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Research article

Enhancing readiness degree for Industrial Internet of Things adoption in manufacturing enterprises: An integrated Pythagorean fuzzy approach

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A R T I C L E I N F O

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Industrial Internet of Things (IIoT)
Technology-organization-environment (TOE)
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A B S T R A C T

This study proposes a hybrid multi-criteria decision-making (MCDM) methodology designed to enhance the readiness for adopting the Industrial Internet of Things (IIoT) in manufacturing enterprises. The Pythagorean fuzzy approach is employed to address uncertainty and imprecision throughout decision-making processes. The development framework in this study incorporates TOE (Technology-Organization-Environment) and HOT fit (Human-Organization-Technology) to pinpoint barriers to IIoT adoption. Additionally, a triple helix model (THM) emphasizing on the synergy among university-industry-government is utilized to formulate pragmatic strategies. The agro-food processing industry in Thailand is used as a case study. In this study, even barriers are identified and validated through the Delphi method. The SWARA (Step-wise Weight Assessment Ratio Analysis) method determines the importance weights of these barriers, revealing "lack of digital culture", "lack of knowledge and expertise," and "job displacement concerns" as the three most critical barriers. The COBRA (COmprehensive Distance Based Ranking) method is employed to prioritize pragmatic strategies under THM, indicating that the role of the university in enhancing human capital capabilities is the most important, followed by the government's roles in enabling national ICT infrastructures and offering investment incentives as the second and third pragmatic strategies, respectively. A sensitivity analysis validates the proposed framework's reliability and robustness. The study's findings emphasize the potential of this integrated framework to guide future research endeavors among scholars and academicians across diverse industries beyond agri-food processing.

Nomenclature list

AROMAN	Alternative Ranking Order Method Accounting for two Step Normalization
BWM	Best-Worst Method
COBRA	COmprehensive Distance Based Ranking
CODAS	Combinative Distance-based Assessment
CRADIS	Compromise Ranking of Alternatives from Distance to Ideal Solution
EDAS	Evaluation Based on Distance from Average Solution
FFS	Fermatean Fuzzy Sets
HOT fit	Human-Organization-Technology
IDOCRIW	Integrated Determination of Objective Criteria Weights

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(*continued*)

IFN	Intuitionistic Fuzzy Number
IFS	Intuitionistic Fuzzy Set
IIoT	Industrial Internet of Things
LOPCOW	LOgarithmic Percentage Change-driven Objective Weighting
PF	Pythagorean fuzzy
PFN	Pythagorean Fuzzy Number
PFS	Pythagorean Fuzzy Set
TOE	Technology-Organization-Environment
MABAC	Multi-Attributive Border Approximation Area Comparison
MCDM	Multi-Criteria Decision-Making
MEREC	MEthod based on the Removal Effects of Criteria
SWARA	Step-wise Weight Assessment Ratio Analysis
THM	Triple Helix Model
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
VIKOR	VIsekriterijumska Optimizacija I KOmpromisno Resenje
PIS_j	Positive Ideal Solution for criterion j
NIS_j	Negative Ideal Solution for criterion j
Q-ROFS	q-rung orthopair fuzzy

1. Introduction

The advent of Industrial Internet of Things (IIoT) technology represents a groundbreaking innovation that has witnessed widespread adoption across embedded networks. It encompasses a diverse spectrum of intelligent devices, autonomous vehicles, IoT automation systems, robots, and interconnected equipment, as observed in prior studies [1,2]. Additionally, it is crucial to recognize that the integration of IIoT stands as an imperative prerequisite for the realization of Industrial 4.0 (I4.0) [3]. I4.0 represents a revolutionary paradigm shift in the realm of manufacturing and industrial practices, characterized by the seamless amalgamation of digital technologies, automation, and data-centric decision-making [4,5]. Within this transformative landscape, IIoT assumes a pivotal role as the foundational infrastructure, furnishing the indispensable connectivity and data backbone requisite for real-time interconnection among machines, devices, and systems [6]. Through IIoT, data can be continually harnessed, subjected to analysis, and seamlessly shared across the entire spectrum of production and supply chain processes [7,8]. This capability facilitates predictive maintenance, process optimization, and an overarching enhancement in operational efficiency, aligning with the core tenets of I4.0 [8,9]. Harnessing data from IIoT systems empowers decision-makers to access valuable insights, facilitating the creation and delivery of value, the virtualization of supply chains, the enhancement of customer engagement, and the encouragement of the adoption of more efficient policies and practices [2,10]. This data-driven approach not only fosters the creation and delivery of enhanced value to customers but also supports the transformation of supply chains into agile, data-centric ecosystems, capable of adapting to dynamic market demands [11,12]. Moreover, the deep understanding gained from IIoT data empowers organizations to cultivate stronger customer relationships by tailoring products and services to meet evolving preferences, ultimately driving sustainable growth and competitive advantage [2,10,13]. The widespread integration of IIoT technology exerts an inevitable and far-reaching influence across all industries, spanning from large corporate entities to small and medium-sized enterprises (SMEs) [11,14]. In the present landscape, industrial stakeholders are increasingly recognizing the manifold benefits that IIoT can bring to the supply chain process, driving a proactive readiness for its adoption [1,5]. However, despite the promising potential of IIoT, many manufacturers, especially in developing countries, have struggled with challenges arising from complexities, inherent risks, formidable barriers, and the substantial costs associated with IIoT adoption [12,15]. The barriers encountered by manufacturers within developing country ecosystems differ significantly in both nature and scope compared to those faced in developed nations. Therefore, it is imperative to recognize and understand these distinctive barriers and remedies in developing countries when striving to enhance the readiness of manufacturing enterprises for IIoT. The adoption of IIoT presents a complex challenge, especially considering the pivotal role manufacturers play in the growth of emerging economies. Enhancing IIoT adoption is essential for manufacturing enterprises seeking to maintain their competitiveness, agility, and efficiency in today's industrial landscape [16]. It's worth noting that, academically, research on IIoT readiness and adoption in manufacturing enterprises has received relatively limited attention in previous studies. This study seeks to fill the existing knowledge gap and make significant contributions to this field. Within the scope of this research, this study delves into the barriers that hinder the adoption of IIoT, while concurrently providing pragmatic strategies and valuable insights for enhancing the resolution of these challenges. These barriers are contextualized within the integration framework of TOE (Technology-Organization-Environment) and HOT fit (Human-Organization-Technology), providing a comprehensive perspective on the hindrances to IIoT adoption. While, pragmatic strategies are framed under the purview of the triple helix model (THM: university-industry-government). Additionally, it employs an integrated multi-criteria decision-making approach under a Pythagorean fuzzy set (PFS) environment to develop a decision model.

1.1. Research motivation

The motivations for this research are as follows:

The successful deployment of IIoT systems requires a thorough understanding of readiness in technology, organization, and workforce competency [17]. However, current literature highlights a significant gap in integrated readiness assessment essential for effective adoption strategies, with limited research in this area. This study aims to address these challenges by developing a framework to evaluate IIoT readiness using a Pythagorean fuzzy set (PFS) approach. The PFS approach is adept at managing high levels of uncertainty, offering a refined and flexible tool for assessing readiness levels.

Moreover, in today's competitive manufacturing landscape, the adoption of IIoT technologies profoundly impacts an enterprise's competitive advantage and sustainability [18,19]. This research endeavors to offer insights and practical tools aimed at enhancing IIoT readiness, thereby fostering innovation, operational excellence, and sustained growth. The proposed framework is expected to guide organizations in identifying key readiness factors and addressing potential gaps. Ultimately, this study seeks to contribute to the body of knowledge by offering a comprehensive and practical methodology for IIoT readiness assessment.

1.2. Research contributions

The contributions of this study can be summarized as follows:

- Explore the key barriers to adopting IIoT systems within manufacturing enterprises, and develop an integration framework combining TOE and HOT fit frameworks. This will be achieved through a comprehensive survey approach grounded in current literature and validated by expert insights.
- Identify the pragmatic strategies within the THM framework aimed at overcoming barriers to adopting IIoT systems within manufacturing enterprises.
- Develop a comprehensive decision-making framework to enhancing readiness degree for IIoT adoption in the context of manufacturing enterprises using an integration of Delphi, SWARA (Step-wise Weight Assessment Ratio Analysis), MEREC, and COBRA (COmprehensive Distance Based Ranking) method within PFS environment.
- Employ the PFS-Delphi method to identify the appropriate set of barriers, and use PFS-SWARA and PFS-MEREC to determine the subjective and objective importance weights of these barriers. Apply the PFS-COBRA method to prioritize pragmatic strategies within the THM framework. This novel combination of approaches has not been utilized in previous research.
- Perform a comparative assessment to demonstrate the robustness of the proposed methodology.
- Conduct a case study in a leading agro-food processing industry in Thailand to illustrate the framework's practical application. This sector, designated by the Thai government as a key area for transformation through advanced manufacturing technologies, contributes around 23 % to the country's GDP. Its substantial workforce and significant R&D investments make it crucial to the national economy.

The subsequent sections of this paper are organized as follows: Section 2 presents a review of the relevant literature. Section 3 introduces the research conceptual framework. Section 4 details the methodology employed in this study. Section 5 describes the application of the proposed framework. Section 6 presents the results. Section 7 covers the validity testing of the framework, while Section 8 presents the findings and discussion. Section 9 discusses the research implications. Section 10 provides the conclusion, and finally, Section 11 suggests directions for future research.

2. Literature review

2.1. Industrial Internet of Things (IIoT)

The Industrial Internet of Things (IIoT), often abbreviated as IIoT, refers to the application of Internet of Things (IoT) technology within the realm of manufacturing processes [20,21]. IIoT is characterized by the seamless integration of Cyber-Physical Systems (CPS), which bridge the gap between the physical and digital domains to effectively manage industrial operations [22]. This concept of CPS enables manufacturers to establish dynamic connections between the tangible and virtual aspects of the entire manufacturing value chain. IIoT has evolved into a widespread technology platform featuring autonomous and intelligent devices [23,24]. The central objective behind the adoption of IIoT is to enhance productivity, operational efficiency, and the effective management of manufacturing processes and assets [3,13]. This is achieved through methods such as product customization, intelligent inspection on the production shop floors, and predictive as well as preventive maintenance of production equipment [25]. Under the umbrella of IIoT, a diverse array of technologies plays a pivotal role, including cloud computing, machine-to-machine (M2M) communication, machine learning, artificial intelligence (AI), and distributed computing [13]. The implications of IIoT transcend technical improvements and extend to broader corporate influences and opportunities [26,27]. The implementation of IIoT in supply chains and operational processes brings about tangible commercial advantages, including reduced risk and costs, increased transparency, enhanced visibility, improved flexibility, streamlined operational flows, and a shift towards virtualization [25,26]. Within the manufacturing industry, businesses have recognized the transformative effects of IIoT from five key perspectives: design and innovation, asset utilization and revenue planning, supply chain and logistics optimization, resource productivity enhancement, and the expansion of stakeholder experiences [26,27]. However, it's essential to acknowledge that the adoption of IIoT remains a challenging endeavor for manufacturers due to its costliness, complexity, and high associated risks. Consequently, the assessment of manufacturers' readiness for IIoT adoption has become an imperative step in navigating this transformative technological landscape.

2.2. Triple helix model

The triple helix model (THM) of innovation is rooted in the fundamental concept of fostering an innovation system through an extensive network of reciprocal connections among government, academia, and industry. This synergy and collaboration among these three pillars give rise to the well-established THM [28]. According to this model, industry, academia, and government form the three helices propelling economic development. The transfer and internalization of knowledge spillover effects take place through the interdependence and collaboration among these three organizations [29]. Each participant actively engages and collaborates with others to strengthen all sectors involved. Academia contributes by generating new knowledge and technology, industry plays a pivotal role in commercializing this knowledge and engaging in production activities, while the government oversees and enforces the overall process [30].

In the context of embracing emerging technologies such as the IIoT, the THM emerges as a robust framework recognizing the interconnectedness of government, industry, and university in driving technological innovation and industrial transformation. By fostering collaboration among these three key stakeholders, the model advocates for a comprehensive and inclusive approach to adopting technological innovations [30,31]. This ensures that the benefits of industrial digitization are realized across diverse sectors and communities. Through this coordinated effort, the THM not only accelerates the adoption of technological innovation but also establishes a sustainable and resilient foundation for the continuous evolution of industrial processes in the digital era [32]. At the core of the THM is the government, serving as a catalyst to foster a supportive regulatory environment and provide incentives that drive the adoption of emerging technologies [33]. Government agencies play a pivotal role in formulating policies that encourage innovation, investing in research and development, and streamlining the implementation of technological solutions across a spectrum of industries [34]. By nurturing an enabling ecosystem, governments not only stimulate economic development and job creation but also ensure that the benefits of technologies reach a broad and inclusive audience [35]. Representing the second helix, the industry contributes valuable practical insights and market-driven perspectives to the collaboration. Companies take the lead in implementing technological innovation solutions, aiming to enhance operational efficiency, reduce costs, and gain a competitive advantage [35]. Through joint endeavors with government and academia, industry stakeholders leverage expertise, tap into cutting-edge research, and

Table 1
Recent applications of MCDM under fuzzy environment approaches in the context of IoT and IIoT.

Author	Journal	Year	Context	Research aim/objectives	MCDM methods
Khan et al. [40]	Computers in Human Behavior Reports	2024	IoT	To propose a hybrid MCDM method to rank the different smart school systems under IoT.	Entropy and TOPSIS approaches
Qi et al. [41]	Technological Forecasting and Social Change	2023	IIoT	To analyze, rank, and evaluate the big data analytics challenges in developing IIoT systems.	CRITIC and MULTIMOORA under q-ROFSs
Yi et al. [42]	Technological Forecasting and Social Change	2023	IIoT	To develop a decision support system model for analyzing the barriers to implementing digital twin, blockchain, and IIoT technologies within the context of Industry 4.0.	MEREC and WASPAS under q-ROFSs
Dehshiri and Amiri [43]	Energy	2023	IoT	To develop risk assessments for integrating IoT into renewable energy systems.	SWARA and
Dahooie et al. [44]	Technology in Society	2023	IoT	To develop a new portfolio matrix for decision-making to identify IoT applications in sustainable urban transportation.	CoCoSo under Triangular fuzzy set
Ali et al. [45]	Computers & Industrial Engineering	2023	IoT	To investigate the drivers of IoT adoption in supply chain management.	DEMATEL under rough set theory
Kumar et al. [46]	Technological Forecasting and Social Change	2023	IoT	To conduct a comprehensive analysis of the enablers for utilizing blockchain-IoT in managing logistics and supply chains.	Fuzzy DEMATEL and Graph Theory
Seker [47]	Technology in Society	2022	IoT	To assess smart waste collection systems utilizing IoT technology.	BWM, FCM, and ARAS
Yu et al. [48]	Computers & Industrial Engineering	2022	IoT	To identify and analyze the barriers to IoT adoption in sustainable supply chains.	Entropy and CODAS under interval-valued under q-ROFSs
Asadi et al. [49]	Technovation	2022	IIoT	To examine the impact of IoT adoption on the performance of manufacturing companies.	DEMATEL and ANFIS
Cui et al. [50]	Technological Forecasting and Social Change	2021	IoT	To identify the important barriers to the adoption of IoT in the circular economy in the manufacturing sector.	SWARA-CoCoSo under Pythagorean fuzzy

participate in collaborative initiatives guiding the development and deployment of new technologies [36]. This cooperative approach empowers companies to adeptly navigate challenges and capitalize on emerging opportunities in the constantly evolving landscape of industrial digitization. The third helix in the model is university, symbolizing the intellectual capital and research capabilities essential for advancing technologies [35]. Universities and research institutions contribute by conducting groundbreaking research, developing innovative technologies, and educating the next generation of professionals in the field of industrial automation [36]. Through collaboration with government and industry partners, academia ensures that the pragmatic strategies being developed are not only cutting-edge but also implemented ethically and sustainably [33]. This helix plays a pivotal role in nurturing a skilled workforce, driving research and development, and facilitating the dissemination of knowledge crucial for the successful adoption of advanced technologies [36].

2.3. Review of MCDM applications under unclear environment guidelines in the context of IoT and IIoT

The application of MCDM methods, particularly those incorporating various fuzzy environments, in the context IoT and IIoT, has garnered significant attention in recent years. MCDM methods offer a structured framework to evaluate and prioritize multiple conflicting criteria, which is crucial in these contexts where numerous factors must be balanced [37]. This systematic approach ensures that decision-makers can thoroughly assess various aspects of IoT and IIoT systems, leading to more informed and effective choices that enhance overall system performance and operational efficiency.

By incorporating MCDM methods under fuzzy environment approaches, known as FMCDM, scholars and practitioners can better manage the inherent complexity of IoT and IIoT deployments. These FMCDM methods effectively address challenges such as scalability, interoperability, and security by accommodating uncertainty and imprecision in the decision-making process [38]. This capability is particularly important in dynamic and complex IoT and IIoT environments, where precise data may not always be available, and decisions often must be made based on incomplete or ambiguous information [39].

