooperation between value chain partners for a whole spectrum of horizontal and vertical integration (Breunig et al., 2016). The seamless integration capabilities can enable real-time visualization and data exchange throughout the supply chain and also can lead to create a superior competitive advantage (Dalenogare et al., 2018). This argument is further in line with Ghobakhloo (2018).

2.2.9. Strategic technology roadmap for digitalization

IIoT Adoption will radically change the business landscape of manufacturers and have a significant impact on short- and long-term performance. On the transition from traditional manufacturing to successful IIoT adoption, manufacturers initially had to formulate a comprehensive strategic technology roadmap to guide their digital transformation (Sarvari et al., 2018). Aligned with Horváth and Szabó (2019), the strategic technology roadmap is an important tool for manufacturers to secure IoT adoption, enabling manufacturers plan for better visibility and understanding for each stage of the integrated mobility as well as to make better decisions.

2.2.10. Employees digital knowledge

As manufacturing becomes more digital, potential employees will need to increase their IT skills and digital knowledge (Kamble et al. (2018). To be in line with this view, Hecklau et al. (2016) discussed that manufacturers need to develop qualified and knowledgeable employees with up-to-date digital skills before IoT implementation. Davis et al. (2015) also placed a great emphasis on the importance of hiring quality staffs to manage digital processes. Thus, the digital literacy of employees will play an important role in integrating IoT adoption in manufacturing facilities (Sivathanu & Pillai, 2018).
2.2.11. Digital culture readiness

Digital culture readiness is described as the values and norms of organizations fostering the adoption of digital innovation (Raj et al., 2020). Previous research has investigated how companies that have been successful in making new digital technologies emphasizes on the development of the digital culture of organization (Büschgens et al., 2013). Duer et al. (2018) reported that there is a positive correlation between the role of digital culture and the successful adoption of advance manufacturing technologies. In line with Bughin and van Zeebroeck (2017), the organizational digital culture can influence the acceptance of new technologies in manufacturing environment. Rajput and Singh (2019) stated that digital culture can shape the organization behavior in which its members recognize the value of adopting digital technologies as a source of competitive advantage. Hence, digital culture should be a prerequisite for IIoT adoption.

2.2.12. Lean practices implementation

A recent study by Mayr et al. (2018) affirmed that lean practices such as continuous flow, waste reduction, and standardization have a positive correlation with the success of the advanced automation technologies implementation in manufacturers. A similar conclusion was drawn by Wang et al. (2016) that lean practices are essential for Industry 4.0. From a technology perspective, the integration between lean practices and Industry 4.0 can help to increase productivity and reduction of waste and costs (Buer et al., 2018).

3. Research methodology

3.1. Interval-valued Pythagorean fuzzy set

The basic concepts of the Interval-valued Pythagorean Fuzzy Set (IVPFS) and their essential mathematical operations are briefly presented.

**Definition 1.** Let $X$ represent a finite nonempty set, and $\tilde{P}$ is a set of IVPFS, which can be defined by the following equation (Peng & Yang, 2016):

$$\tilde{P} = \{\langle x, [[\mu^L_P(x), \mu^U_P(x)], [v^L_P(x), v^U_P(x)]] \rangle | x \in X\}$$  \hspace{1cm} (1)

where $[\mu^L_P(x), \mu^U_P(x)]$ is the interval-valued degree of membership and $[v^L_P(x), v^U_P(x)]$ is the interval-valued non-degree of membership of element $X$ on the IIVFS $P$. The conditions of $\mu^L_P(x), \mu^U_P(x), v^L_P(x), v^U_P(x) \in [0, 1]$, $0 \leq \mu^L_P(x) \leq \mu^U_P(x) \leq 1$, $0 \leq v^L_P(x) \leq v^U_P(x) \leq 1$, and $0 \leq (\mu^L_P(x))^2 + (v^L_P(x))^2 \leq 1$ need to be satisfied. In addition, the degree of hesitancy of $x$ to $\tilde{P}$ can be defined by the following formula:

$$\pi_P(x) = \left[\sqrt{1 - (\mu^U_P(x))^2 - (v^L_P(x))^2}, \sqrt{1 - (\mu^L_P(x))^2 - (v^U_P(x))^2}\right].$$ \hspace{1cm} (2)

**Definition 2.** Let $\tilde{P}_1 = [\mu^L_1, \mu^U_1], [v^L_1, v^U_1]$ and $\tilde{P}_2 = [\mu^L_2, \mu^U_2], [v^L_2, v^U_2]$ represent two interval-valued Pythagorean fuzzy numbers (IVPFNs), then the mathematical operations of IVPFNs are defined as follows (Peng & Yang, 2016):

...
\[\tilde{P}_1 \oplus \tilde{P}_2 = \langle \sqrt{(\mu_1^2 + \mu_2^2 - (\mu_1^2)(\mu_2^2)}, \sqrt{(\mu_1^U)^2 + (\mu_2^U)^2 - (\mu_1^U)(\mu_2^U)} \rangle \]  

(3)

\[\tilde{P}_1 \otimes \tilde{P}_2 = \langle [\mu_1^l \mu_2^l, \mu_1^U \mu_2^U], \left[\sqrt{(v_1^l)^2 + (v_2^l)^2 - (v_1^l)(v_2^l)}, \sqrt{(v_1^U)^2 + (v_2^U)^2 - (v_1^U)(v_2^U)} \right] \rangle \]  

(4)

\[\lambda \tilde{P}_1 = \langle \left[\sqrt{1 - (1 - (\mu_1^l)^2)} \right]^\lambda, \sqrt{1 - (1 - (\mu_1^U)^2)} \rangle, \langle (v_1^l)^\lambda, (v_1^U)^\lambda \rangle \rangle, \lambda > 0; \]  

(5)

\[\tilde{P}_1^\lambda = \langle \left[\mu_1^l\right]^\lambda, \left[\mu_1^U\right]^\lambda \rangle, \left[\sqrt{1 - (1 - (v_1^l)^2)} \right]^\lambda, \left[\sqrt{1 - (1 - (v_1^U)^2)} \right]^\lambda \rangle, \lambda > 0 \]  

(6)

**Definition 3.** Let \( \tilde{P} = \{\tilde{P}_j\} (j = 1, 2, \ldots, k) \) be a collection of IVPFNs by using Table 1, \( \tilde{P}_j = [\mu_1^l j, \mu_1^U j, v_1^l j, v_1^U j] \). Then, the group aggregated values by the interval-valued Pythagorean Fuzzy Weighted Geometric (IVPFWG) operators can be described as \( \tilde{P}^n \rightarrow \tilde{P} \), and the IVPFPLWA operator is described as follows (Du et al., 2017):

**IVPFWG**

\( (\tilde{P}_1, \tilde{P}_2, \ldots, \tilde{P}_n) = \left( \prod_{k=1}^{K} (\mu_1^l k)^\lambda_k, \prod_{j=1}^{k} (\mu_1^U k)^\lambda_k \right), \left[ \sqrt{1 - \prod_{k=1}^{K} (1 - (v_1^l k)^2)^\lambda_k}, \sqrt{1 - \prod_{j=1}^{k} (1 - (v_1^U k)^2)} \right] \) \]  

(7)

\[\lambda_k = \sqrt{\frac{1}{2} \left[ \left(1 - \pi_1^l k \right)^2 + \left(1 - \pi_1^U k \right)^2 \right]} / \sum_{k=1}^{K} \sqrt{\frac{1}{2} \left[ \left(1 - \pi_1^l k \right)^2 + \left(1 - \pi_1^U k \right)^2 \right]} \]  

(8)

where \( \lambda_j = (\lambda_1, \lambda_2, \ldots \lambda_k)^T \) is the weighted vector of \( \tilde{P}_j, i = 1, 2, \ldots k \), with \( \lambda_j \in [0, 1] \) and \( \sum_{j=1}^{k} \lambda_j = 1 \).

**Table 1.** Linguistic term and the corresponding interval-valued pythagorean fuzzy numbers (IVPFN).

| Linguistic terms     | IVPFN                  |
|----------------------|------------------------|
| Very good (VG)       | ([0.80, 0.95], [0.00, 0.15]) |
| Good (G)             | ([0.70, 0.80], [0.15, 0.25]) |
| Medium good (MG)     | ([0.55, 0.70], [0.25, 0.40]) |
| Medium (M)           | ([0.45, 0.55], [0.40, 0.55]) |
| Medium poor (MP)     | ([0.30, 0.45], [0.55, 0.70]) |
| Poor (P)             | ([0.20, 0.30], [0.70, 0.80]) |
| Very poor (VP)       | ([0.00, 0.20], [0.80, 0.95]) |
Definition 4. Let $\tilde{P} = (\mu_L, \mu_U, v_L, v_U)$ be an IVPFN. $\pi_L$ and $\pi_U$ are the hesitancy degrees of the lower and upper points of $A$, respectively. This can be calculated as in Equation 9 and Equation 10 (Peng & Yang, 2016),

$$\pi_L^2 = 1 - (\mu_L^2 + v_L^2),$$

$$\pi_U^2 = 1 - (\mu_U^2 + v_U^2).$$

Definition 5. Let $\tilde{P} = (\mu^k, \mu^U, v^k, v^U)$ be an IVPFN. The defuzzification of this number is calculated Equation 11. This defuzzification equation is based on dilation and concentration operations on membership and non-membership degrees (Haktanir & Kahraman, 2019),

$$D(\tilde{P}) = \frac{1}{6} \left( \mu_L^2 + \mu_U^2 + (1 - \mu_U^2 - \pi_U^2) + (1 - \mu_L^2) + \mu_L \mu_U + \sqrt{(1 - \mu_U^2 - \pi_U^2) \times (1 - \mu_L^2)} \right)$$

A larger value of $P_D(\tilde{A})$ indicates a large $\tilde{A}$ since $0 \leq \mu_U^2 + v_U^2 \leq 1$, $P_D(\tilde{A}) \in [0, 1]$.

Definition 6. Let $B_1^t(t = l, \ldots, n)(\hat{k} = 1, \ldots, l)$ be a group of crisp numbers and $\alpha^j = (\mu_{B_1^t}, v_{B_1^t})(t = l, \ldots, n)(\hat{k} = \hat{i} + 1, \ldots, m)$ be a group of intuitionistic fuzzy numbers (IFNs). Therefore, the aggregated value, which is represented by AIFIS, is also an IFN (Perez-Dominguez, et al., 2018b),

$$\text{AIFIS}_i(B_1^t, \ldots, B_i^t, \beta_{i+1}^t, \ldots, \beta_m^t) = \left( \prod_{k=1}^{l} B_k^t \right)^{w_j} \otimes \left( \prod_{k=l+1}^{m} \beta_k^t \right)^{w_j}$$

$$= \left(1 - \left(1 - \prod_{k=l+1}^{m} (\mu_{B_k^t})^{w_j} \right) \left( \prod_{k=l+1}^{m} (1 - v_{B_k^t})^{w_j} \right) \right) \left(1 - \left( \prod_{k=l+1}^{m} (1 - \mu_{B_k^t})^{w_j} \right) \left( \prod_{k=l+1}^{m} (1 - v_{B_k^t})^{w_j} \right) \right)$$

where AIFIS$_i$ represents the aggregated intuitionistic fuzzy index of similarity for alternative $i$.

$w_j (j = 1, \ldots, m)$ is the corresponding crisp weight for criterion $j$ satisfying $w_j > 0 (j = 1, \ldots, m)$ and $\sum_{j=1}^{m} w_j = 1$.

### 3.2. Determining the weights of IIoT adoption readiness criteria by interval-valued Pythagorean fuzzy AHP

The IVPF-AHP method has been mainly applied to determine the criteria weight of the evaluation criteria. Also, the IVPF-AHP approach has been developed for managing multi-criteria decision-making problems, such as a risk evaluation and prevention in hydropower plant operations (Yucesan & Kahraman, 2019), occupational health and safety risk assessment (Gul, 2018), a comparative outline for quantifying risk ratings in occupational health and safety risk assessment (Gul & Ak, 2018), and the quality
evaluation of hospital service (Yucesan & Gul, 2020). By applying the linguistic terms, a pairwise comparison for evaluation criteria is made to the weights of criteria using the IVPFN. The weighting scale IVPF-AHP is presented in Table 2.