Recently, various specific FMCDM methods have been implemented to address diverse challenges within IIoT systems. These include: selection of a smart and secure education school system under IoT [40], big data analytic to implement IIoT in sustainable manufacturing [41], barriers of digital twin and blockchain in IIoT [42], evaluating the risks of the IoT in renewable energy systems [43], portfolio selection of IoT application for sustainable urban transportation [44], analyzing drivers of IoT adoption in supply chain management [45], integrating blockchain with IoT for sustainable supply chains [46], evaluation the IoT based sustainable smart waste management system [47], analyzing the barriers of IoT in sustainable supply chain [48], analyzing effect of IoT on manufacturing performance [49], and exploring IoT adoption barriers for the circular economy [50]. The details of relevant studies are illustrated in Table 1.

2.4. Review the advantage of the proposed combination of MCDM methods

In this study, the integration of Delphi, SWARA, MEREC, and COBRA under Pythagorean fuzzy methods is employed to evaluate the readiness degree for IIoT adoption in manufacturing enterprises. Each of these proposed methods offers advantages when compared to various other MCDM methods for solving real-world problems. This comprehensive approach ensures a robust and multifaceted evaluation, addressing the complexities and uncertainties inherent in IIoT adoption. The distinct advantages of the proposed methods in this study are outlined as follows:

The Delphi method is a structured communication technique frequently used in MCDM to gather and refine expert opinions through iterative rounds of surveys [51]. The key advantages of using the Delphi method in MCDM include its ability to achieve consensus among experts by iteratively refining their opinions, leading to more accurate and reliable decision-making outcomes [52]. The method's flexibility allows it to be applied to a wide range of decision-making scenarios, accommodating diverse fields and complex problems [52]. By involving experts from various disciplines, the Delphi method ensures that multiple perspectives are considered, resulting in a more comprehensive evaluation of the decision criteria.

SWARA is utilized to analyze the subjective importance weights of criteria. It stands out due to several key advantages. Firstly, it is straightforward and easy to understand, making it accessible to decision-makers who may not have extensive experience with complex mathematical models [53]. Secondly, it effectively determines the relative importance of criteria by comparing them in pairs and adjusting weights based on their relative significance. This leads to more accurate and balanced weight assignments [54]. Additionally, SWARA allows for the incorporation of expert judgments and opinions, enabling a more comprehensive evaluation that reflects practical insights and experience. This combination of simplicity and the ability to integrate expert knowledge makes SWARA a valuable tool for effectively prioritizing criteria in diverse decision-making scenarios [54]. Unlike AHP and ANP, which require the creation and analysis of pairwise comparison matrices that can become large and complex, SWARA involves a more direct process for assessing the relative importance of criteria. This reduces computational complexity and makes the method more efficient [53].

MEREC is used to determine the objective importance weights of criteria, presenting a notable advantage over the commonly used entropy method [55]. A key strength of MEREC is its ability to account for the causal relationships between criteria. When a criterion with significant influence is removed, MEREC adjusts the weights to reflect its higher importance, thereby ensuring a more accurate prioritization [56]. The method's adaptability to changing conditions makes it especially valuable in dynamic and complex environments. By addressing the interdependencies among criteria, MEREC enhances the reliability of the evaluation process and facilitates more informed and effective decision-making [55].

COBRA is used to rank alternatives by employing a comprehensive distance measure derived from a combination of Euclidean and Taxicab distance metrics [57]. One of its key advantages is that it requires minimal input from decision-makers during the ranking process, which reduces the potential for bias and subjectivity, leading to more objective and reliable results [57]. The method is stable and user-friendly, making it accessible for practitioners without requiring extensive computational expertise [58]. Its straightforward implementation and interpretation enhance its practical applicability in real-world scenarios.

2.5. *Review of the application of Pythagorean fuzzy sets (PFSs)*

In this study, Pythagorean fuzzy sets (PFSs) are employed to address uncertainty in decision-making. The key advantage of PFSs is their flexibility: they permit the sum of a membership degree and a non-membership degree to exceed 1, provided that the sum of their squares does not exceed 1 [50]. This capability makes PFSs more versatile than Intuitionistic Fuzzy Sets (IFS). PFSs can tackle problems that IFSs cannot. For example, if a decision maker assigns a membership degree of 0.7 and a non-membership degree of 0.5, IFS cannot handle it (since $0.7 + 0.5 > 1$). However, PFSs can manage such cases because $(0.7)^2 + (0.5)^2 \leq 1$. Therefore, PFSs are viewed as superior to IFSs, as they can handle higher levels of uncertainty [50]. The literature extensively studies the application of PFSs in real-world problems, as illustrated in Table 2.

3. Research conceptual framework

In this study, the research conceptual framework is formulated and illustrated in Fig. 1. The barriers hindering the adoption of IIoT within manufacturing enterprises are grounded in the integration of the TOE model and HOT fit framework. Meanwhile, the strategies to surmount these barriers are structured within the context of the Triple Helix model (THM).

4. Methodology

4.1. *Preliminaries*

Definition 1. The mathematical foundation of an intuitionistic fuzzy set (IFS) denoted as M on a given set $\mathrm{U} = \{u_1, u_2, \ldots, u_n\}$ is precisely expressed in Eq. (1), as defined by Atanassov [71].

$$\mathrm{M} = \{\langle u_1, (u_M)(u_i), \upsilon_M(u_i)\rangle | u_i \in U\} \tag{1}$$

where $u_M : U \rightarrow [0, 1]$ denotes the membership grade, and $\upsilon_M : U \rightarrow [0, 1]$ represents the non-membership grade for an element $u_i \in U$ in M in the intuitionistic fuzzy set M. It is essential for the condition $0 \leq u_M(u_i) + \upsilon_M(u_i) < 1$ to be satisfied. The indeterminacy membership grade of $u_i \in U$ in M is determined by $\pi_M(u_i) = 1 - u_M(u_i) - \upsilon_M(u_i)$. For simplicity, the intuitionistic fuzzy number (IFN) is denoted by $\alpha = (\mu_\alpha, \nu_\alpha)$ satisfying $\mu_\alpha, \upsilon_\alpha \in [0, 1]$ and $0 \leq u_\alpha + \nu_\alpha \leq 1$. Thus, the intuitionistic fuzzy number (IFN) is represented by $\alpha = (\mu_\alpha, \nu_\alpha)$, subject to the constraints $\mu_\alpha, \upsilon_\alpha \in [0, 1]$ and $0 \leq u_\alpha + \nu_\alpha \leq 1$.

Table 2
The application of PFSs in real-world problems.

Author	Journal	Year	Research aim/objectives	MCDM methods
Yahya [59]	Advanced Engineering Informatics	2024	To optimize cloud resource utilization in the digital economy.	PF-SWARA
Kuma and Mahanta [60]	Applied Soft Computing	2024	To optimal selection of solar panel.	PF-MEREC-SWARA-VIKOR
Pandey and Khurana [61]	Expert Systems With Applications	2024	To prioritize solutions for mitigating risks associated with Industry 4.0.	PF-SWARA-COPRAS
Otay et al. [62]	Expert Systems With Applications	2024	To evaluate sustainable energy systems in smart cities.	PF-BWM -TOPSIS
Wang et al. [63]	Information Sciences	2024	To select sustainable food suppliers.	PF-CRITIC-MARCOS
Göçer and Büyüközkan [64]	Heliyon	2023	To develop decision support system for new product development.	PF-MULTIMOORA
Sarkar et al. [65]	Applied Soft Computing	2023	To select sustainable transport system.	PF-Entropy
Soltani et al. [66]	Journal of Cleaner Production	2023	To enhance the application process of the conventional lean manufacturing approach.	PF-DEMATEL-TOPSIS
Akram [67]	Engineering Applications of Artificial Intelligence	2023	To select optimal industrial waste management strategy.	PF-CRITIC-EDAS
Mao et al. [68]	Journal of Energy Storage	2023	To develop investment decision for offshore wind-solar-seawater	PF- -DEMATEL-PROMETHEE II
Saeidi et al. [69]	Journal of Cleaner Production	2022	To evaluate sustainable human resource management in the manufacturing companies.	PF-SWARA-TOPSIS
Ayyildiz [70]	Transportation Research Part D	2022	To select e-scooter charging station location.	PF-SWARA-CODAS

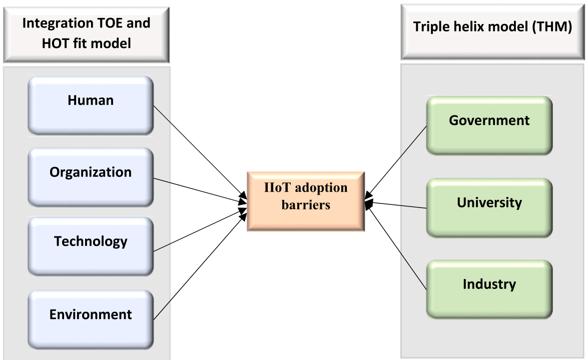

Fig. 1. Research conceptual framework.

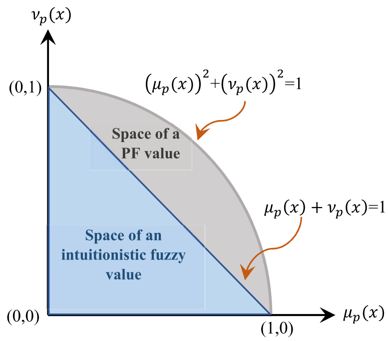

Fig. 2. Comparison between membership grade spaces in PFS and IFS.

Definition 2. A Pythagorean fuzzy set (PFS) X on a given set U is defined by Zhang and Xu [72] in Eq. (2) as follows.

$$X = \{\langle u_1, (u_X)(u_i), \upsilon_X(u_i)\rangle | u_i \in U\} \tag{2}$$

where $u_X : U \rightarrow [0,1]$ and $\upsilon_X : U \rightarrow [0,1]$ represent the membership grade and non-membership grade, $u_i \in U$ *to* X, respectively, of an element $u_i \in U$ in the Pythagorean fuzzy set X. The constraint that must be satisfied is $0 \leq (u_X(u_i))^2 + (\upsilon_X(u_i))^2 \leq 1$. The indeterminacy membership grade of $u_i \in U$ in M is determined by $\pi_M(u_i) = \sqrt{1 - \mu_X^2(u_i) - \upsilon_X^2(u_i)}$, each $u_i \in U$. The Pythagorean fuzzy number (PFN) is defined by $\eta = (\mu_\eta, \upsilon_\eta)$ which fulfills $\mu_\eta, \upsilon_\eta \in [0,1]$ *and* $0 \leq \mu_\eta^2 + \upsilon_\eta^2 \leq 1$ [72,73]. As illustrated in Fig. 2, the domain of IFS membership grades is a subset within the space of PFS membership grades. Thus, it can be asserted that PFS is more suitable than IFS for effectively addressing uncertainty in MCDM problems.

Definition 3. Let $\eta = (\mu_\eta, \upsilon_\eta)$ represents a PFN. The score function ($\mathbb{S}(\eta)$) and the corresponding normalized score function ($\mathbb{S}^*(\eta)$) for η can be calculated using Eq. (3) and Eq. (4), respectively, as defined by Peng and Tang [74].

$$\mathbb{S}(\eta) = (\mu_\eta)^2 - (\upsilon_\eta)^2 \tag{3}$$

$$\mathbb{S}^*(\eta) = \frac{1}{2}(\mathbb{S}(\eta) + 1) \tag{4}$$

where $\mathbb{S}(\eta) \in [-1,1]$ and $\mathbb{S}^*(\eta) \in [0,1]$.

Definition 4. Let $\eta = (\mu_\eta, \upsilon_\eta)$ represents a PFN. The accuracy function ($\hbar(\eta)$) and the corresponding normalized accuracy function ($\hbar^o(\eta)$) for η can be calculated using Eq. (5) and Eq. (6), respectively, as defined by Peng and Tang [74].

$$\hbar(\eta) = (\mu_\eta)^2 + (\upsilon_\eta)^2, \tag{5}$$

$$\hbar^o(\eta) = 1 - \hbar(\eta) \tag{6}$$

Table 3
Linguistic terms used in this study [70].

Pythagorean linguistic terms	Abbreviation	Pythagorean fuzzy numbers (PFNs)
Very very low	VVL	(0.200,0,950)
Very low	VL	(0.250, 0.850)
Low	L	(0.350, 0.750)
Medium low	ML	(0.400, 0.650)
Average	A	(0.500, 0.550)
Medium high	MH	(0.650, 0.450)
High	H	(0.700, 0.400)
Very high	VH	(0.850, 0.350)
Perfectly high	PH	(0.950, 0.200)

where $\hbar(\eta) \in [-1,1]$ *and* $\hbar^o(\eta) \in [0,1]$.

Definition 5. For any two PFNs $\eta_1 = (\mu_{\eta 1}, \upsilon_{\eta 1})$ *and* $\eta_2 = (\mu_{\eta 2}, \upsilon_{\eta 2})$, their comparison can be conducted using Eq. (7) through Eq. (10), as described by Saeidi et al. [75].

$$\text{If } \mathbb{S}^*(\eta_1) > \mathbb{S}^*(\eta_2), \textit{then } \eta_1 > \eta_2, \tag{7}$$

$$\text{If } \mathbb{S}^*(\eta_1) = \mathbb{S}^*(\eta_2), \textit{then } \eta_1 = \eta_2, \tag{8}$$

$$\text{If } \hbar^o(\eta_1) > \hbar^o(\eta_2), \textit{then } \eta_1 > \eta_2, \tag{9}$$

$$\text{If } \hbar^o(\eta_1) = \hbar^o(\eta_2), \textit{then } \eta_1 = \eta_2 \tag{10}$$

Definition 6. Let $\eta = (\mu_\eta, \upsilon_\eta), \eta_1 = (\mu_{\eta_1}, \upsilon_{\eta_1})$ *and* $\eta_2 = (\mu_{\eta_2}, \upsilon_{\eta_2})$ be PFNs. The operation involving two PFNs is defined as $\eta^c = (\upsilon_\eta, \mu_\eta)$, and is expressed through Eq. (11) to Eq. (14), as described by Ayyildiz [70].

$$\eta_1 \bigoplus \eta_2 = \left(\sqrt{\mu_{\eta_1}^2 + \mu_{\eta_2}^2 - \mu_{\eta_1}^2 \mu_{\eta_2}^2}, \upsilon_{\eta_1}, \upsilon_{\eta_2} \right) \tag{11}$$

$$\eta_1 \bigotimes \eta_2 = \left(\mu_{\eta_1}, \mu_{\eta_2} \sqrt{\upsilon_{\eta_1}^2 + \upsilon_{\eta_2}^2 - \upsilon_{\eta_1}^2 \upsilon_{\eta_2}^2} \right) \tag{12}$$

$$\lambda\eta = \left(\sqrt{1 - (1 - \mu_\eta^2)^\lambda}, (\upsilon_\eta)^\lambda \right), \lambda > 0 \tag{13}$$

$$\eta^\lambda = \left((\mu_\eta)^\lambda, \sqrt{1 - (1 - \upsilon_\eta^2)^\lambda} \right), \lambda > 0 \tag{14}$$

Definition 7. Let $\widetilde{G} = (g^{(k)}), (k = 1, 2, \ldots, l)$ is a collection of PFNs, by using Table 1, $g^{(k)} = (\mu_k, \upsilon_k)$. Then, the group aggregated values by the Pythagorean Fuzzy Weighted Average (PFWG) operator can be described as follows [70].

$$PFWA_\omega(g^{(1)}, g^{(2)}, \ldots, g^{(l)}) = \left(\sqrt{1 - \prod_{k=1}^{\ell} (1 - \mu_k^2)^{\lambda_k}}, \prod_{k=1}^{\ell} (\upsilon_k)^{\lambda_k} \right) \tag{15}$$

where λ_k can be calculated using Eq. (16)

$$\lambda_k = \frac{\left(\mu_k^2 + \pi_k^2 \times \left(\frac{\mu_k^2}{\mu_k^2 + \upsilon_k^2} \right) \right)}{\sum_{k=1}^{\ell} \left(\mu_k^2 + \pi_k^2 \times \left(\frac{\mu_k^2}{\mu_k^2 + \upsilon_k^2} \right) \right)}, k = 1, 2, \ldots \ell \tag{16}$$

where λ_k denoted as the importance weights assigned to k^{th}, $\lambda_k \in [0,1]$ and $\sum_{k=1}^{l} \lambda_k = 1$.

4.2. Pythagorean fuzzy linguistic terms and measuring scales

This study employs Pythagorean fuzzy linguistic terms and measuring scales, as depicted in Table 3.

4.3. Pythagorean fuzzy Delphi

The Fuzzy Delphi method optimizes the consensus-building process by reducing the number of iterations required to achieve consistency among experts' judgments, thereby minimizing the time and effort involved in administering and collecting questionnaires [76]. In contrast to the traditional Delphi, where panel members face potential exclusion if their opinions deviate from the group average, Fuzzy Delphi addresses this by assigning a membership function to each response, mitigating the risk of information loss. This method signifies a progression that incorporates fuzzy logic and expert consensus into the selection process, elevating the precision and relevance of identified critical factors in the given context [77]. The integration of fuzzy sets in the Delphi technique provides a more nuanced and adaptable approach to handling ambiguous data, aligning the selection process more closely with expert insights and the specific requirements of the problem at hand [78]. In this study, the Delphi method is coupled with Pythagorean fuzzy (PF-Delphi) to assess the significance of evaluation criteria. The procedural steps in the PF-Delphi method are outlined in Algorithm I (adapted from Sindhwani et al. [79]).