A basic concept related to IVPF-AHP is shown in the following steps.

Step 1. Construct the pairwise comparison matrix $X = (x_{ij})_{n \times n}$ with respect to each expert opinion based on Table 3.

Step 2. Compute the differences matrix $D = (d_{jk})_{n \times n}$ between lower and upper values of the membership and non-membership functions by using Equation 13 and Equation 14),

$$d_{jkL} = \mu_{jkL}^2 - \nu_{jkL}^2,$$

$$d_{jkU} = \mu_{jkU}^2 - \nu_{jkU}^2.$$

Step 3. Find the interval multiplicative matrix $S = (S_{jk})_{n \times n}$ by using Equation 15 and Equation 16),

$$S_{jkL} = \sqrt{1000d_{jkL}},$$

$$S_{jkU} = \sqrt{1000d_{jkU}}.$$

Step 4. Calculate the determinacy value $\tau = (\tau_{jk})_{n \times n}$ of $x_{jk}$ by using Equation 17,

$$\tau_{jk} = 1 - (\mu_{jkU}^2 - \mu_{jkL}^2) - (\nu_{jkU}^2 - \nu_{jkL}^2).$$

Step 5. Multiply the determinacy degrees with the $S = (S_{jk})_{n \times n}$ matrix for obtaining the matrix of weights, $T = (t_{jk})_{m \times m}$, before normalization using Equation 18,
\[ t_{jk} = \left( \frac{S_{jkU} + S_{jkL}}{2} \right) \tau_{jk}. \]  

(18)

Step 6. Find the normalized priority weights \((w_j)\) by using Equation 19,

\[ w_j = \frac{\sum_{k=1}^{n} t_{jk}}{\sum_{i=1}^{n} \sum_{k=1}^{n} t_{jk}}. \]  

(19)

### 3.3. Obtaining the rating of readiness for IIoT adoption

The IVPFS procedure for rating the readiness of IIoT adoption is presented below (Malviya & Kant, 2016):

#### 3.3.1. Step 1: Identify the rating of readiness criteria for IIoT adoption

By using the linguistic term and corresponding IVPN in Table 1, the decision-makers \((E^i, i = 1, 2, \ldots, m)\) are requested to provide their rating of readiness for IIoT adoption with respect to each criteria \((C_j) j = 1, 2, \ldots, n\). The decision matrix \(R = (r_{ij})_{m \times n}\) is constructed as follows:

\[
\begin{align*}
    & E^1 & E^2 & E^3 & \cdots & E^m \\
    C_1 & \left( \tilde{x}_{11} & \tilde{x}_{12} & \tilde{x}_{13} & \cdots & \tilde{x}_{1m} \right) \\
    C_2 & \left( \tilde{x}_{21} & \tilde{x}_{22} & \tilde{x}_{23} & \cdots & \tilde{x}_{2m} \right) \\
    C_3 & \left( \tilde{x}_{31} & \tilde{x}_{32} & \tilde{x}_{33} & \cdots & \tilde{x}_{3m} \right) \\
    \vdots & \vdots & \vdots & \vdots & \vdots \\
    C_n & \left( \tilde{x}_{n1} & \tilde{x}_{n2} & \tilde{x}_{n3} & \cdots & \tilde{x}_{nm} \right)
\end{align*}
\]

(20)

where \(m\) represents the number of decision-makers and \(n\) is the number of readiness criteria, \(r_{ij}= \langle [\mu_{ij}^L, \mu_{ij}^U], [\nu_{ij}^L, \nu_{ij}^U] \rangle\) indicate the fuzzy performance value of the \(j^{th}\) criterion assessed by the \(i^{th}\) decision-maker.

#### 3.3.2. Step 2: Construct aggregated matrix

According to decision matrix \(R\) in Step 1, the interval-valued Pythagorean Fuzzy Weighted Geometric (IVPFWG) operator is applied to aggregate IVPFN into group by using Equation (7) and DMs weights are calculated by Equation (8).

#### 3.3.3. Step 3: Defuzzifying the aggregated IVPFN

The aggregated IVPFN from Step 2 is defuzzied into crisp values by Equation (11).
3.4. Determining the overall readiness degree of IIoT adoption

By applying the concept proposed by Malviya & Kant (2016), the overall readiness degree of IIoT adoption \( Z \) is determined by multiplying the weights of readiness criteria and possible rating of readiness for IIoT adoption, by the following formula:

\[
Z_{\text{read}} = \sum_{j=1}^{n} r_j w_j
\]  

(21)

where \( r_j \) denotes the possible rating of readiness IIoT adoption regarding the \( j^{th} \) criteria and \( w_j \) represents the weight of the \( j^{th} \) readiness criterion. As the possibility of readiness is known, the readiness degree is known, the unreadiness degree is simultaneous calculated as follows:

\[
\tilde{Z} = 1 - Z_{\text{read}}
\]  

(22)

As discussion with experts, the overall readiness degree is less than 0.6 indicates that an organization is unready to adopt IIoT.

4. Empirical case study

4.1. Problem description

To demonstrate the application of the proposed framework, an empirical case study of a Thai agro-food processing manufacturer was conducted. The case company (denoted as ABC) conducted for this study is one of the leading agro-processed food product manufacturers in Thailand. Company ABC produces semicooked and cooked meats, ready-made meals, and other food products and provides breeding and farming services. It has been listed on the Stock Exchange of Thailand since 2001. At present, company has total revenues of over 18 billion Thai Baht, with 15 subsidiary group companies and more than 12,000 employees in nationwide and abroad. To maintain a long-term competition in the global market, the managerial staff of ABC company are considering to upgrade the manufacturing technology by adopting IIoT. However, an IIoT investment is a critical decision because it is extremely costly in terms of money, time, and risk. The evaluation of IIoT adoption readiness including an appropriate framework for self-assessment is then very essential for management. Therefore, this article proposes a group decision-making framework under the IVPFS approach to evaluate the degree of readiness of IIoT adoption. The following shows how ABC company employs the proposed framework to evaluate the readiness.