Algorithm 1. Pseudo representation of PF-Delphi

Algorithm 1: Pseudo representation of PF-Delphi

Input: (1) Index of criteria (j), number of criteria (n), C_j is criterion j^{th}, $j = 1,2,3,..,n$.
(2) Index of expert (k), number of decision-makers (l), $k = 1,2,3,..,l$.
(3) Threshold value (δ)

Output: The criterion (C_j) is accepted when the normalized score of C_j, denoted as $\mathbb{S}^*(C_j) \geq \delta$.

Begin

Step 1: The relevant criteria are identified based on literature review.

Step 2: The determination of importance weights for experts involves an evaluation of their distinct skills, qualifications, and experiences. This assessment is conducted using a Pythagorean fuzzy linguistic scale, as outlined in Table 1. Subsequent to this evaluation, the importance assigned to each expert (λ_k) can be calculated using Eq. (16).

Step 3: Experts articulate their viewpoints regarding the importance of criteria by employing the Pythagorean fuzzy linguistic scale outlined in Table 2. In this context, $I_{jk} = (\mu_{jk}, \nu_{jk})$ denotes the assessment of the significance of the j^{th} criterion by the expert k^{th}.

Step 4: The aggregation of criteria importance across all experts for the j^{th} criterion can be calculated using the Pythagorean Fuzzy Weighted Aggregation (PFWA) operation, as expressed in Eq. (15).

Step 5: The PFNs of the aggregated importance for each criterion obtained from all experts are converted into crisp score ($\mathbb{S}^*(C_j)$) using Eq. (3)-(4).

Step 6: The criterion (C_j) is accepted when the condition $\mathbb{S}^*(C_j) \geq \delta$ is satisfied, otherwise it is rejected.

End

4.4. Pythagorean fuzzy SWARA

SWARA, MCDM technique developed by Keršuliene et al. [80], offers distinct advantages when compared to other methods in the field. Its inherent simplicity enhances accessibility, making it easily understandable for a diverse range of decision-makers. Unlike more complex MCDM techniques that require advanced mathematical or computational proficiency, SWARA employs a step-wise assessment process that is intuitively comprehensible [81]. This straightforward approach increases its applicability in real-world decision-making problems. Moreover, SWARA exhibits robustness in handling qualitative and subjective data, proving effective in situations where obtaining precise quantitative data is challenging [82]. This adaptability makes SWARA versatile for various applications, particularly in cases where traditional quantitative MCDM methods face limitations due to data constraints or the need to integrate human expertise and preferences [83]. In this study, SWARA is integrated with PFS as outlined in Algorithm II (adapted from Cui et al. [50]).

Algorithm II. Pseudo representation of SWARA under PFS

Algorithm II: Pseudo representation of SWARA under PFS

Input: (1) Index of criteria (j), number of criteria (n), C_j is criterion j^{th}, $j = 1,2,3,..,n$.
(2) Index of decision-maker (k), number of decision-makers (l), $p = 1,2,3,..,l$.
(3) Outcome from PF-Delphi

Output: Subjective weights of criteria ω_j, $j = 1,2,3,..,n$

Begin

Step 1: Rank the criteria in descending order

The accepted criteria (C_j) obtained from PF-Delphi (Algorithm I) are arranged in descending order based on their crisp scores $(\mathbb{S}^*(C_j))$

Step 2: Determining the relative significance of the score value $(S^*(j))$

The relative significance of the score for each criterion $(S^*(j))$ is determined by calculating the difference between the crisp score of criteria j and criterion $j-1$, beginning with the second-preferred criteria. This computation provides insight into the degree to which criterion j is considered more important than criterion $j-1$, as expressed in Eq. (17) through Eq. (20), as defined by Saeidi et al. [75]

$$S^*(j) = \begin{cases} 0, & j = 1 \\ \mathbb{S}^*(C_j) - \mathbb{S}^*(C_{j-1}), & j = 2, \dots, n \end{cases} \tag{17}$$

Step 3: Computation the comparative coefficient $(\widetilde{k_j})$

for $j = 1{:}n$ do

$$\widetilde{k_j} = \begin{cases} 1, & j = 1 \\ S^*(j) + 1, & j = 2,3,\dots,n \end{cases} \tag{18}$$

end for

Step 4: Calculation the recalculated weight (q_j)

for $j = 1{:}n$ do

$$q_j = \begin{cases} 1, & j = 1 \\ \frac{q_{(j-1)}}{\widetilde{k_j}}, & j = 2,3,\dots,n \end{cases} \tag{19}$$

end for

Step 7: Obtaining the final criteria weights

for $j = 1{:}n$ do

$$\omega_j^s = \frac{q_j}{\sum_{j=1}^{n} q_j} \tag{20}$$

end for

End

4.5. Pythagorean fuzzy MEREC

The MEREC method, developed by Keshavarz-Ghorabaee et al. [84], represents a novel approach to evaluating the influence of each criterion on alternatives by systematically excluding them from the assessment process. This innovative technique assigns weights to each criterion based on their minimal impact on the alternatives, ensuring a comprehensive analysis of their significance [85]. Despite being a recent development, the MEREC method has rapidly gained significant attention and has been widely adopted for various multi-criteria selection problems within a short timeframe. Its effectiveness and versatility have made it a valuable tool in decision-making processes, contributing to its growing popularity and application across diverse fields [84]. As more researchers and practitioners recognize its potential, the MEREC method is expected to continue influencing multi-criteria decision-making methodologies. In this study, MEREC is integrated with PFS as outlined in Algorithm III (adapted from Kumar and Mahanta [60]).

Algorithm III. Pseudo Representation of MEREC under PFS

Algorithm III: Pseudo Representation of MEREC under PFS

Input: (1) index of alternative (i), number of alternatives (m), A_i is alternative i^{th}, $i = 1,2,3,..,m$.
(2) index of criteria (j), number of criteria (n), C_j is criterion j^{th}, $j = 1,2,3,..,n$.
(3) Index of decision-maker (k), number of decision-makers (l), $k = 1,2,3,..,l$.

Output: Ranking alternatives $(A_1, A_2, A_3, \dots, A_m)$

Begin

Step 1: Conduct the evaluations a_{ij} of alternative i $(i = 1,2,\dots,m)$, with respect to criteria j $(j = 1,2,\dots,n)$ for each expert. Subsequently, establish the decision matrix for each expert $Z^P = [z_{ij}^p]_{mxn}$, where $z_{ij}^p = (\mu_{jk}, \nu_{jk})$, using Eq. (21).

$$Z = \begin{array}{c c} & \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_m \end{array} & \begin{bmatrix} z_{11}^p & z_{12}^p & \cdots & z_{1n}^p \\ z_{21}^p & z_{22}^p & \cdots & z_{2n}^p \\ \vdots & \vdots & \ddots & \vdots \\ z_{m1}^p & z_{m2}^p & \cdots & z_{mn}^p \end{bmatrix} \end{array} \tag{21}$$

Step 2: Aggregation the evaluation data into a group decision-making, using Eq. (15)

Step 3: Converting PFNs in the aggregate group decision-making matrix to crisp scores, denoted as $S = [s_{ij}]_{mxn}$, using Eq. (3)-(4).

Step 4: In Step 3, each element within the score matrix (S) is normalized to a scale ranging from 0 to 1. This normalization process uses Eq. (22) for cost criteria ($j \in C$). and Eq. (23) for benefit criteria ($j \in B$).

$$n_{ij} = \frac{s_{ij}}{\max(s_{ij})}, j \in C \tag{22}$$

$$n_{ij} = \frac{\min(s_{ij})}{s_{ij}}, j \in B \tag{23}$$

Step 5: The overall performance for each alternative $(S_i)$is determined using a logarithmic term, as defined by Eq. (24).

$$S_i = \ln\left(1 + \left(\frac{1}{n}\sum_{j=1}^{n}\left|\ln(d_{ij}\right|\right)\right) \tag{24}$$

Step 6: The overall performance for each alternative, after removing each criterion $(\acute{S}_{ik})$, is calculated using Eq. (25).

$$\acute{S}_{ik} = \ln\left(1 + \left(\frac{1}{n}\sum_{k=1,k\neq j}^{n}\left|\ln(d_{ij}\right|\right)\right) \tag{25}$$

Step 7: The absolute deviation for each criterion (E_j) is computed through Eq. (26).

$$E_j = \sum_{i=1}^{m}\left|\acute{S}_i - S_i\right| \tag{26}$$

Step 8: The final objective weight for each criterion can be obtained through Eq. (27).

$$\omega_j^o = \frac{E_j}{\sum_{j=1}^{n} E_j} \tag{27}$$

End

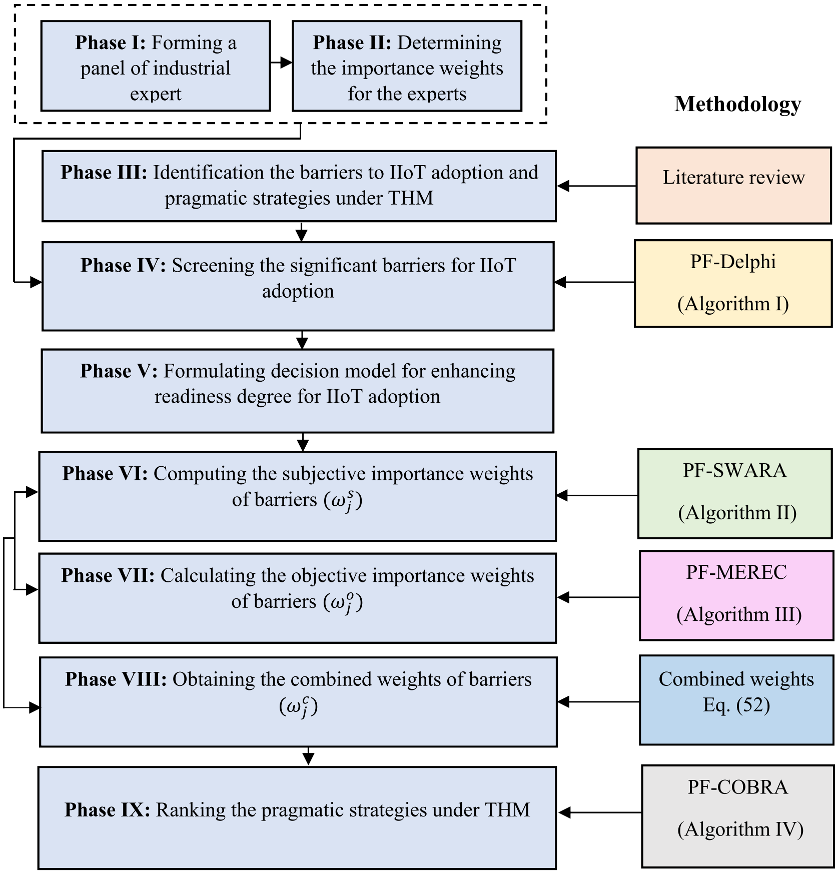

Fig. 3. The proposed framework in this study.

4.6. *Combined weights of criteria*

To incorporate both the subjective and objective weighting information provided by experts, the subjective weights $\left(\omega_j^s\right)$ and objective weights $\left(\omega_j^o\right)$ for each criterion are combined using the nonlinear weighting method proposed by Kumar and Mahanta [60]). as expressed in Eq. (28). The resulting combined weights for each criterion are denoted as ω_j^c.

$$\omega_j^c = \frac{\sqrt{\omega_j^s * \omega_j^o}}{\sum_{j=1}^{n} \sqrt{\omega_j^s * \omega_j^o}} \tag{28}$$

4.7. *Pythagorean fuzzy COBRA*

The COBRA method, pioneered by Krstic' et al. [57], adopts a unique approach to rank alternatives, employing a comprehensive distance measure derived from a combination of Euclidean and Taxicab distance metrics. This method assesses multiple solutions, including positive ideal, negative ideal, and average solution [58]. Its notable strengths, such as the ability to find compromise solutions, consider diverse criteria with distinct measures, necessitate minimal decision-maker intervention, and ensure stability and ease of use, played a crucial role in its selection for ranking alternatives in this study [57,58]. The COBRA method represents a recent and innovative addition to the field of MCDM methods. Its preference is underscored by the clear advantages it offers when compared to other distance-based methodologies. In this study, COBRA is integrated with PFS as outlined in Algorithm IV (adapted from Krstic' et al. [58]).

Algorithm IV. Pseudo Representation of COBRA under PFS

Input: (1) index of alternative (i), number of alternatives (m), A_i is alternative i^{th}, $i = 1,2,3,..,m$.
(2) index of criteria (j), number of criteria (n), C_j is criterion j^{th}, $j = 1,2,3,..,n$.
(3) Index of decision-maker (k), number of decision-makers (l), $k = 1,2,3,..,l$.

Output: Ranking alternatives $(A_1, A_2, A_3, \ldots, A_m)$

Begin

Step 1: Conduct the evaluations a_{ij} of alternative i $(i = 1,2,\ldots,m)$, with respect to criteria j $(j = 1,2,\ldots,n)$ for each expert. Subsequently, establish the decision matrix for each expert $Z^P = [z_{ij}^p]_{mxn}$, where $z_{ij}^p = (\mu_{jk}, \nu_{jk})$, using Eq. (21).

Step 2: Aggregation the evaluation data into a group decision-making, using Eq. (15)

Step 3: Converting PFNs in the aggregate group decision-making matrix to crisp scores, using Eq. (3)-(4).

Step 4: Normalize all elements within a group decision-making matrix $(\tilde{Z})$, thus normalized matrix $D = [d_{ij}]_{mxn}$, is constructed, using Eq. (29).

$$d_{ij} = \frac{\tilde{z}_{ij}}{\max_{j} \tilde{z}_{ij}} \tag{29}$$

Step 5: Calculate the weighted normalized decision matrix (Δ_ω), using Eq. (30).

$$\Delta_\omega = [\omega_j \times d_{ij}]_{mxn} \tag{30}$$

where ω_j is the relative importance weight of criterion j

Step 6: Compute the positive ideal (PIS_j), negative ideal (NIS_i) and average solution (AS_i), using Eq. (31)-(33).

$$PIS_j = \max_i(\omega_j \times d_{ij}), \forall j = 1,2,3,\ldots,n, j\epsilon B / \, PIS_j = \min_i(\omega_j \times d_{ij}), \forall j = 1,2,3,\ldots,n, j\epsilon C \tag{31}$$

$$NIS_j = \min_i(\omega_j \times d_{ij}), \forall j = 1,2,3,\ldots,n, j\epsilon B / NIS_j = \max_i(\omega_j \times d_{ij}), \forall j = 1,2,3,\ldots,n, j\epsilon C \tag{32}$$

$$AS_j = \sum_i^m \frac{(\omega_j \times d_{ij})}{m}, \forall j = 1,2,3,\ldots,m, j\epsilon B, j\epsilon C \tag{33}$$

where B represents benefit criteria (greater is better), and C represents cost criteria (smaller is better).

Step 7: Calculate Euclidian and Taxicab distances, using Eq. (34)-(43).

$$dE(PIS_j)_i = \sqrt{\sum_{j=1}^n (PIS_j - \omega_j \times d_{ij})^2}, \forall i = 1,2,3,\ldots,m, \forall j = 1,2,3,\ldots,n \tag{34}$$

$$dE(NIS_j)_i = \sqrt{\sum_{j=1}^{n}(NIS_j - \omega_j \times d_{ij})^2}\ , \forall i = 1,2,3,\dots,m, \forall j = 1,2,3,\dots,n \quad (35)$$

$$dE(AS_j)_i^+ = \sqrt{\sum_{j=1}^{n}\tau^+(AS_j - \omega_j \times d_{ij})^2}\ , \forall i = 1,2,3,\dots,m, \forall j = 1,2,3,\dots,n \quad (36)$$

$$dE(AS_j)_i^- = \sqrt{\sum_{j=1}^{n}\tau^-(AS_j - \omega_j \times d_{ij})^2}\ , \forall i = 1,2,3,\dots,m, \forall j = 1,2,3,\dots,n \quad (37)$$

$$dT(PIS_j)_i = \sum_{j=1}^{n}\left|PIS_j - \omega_j \times d_{ij}\right|, \forall i = 1,2,3,\dots,m, \forall j = 1,2,3,\dots,n \quad (38)$$

$$dT(NIS_j)_i = \sum_{j=1}^{n}\left|NIS_j - \omega_j \times d_{ij}\right|, \forall i = 1,2,3,\dots,m, \forall j = 1,2,3,\dots,n \quad (39)$$

$$dT(AS_j)_i^+ = \sum_{j=1}^{n}\tau^+\left|AS_j - \omega_j \times d_{ij}\right|\ , \forall i = 1,2,3,\dots,m, \forall j = 1,2,3,\dots,n \quad (40)$$

$$dT(AS_j)_i^- == \sum_{j=1}^{n}\tau^-\left|AS_j - \omega_j \times d_{ij}\right|, \forall i = 1,2,3,\dots,m, \forall j = 1,2,3,\dots,n \quad (41)$$

$$\tau^+ = \begin{cases}1 & if\ AS_j < \omega_j \times d_{ij}\\ 0 & if\ AS_j > \omega_j \times d_{ij}\end{cases} \quad (42)$$

$$\tau^- = \begin{cases}1 & if\ AS_j > \omega_j \times d_{ij}\\ 0 & if\ AS_j < \omega_j \times d_{ij}\end{cases} \quad (43)$$

where $dE(PIS_j)_i, dE(NIS_j)_i, dE(AS_j)_i^+$, $dE(AS_j)_i^-$ are Euclidian distances, while $dT(PIS_j)_i, dT(NIS_j)_i, dT(AS_j)_i^+$, $dT(AS_j)_i^-$ are Taxicab distance, and τ^+ and τ^- stands for the threshold function.

Step 8: Calculate the distance from both the positive ideal solution ($d(PIS_j)_i$) and negative ideal solution ($dE(NIS_j)_i$) solutions, along with the positive ($d(AS_j)_i^+$) and negative ($d(AS_j)_i^-$) distances from the average solutions, using Eq (44)-(51).

$$d(PIS_j)_i = dE(PIS_j)_i + \sigma(PIS_j)_i \times dE(PIS_j)_i \times dT(PIS_j)_i, \forall i = 1,2,3,\dots,m \quad (44)$$

$$d(NIS_j)_i = dE(NIS_j)_i + \sigma(NIS_j)_i \times dE(NIS_j)_i \times dT(NIS_j)_i, \forall i = 1,2,3,\dots,m \quad (45)$$

$$d(AS_j)_i^+ = dE(AS_j)_i^+ + \sigma(AS_j)_i^+, \times dE(AS_j)_i^+ \times dT(AS_j)_i^+, \forall i = 1,2,3,\dots,m \quad (46)$$

$$d(AS_j)_i^- = dE(AS_j)_i^- + \sigma(AS_j)_i^- \times dE(AS_j)_i^- \times dT(AS_j)_i^-, \forall i = 1,2,3,\dots,m \quad (47)$$

where $dE(PIS_j)_i, dE(NIS_j)_i, dE(AS_j)_i^+, dE(AS_j)_i^-$ are Euclidian distances, while $dT(PIS_j)_i, dT(NIS_j)_i, dT(AS_j)_i^+), dT(AS_j)_i^-$, are Taxicab distance.

$$\sigma(PIS_j)_i = \max(dE(PIS_j)_i) - \min(dE(PIS_j)_i) \quad (48)$$

$$\sigma(NIS_j)_i = \max(dE(NIS_j)_i) - \min(dE(NIS_j)_i) \quad (49)$$

$$\sigma(AS_j)_i^+ = \max(dE(AS_j)_i^+) - \min(dE(AS_j)_i^+) \quad (50)$$

$$\sigma(AS_j)_i^- = \max(dE(AS_j)_i^-) - \min(dE(AS_j)_i^-) \quad (51)$$

where $\sigma(PIS_j)_i, \sigma(NIS_j)_i, \sigma(AS_j)_i^+$, and $\sigma(AS_j)_i^-$ are correlation coefficient of $(PIS_j)_i$, $(NIS_j)_i$, $(AS_j)_i^+$, and $(AS_j)_i^-$ respectively.

Step 9: Rank the considered alternatives in ascending order based on the comprehensive distances which is defined by using Eq. (52).

$$dC_i = \frac{d(PIS_j)_i - d(NIS_j)_i - d(AS_j)_i^+ + d(AS_j)_i^-}{4}, \forall i = 1,2,3,\dots,m \quad (52)$$

End

. (*continued*).

5. Application of the proposed framework

5.1. Proposed framework

The proposed framework in this study is divided into seven phases as illustrated in Fig. 3.

5.2. In-depth case study analysis

5.2.1. Challenges, successes, and lessons learned from implementing IIoT technologies in this Thai agro-food processing sector

The Thai agro-food processing industry stands at a pivotal moment with the integration of IIoT technologies. A detailed analysis of the specific challenges faced by this sector can provide valuable insights. Key challenges include the high initial cost of IIoT implementation, the necessity for skilled labor to manage and maintain these technologies, and the integration of new systems with existing, often outdated, infrastructure [86]. Additionally, concerns around data security and privacy, especially given the sensitive nature of agricultural data, pose significant hurdles [87,88]. Understanding these challenges is crucial for devising effective mitigation strategies.

Successes in the Thai agro-food processing industry through IIoT adoption highlight the transformative potential of these technologies. Implementing precision farming techniques has led to increased crop yields and more efficient resource usage [86]. Real-time monitoring and data analytics have enabled better decision-making, reducing waste and improving product quality [88]. Case studies of successful IIoT implementations can serve as benchmarks, showcasing the tangible benefits and encouraging broader adoption within the industry. These successes underscore the value of IIoT in enhancing competitiveness and sustainability in the agro-food sector.

Lessons learned from implementing IIoT technologies in the Thai agro-food processing industry can guide future endeavors. A phased strategy for IIoT adoption, allowing for gradual integration and minimizing disruption, is crucial. Training and development programs for workers are essential to build the necessary skills for managing advanced technologies [89]. Collaboration between stakeholders, including government bodies, private enterprises, and educational institutions, can facilitate knowledge sharing and drive innovation. By analyzing these experiences, other regions and sectors can adopt best practices, ensuring more successful and sustainable IIoT implementations.

5.2.2. Comparative analysis between the agro-food processing industry in Thailand and similar industries

A comparative analysis between the agro-food processing industry in Thailand and similar industries in other countries can provide a broader perspective on IIoT adoption challenges and strategies. This analysis involves examining how different countries implement IIoT technologies, the obstacles they face, and the strategies they use to overcome these challenges. By contrasting the experiences of various regions, researchers can identify patterns and best practices effective across different contexts. For example, while Thailand might struggle with high initial costs and limited technical training, another country might have developed innovative financing models or robust educational programs to address these issues. Understanding these different approaches can help Thai enterprises and policymakers adapt and implement strategies that have been successful elsewhere.

Moreover, this comparative analysis can highlight unique challenges specific to certain regions, leading to more tailored solutions. For instance, data security concerns might be more pronounced in one country due to stricter regulations, whereas another country might face greater issues with infrastructure compatibility [89,90]. By examining these regional nuances, stakeholders can develop more comprehensive strategies that address both common and unique challenges associated with IIoT adoption.

Cross-country knowledge exchange facilitated by such comparative studies can foster collaboration and innovation. Sharing insights and solutions from different regions can inspire new ideas and approaches, accelerating the adoption and optimization of IIoT technologies [91]. For example, a country with advanced IIoT integration in its agro-food processing industry might share its experiences through workshops, publications, or joint projects, benefiting other countries looking to enhance their own IIoT implementations. This collaborative approach not only enhances the global understanding of IIoT adoption but also builds a network of support and expertise that can drive the industry forward on an international scale.

5.2.3. Problem description

An empirical case study was conducted on a prominent Thai agro-food processing industry to illustrate the application of the proposed framework. In this sector, IIoT enhances connectivity and automation, improving production quality, safety, and cost efficiency through smart sensors, devices, and predictive maintenance. Despite its benefits, IIoT adoption faces challenges due to human resources, organizational dynamics, technological innovation, and institutional constraints. Addressing these challenges requires a collaborative effort from the public and private sectors to invest in research, infrastructure, and skill development. The Triple Helix Model (THM), involving academia, industry, and government, is proposed to overcome these barriers and foster innovation, ensuring the industry's global competitiveness. This study presents a decision framework to assist stakeholders in prioritizing strategies under THM to facilitate IIoT adoption.

6. Results

Phase I. Forming a panel of industrial experts

In this phase, a panel of experts is assembled, including three managerial professionals experienced in IIoT implementation in Thai agro-food processing, one academician, and one government industrial expert. All panel members have extensive IIoT knowledge and experience in advanced manufacturing technology projects, and have participated in collaborative government, academia, and industry initiatives. Their task is to validate and confirm the barriers and strategies under the Triple Helix Model (THM) for IIoT adoption. Specific qualifications of the experts are detailed in Table 4.

Phase II. Determining the importance weights for the experts

The substantial weight assigned to each expert is determined through a comprehensive evaluation of their (i) relevant experience in advanced manufacturing technology implementation, (ii) technical proficiency in IIoT, and (iii) their organizational role. This evaluation leverages the linguistic terms presented in Table 1 to measure the significance of each expert, which is subsequently translated into corresponding PFNs. The significant weight of each expert is then calculated using Eq. (16), and the outcomes are detailed in Table 5. To illustrate this process, this study provides a sample computation for the most important expert (*E3*), with the importance weight denoted as λ_3, as follows:

$$\lambda_3 = \frac{(0.750)^2 + \left((0.537)^2 \times \left[\frac{(0.750)^2}{(0.750)^2+(0.400)^2}\right]\right)}{\left[(0.700)^2 + \left((0.456)^2 \times \left[\frac{(0.700)^2}{(0.700)^2+(0.550)^2}\right]\right)\right] + \ldots + \left[(0.700)^2 + \left((0.456)^2 \times \left[\frac{(0.700)^2}{(0.700)^2+(0.550)^2}\right]\right)\right]}$$

$$= 0.257$$

Phase III. Identification the barriers to IIoT adoption and pragmatic strategies under THM

This study draws upon a rigorous literature review firmly grounded in the integration framework of TOE and the Hot Fit model to discern barriers to IIoT adoption. The research involved exhaustive searches spanning from 2018 to 2023 in two reputable digital academic databases, ScienceDirect and Web of Science. These databases are chosen for their extensive coverage of emerging technologies, with a specific emphasis on the IIoT domain, thus forming a strong foundation for this research. Relevant keywords, such as "IIoT barriers to adoption," "organizational barrier to IIoT adoption," and "emerging technologies barriers to adoption," etc. are used to refine the criteria for identifying these barriers. This study successfully identifies fifteen barriers for IIoT adoption, categorized within the dimensions of human, organizational, technological, and institutional environments, as presented in Table 6. Simultaneously, twelve practical solutions, centered around the pragmatic strategies under THM involving university, industry, and government dimensions are depicted in Table 7.

Phase IV. Screening the significant barriers for IIoT adoption

Five experts assess barriers to IIoT adoption using linguistic terms from Table 3. The outcomes are detailed in Table 8. The PF-Delphi algorithm (Algorithm I in Section 4.3) screens significant barriers. First, linguistic terms are converted to PFNs and aggregated using PFWA operation (Eq. (15) and (16)). Then, PFNs are converted to crisp numbers via score functions and normalized scores (Eqs. (3) and (4)). A threshold value (δ) of 0.6 identifies significant barriers, rejecting those below this threshold. Table 9 shows that barriers like aversion to training, lack of organizational tech policies, implementation complexity, and rapid technological advancements are rejected. Eleven significant barriers are coded for further study.

Phase V. Formulating decision model for enhancing readiness degree for IIoT adoption

The decision model is formulated based on the conceptual model depicted in Fig. 1 and the results of validated barriers obtained in Phase IV. This decision model is visually presented in Fig. 4.

Phase VI. Computing the subjective importance weights of barriers $\left(\omega_j^s\right)$

The computation of subjective importance weights of barriers is performed utilizing PF-SWARA algorithm described in Algorithm II (Section 4.4). This algorithm is applied to derive a consolidated assessment of the barriers' importance. The final result is the assignment of relative importance weights to each barrier, providing a clear and quantifiable measure of their impact within the context under consideration. The procedural steps for this computation are demonstrated below.

Step 1. Rank barriers in descending order

Table 4
The specific qualifications regarding the panel of industrial experts.

Expert (E)	Experience (years)	Position	Organization	Area of expertise
E1	18	Factory manager	Argo-food processing manufactures	Production management
E2	11	Production engineering director	Argo-food processing manufactures	Advance manufacturing technology
E3	9	Chief technology officer	Argo-food processing manufactures	Technology management
E4	12	Academician	Engineering department of a research university	Additive manufacturing
E5	21	Director	Industrial promotion department of a government agency	Industrial innovation development

Table 5
The importance weights of each experts.

Expert	Importance rating in linguistic terms	μ_{jk}	ν_{jk}	π_{jk}	λ_p
E1	VI	0.700	0.550	0.456	0.202
E2	VI	0.700	0.550	0.456	0.202
E3	VVI	0.750	0.400	0.537	0.257
E4	I	0.600	0.700	0.387	0.138
E5	VI	0.700	0.550	0.456	0.202

Table 6
The identification of the barriers to IIoT adoption.

Dimensions	Barriers	Brief description	References
Human (H)	Job displacement concerns	Employees may perceive the introduction of advanced technologies such as IIoT as a potential threat to their job security. They may be apprehensive that the adoption of automation and data-driven systems could render their positions obsolete. These concerns often lead to resistance among workers	[2,92,93]
	Aversion to training	Introducing cutting-edge technologies like IIoT frequently requires training and upskilling employees. However, certain workers may resist this extra training, finding it burdensome or fearing challenges in adapting to the new technologies.	[2,14,92–97]
	Loss of autonomy	Traditional processes often empower workers with a sense of control. The advent of technologies like IIoT, with its automation and data-driven decision-making, might cause employees to perceive a diminishing sense of control over their work, which can subsequently fuel resistance.	[92,98–100]
Organiza-tion (O)	Substantial upfront investment cost	One of the key obstacles is the substantial upfront investment required for the acquisition and deployment of emerging technology infrastructure such as IIoT, encompassing the costs of sensors, network upgrades, and data analytics tools.	[14,92,101], [102],
	Lack of top management commitment	Top management is responsible for allocating resources and making strategic decisions. Without their commitment, it can be challenging to secure the necessary budget and resources for emerging technology infrastructure such as IIoT project.	[14, 102–104],
	Absence of organizational technology policies	Technology policies play a crucial role in providing a framework for the evaluation, adoption, and responsible use of new technologies. Without such policies in place, organizations can slow down the adoption process and result in inefficient or misaligned technology implementations.	[104–106]
	Lack of digital culture	A digital culture refers to the collective mindset, values, and behaviors within a company that prioritize and embrace digital technology as an integral part of its operations. Without a digital culture, organizations can struggle to effectively integrate and leverage new technologies like IIoT.	[105–107]
	Complexity of Implementation	Implementing IIoT technology is often a complex endeavor. It requires expertise in areas such as sensor deployment, data analytics, network management, and more. Companies may face uncertainty regarding their ability to successfully implement and manage these technologies. This complexity can lead to concerns about cost overruns, time delays, and disruptions to existing operations.	[92,93, 108–111]
	Lack of knowledge and expertise	The adoption emerging technology as IIoT involves complex systems and interconnected devices. Without a knowledgeable workforce, organizations may struggle to understand, implement, and maximize the benefits of this transformative technology.	[2,92, 106–108]
Technology (T)	Interoper-ability issue	IIoT involves a multitude of devices and systems that must work seamlessly together. Compatibility and communication challenges between different devices, protocols, and standards can hinder integration.	[66,69,80, 81]
	Security concerns	The increased connectivity in IIoT creates vulnerabilities to cyberattacks and data breaches. Ensuring the security of devices, networks, and data is a critical challenge.	[14,57,60,66, 80]
	Scalability issue	The concept of scalability refers to the ability of a technology solution to grow and adapt to changing demands and requirements. Scalability challenges can emerge if the initial IIoT infrastructure is not designed to accommodate this growth, potentially leading to bottlenecks, reduced performance, or costly system overhauls.	[2,14,80,96, 97]
	Rapid technological advancements	IIoT is characterized by rapid technological advancements, including sensors, communication protocols, edge computing, and cloud platforms. Keeping up with these innovations can be daunting, and. companies may hesitate to adopt a specific technology if they fear it will quickly become obsolete. As a result, organizations may delay adoption or invest in technology that does not fully align with their long-term goals	[92,93,108, 110],
Institutional (I)	Absence of universal IIoT standards	The absence of universal IIoT standards creates significant challenges for industrial organizations, leading to a fragmented landscape of proprietary solutions. This results in difficulties in selecting suitable technologies, potential vendor lock-in, increased long-term costs, and hindered interoperability among different IIoT systems.	[112–115]
	Liability allocation in complex ecosystems	IIoT ecosystems involve multiple parties, including equipment manufacturers, software developers, service providers, and end-users. When issues arise, pinpointing the source can be difficult, leading to disputes and legal battles, which delay problem resolution and increase liability costs.	[2,99]

In this phase, the eleven significant barriers are ranked in descending order based on their crisp scores ($\mathbb{S}^*(C_j)$), as shown in Table 10.

Step 2. Determine the relative significance of the score value ($S^*(j)$)

The relative significance of the score for each barrier ($S^*(j)$) is determined using Eq. (17), and the results are presented in Table 11.

Step 3. Compute the comparative coefficient $\widetilde{(k_j)}$

The comparative coefficient $\widetilde{(k_j)}$ for each barrier is computed using Eq. (18), and the result is displayed in Table 11.

Step 4. Calculate recalculated weight $\left(q_j\right)$ of each barrier

The recalculated weight $\left(q_j\right)$ for each barrier is calculated using Eq. (19). Table 11 provides the significant weight $\left(q_j\right)$ assigned to each barrier.