4.2. Proposed framework for evaluating readiness degree for IIoT adoption

The proposed framework for evaluating the readiness degree for IIoT adoption in manufacturing enterprises is divided into seven phases, as displayed in Figure 1.
4.2.1. **Phase I: form a qualified panel of experts**

In this phase, a panel of experts is established, which comprises three managerial staff from different companies, which succeed in implementing IIoT, one academician, and one industrial expert. All of them have knowledge and experiences in IIoT including other advance manufacturing technologies projects implementation. The qualifications of each expert (E) are shown in Table 4.

![Diagram](image-url)
4.2.2. Phase II: Identify and validate the readiness criteria of IIoT readiness to adopt

Based on extant literature review, twelve criteria related to organizational readiness for IIoT adoption are identified as shown in Section 2. The panel of experts is invited to a brainstorming session. Twelve criteria and their descriptions are presented to the panel of experts, and then each of experts justifies the eligibility of criteria. After several rounds of scrutiny, the experts agree upon to use the twelve criteria for this research.

4.2.3. Phase III: Formulate a decision model

Based on the result from Phase II, a decision model for evaluating the readiness degree for IIoT adoption is formulated as shown in Figure 2.

4.2.4. Phase IV: Compute the significant weight of each expert

In this study, the significant weight of each expert is determined based on his/her (i) relevant experience in advance manufacturing technology implementation, (ii) technical knowledge in IIoT, and (iii) the organizational position of the expert. By using the linguistic terms in Table 1, the importance of each expert is assessed and then converted to corresponding IVPFN. By utilizing Equation (8), the significant weight of each expert is computed and the results are shown in Table 5. A sample computation of expert 1 ($\lambda_1$) is illustrated as follows:
Table 5. The significant weight of each expert.

| Expert | Linguistic terms | $\mu_L$ | $\mu_U$ | $v_L$ | $v_U$ | $\nu_L$ | $\nu_U$ | $\lambda$ | $\lambda_8$ |
|--------|------------------|---------|---------|-------|-------|---------|---------|-----------|-----------|
| E1     | G                | 0.700   | 0.800   | 0.15  | 0.250 | 0.698   | 0.545   | 0.385     | 0.186     |
| E2     | G                | 0.700   | 0.800   | 0.15  | 0.250 | 0.698   | 0.545   | 0.385     | 0.186     |
| E3     | VG               | 0.800   | 0.950   | 0.00  | 0.150 | 0.600   | 0.273   | 0.586     | 0.283     |
| E4     | M                | 0.550   | 0.700   | 0.250 | 0.400 | 0.796   | 0.591   | 0.322     | 0.156     |
| E5     | G                | 0.700   | 0.800   | 0.150 | 0.250 | 0.698   | 0.545   | 0.385     | 0.186     |

$$\lambda_1 = 0.186 = \frac{\sqrt{\frac{1}{2}[(1 - 0.698)^2 + (1 - 0.545)^2]}}{\sqrt{\frac{1}{2}[(1 - 0.698)^2 + (1 - 0.545)^2]} + \sqrt{\frac{1}{2}[(1 - 0.600)^2 + (1 - 0.273)^2]} + \sqrt{\frac{1}{2}[(1 - 0.796)^2 + (1 - 0.591)^2]}} + \sqrt{\frac{1}{2}[(1 - 0.698)^2 + (1 - 0.545)^2]}.$$ 

The remaining computations of significant weight of other experts are displayed in Appendix II.

4.2.5. Phase V: Determine the relative importance weights of criteria

In this stage, the twelve criteria are weighted based on pairwise comparison with the IVVPF-AHP method as described in Section 3.2. By using linguistic terms from Table 2, each expert is requested to assess the relative importance of the twelve criteria based on pairwise comparisons. Thereafter, the linguistic terms are converted into their equivalent IVVPFN. By using Table 3, a pairwise comparison is constructed. As the important ratings of these decisionmakers are different, therefore, the aggregated pairwise comparison of experts’ subjective judgments is required by utilizing Equation (7), and the result is shown in Table 6. Equation 13 to Equation 19 are used to compute the relative importance weight of each evaluation criterion, and the results are demonstrated in Table 7–10, i.e. the different lower and upper values of membership and nonmembership functions, the interval multiplicative matrix, the determinacy value, and the normalized priority weights, respectively. As seen in Table 10, the ranking of relative importance weights in descending order is as follows: C1(0.280) > C9(0.178) > C11(0.128) > C4(0.117) > C6(0.09) > C2(0.061) > C3(0.028) > C8(0.026) > C7(0.024) > C10(0.016) > C12(0.015) ≥ C5(0.015).

Table 6. The aggregated pairwise comparison of experts.

| $C_i$ | $\mu_L$ | $\mu_U$ | $v_L$ | $v_U$ | $\mu_L$ | $\mu_U$ | $v_L$ | $v_U$ | $\mu_L$ | $\mu_U$ | $v_L$ | $v_U$ |
|-------|---------|---------|-------|-------|---------|---------|-------|-------|---------|---------|-------|-------|
| $C_1$ | 0.196   | 0.196   | 0.197 | 0.197 | 0.785   | 0.902   | 0.123 | 0.226 | ...     | 0.771   | 0.893 | 0.134 | 0.242 |
| $C_2$ | 0.187   | 0.199   | 0.817 | 0.196 | 0.196   | 0.196   | 0.197 | 0.197 | ...     | 0.395   | 0.547 | 0.480 | 0.626 |
| $C_3$ | 0.200   | 0.350   | 0.650 | 0.800 | 0.482   | 0.582   | 0.420 | 0.520 | ...     | 0.450   | 0.550 | 0.450 | 0.550 |
| $C_4$ | 0.450   | 0.550   | 0.450 | 0.550 | 0.650   | 0.800   | 0.200 | 0.350 | ...     | 0.703   | 0.805 | 0.224 | 0.315 |
| $C_5$ | 0.200   | 0.350   | 0.650 | 0.800 | 0.200   | 0.350   | 0.650 | 0.800 | ...     | 0.450   | 0.550 | 0.450 | 0.550 |
| $C_6$ | 0.000   | 0.000   | 0.822 | 1.000 | 0.702   | 0.836   | 0.170 | 0.304 | ...     | 0.650   | 0.800 | 0.200 | 0.350 |
| $C_7$ | 0.200   | 0.350   | 0.650 | 0.800 | 0.516   | 0.632   | 0.381 | 0.490 | ...     | 0.516   | 0.632 | 0.381 | 0.490 |
| $C_8$ | 0.284   | 0.409   | 0.592 | 0.719 | 0.384   | 0.485   | 0.517 | 0.617 | ...     | 0.510   | 0.610 | 0.392 | 0.492 |
| $C_9$ | 0.450   | 0.550   | 0.450 | 0.550 | 0.740   | 0.861   | 0.146 | 0.268 | ...     | 0.740   | 0.861 | 0.146 | 0.268 |
| $C_{10}$ | 0.200  | 0.350   | 0.650 | 0.800 | 0.270   | 0.414   | 0.591 | 0.734 | ...     | 0.566   | 0.695 | 0.323 | 0.441 |
| $C_{11}$ | 0.450  | 0.550   | 0.450 | 0.550 | 0.650   | 0.800   | 0.200 | 0.350 | ...     | 0.650   | 0.800 | 0.200 | 0.350 |
| $C_{12}$ | 0.100  | 0.200   | 0.800 | 0.900 | 0.264   | 0.408   | 0.596 | 0.741 | ...     | 0.196   | 0.196 | 0.197 | 0.197 |
4.2.6. Phase VI: Determine the possible rating of readiness for IIoT adoption

To explore the real situation of the case company, five decision-makers (DMs) from ABC company (one factory manager, one general manager from engineering department, one general manager from information and communication technology department, and two
Table 10. The normalized priority weights ($w_j$)

|   | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ | $C_7$ | $C_8$ | $C_9$ | $C_{10}$ | $C_{11}$ | $C_{12}$ | $\sum_{k=1}^{m} f_{ik}$ | $w_j$ | Ranking |
|---|------|------|------|------|------|------|------|------|------|--------|--------|--------|------------------|------|---------|
| $C_1$ | 0.922 | 8.404 | 1.182 | 2.504 | 8.023 | 3.917 | 4.599 | 3.331 | 15.529 | 6.134 | 3.917 | 7.595 | 66.058 | 0.280 | 1 |
| $C_2$ | -0.040 | 0.922 | 0.982 | -0.328 | 9.270 | -0.045 | -0.015 | 3.331 | -0.046 | 0.328 | -0.036 | 0.201 | 14.523 | 0.062 | 6 |
| $C_3$ | -0.035 | 0.588 | 4.122 | -0.082 | 0.588 | -0.035 | 0.792 | 0.263 | -0.046 | 0.092 | -0.044 | 0.418 | 6.620 | 0.028 | 7 |
| $C_4$ | 0.418 | 3.331 | 0.982 | 4.122 | 3.331 | 0.000 | 3.331 | 4.599 | 0.035 | 3.331 | 0.000 | 4.115 | 27.592 | 0.117 | 4 |
| $C_5$ | -0.035 | -0.035 | 2.750 | -0.322 | 0.922 | -0.045 | -0.046 | 0.051 | -0.040 | -0.035 | -0.040 | 0.418 | 3.543 | 0.015 | 12 |
| $C_6$ | -0.043 | 4.741 | 1.618 | 1.705 | 4.741 | 0.922 | 3.331 | 1.684 | 0.418 | 3.331 | 0.005 | 3.331 | 25.783 | 0.109 | 5 |
| $C_7$ | -0.035 | 0.842 | 0.483 | -0.413 | 1.412 | -0.035 | 0.922 | 0.054 | 0.051 | 1.684 | -0.043 | 0.842 | 5.763 | 0.024 | 9 |
| $C_8$ | 0.017 | 0.178 | 2.513 | -0.112 | 0.787 | -0.030 | 0.418 | 0.922 | -0.045 | 0.787 | 0.051 | 0.787 | 6.273 | 0.027 | 8 |
| $C_9$ | 0.418 | 6.134 | 1.040 | 2.835 | 4.741 | 1.412 | 6.134 | 4.741 | 0.922 | 6.134 | 1.412 | 6.134 | 42.057 | 0.178 | 2 |
| $C_{10}$ | -0.035 | 0.005 | 0.601 | -0.065 | 0.787 | -0.045 | 0.178 | 0.178 | -0.045 | 0.922 | -0.045 | 1.412 | 3.847 | 0.016 | 10 |
| $C_{11}$ | 0.418 | 3.331 | 1.033 | 1.970 | 9.270 | 0.588 | 2.265 | 3.331 | 0.418 | 3.331 | 0.922 | 3.331 | 30.206 | 0.128 | 3 |
| $C_{12}$ | -0.045 | 0.000 | -0.001 | -0.081 | 0.792 | 0.000 | 0.418 | 0.792 | 0.006 | 0.792 | 0.000 | 0.922 | 3.594 | 0.015 | 11 |
production managers) are asked to conduct self-assessment of their organization. Based on readiness criteria in Phase I, each decision-maker provides his/her rating of readiness for IIoT adoption with respect to each evaluation criterion by using linguistic terms in Table 1. Subsequently, the linguistic terms are transformed into their corresponding IVPFN. By using Equation (7), the aggregations of rating values are obtained and presented in Table 11. In this case, the importance weights of decision-makers are assumed to be equal ($\lambda_k = 0.2$, $k = 1, 2, 3, \ldots, 5$). Thereafter, each aggregated rating value in Table 11 is defuzzied into crisp value by Equation 11.