Step 5. *Obtaining the final weight* $\left(\omega_j^s\right)$ *of each barrier*

The final weight for each barrier $\left(\omega_j^s\right)$ is obtained using Eq. (20). Table 11 provides the final weight assigned to each barrier. As illustrated in Table 9, the values of ω_j^s are as follows:

B1 ($\omega_1^s = 0.265$) $>$ *B2* ($\omega_2^s = 0.190$) $>$ *B3* ($\omega_3^s = 0.158$) $>$ *B4* ($\omega_4^s = 0.109$) $>$ *B5* ($\omega_5^s = 0.077$) $>$ *B6* ($\omega_6^s = 0.064$) $>$ *B7* ($\omega_7^s = 0.045$) $>$ *B8* ($\omega_8^s = 0.033$) $>$ *B9* ($\omega_9^s = 0.027$) $>$ *B10* ($\omega_{10}^s = 0.019$) $>$ *B11* ($\omega_{11}^s = 0.014$).

Phase VII. Calculating the objective importance weights of barriers $\left(\omega_j^o\right)$

In this stage, the MEREC approach, detailed in Section 4.3, is used to calculate the objective weights of the barrier criteria $\left(\omega_j^o\right)$. The computation steps are outlined below.

Step 1. Conduct the evaluations of THM pragmatic strategies to overcome barriers

Table 7
The identification of the pragmatic strategies under THM.

Dimension	Code	Barriers	Description	Reference
Government (G)	*G1*	Funding research and development	Government support for IIoT R&D includes grants, subsidies, and collaborations with academia and industry partners.	[116–118]
	G2	Investment incentives	Governments boost IIoT adoption by providing financial support and favorable regulations to encourage integration of IIoT technologies by businesses and industries.	[97,99,112]
	G3	Promoting awareness campaigns and programs	Government awareness initiatives offer workshops, seminars, and training to provide practical insights into IIoT integration, helping businesses and professionals make informed adoption decisions.	Experts' opinion
	G4	Enabling national ICT infrastructures	Governments invest in high-speed communication networks like broadband and 5G to ensure uninterrupted connectivity for IIoT devices, which is essential for real-time data transmission and successful IIoT deployment.	[119,120]
	G5	Developing national cybersecurity framework	Developing a national cybersecurity framework involves creating standards and protocols for securing IIoT systems. Governments collaborate with experts, industry stakeholders, and regulators to ensure data confidentiality, integrity, and availability.	[89,93,94]
University (U)	*U1*	Research and Development	Universities act as innovation hubs where researchers develop new IIoT technologies and theoretical frameworks. These efforts lead to inventive solutions and protocols that streamline industrial processes, enhance efficiency, and address challenges in integrating IIoT technologies.	[100,119, 121,122]
	U2	Testbeds and Laboratories	University testbeds support IIoT standardization and interoperability by providing controlled testing environments. Researchers develop best practices and protocols, ensuring seamless integration of IIoT devices and advancing adoption across industries.	Experts' opinion
	U3	Incubators and Accelerators	University incubators provide workspaces, mentorship, funding, and access to industry experts and investors. They are crucial for transforming academic research into tangible products and services in the IIoT sector.	Experts' opinion
Dimension	*U4*	Enhancing capabilities of human capita/Curriculum Development	Universities enhance human capital in IIoT by developing specialized courses and programs, equipping students with the skills needed to handle IIoT technologies.	[96], [97,98], [99,100]
Industry	*I1*	Establishment of standards and reference architectures	Creating IIoT standards and reference architectures relies on substantial input from industry stakeholders, ensuring interoperability, security, and consistency in technology deployment.	[2,90,97,98]
	I2	Cultivating the collaboration and best practice sharing	Industries foster collaboration and best practice exchange in IIoT by sharing lessons, case studies, and practical insights from real-world deployments. This knowledge-sharing enhances understanding and implementation of IIoT technologies.	Experts' opinion

Table 8
The results of assessing fifteen barriers using linguistic terms by five industrial experts.

Dimension	Barriers	*E1*	*E2*	*E3*	*E4*	*E5*
Human (H)	Job displacement concerns	VH	PH	H	VH	H
	Aversion to training	ML	L	VL	ML	L
	Loss of Autonomy	H	H	MH	H	MH
Organization (O)	Substantial upfront investment cost	VH	PH	H	H	H
	Lack of top management commitment	H	VH	VH	H	H
	Absence of organizational technology policies	ML	L	ML	L	VL
	Lack of digital culture	VH	H	VH	PH	PH
	Complexity of implementation	L	VL	L	VL	ML
	Lack of knowledge and expertise	H	VH	PH	H	VH
Technology (T)	Interoperability issue	H	H	MH	MH	H
	Security Concerns	H	VH	H	H	H
	Scalability issue	H	MH	MH	H	MH
	Rapid technological advancements	L	VL	L	ML	L
Institutional environment	Absence of universal IIoT standards	H	H	H	MH	MH
	Liability allocation in complex ecosystems	H	MH	MH	H	MH

Five industry experts are assigned the responsibility of assessing the prioritization of implementing eleven pragmatic strategies under THM to overcome each barrier in IIoT adoption. They employ the linguistic terms provided in Table 3 for their evaluation, with the results presented in Table 12. Subsequently, all linguistic terms are converted into their corresponding PFNs. Due to space limitations, sample data from Expert 1 (*E1*) is provided in Table 13.

Step 2. Aggregation the evaluation data into a group decision-making

The evaluation data in the form of PFNs provided by the five experts is subsequently aggregated to create a group decision-making PFN through the application of the PFWA operation, defined in Eqs. (15) and (16). As a result, the decision-making matrix is constructed, and presented in Table 14.

Step 3. Converting the PFNs in the aggregate group decision-making matrix to crisp scores

All PFN elements within the aggregate group decision-making matrix are converted into crisp scores using Eqs. (3) and (4), respectively. These crisp scores for the aggregate group decision-making matrix as expressed in Eq. (21), and displayed in Table 15.

Step 4. Normalizing the aggregate group decision-making matrix

Using the outcomes from Step 3, Eq. (22) is employed to normalize all crisp values within the aggregate group decision-making matrix, as all barriers are cost criteria. This process results in the normalized decision-making matrix presented in Table 16.

Step 5. Determination the overall performance for each THM pragmatic strategies

Using the normalized decision matrix, the overall performance for each THM pragmatic strategy, denoted as S_i, is determined through the application of Eq. (24). The overall performance results for all THM pragmatic strategies are presented in Table 17. Below is an illustrative numerical example demonstrating the overall performance for the THM strategy "funding research and development" (S_1) .

$$S_1 = \ln\left(1 + \left(\frac{|\ln(0.308)| + |\ln(0.831)| + \ldots + |\ln(1.000)|}{11}\right)\right) = 0.360$$

Step 6. Calculation the overall performance for each THM pragmatic strategy after removing effect of each barrier

To assess the effect of removing individual criteria on the performance of the i^{th} alternative, the overall performance for each alternative, denoted as $\acute{S}_i$ using Eq. (25). The results are then presented in Table 18. Below, an illustrative numerical example of the overall performance for the THM pragmatic strategy "funding research and development" (S_1), when remove the effect of *C1* $(\acute{S}_{11,k\neq 1})$.

$$\acute{S}_{11,k\neq 1} = \ln\left(1 + \left(\frac{|\ln(0.017)| + \ldots + |\ln(0.028)|}{11}\right)\right) = 0.078$$

Step 7. *Computation absolute deviations for each criterion* (E_j)

Base on S_i and $\acute{S}_i$ in Step 4 and Step 5, the absolute deviations for each barrier (E_j) is computed deployed Eq. (26), and the results are presented in Table 19. An illustrative numerical example of absolute deviations for the barrier "job displacement concerns" (E_1) is provided below.

$$E_1 = |0.467 - 0.360| + |0.162 - 0.372| + \ldots + |0.233 - 0.329| + |0.091 - 0.097| = 0.470$$

Step 8. Obtaining the final objective weight for each criterion $\left(\omega_j^o\right)$

Table 9
The outcomes of the barrier screening process.

Dimension	Barriers	E1	E2	E3	E4	E5	Aggre-gation	Normalize score	Accepted/ Rejected
Human (H)	Job displacement concerns	(0.850,0.350)	(0.950,0.200)	(0.700,0.400)	(0.850,0.350)	(0.700, 0.400)	(0.839,0.325)	0.798	Accepted
	Aversion to training	(0.400, 0.650)	(0.350, 0.750)	(0.250, 0.850)	(0.400, 0.650)	(0.350, 0.750)	(0.347,0.737)	0.288*	Rejected
	Loss of Autonomy	(0.700, 0.400)	(0.700, 0.400)	(0.650, 0.450)	(0.700, 0.400)	(0.650, 0.450)	(0.679,0.421)	0.641	Accepted
Organiza- tion (O)	Substantial upfront investment cost	(0.850, 0.350)	(0.950, 0.200)	(0.700, 0.400)	(0.700, 0.400)	(0.700, 0.400)	(0.823,0.338)	0.781	Accepted
	Lack of top management commitment	(0.700, 0.400)	(0.850, 0.350)	(0.850, 0.350)	(0.700, 0.400)	(0.700, 0.400)	(0.784,0.376)	0.737	Accepted
	Absence of organizational technology policies	(0.400, 0.650)	(0.350, 0.750)	(0.400, 0.650)	(0.350, 0.750)	(0.250, 0.850)	(0.358,0.720)	0.305*	Rejected
	Lack of digital culture	(0.850, 0.350)	(0.700, 0.400)	(0.850, 0.350)	(0.950, 0.200)	(0.950, 0.200)	(0.883,0.297)	0.846	Accepted
	Complexity of implementation	(0.350, 0.750)	(0.250, 0.850)	(0.350, 0.750)	(0.250, 0.850)	(0.400, 0.650)	(0.332,0.760)	0.266*	Rejected
	Lack of knowledge and expertise	(0.700, 0.400)	(0.850, 0.350)	(0.950, 0.200)	(0.700, 0.400)	(0.850, 0.350)	(0.860,0.317)	0.820	Accepted
Technology (T)	Interoperability issue	(0.700, 0.400)	(0.700, 0.400)	(0.650, 0.450)	(0.650, 0.450)	(0.700, 0.400)	(0.682,0.419)	0.645	Accepted
	Security Concerns	(0.700, 0.400)	(0.850, 0.350)	(0.700, 0.400)	(0.700, 0.400)	(0.700, 0.400)	(0.741,0.418)	0.687	Accepted
	Scalability issue	(0.700, 0.400)	(0.650, 0.450)	(0.650, 0.450)	(0.700, 0.400)	(0.650, 0.450)	(0.668,0.432)	0.630	Accepted
	Rapid technological advancements	(0.350, 0.750)	(0.250, 0.850)	(0.350, 0.750)	(0.400, 0.650)	(0.350, 0.750)	(0.341,0.752)	0.275*	Rejected
Institutional environment (IE)	Absence of universal IIoT standards	(0.700, 0.400)	(0.700, 0.400)	(0.700, 0.400)	(0.650, 0.450)	(0.650, 0.450)	(0.684,0.426)	0.648	Accepted
	Liability allocation in complex ecosystems	(0.700, 0.400)	(0.650, 0.450)	(0.650, 0.450)	(0.700, 0.400)	(0.650, 0.450)	(0.668,0.432)	0.638	Accepted

Remark: "*" The value has lower than threshold value (δ) of 0.6.

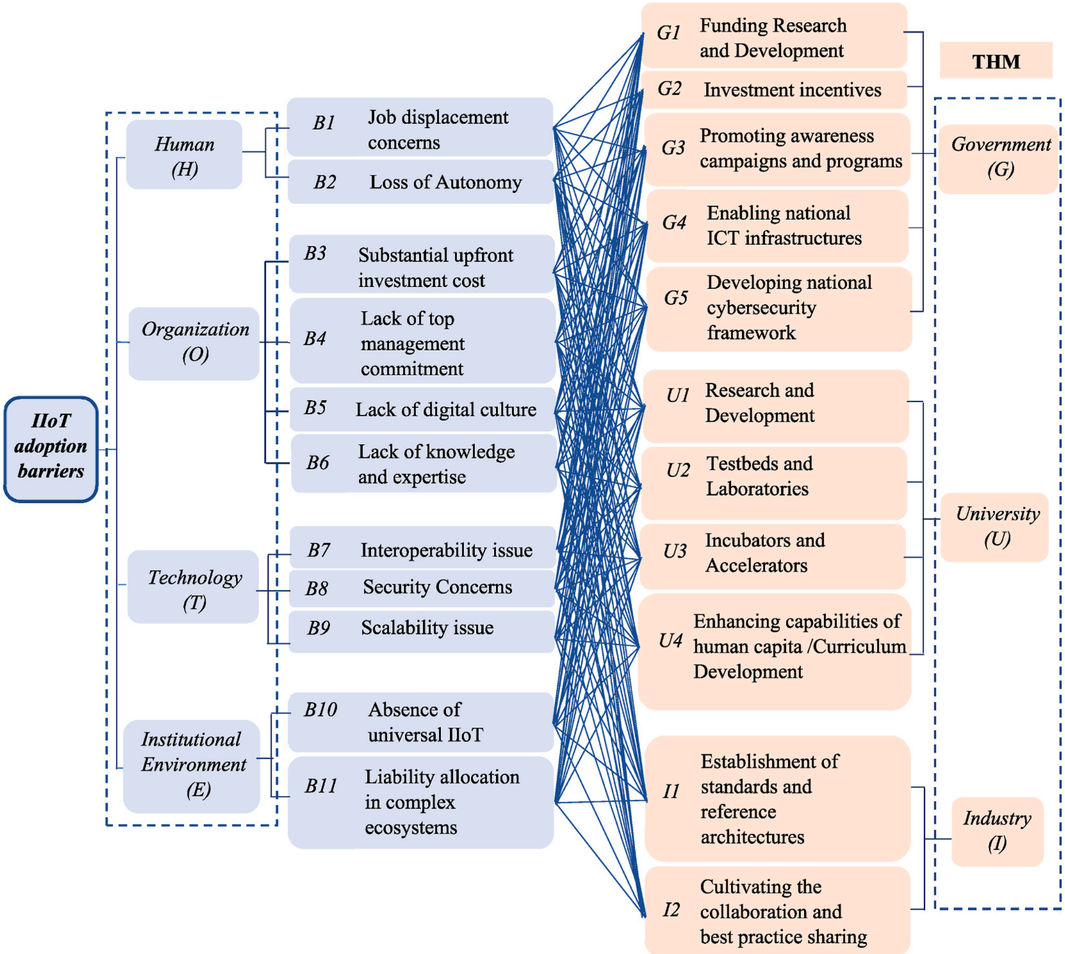

Fig. 4. Decision model for enhancing readiness degree for IIoT adoption.

Table 10
The descending order of barrier ranking.

Code	Barriers	Type of criteria	Crisp scores ($\mathbb{S}^*(C_j)$)	Rank
B1	Lack of digital culture	Cost	0.846	1
B2	Lack of knowledge and expertise	Cost	0.820	2
B3	Job displacement concerns	Cost	0.798	3
B4	Substantial upfront investment cost	Cost	0.781	4
B5	Lack of top management commitment	Cost	0.737	5
B6	Security concerns	Cost	0.687	6
B7	Absence of universal IIoT standards	Cost	0.648	7
B8	Interoperability issue	Cost	0.645	8
B9	Loss of autonomy	Cost	0.641	9
B10	Liability allocation in complex ecosystems	Cost	0.638	10
B11	Scalability issue	Cost	0.630	11

The final objective weight for each criterion $\left(\omega_j^o\right)$ is obtained using Eq. (27), and the corresponding results are presented in Table 19. As illustrated in Table 19, the values of ω_j^o are as follows:

B9 ($\omega_9^o = 0.190$) > *B3* ($\omega_3^o = 0.176$) > *B1* ($\omega_1^o = 0.169$) > *B10* ($\omega_{10}^o = 0.084$) > *B7* ($\omega_7^o = 0.074$) > *B4* ($\omega_4^o = 0.072$) > *B6* ($\omega_6^o = 0.071$) > *B2* ($\omega_2^o = 0.058$) > *B8* ($\omega_8^o = 0.048$) > *B11* ($\omega_{11}^o = 0.033$) > *B5* ($\omega_5^o = 0.026$).

A numerical example illustrating the final objective weight for the barrier "job displacement concerns" $\left(\omega_1^o\right)$ is provided below.

$$\omega_1^o = \frac{0.470}{0.470 + 0.162 + \ldots + 0.233 + 0.091} = 0.169$$

Table 11
The values of $\mathbb{S}^*(C_j)$, $S^*(j)$, $\widetilde{k_j}$, q_j.

Barriers	Crisp scores ($\mathbb{S}^*(C_j)$)	Relative significance score ($S^*(j)$)	Comparative coefficients ($\widetilde{k_j}$)	Recalculated weights $\left(q_j\right)$	Final criteria subjective weights $\left(\omega_j^s\right)$
B1	0.846	–	1	1.000	0.103
B2	0.820	0.026	1.026	0.975	0.101
B3	0.798	0.022	1.022	0.954	0.098
B4	0.781	0.017	1.017	0.938	0.096
B5	0.737	0.044	1.044	0.898	0.093
B6	0.687	0.050	1.050	0.855	0.088
B7	0.648	0.039	1.039	0.823	0.085
B8	0.645	0.003	1.003	0.821	0.084
B9	0.641	0.004	1.004	0.818	0.084
B10	0.638	0.003	1.003	0.815	0.084
B11	0.630	0.008	1.008	0.809	0.083

Table 12
The assessment of practical strategies under THM to overcome barriers in linguistic terms.

Barriers	G1	G2	G3	…	I1
B1	L, VL, L, L, VL	L, VL, VL, L, VL	H, VH, H, H, VH	…	H, H, H, H, H
B2	H, H, H, H, H	H, H, MH, H, H	MH, H, MH, MH, MH	…	H, H, H, H, H
B3	VL, VL, VL, VL, VL	L, L, H, L, L	H, H, H, H, H	…	H, VH, H, H, VH
B4	MH, H, H, MH, H	VH, VH, VH, VH, VH	M, L, L, M, L	…	H, MH, MH, H, MH
B5	MH, MH, MH, MH, MH	H, MH, H, H, MH	H, H, H, H, H	…	H, H, MH, H, H
B6	MH, H, H, MH, H	MH, MH, MH, MH, MH	ML, MH, ML, ML, MH	…	H, H, MH, H, H
B7	MH, MH, MH, MH, MH	MH, ML, MH, MH, ML	ML, ML, ML, ML, ML	…	H, H, VH, H, H
B8	H, H, MH, H, H	MH, MH, M, MH, MH	M, ML, L, M, ML,	…	MH, MH, H, MH, MH
B9	L, L, VL, L, L	L, L, VL, L, L	H, MH, H, H, MH	…	H, H, H, H, H
B10	H, H, MH, H, H	L, MH, VL, L, L	L, L, VL, L, L	…	VH, H, H, VH, H
B11	H, H, H, H, H	MH, H, MH, MH, H	L, ML, L, L, ML	…	H, MH, MH, H, MH

Table 13
The sample data of corresponding PFNs from "Expert No. 1" (*E1*).

Pragmatic strategies under THM	Code	Barriers				
		B1	B2	B3	…	B11
Government	*G1*	(0.250, 0.850)	(0.700, 0.400)	(0.250, 0.850)	…	(0.700, 0.400)
	G2	(0.350, 0.750)	(0.700, 0.400)	(0.350, 0.750)	…	(0.650, 0.450)
	G3	(0.700,0.400)	(0.650, 0.450)	(0.700, 0.400)	…	(0.350, 0.750)
	G4	(0.650,0.450)	(0.350, 0.750)	(0.350, 0.750)	…	(0.650, 0.450)
	G5	(0.450,0.650)	(0.350, 0.750)	(0.250, 0.850)	…	(0.400, 0.650)
University	*U1*	(0.350, 0.750)	(0.850, 0.350)	(0.650, 0.450)	…	(0.700, 0.400)
	U2	(0.850, 0.350)	(0.700, 0.400)	(0.850, 0.350)	…	(0.700, 0.400)
	U3	(0.350, 0.750)	(0.700, 0.400)	(0.650, 0.450)	…	(0.700, 0.400)
	U4	(0.250, 0.850)	(0.650, 0.450)	(0.250, 0.850)	…	(0.700, 0.400)
Industry	*I1*	(0.250, 0.850)	(0.350, 0.750)	(0.350, 0.750)	…	(0.700, 0.400)
	I2	(0.700, 0.400)	(0.700, 0.400)	(0.700, 0.400)	…	(0.700, 0.400)

Phase VIII. Obtaining the combined weights of barriers $\left(\omega_j^c\right)$

The combined weights $\left(\omega_j^c\right)$ of barriers, integrating subjective weights $\left(\omega_j^s\right)$ obtained from PFS-SWARA (Algorithm II) and objective weights $\left(\omega_j^o\right)$ from PFS-MEREC (Algorithm III), are calculated using Eq. (28) in Section 4.8. Results are shown in Table 20 indicated that

B1 $(\omega_9^c = 0.138) >$ *B3* $(\omega_3^c = 0.137) >$ *B9* $(\omega_9^o = 0.132) >$ *B10* $(\omega_{10}^o = 0.088) >$ *B4* $(\omega_4^o = 0.087) >$ *B7* $(\omega_7^o = 0.083) =$ *B6* $(\omega_6^o = 0.083) >$ *B2* $(\omega_2^o = 0.080) >$ *B9* $(\omega_9^o = 0.066) >$ *B11* $(\omega_{11}^o = 0.055) >$ *B5* $(\omega_5^o = 0.051)$.

Below is a numerical example illustrating the combined weight for the barrier " lack of digital culture " criterion $\left(\omega_1^c\right)$.

$$\omega_1^c = \frac{\sqrt{0.103*0.169}}{\left(\sqrt{0.103*0.169}\right) + \left(\sqrt{0.101*0.077}\right) + \ldots + \left(\sqrt{0.084*0.084}\right) + \left(\sqrt{0.083*0.033}\right)} = 0.138$$

Phase IX. Ranking the pragmatic strategies under THM

Table 14
The aggregation of evaluation data from five experts into a group decision-making matrix.

Pragmatic strategies under THM	Code	Barriers				
		B1	B2	B3	…	B11
Government	*G1*	(0.314, 0.789)	(0.700, 0.400)	(0.250, 0.850)	…	(0.700, 0.400)
	G2	(0.289, 0.814)	(0.688, 0.412)	(0.328, 0.774)	…	(0.672, 0.429)
	G3	(0.776,0.379)	(0.672,0.429)	(0.700,0.400)	…	(0.371,0.708)
	G4	(0.497,0.607)	(0.517,0.588)	(0.328,0.774)	…	(0.672,0.429)
	G5	(0.381,0.688)	(0.578,0.535)	(0.295,0.808)	…	(0.604,0.494)
University	*U1*	(0.460,0.658)	(0.850,0.350)	(0.650.0.450)	…	(0.700,0.400)
	U2	(0.822,0.362)	(0.776,0.379)	(0.765,0.382)	…	(0.668,0.432)
	U3	(0.578,0.535)	(0.700,0.400)	(0.673,0.429)	…	(0.625,0.475)
	U4	(0.320,0.782)	(0.684,0.416)	(0.295,0.808)	…	(0.625,0.475)
Industry	*I1*	(0.320,0.588)	(0.578,0.535)	(0.328,0.774)	…	(0.700,0.400)
	I2	(0.700,0.400)	(0.700,0.400)	(0.776,0.379)	…	(0.668,0.432)

Table 15
These crisp scores for the aggregate group decision-making matrix.

Pragmatic strategies under THM	Code	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11
Government	*G1*	0.238	0.665	0.170	0.648	0.610	0.648	0.610	0.652	0.254	0.652	0.665
(G)	*G2*	0.210	0.652	0.254	0.800	0.644	0.610	0.528	0.579	0.254	0.461	0.634
	G3	0.729	0.634	0.665	0.356	0.665	0.496	0.369	0.389	0.644	0.254	0.319
	G4	0.439	0.461	0.254	0.648	0.610	0.619	0.528	0.513	0.170	0.339	0.634
	G5	0.336	0.524	0.217	0.625	0.610	0.800	0.610	0.610	0.170	0.652	0.560
University	*U1*	0.390	0.800	0.610	0.665	0.610	0.634	0.634	0.665	0.579	0.634	0.665
(U)	*U2*	0.773	0.729	0.720	0.665	0.665	0.605	0.560	0.652	0.720	0.579	0.630
	U3	0.524	0.665	0.634	0.610	0.610	0.560	0.560	0.610	0.528	0.542	0.583
	U4	0.245	0.648	0.217	0.630	0.444	0.569	0.528	0.560	0.238	0.486	0.583
Industry	*I1*	0.378	0.524	0.254	0.585	0.524	0.634	0.755	0.708	0.210	0.665	0.665
(I)	*I2*	0.665	0.665	0.729	0.630	0.652	0.652	0.708	0.625	0.665	0.720	0.630

Table 16
The normalized aggregate group decision-making matrix.

Pragmatic strategies under THM	Code	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11
Government	*G1*	0.308	0.831	0.233	0.810	0.917	0.810	0.808	0.921	0.353	0.906	1.000
(G)	*G2*	0.272	0.815	0.348	1.000	0.968	0.763	0.699	0.818	0.353	0.640	0.953
	G3	0.943	0.793	0.912	0.445	1.000	0.620	0.489	0.549	0.894	0.353	0.480
	G4	0.568	0.576	0.348	0.810	0.917	0.774	0.699	0.725	0.236	0.471	0.953
	G5	0.435	0.655	0.298	0.781	0.917	1.000	0.808	0.862	0.236	0.906	0.842
University	*U1*	0.505	1.000	0.837	0.831	0.917	0.793	0.840	0.939	0.804	0.881	1.000
(U)	*U2*	1.000	0.911	0.988	0.831	1.000	0.756	0.742	0.921	1.000	0.804	0.947
	U3	0.678	0.831	0.870	0.763	0.917	0.700	0.742	0.862	0.733	0.753	0.877
	U4	0.317	0.810	0.298	0.788	0.668	0.711	0.699	0.791	0.331	0.675	0.877
Industry	*I1*	0.489	0.655	0.348	0.731	0.788	0.793	1.000	1.000	0.292	0.924	1.000
(I)	*I2*	0.860	0.831	1.000	0.788	0.980	0.815	0.938	0.883	0.924	1.000	0.947

Table 17
The overall performance for each THM pragmatic strategies.

THM pragmatic strategies	Government (*G*)					University (*U*)				Industry (*I*)	
	G1	G2	G3	G4	G5	U1	U2	U3	U4	I1	I2
Overall performance (S_i)	0.360 (S_1)	0.372 (S_2)	0.367 (S_3)	0.414 (S_4)	0.367 (S_5)	0.163 (S_6)	0.105 (S_7)	0.212 (S_8)	0.422 (S_9)	0.329 (S_{10})	0.097 (S_{11})

The ranking of pragmatic strategies under THM is accomplished through the utilization of the PF-COBRA algorithm, as detailed in Algorithm IV (Section 4.7). This pioneering approach facilitates a rigorous and methodical appraisal of the available solutions, considering both their practicality and efficacy. Through the utilization of the PF- COBRA algorithm, each solution receives a quantitative ranking, enabling decision-makers to make well-informed choices grounded in a comprehensive evaluation of their real-world relevance. Consequently, this methodology elevates the decision-making process, resulting in the prioritization of more effective and practical solutions. The procedural steps for this computation are demonstrated below.

Step 1. Assessing the prioritization of implementing practical solutions to overcome barriers

Table 18
The overall performance for each THM pragmatic strategy after removing effect of each barrier.

Pragmatic strategies under THM	Code	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11
Government	*G1*	0.078	0.012	0.097	0.013	0.005	0.013	0.014	0.005	0.068	0.006	0.000
(G)	*G2*	0.085	0.013	0.068	0.000	0.002	0.017	0.023	0.013	0.068	0.028	0.003
	G3	0.004	0.015	0.006	0.052	0.000	0.031	0.046	0.038	0.007	0.068	0.047
	G4	0.035	0.034	0.065	0.013	0.005	0.016	0.022	0.020	0.091	0.046	0.003
	G5	0.054	0.027	0.079	0.016	0.005	0.000	0.014	0.009	0.095	0.006	0.011
University	*U1*	0.054	0.000	0.014	0.014	0.007	0.018	0.014	0.005	0.017	0.010	0.000
(U)	*U2*	0.000	0.008	0.001	0.015	0.000	0.023	0.025	0.007	0.000	0.018	0.004
	U3	0.029	0.014	0.010	0.020	0.006	0.027	0.022	0.011	0.023	0.021	0.010
	U4	0.071	0.013	0.075	0.014	0.024	0.021	0.022	0.014	0.068	0.024	0.008
Industry	*I1*	0.048	0.028	0.071	0.021	0.016	0.015	0.000	0.000	0.084	0.005	0.000
(I)	*I2*	0.012	0.015	0.000	0.020	0.002	0.017	0.005	0.010	0.007	0.000	0.004

The results are shown in Tables 12 and 13.

Step 2. Aggregation the evaluation data into a group decision-making

Using Eqs. (15) and (16), the data are aggregated into a group decision-making format, as illustrated in Table 14.

Step 3. Converting the PFNs in the aggregate group decision-making matrix to crisp scores

Using Eqs. (3) and (4), all in the aggregate group decision-making matrix PFNs are converted into crisp scores, as shown in Table 15.

Step 4. Normalizing the aggregate group decision-making matrix

Using Eq. (20), all elements in the aggregated group decision-making matrix are normalized, as shown in Table 16.

Step 5. Calculation the weighted normalized decision matrix

Using the combined weights $\left(\omega_j^c\right)$ of barriers from Phase VIII, a weighted normalized decision matrix is calculated according to Eq. (30) and presented in Table 21.

Step 6. Determining the positive ideal (PIS_i), negative ideal (NIS_i) and average solution (AS_i)

The positive ideal (PIS_i), negative ideal (NIS_i) are determined using Eq. (31) and (32), respectively, while the average solution (AS_i) is determined according to Eq. (33). The resulting values for PIS_i, NIS, and AS_i are displayed in Table 22.

Step 7. Calculating Euclidian and Taxicab distances

The Euclidian distances, denoted as $dE(PIS_i)$, $dE(NIS_i)$, $dE\left(AS_j\right)_i^+$, and $dE\left(AS_j\right)_i^-$, are calculated utilizing Eq. (34)–(37) respectively. Concurrently, the Taxicab distances, $dT(PIS_i)$, $dT(NIS_i)$, $dT\left(\left(AS_j\right)_i^+\right)$, and $dT\left(AS_j\right)_i^-$, are calculated according to Eq. (38)–(43), respectively. The resulting values for all Euclidian and Taxicab distances are displayed in Table 23.

Step 8. Computing distances between each THM solution

The distances between each THM solution and PIS_j, NIS_j, AS_j , denoted as $d\left(PIS_j\right)_i$, $d\left(NIS_j\right)_i$, $d\left(AS_j\right)_i^+$, and $d\left(AS_j\right)_i^-$, are calculated utilizing Eqs. (44)–(51), respectively. The results values for all distances are presented in Table 24.

Step 9. Rank the THM solutions in ascending order

The comprehensive distances for each THM solution, denoted as dC_i, are computed utilizing Eq. (52). The THSs are then ranked in ascending order based on their dC_i values, and the rankings are presented in Table 24. As shown in Table 24, the THM solutions are ranked according to their ascending dC_i values as follows.

U4(-0.030) > *G4*(-0.026) > *G2*(-0.025) > *G1*(-0.023) > *G5*(-0.022) > *I1*(-0.017) > *G3*(0.014) > *U3*(0.016) > *U1*(0.017) > *I2*>(0.040) > *U2*>(0.041)

Table 19
The absolute deviations $\left(E_j\right)$ and final objective weight $\left(\omega_j^o\right)$ for each criterion.

	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11
E_j	0.470	0.162	0.487	0.199	0.073	0.197	0.205	0.132	0.528	0.233	0.091
ω_j^o	0.169	0.058	0.176	0.072	0.026	0.071	0.074	0.048	0.190	0.084	0.033

Table 20
The combined weights of barriers.

Importance weights	Barriers										
	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11
ω_1^s (PFS SWARA)	0.103	0.101	0.098	0.096	0.093	0.088	0.085	0.084	0.084	0.084	0.083
ω_1^o (PFS MEREC)	0.169	0.058	0.176	0.072	0.026	0.071	0.074	0.048	0.19	0.084	0.033
ω_1^c (PFS SWARA-MEREC)	0.138	0.080	0.137	0.087	0.051	0.083	0.083	0.066	0.132	0.088	0.055
Rank	1	8	2	5	11	7	6	9	3	4	10

7. Validation test of proposed framework

The validity test of the proposed framework's robustness and applicability are validated through a rigorous two-stage sensitivity analysis. This analysis includes evaluating the impact of altering criteria weights, and conducting a comparative study with other novel MCDM ranking methods. These comprehensive examinations ensure a thorough understanding of the framework's performance and suitability for a wide range of applications. The subsequent sections provide a detailed exposition of these analyses.

7.1. Impact of altering the criteria weights

This study explores how alternating the weight criteria within the integration of TOE and HOT-fit framework effect to the overall ranking results of eleven pragmatic strategies under THM. To achieve this goal, this study employs the procedure outlined in Eqs. (53)–(55), following the methodology established by Zolfani et al. [123].

$$\widehat{\omega}_{jp} = \omega_{jp} + \gamma\omega_{jp} \tag{53}$$

$$\widehat{\omega}_{js} = \frac{\omega_{js}\left(1 - \widehat{\omega}_{jp}\right)}{\left(1 - \omega_{jp}\right)} \tag{54}$$

$$\widehat{\omega}_{jp} + \sum_{j=1}^{n-1} \widehat{\omega}_{js} = 1 \tag{55}$$

where, $\widehat{\omega}_{jp}$ denotes the updated weight value of j^{th} criterion, while ω_{jp} represents the previous weight value. The symbol γ represents the modification degree expressed as a percentage and lie within the range $\gamma \in [-50\%, 50\%]$. Additionally, ω_{js} denotes the previous values of the remaining criteria, and $\widehat{\omega}_{js}$ represent the new weight values of the remaining criteria. The variable n denoted the number of criteria.