### 4.2.7. Phase VII: Obtain the overall readiness degree of IIoT adoption

The overall readiness degree of IIoT adoption of ABC company ($Z_{ABC}$) is obtained by multiplying the weights of criteria with their respect readiness rating values as shown in Table 12. According to Table 12, ($Z_{ABC}$) is 0.461 (or 46.1%); meanwhile, the overall unreadiness degree is 0.539. The computations of overall readiness/unreadiness degrees are illustrated as follows:

$$Z_{\text{read}}^\text{ABC} = (0.280 \times 0.687) + (0.061 \times 0.462) + (0.028 \times 0.233) + \ldots + (0.015 \times 0.262) = 0.461$$

$$\bar{Z} = 1-Z_{\text{read}}^\text{ABC} = 1-0.461 = 0.539.$$  

Table 12 also shows the overall readiness degree of a food processing manufacturer who has successfully implemented IIoT. The overall readiness degree of successful company ($Z_{\text{read}}^\text{success}$) is 0.648 (or 64.8%), and the computation $Z_{\text{read}}^\text{success}$ is illustrated as follows:

$$Z_{\text{read}}^\text{success} = (0.280 \times 0.850) + (0.061 \times 0.638) + (0.028 \times 0.693) + \ldots + (0.015 \times 0.448) = 0.648.$$
Table 12. The overall readiness degree of IIoT adoption.

| Readiness criteria                                         | ABC Company  | Success Company | % Gap values of readiness Degree* |
|------------------------------------------------------------|--------------|-----------------|----------------------------------|
| Top management commitment and support (C1)                 | 0.280        | 0.687           | 0.192                            | 0.850 | 0.238 | 19.32 |
| Financial capability (C2)                                 | 0.062        | 0.462           | 0.028                            | 0.638 | 0.039 | 28.20 |
| Managing cyber security and privacy (C3)                   | 0.028        | 0.233           | 0.006                            | 0.692 | 0.019 | 68.42 |
| Digital business model development capability (C4)         | 0.116        | 0.300           | 0.035                            | 0.587 | 0.068 | 48.53 |
| Technology infrastructure capability (C5)                  | 0.015        | 0.336           | 0.005                            | 0.638 | 0.009 | 44.44 |
| Change management capability (C6)                          | 0.109        | 0.361           | 0.039                            | 0.554 | 0.060 | 35.00 |
| Data management and analytics capabilities (C7)             | 0.024        | 0.617           | 0.015                            | 0.660 | 0.016 | 6.25  |
| Seamless value-chain integration capability (C8)            | 0.027        | 0.490           | 0.013                            | 0.589 | 0.015 | 13.33 |
| Strategic technology roadmap for digitalization (C9)        | 0.178        | 0.376           | 0.067                            | 0.532 | 0.094 | 28.72 |
| Employees digital knowledge capabilities (C10)              | 0.016        | 0.450           | 0.007                            | 0.673 | 0.010 | 30.00 |
| Digital culture readiness (C11)                            | 0.128        | 0.372           | 0.047                            | 0.533 | 0.068 | 30.88 |
| Lean practice implementation (C12)                         | 0.015        | 0.262           | 0.003                            | 0.448 | 0.006 | 50.00 |
| Overall readiness degree                                   | 0.461        | 0.648           | 0.192                            | 0.648 | 0.648 | 50.00 |
| Overall unreadiness degree                                 | 0.539        | 0.352           | 0.539                            | 0.539 | 0.648 | 50.00 |

*Note: % Gap values of readiness Degree* = \( \frac{|Z_{\text{success}} - Z_{\text{ABC}}| \times 100}{Z_{\text{success}}} \)

5. Discussions of findings

The findings of all results in terms of the relative importance weights, readiness degree, and % Gap values of readiness degree between ABC company and success company can be summarized in Table 13. The discussions of overall evaluation of readiness degree, the readiness degree evaluation of case company, and a benchmarking study are explained in subsection 5.1, 5.2, and 5.3, respectively.

5.1. Relative importance weight of readiness factors

According to a proposed decision model of this research, twelve criteria were extracted from the extensive literature review and confirmed by a group of experts. It is to evaluate the readiness degree to IIoT adoption in manufacturing enterprises. The findings from Table 10 displayed that the three most important readiness criteria in terms of the relative importance weights are ‘top management commitment and support (C1)’, ‘strategic technology roadmap for digitalization (C9)’ and ‘digital culture readiness (C11)’. This means that these readiness criteria are considered as the most critical factors and need to be addressed by firms on the highest priority for
improvement. Through the degree of importance assigned by each experts’ opinions, ‘top management commitment and support’ (C1) is the first priority to develop, among twelve criteria. Previous research also showed that the top management criterion is broadly recognized as an important factor for advanced manufacturing technology adoption through firms’ strategic goals (Sony & Naik, 2019). Also, it plays a vital role in allocating sufficient financial support and essential resources to new technologies implementation effort. Then, a success of technological projects implementation heavily relies on top management commitment and support (Sony & Naik, 2019). Moreover, the positive attitude of top management toward adopting new technology can mitigate the changing resistance of employees.

Next, based on the relative importance weights, the ‘strategic technology roadmap for digitalization’ (C9) shows the second rank for a core evaluating criterion of the IIoT adoption readiness. This result is consistent with the finding of Ghobakhloo (2018), identifying that a strategic technology roadmap is the most determinant of smart manufacturing technologies adoption. Also, it can direct manufacturers to develop and implement future technologies for competitive advantages (Raj et al., 2020).