By following the prescribed procedure, 110 scenarios are generated by adjusting the eleven criteria within the TOE-HOT fit framework, within the range of ±50 %. The resulting rankings for all scenarios pertaining to eleven pragmatic strategies under THM are detailed in Table 25 and visually depicted in Fig. 5. Notably, over 80 % of scenarios exhibit consistent rankings for each pragmatic strategy under THM, yielding a high average ranking consistency of 90.16 %. This high level of uniformity and consensus in the rankings is deemed satisfactory. Although minor variations are present, their impact on the final outcomes is considered negligible. Furthermore, the consistent top and second-ranked factors, "enhancing capabilities of human capita" (*U4*) and "enabling national ICT infrastructures" (*G4*), emphasize the robustness and stability of the proposed decision-making framework.

Table 21
The weighted normalized decision matrix.

Pragmatic strategies under THM	Code	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11
Government	*G1*	0.043	0.067	0.032	0.070	0.047	0.067	0.067	0.061	0.047	0.080	0.055
	G2	0.038	0.065	0.048	0.087	0.049	0.063	0.058	0.054	0.047	0.056	0.052
	G3	0.130	0.063	0.125	0.039	0.051	0.051	0.041	0.036	0.118	0.031	0.026
	G4	0.078	0.046	0.048	0.070	0.047	0.064	0.058	0.048	0.031	0.041	0.052
	G5	0.060	0.052	0.041	0.068	0.047	0.083	0.067	0.057	0.031	0.080	0.046
University	*U1*	0.070	0.080	0.115	0.072	0.047	0.066	0.070	0.062	0.106	0.077	0.055
	U2	0.138	0.073	0.135	0.072	0.051	0.063	0.062	0.061	0.132	0.071	0.052
	U3	0.094	0.067	0.119	0.066	0.047	0.058	0.062	0.057	0.097	0.066	0.048
	U4	0.044	0.065	0.041	0.068	0.034	0.059	0.058	0.052	0.044	0.059	0.048
Industry	*I1*	0.068	0.052	0.048	0.064	0.040	0.066	0.083	0.066	0.039	0.081	0.055
	I2	0.119	0.067	0.137	0.068	0.050	0.068	0.078	0.058	0.122	0.088	0.052

Table 22
The values of PIS_i, NIS, and AS_i.

Pragmatic strategies under THM	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11
PIS_i	0.038	0.046	0.032	0.039	0.034	0.051	0.041	0.036	0.031	0.031	0.026
NIS_i	0.138	0.080	0.137	0.087	0.051	0.083	0.083	0.066	0.132	0.088	0.055
AS_i	0.080	0.063	0.081	0.068	0.046	0.064	0.064	0.056	0.074	0.067	0.049

Table 23
The values for all Euclidian and Taxicab distances.

Pragmatic strategies under THM	Code	$dE(PIS_j)_i$	$dT(PIS_j)_i$	$dE(NIS_j)_i$	$dT(NIS_j)_i$	$dE(AS_j)_i^+$	$dT(AS_j)_i^+$	$dE(AS_j)_i^+$	$dT(AS_j)_i^-$
Government	*G1*	0.081	0.229	0.169	0.365	0.000	0.036	0.005	0.114
	G2	0.074	0.212	0.167	0.382	0.001	0.522	0.004	0.103
	G3	0.159	0.307	0.104	0.288	0.004	0.339	0.006	0.139
	G4	0.067	0.179	0.163	0.415	0.001	0.427	0.003	0.077
	G5	0.081	0.227	0.165	0.368	0.001	0.500	0.004	0.103
University	*U1*	0.144	0.414	0.082	0.180	0.001	0.529	0.002	0.077
	U2	0.191	0.504	0.038	0.090	0.000	0.504	0.010	0.171
	U3	0.138	0.375	0.076	0.220	0.000	0.471	0.002	0.075
	U4	0.058	0.167	0.170	0.428	0.000	0.444	0.004	0.106
Industry	*I1*	0.090	0.256	0.153	0.339	0.001	0.507	0.002	0.081
	I2	0.183	0.501	0.036	0.093	0.001	0.698	0.007	0.143

Table 24
The ranking of THM solutions.

Pragmatic strategies under THM solutions	Code	$d(PIS_j)_i$	$d(NIS_j)_i$	$d(AS_j)_i^+$	$d(AS_j)_i^-$	dC_i	Rank
Government	*G1*	0.084	0.177	0.000	0.000	−0.023	4
	G2	0.076	0.175	0.001	0.000	−0.025	3
	G3	0.166	0.108	0.004	0.000	0.014	7
	G4	0.069	0.172	0.001	0.000	−0.026	2
	G5	0.083	0.173	0.001	0.000	−0.022	5
University	*U1*	0.152	0.084	0.001	0.000	0.017	9
	U2	0.204	0.039	0.000	0.000	0.041	11
	U3	0.145	0.079	0.000	0.000	0.016	8
	U4	0.060	0.180	0.000	0.000	−0.030	1
Industry	*I1*	0.093	0.160	0.001	0.000	−0.017	6
	I2	0.195	0.037	0.000	0.000	0.040	10

7.2. Comparative study of others novel MCDM raking methods

In the second phase of the sensitivity analysis, this study conducts a comparative evaluation of rankings for pragmatic strategies under THM. These rankings, generated using the proposed framework, are compared with rankings obtained from other established distance-based methodologies, including PF-TOPSIS (Hajiaghaei-Keshteli et al. [124]), PF-VIKOR (Mete et al. [125]), PF-CODAS (Ayyildiz [70]), PF-EDAS (Lui et al. [126]), and PF- MABAC (Chakraborty et al. [127]). The selection of these specific methods is grounded in their extensive application in addressing various real-world MCDM problems, consistently yielding reliable and unbiased results. After conducting the ranking process, as illustrated in Table 26 and Fig. 6, it is noteworthy that the THM pragmatic strategy of "enhancing capabilities of human capital" (*U4*) consistently maintains its top-ranking position across all methods, except for PF-MABAC. Although there are slight variations in the ranking results across the methods, these discrepancies have minimal impact on the overall outcomes.

Furthermore, this study highlights the advantages of the proposed model over other MCDM benchmark methods, as outlined in Table 27.

7.3. Statistical comparison of ranking methods using and Spearman's coefficient

When alternatives are ranked using various decision-ranking techniques, the resulting rankings can differ in their level of similarity. To evaluate the extent of these differences, non-parametric statistical tests are employed. These tests determine whether different decision-making approaches yield similar or divergent rankings. This study utilizes Spearman's rank correlation coefficient to analyze the rankings produced by different methods, focusing on their pairwise correlations. Spearman's coefficient, a non-parametric measure, assesses the strength and direction of correlation between the rank orders of two groups, providing insights into the alignment of rankings across different methods.

To evaluate the relationship between pairs of ranked data, Spearman's rank correlation coefficient, Spearman's correlation is calculated. The Spearman rank correlation coefficient, denoted as r_s, is determined using Eq. (56), while the corresponding statistical significance, denoted as T, is assessed with the test specified in Eq. (57), as detailed below.

$$r_s = 1 - \frac{6\sum d_i^2}{n(n^2-1)} \tag{56}$$

$$T = \frac{r_s}{\sqrt{(1-r_s^2)/(n-2)}} \tag{57}$$

here, d_i denotes difference between the two ranks of each MCDM method, n represents number of ranking comparisons.

Using Eq. (56), the Spearman's correlation (r_s) is calculated to determine correlation between the rankings from pairs of different MCDM methods. The correlation coefficients between PF-COBRA and the other employed methods (PF-TOPSIS, PF-VIKOR, PF-CODAS, PF-EDAS, and PF- MABAC) are as follows: 0.927, 0.972, 0.963, 0.972, and 0.972, respectively, resulting in an average of 0.961, as presented in Table 28 and correlation heat map shown in Fig. 7. A correlation coefficient (r_s) equal to or greater than 0.8 signifies a notably strong correlation with the other MCDM methods according to Raheja et al. [128]. This is outlined in Table 29.

Subsequently, statistical correlation coefficient tests at a significance level of 0.5 ($\alpha = 0.05$) are conducted between the rankings from pairs of different MCDM methods using Eq. (57), and the results. The results, shown in Table 30, indicate that all pairs of different MCDM methods are statistically significant. This underscores that the suggested framework exhibits a high degree of consistency and stability in decision-making at a commendable level.

To validate the proposed framework based on PFS-SWARA-MEREC-COBRA, this study conducts a comparative analysis with frameworks based on FFS-SWARA-MEREC-COBRA and Q-ROFS-SWARA-MEREC-COBRA. This analysis aims to determine the relative strengths and weaknesses of each approach, thereby identifying the most effective method for evaluating IIoT adoption readiness in manufacturing enterprises. The ranking comparison results among these three fuzzy types are illustrated in Table 31 and Fig. 8. Notably, the THM pragmatic strategies of "enhancing capabilities of human capital" (*U4*) and "enabling national ICT infrastructures" (*G4*) consistently maintain their top-ranking and second-ranking positions across all methods.

Furthermore, the Spearman's rank correlation coefficient test, conducted using Eq. (56), indicates that the correlation coefficients between the proposed framework (PFS-SWARA-MEREC-COBRA) and the other employed fuzzy types (FFS-SWARA-MEREC-COBRA, Q-ROFS-SWARA-MEREC-COBRA) are 0.709 and 0.681, respectively. This results in an average correlation coefficient of 0.695, as shown in Table 32. Additionally, the correlation heat map illustrating the relationships among the three fuzzy approaches is presented in Fig. 9. According to Raheja et al. [128], a correlation coefficient (r_s) equal to or greater than or equal 0.6 signifies a notably strong correlation with the other MCDM methods. This highlights that the proposed framework achieves a notable level of consistency and stability in decision-making.

7.4. Comparative study of others fuzzy types

In Pythagorean Fuzzy Sets (PFS), the sum of the squares of the membership and non-membership degrees must be less than or equal to 1 $\left(0 \leq (u_X(u_i))^2 + (\upsilon_X(u_i))^2 \leq 1\right)$. This constraint limits the range of uncertainty that can be modeled. Fermatean Fuzzy Sets (FFS) extend this by requiring the sum of the cubes of the membership and non-membership degrees to be less than or equal to 1 $\left(0 \leq (u_X(u_i))^3 + (\upsilon_X(u_i))^3 \leq 1\right)$, offering an advantage over PFS by allowing for a broader range of uncertainty. In q-rung orthopair fuzzy ($Q{-}ROFS$), the sum of the q^{th} powers of the membership and non-membership degrees must be less than or equal to 1 $(0 \leq (u_X(u_i))^q + (\upsilon_X(u_i))^q \leq 1)$. The parameter q can be adjusted to provide more flexibility, with higher values of q allowing for a wider range of membership and non-membership degrees.

Table 25
The ranking of pragmatic strategies under THM across 110 tested scenarios.

Pragmatic strategies under THM	Code	Original raking from proposed framework (PF-COBRA approach)	Total tested scenarios (a)	The number of scenarios with different ranking (b)	The number of scenarios that maintained their ranking (c)	% Consistency [(c)/(a)] *100
Government	*G1*	4	110	16	110	85.45 %
	G2	3	110	19	110	82.72 %
	G3	7	110	10	110	90.90 %
	G4	2	110	–	110	100.00 %
	G5	5	110	21	110	80.90 %
University	*U1*	9	110	–	110	100.00 %
	U2	11	110	22	110	80.00 %
	U3	8	110	–	110	100.00 %
	U4	1	110	–	110	100.00 %
Industry	*I1*	6	110	8	110	92.72 %
	I2	10	110	23	110	79.09 %
	Average consistency percentage					90.16 %

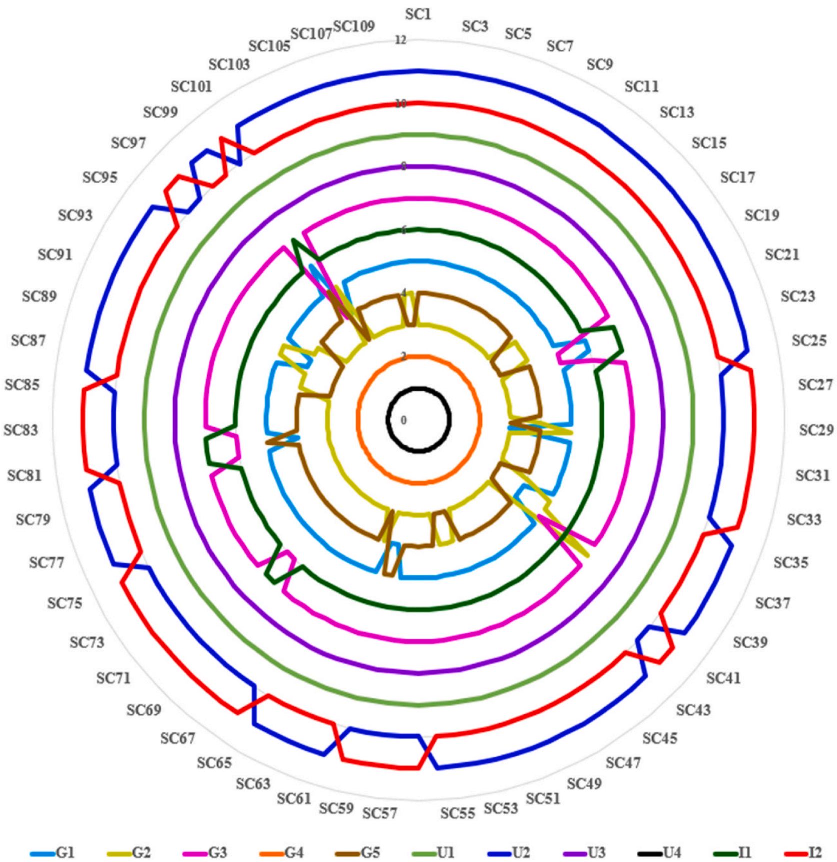

Fig. 5. The ranking results for pragmatic strategies under THM across all 110 tested scenarios.

Table 26
The results of the ranking determined through established MCDM approaches.

Pragmatic strategies under THM	Code	PF-COBRA	PF-TOPSIS	PF-VIKOR	PF-CODAS	PF-EDAS	PF-MABAC
Government	*G1*	4	2	5	4	5	3
	G2	3	5	3	3	4	4
	G3	7	7	6	8	7	6
	G4	2	3	2	2	2	2
	G5	5	6	4	5	3	5
University	*U1*	9	9	9	7	9	9
	U2	11	10	10	10	11	10
	U3	8	8	8	9	8	8
	U4	1	1	1	1	1	1
Industry	*I1*	6	4	7	6	6	7
	I2	10	11	11	11	10	11

8. Findings and discussions

According to PF-Delphi's research, eleven barriers impede the widespread adoption of the IIoT in agro-food processing industry. These barriers are "Lack of digital culture" (*B1*), "Lack of knowledge and expertise" (*B2*), "Job displacement concerns" (*B3*), "Substantial upfront investment cost" (*B4*), "Lack of top management commitment" (*B5*), "Security concerns" (*B6*), "Absence of universal IIoT standards" (*B7*), "Interoperability issue" (*B8*), "Loss of autonomy" (*B9*), "Liability allocation in complex ecosystems" (*B10*), and "Scalability issue" (*B11*).

Remarkably, according to the PF-SWARA analysis, the top three significant IIoT adoption barriers are identified as "Lack of digital culture" (B1) with a relative importance weight of 0.112, closely followed by "Lack of knowledge and expertise" (*B2*) with a weight of 0.110, and "Job displacement concerns" (*B3*) with a weight of 0.107. These findings can be further elucidated as follows. The top-ranking barrier, "Lack of Digital Culture" (*B1*), underscores the crucial role played by fostering a digital culture in overcoming resistance to IIoT adoption. These findings are consistent with existing literature, which emphasizes the importance of digital

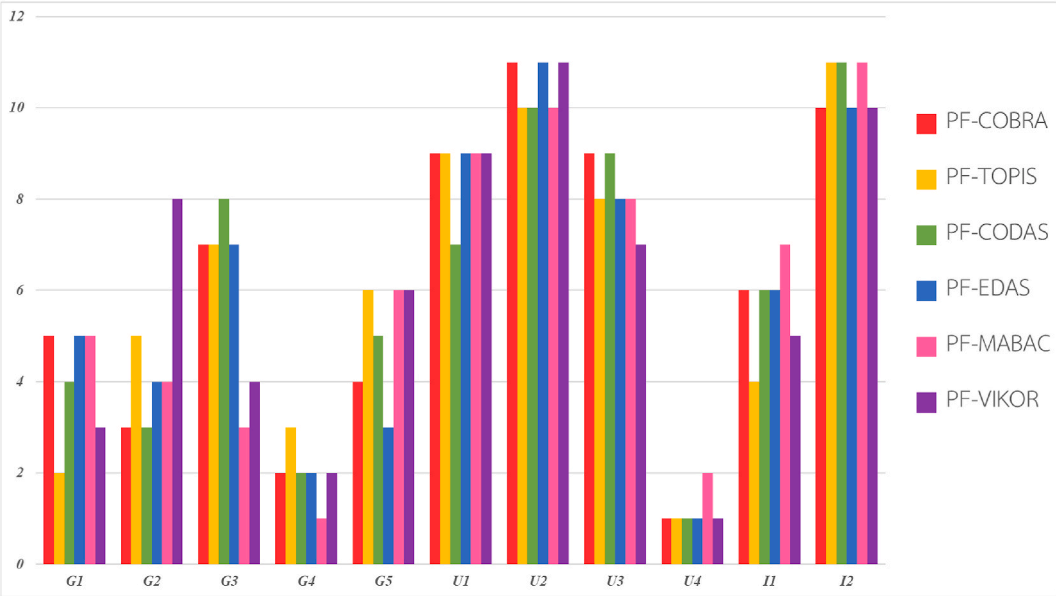

Fig. 6. Comparative ranking of others novel MCDM raking methods.