Then, ‘digital culture readiness’ (C11) is the third ranked readiness criteria to IIoT adoption in lights of the relative importance weights. Digital culture readiness is to mutually share values and practices in digital product innovation to workforces under environment changes. It is also considered as one of the essential factors to encourage a whole organization to realize the merits of digital adoption toward firm’s competitiveness (Martinez-Caro et al., 2020). The relationship of technology and culture is influenced by one another (Duerr et al., 2018). As digital technology is rapidly developed and transformed, cultures also change, especially by human influences. The congruence between organizational digital culture and a new technologies introduction allows firms to fully exploit the potential benefits of digital technologies adoption Duerr et al., 2018).

| Table 13. Summary of result comparisons |
|----------------------------------------|
| C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 | C10 | C11 | C12 | Overall readiness degree value |
|----------------------------------------|
| Weight | 0.28 | 0.062 | 0.028 | 0.116 | 0.015 | 0.109 | 0.024 | 0.027 | 0.178 | 0.016 | 0.128 | 0.015 | - |
| Rating score | 0.687 | 0.462 | 0.233 | 0.300 | 0.336 | 0.361 | 0.617 | 0.490 | 0.376 | 0.450 | 0.372 | 0.262 | - |
| Readiness degree | 0.192 | 0.028 | 0.006 | 0.035 | 0.005 | 0.039 | 0.015 | 0.013 | 0.067 | 0.007 | 0.047 | 0.003 | 0.461 (46.1%) |
| Rating score | 0.850 | 0.638 | 0.692 | 0.587 | 0.638 | 0.554 | 0.660 | 0.589 | 0.532 | 0.673 | 0.533 | 0.448 | 0.648 (64.8%) |
| Readiness degree | 0.238 | 0.039 | 0.019 | 0.068 | 0.009 | 0.060 | 0.016 | 0.015 | 0.094 | 0.010 | 0.068 | 0.006 | 0.850 |
| % Gap values of reading degree | 19.32 | 28.20 | 68.42 | 48.53 | 44.44 | 36.00 | 6.25 | 13.33 | 28.72 | 30.00 | 30.88 | 50.00 | 10 9 1 3 4 5 12 11 8 7 6 2 |
5.2. The readiness degree evaluation of case company

Regarding Table 12, the rating score \(r_{ABC}^{\text{read}}\) of each readiness criterion of ABC company shows the degree of readiness to adopt IIoT of ABC company. The lower the rating score it is, the higher the improvement it takes. In this research, it is found that top three worst readiness factors with the lowest scores are ‘lean practice implementation (C_{12})’, ‘technology infrastructure capability (C_3)’, and ‘managing cyber security and privacy (C_3)’, with values of 0.003, 0.005, and 0.006, respectively. Hence, when taking into an account, ABC company first needs to accelerate improve these three readiness criteria in a stepwise manner.

Moreover, the bottom line of Table 12 shows that the overall readiness degree value of ABC company \(Z_{ABC}^{\text{read}}\) is quite low, equaling to 0.461 or 46.1%, which is less than 50%. Based on the overall readiness scores of ABC company, it may not be ready to adopt IIoT in a moment. However, it is expected that after improvement of those weak readiness criteria, ABC company will be more readily available to adopt IIoT.

5.3. A benchmarking study

Regarding Table 12, the results also demonstrate the different scores of each readiness criterion of both ABC company and a reference success company, which is in the same industry as ABC company. From overview of comparisons, the results show that the overall readiness degree value of a success company \(Z_{\text{success}}^{\text{read}}\) is 0.648 (or 64.8%), while that of ABC company is 0.461 (or 46.1%). Therefore, it can be concluded that the reference company has a higher readiness level of IIoT adoption than ABC company has. In the same way, the reference company is ready to adopt IIoT but not for ABC company. When further analyzing, it shows that each score of readiness criteria of ABC company is also totally lower than that of a reference company. The difference of each readiness score between two companies is computed in terms of % gap values of readiness degree, as presented in the last column of Table 12. The results from the benchmark for gap values between two companies indicate that ‘managing cyber security and privacy (C_3)’, ‘lean practice implementation (C_{12})’, and ‘digital business model development capability (C_4)’ are the highest three percentage gap values of 68.42, 50.00, and 48.53, respectively. Thus, ABC company can simultaneously consider these benchmarking values to improve the readiness factors.

The more the % gap values obtained, the higher improvement of readiness criteria is required. For example, the readiness criteria degree of managing cyber security and privacy (C_3) for ABC company is 0.006, while that of the reference company is 0.019. Then, the % gap value is shown 68.42%, which is the also highest gap value among other readiness criteria. This implies that ABC company must pay its first and highest attention to improve the cyber security management and privacy. The comparison of readiness indexes between both companies is depicted in Figure 3.

6. Managerial implications

Since the readiness of manufacturing organization is a key driver for a success of IIoT adoption, the results of this study provide substantial implications for practitioners, aiming to adopt IIoT. The proposed systematic framework could guide managers to evaluate the
organizational readiness and prioritize the areas for improvement. The twelve key readiness factors are identified, which would help manufactures understand what efforts and resources they have to invest. By considering the relative importance of the readiness factors, this study recommends that top management should provide strong support and formulate clear strategies for achieving a higher degree of IIoT adoption.

In addition, top management plays pivotal roles in initiating strategic technology roadmap, fostering digital culture, and driving the change management of transition to IIoT adoption. The development of a precise strategic technology roadmap will provide and address the effective ways to initiate collaboration and integration among key suppliers. This roadmap is also to assist managers to prepare the physical infrastructure, workforce capabilities, and internal cross-functions integration. Regarding digital culture, the practitioners strongly need to cultivate a digital culture that can reduce organizational opposition and encourage collaboration in adoption IIoT. In the context of case company, managers can use this proposed methodological framework for self-assessment to pinpoint the areas that significantly need an improvement. As compared to a success company, the results indicate that cybersecurity and privacy management, and lean practice implementation are the two most vulnerable areas for case company.

7. Conclusion

The adoption of IIoT technology enables manufacturing enterprises to reduce production costs, generate additional revenues, strengthen business relationships with customers, and increase asset utilization. Despite the enormous benefits of adopting IIoT
technologies, it is a complex, time-consuming, costly process and has a high failure rate. As a result, most manufacturing enterprises are reluctant to adopt IIoT without evidence of their readiness. To increase the effectiveness and success of IIoT adoption in the manufacturing sector, this study proposes a quantitative framework to evaluate the readiness level of IIoT technology implementation. This proposed framework is developed for a general IIoT adoption for manufacturing enterprises. To reduce the uncertainty and ambiguity of human judgment in the decision-making process, the IVPFS approach is applied to resolve these problems. Through literature review, the twelve readiness criteria are determined and validated by a panel of experts from industries, government agencies, and academics sectors. The relative importance weights of readiness criteria are derived by deploying the IVPF-AHP approach. This study reveals that top management commitment and support, strategic technology roadmap for digitalization, and digital culture readiness are the three most important readiness factors. Also, an empirical study of food processing manufacturers in Thailand is presented by measuring the readiness degree for IIoT adoption. The results indicate that the overall readiness degree is 46.1% compared to one of the success in the same industry, 64.8%. Based on evaluation results, it suggests that the case company was not ready to adopt IIoT.

8. Future research

For future research, this study suggests several guidelines or directions including (i) to explore the inter-relationships between criteria; (ii) to conduct a comparative study by applying the neutrosophic fuzzy approach; (iii) a proposed framework can be applied in other industrial cases such as automobile industry, pharmaceutical industry, etc.; and (iv) this proposed application can be extended to evaluate the readiness of other emerging technology adoption such as blockchain.

Biographical note

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Disclosure statement

No potential conflict of interest was reported by the author(s).

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Appendix I: The abbreviation

| Abbreviation | Definition/Explanation |
|--------------|------------------------|
| AHP          | Analytic Hierarchy Process |
| AI           | Artificial Intelligence |
| AIFDA        | Aggregated Intuitionistic Fuzzy Dimensional Analysis |
| AIFIS        | Aggregated Intuitionistic Fuzzy Index of Similarity |
| CPS          | Cyber-Physical Systems |
| DM           | Decision Maker |
| FMCDEM       | Fuzzy Multi Criteria Decision Making |
| GDP          | Gross Domestic Product |
| IFN          | Intuitionistic Fuzzy Numbers |
| IFS          | Intuitionistic Fuzzy Sets |
| IIoT         | Industrial Internet of Things |
| IoT          | Internet of Things |
| IT           | Information Technology |
| IT2FS        | Interval Two-Type Fuzzy Sets |
| IVFNS        | Interval-valued Pythagorean Fuzzy Number |
| IVFPLWA      | Interval-valued Pythagorean Fuzzy Weighted Geometric |
| MCDM         | Multi Criteria Decision Making |
| M2M          | Machine-to-Machine |
| PFS          | Pythagorean Fuzzy Set |
| PFAHP        | Pythagorean Fuzzy Analytical Hierarchy Process |
| TFS          | Triangular Fuzzy Set |

Appendix II: The remaining of the significant weight of expert

The significant weights of expert 2 ($\lambda_2$), expert 3 ($\lambda_3$), expert 4 ($\lambda_4$), expert 5 ($\lambda_5$) are calculated by Equation (8), as follows:

$$\lambda_2 = 0.186 = \frac{\sqrt{\frac{1}{2} [(1 - 0.698)^2 + (1 - 0.545)^2]} + \sqrt{\frac{1}{2} [(1 - 0.600)^2 + (1 - 0.273)^2]} + \sqrt{\frac{1}{2} [(1 - 0.698)^2 + (1 - 0.545)^2]} + \sqrt{\frac{1}{2} [(1 - 0.796)^2 + (1 - 0.591)^2]} + \sqrt{\frac{1}{2} [(1 - 0.698)^2 + (1 - 0.545)^2]}}{\sqrt{\frac{1}{2} [(1 - 0.698)^2 + (1 - 0.545)^2] + \sqrt{\frac{1}{2} [(1 - 0.698)^2 + (1 - 0.545)^2]} + \sqrt{\frac{1}{2} [(1 - 0.698)^2 + (1 - 0.545)^2]} + \sqrt{\frac{1}{2} [(1 - 0.796)^2 + (1 - 0.591)^2]} + \sqrt{\frac{1}{2} [(1 - 0.698)^2 + (1 - 0.545)^2]}}$$

$$\lambda_3 = 0.283 = \frac{\sqrt{\frac{1}{2} [(1 - 0.600)^2 + (1 - 0.273)^2]}}{\sqrt{\frac{1}{2} [(1 - 0.698)^2 + (1 - 0.545)^2] + \sqrt{\frac{1}{2} [(1 - 0.698)^2 + (1 - 0.545)^2]} + \sqrt{\frac{1}{2} [(1 - 0.698)^2 + (1 - 0.545)^2]} + \sqrt{\frac{1}{2} [(1 - 0.796)^2 + (1 - 0.591)^2]} + \sqrt{\frac{1}{2} [(1 - 0.698)^2 + (1 - 0.545)^2]}}$$
\[ \lambda_4 = 0.156 = \frac{\sqrt{\frac{1}{2} [(1 - 0.796)^2 + (1 - 0.591)^2]}}{\sqrt{\frac{1}{2} [(1 - 0.698)^2 + (1 - 0.545)^2]} + \sqrt{\frac{1}{2} [(1 - 0.698)^2 + (1 - 0.545)^2]} + \sqrt{\frac{1}{2} [(1 - 0.600)^2 + (1 - 0.273)^2] + \sqrt{\frac{1}{2} [(1 - 0.796)^2 + (1 - 0.591)^2]} + \sqrt{\frac{1}{2} [(1 - 0.698)^2 + (1 - 0.545)^2]} + \sqrt{\frac{1}{2} [(1 - 0.698)^2 + (1 - 0.545)^2]}} \]

\[ \lambda_5 = 0.186 = \frac{\sqrt{\frac{1}{2} [(1 - 0.698)^2 + (1 - 0.545)^2]}}{\sqrt{\frac{1}{2} [(1 - 0.698)^2 + (1 - 0.545)^2]} + \sqrt{\frac{1}{2} [(1 - 0.698)^2 + (1 - 0.545)^2]} + \sqrt{\frac{1}{2} [(1 - 0.600)^2 + (1 - 0.273)^2] + \sqrt{\frac{1}{2} [(1 - 0.796)^2 + (1 - 0.591)^2]} + \sqrt{\frac{1}{2} [(1 - 0.698)^2 + (1 - 0.545)^2]} + \sqrt{\frac{1}{2} [(1 - 0.698)^2 + (1 - 0.545)^2]}} \]