Table 27
The advantages of the proposed model over other MCDM benchmark methods.

	PF-TOPSIS Hajiaghaei-Keshteli et al. [124]	PF-VIKOR Mete et al. [125]	PF-CODAS Ayyildiz [70]	PF-EDAS Lui et al. [126]	PF- MABAC Chakraborty et al. [127]
PF-COBRA (Proposed Framework in this study)	PF-TOPSIS aims to find the best alternative closest to the ideal solution and farthest from the negative-ideal solution. It may not handle the benefit-risk balance as comprehensively as COBRA.	PF-VIKOR focuses on ranking and selecting alternatives to determine a compromise solution, balancing majority and minority views, but may not align with a thorough benefit-risk assessment.	PF-CODAS uses the Euclidean distance and Taxicab distance for the evaluation. It is efficient but might not offer the nuanced risk analysis provided by COBRA.	PF-EDAS evaluates alternatives based on their distances from the average solution. While practical, it might lack the detailed benefit-risk trade-off analysis of COBRA.	PF-MABAC, based on the distance from the border approximation area, is effective but may not address uncertainty and qualitative judgments as thoroughly as COBRA.

Table 28
The Spearman's correlation coefficients (r_s) among employed MCDM methods.

	PF-COBRA	PF-TOPSIS	PF-VIKOR	PF-CODAS	PF-EDAS	PF-MABAC
PF-COBRA	1.000	0.927	0.972	0.963	0.972	0.972
PF-TOPSIS	–	1.000	0.872	0.909	0.882	0.936
PF-VIKOR	–	–	1.000	0.945	0.972	0.972
PF-CODAS	–	–	–	1.00	0.936	0.945
PF-EDAS	–	–	–	–	1.000	0.945
PF-MABAC	–	–	–	–	–	1.000

transformation in facilitating IIoT readiness, as detailed below.

Absence of such a culture may result in employees being uninformed about the potential benefits of IIoT, hindering acceptance and complicating communication regarding its advantages in manufacturing processes [105,106]. For instance, in the agro-food processing industry, cultivating a digital culture becomes imperative for embracing and integrating digital technologies across the production chain. This entails establishing a shared understanding among employees about the benefits of digitalization in agro-food processing, spanning farm-to-fork operations and supply chain management.

The second-ranked barrier, "Lack of knowledge and expertise," is particularly noteworthy in the intricate domain of data management within IIoT initiatives. This complexity amplifies the challenges stemming from a knowledge deficit [106,107]. The successful implementation of IIoT in agro-food processing requires a specialized skill set, involving proficiency in data analytics, sensor technology, and connectivity solutions. The absence of internal expertise in these areas has the potential to hinder the efficient adoption of

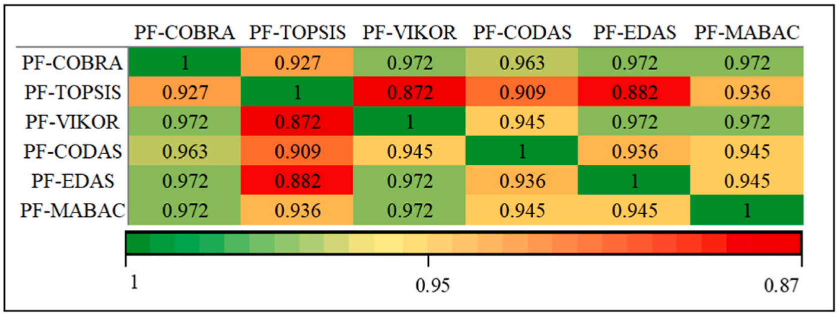

Fig. 7. Correlation heat map between the rankings from pairs of different MCDM methods.

Table 29
Evaluating the degree of correlation strength through the application of Spearman's correlation coefficient (Raheja et al. [128]).

Spearman's correlation coefficients	Degree of conformity
$r_s < 0.2$	Very weak
$0.2 \leq r_s < 0.4$	Weak
$0.4 \leq r_s < 0.6$	Moderate
$0.6 \leq r_s < 0.8$	Strong
$r_s \geq 0.8$	Very strong

Table 30
Statistical comparison of ranking methods using and Spearman's coefficient.

		PF-TOPSIS Hajiaghaei-Keshteli et al. [124]	PF-VIKOR Mete et al. [125]	PF-CODAS Ayyildiz [70]	PF-EDAS Lui et al. [126]
PF-COBRA (Proposed framework)	Spearman's correlation coefficient (r_s)	0.925*	0.972*	0.963*	0.972*
	Sig. (2-tailed) $\alpha = 0.05$	0.001	0.00	0.00	0.00
	n	11	11	11	11
PF-TOPSIS Hajiaghaei-Keshteli et al. [124]	Spearman's correlation coefficient (r_s)	1.00*	0.872*	0.909*	0.882*
	Sig. (2-tailed) $\alpha = 0.05$	0.00	0.02	0.01	0.01
	n	11	11	11	11
PF-VIKOR Mete et al. [125]	Spearman's correlation coefficient (r_s)	0.872*	1	0.945*	0.972*
	Sig. (2-tailed) $\alpha = 0.05$	0.02	0.00	0.00	0.00
	n	11	11	11	11
PF-CODAS Ayyildiz [70]	Spearman's correlation coefficient (r_s)	0.909*	0.945*	1.00*	0.936*
	Sig. (2-tailed) $\alpha = 0.05$	0.00	0.00	0.00	0.00
	n	11	11	11	11
PF-EDAS Lui et al. [126]	Spearman's correlation coefficient (r_s)	0.882*	0.972*	0.936*	1.00*
	Sig. (2-tailed) $\alpha = 0.05$	0.02	0.00	0.00	0.00
	n	11	11	11	11
PF-MABAC Chakraborty et al. [127]	Spearman's correlation coefficient (r_s)	0.936*	0.972*	0.945*	0.945*
	Sig. (2-tailed) $\alpha = 0.05$	0.00	0.00	0.00	0.00
	n	11	11	11	11

Remark: "*" Correlation is significant at the $\alpha = 0.05$ (2-tails).

Table 31
Comparative ranking of THM pragmatic strategies among PFS, FFS, and Q-ROFS.

Pragmatic strategies under THM	Code	PFS-SWARA-MEREC-COBRA	FFS - SWARA-MEREC-COBRA	Q-ROFS SWARA-MEREC-COBRA
Government	*G1*	4	3	3
	G2	3	5	7
	G3	7	11	6
	G4	2	2	2
	G5	5	6	4
University	*U1*	9	9	11
	U2	11	10	8
	U3	8	7	10
	U4	1	1	1
Industry	*I1*	6	8	9
	I2	10	4	5

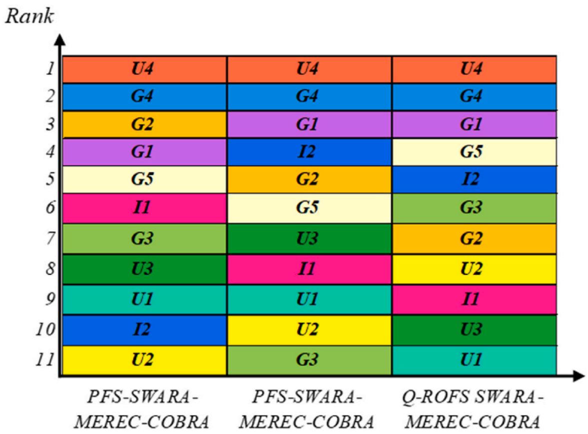

Fig. 8. The ranking comparison results among these three fuzzy types.

IIoT. Manufacturers might face obstacles in selecting, implementing, and maintaining suitable IIoT solutions in the absence of a skilled and knowledgeable workforce [108].

Ranked third among the barriers is "Job displacement concerns" (*B3*). The integration of IIoT often involves the automation of certain tasks and processes, which can lead to concerns among the workforce about the potential displacement of jobs [92,93]. In agro-food processing, where manual labor has traditionally played a significant role, the fear of job loss may create resistance to the adoption of IIoT technologies, impacting the overall morale and engagement of employees.

Furthermore, the PF-COBRA findings indicate that, within the realm of pragmatic strategies under THM, the foremost priorities are "Enhancing capabilities of human capital" (*U4*), "Enabling national ICT infrastructures" (*G4*), and "Investment incentives" (*G2*), ranking as the top three in importance among the Triple-helix solutions (THS) for argo-food processing industry. These findings can be further elaborated as follows.

Universities contribute to human capital enhancement by developing specialized curricula and training programs tailored to the needs of the agro-food processing industry [119]. Academic programs can cover a spectrum of relevant subjects, including data analytics, sensor technology, automation, and cybersecurity. By incorporating hands-on experiences, case studies, and industry collaborations into their curricula, universities ensure that students acquire both theoretical knowledge and practical skills necessary for navigating the intricacies of IIoT adoption in agro-food processing [121,122].

Next, governmental roles play a significant part in advancing IIoT adoption by taking the lead in developing vital ICT infrastructure. This includes the establishment of high-speed broadband networks, data centers, and communication systems that form the

Table 32
The Spearman's correlation coefficients (r_s) among.

	PFS-SWARA-MEREC-COBRA	FFS - SWARA-MEREC-COBRA	Q-ROFS SWARA-MEREC-COBRA
PFS-SWARA-MEREC-COBRA	1.000	0.709	0.681
FFS -SWARA-MEREC-COBRA	–	1.000	0.763
Q-ROFS-SWARA-MEREC-COBRA	–	–	1.000

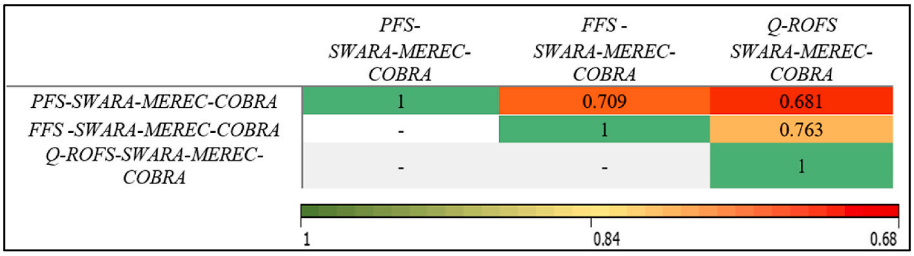

Fig. 9. Correlation heat map between the PFS, FFS, and Q-ROFS.

foundational framework for IIoT [119]. These infrastructures serve as the backbone of IIoT, facilitating essential connectivity for seamless communication and real-time data exchange among devices, sensors, and systems.

The government's responsibility in ensuring widespread and dependable connectivity holds critical importance for the agro-food processing industry. This commitment enables the seamless integration of IIoT applications across the entirety of the value chain, extending from farms and production facilities to distribution networks and retail outlets [120]. Additionally, governmental investment incentives for IIoT adoption in the agro-food processing industry can take various forms. These may include tax credits, subsidies, grants, and low-interest loans tailored to support businesses seeking to integrate IIoT technologies. These incentives are instrumental in offsetting some of the initial costs associated with implementing IIoT solutions, making it more financially viable for companies to embark on technological upgrades that enhance efficiency, sustainability, and overall operational effectiveness [97].

9. Research implication

This study yields implications of both theoretical and practical significance. Theoretical insights deepen our comprehension of underlying concepts, while practical implications offer actionable recommendations for real-world application. The subsequent details elucidate these implications.

9.1. Theoretical implications

This study makes a significant contribution to the existing literature on IIoT adoption in several ways. Firstly, it initiates the proposal of a comprehensive framework designed to identify barriers impeding the adoption of IIoT in manufacturing enterprises. This framework integrates TOE and HOT fit. Additionally, the study not only explores practical solutions and valuable insights to address these barriers but also focuses on enhancing the readiness degree for IIoT adoption. This is achieved through the utilization of the pragmatic strategies under THM, fostering university-industry-government cooperation. The THM not only establishes an innovation ecosystem but also ensures a synergistic approach vital for overcoming barriers and facilitating the widespread adoption of IIoT technologies in the manufacturing sector.

Secondly, a research gap is addressed, as there is a lack of studies on the adoption of IIoT within the agri-food processing industry in developing countries, including Thailand. This industry plays a crucial role not only in bolstering the national economy but also contributing to global food security. Thirdly, the study introduces a novel approach by integrating Delphi, SWARA, and COBRA under PFS, marking the first application of this hybrid MCDM technique. This innovative method enhances the precision of decision-making processes and adds a valuable dimension to the existing literature on IIoT adoption. Finally, the study's findings underscore the potential of the integrated framework to serve as a guide for future research endeavors among scholars and academicians across diverse industries beyond agri-food processing. This emphasizes its adaptability and relevance for a spectrum of broader applications.

9.2. Practical implications

The study imparts valuable insights for practitioners in the agro-food processing industry. The emphasis on enhancing readiness for IIoT adoption underscores the critical nature of collaboration within interconnected ecosystems. The research highlights the THM as a pragmatic strategic framework, emphasizing its significance in fostering partnerships among diverse stakeholders such as knowledge providers, industry experts, and regulatory bodies. This collaborative approach is essential for enhancing the industry's readiness to adopt IIoT. In the context of the agro-food processing industry, the study advocates for the THM, promoting university-industry-government cooperation. This collaborative framework ensures that the integration of IIoT aligns seamlessly with industry standards, regulations, and best practices. Consequently, it cultivates a cohesive and supportive environment, elevating the industry's readiness for IIoT adoption.

The study underscores the pivotal role of universities as key contributors to this collaborative ecosystem, providing essential knowledge, research, and bridging the gap between students and industry through practical experiences. Moving beyond industry practices, the study suggests a role for the government as a policy maker in advancing IIoT adoption. It recommends allocating resources and investments in the development of robust ICT infrastructure. A well-developed infrastructure serves as the backbone for seamless communication and data transfer, essential for the efficient functioning of IIoT applications in agro-food processing.

Additionally, government initiatives can incentivize private sector involvement through financial incentives, tax breaks, and research grants, encouraging companies in the agro-food processing sector to invest in and adopt IIoT technologies.

Furthermore, the study suggests the responsibility of the industry itself. Industry engagement is crucial, involving the dissemination of valuable lessons, successful case studies, and practical insights derived from hands-on experiences in real-world IIoT deployments. Sharing these experiences contributes to a collective knowledge pool, fostering a culture of learning and innovation within the industry, thereby accelerating the readiness to adoption of IIoT technologies.

10. Conclusion

The integration of IIoT has marked a crucial paradigm shift in the manufacturing industry. To sustain competitiveness, agility, and efficiency in today's industrial landscape, it is imperative for manufacturing enterprises to enhance their adoption of IIoT. This study proposes a framework designed to enhance the readiness for IIoT implementation in manufacturing enterprises. Employing a comprehensive literature review and the PF-Delphi method, this study identifies and validates eleven barriers within the integration of the TOE and HOT fit frameworks, utilizing a panel of experts. Pragmatic strategies to address these barriers are developed within the context of the THM, with a specific focus on the agro-food processing industry in Thailand as a case study.

The PF-SWARA approach is used to determine the subjective weights of the barriers, while the PF-MEREC method is employed to derive their objective weights. By integrating these two methods, the combined weights of IIoT adoption barriers are determined. The study identifies "Lack of digital culture," "Job displacement concerns," and "Loss of autonomy" as the three most critical barriers, with subjective importance weights of 0.138, 0.137, and 0.132, respectively.

Subsequently, through the application of PF-COBRA, THM strategies are prioritized, revealing "Enhancing capabilities of human capital," "Enabling national ICT infrastructures," and "Investment incentives" as the top three THC priorities. The study recommends that these three pragmatic strategies under THM take precedence in overcoming barriers hindering the adoption of IIoT in the agro-food processing industry in Thailand.

Additionally, various sensitivity analysis methods are conducted to scrutinize the robustness of these prioritizations. This includes altering the criteria weights, conducting comparative studies with other novel MCDM ranking methods, applying Spearman's coefficient and statistical significance tests, and comparing different types of fuzzy methods to validate the consistency and stability of the proposed framework.

The innovative value of this study can be evaluated from several perspectives:

- Proposed Framework: This study introduces an innovative decision framework model designed to advance IIoT adoption readiness specifically within the agro-food processing sector. It distinguishes itself from prior research in several notable ways. Firstly, it uniquely integrates the TOE framework with the HOT fit framework to comprehensively identify barriers to IIoT adoption. Secondly, this research pioneers the application of THM pragmatic strategies, focusing on fostering collaboration among key stakeholders (Government-University -Industry) to enhance IIoT adoption readiness. This approach not only addresses the technical and organizational aspects but also emphasizes the strategic importance of stakeholder synergy in overcoming adoption challenges.
- Methodological Approach: By integrating advanced fuzzy multi-criteria modeling techniques specifically DELPHI, SWARA, MEREC, and COBRA under PFS this study develops a novel model for prioritizing pragmatic strategies within the THM framework. This approach offers a novel contribution to the literature by uniquely combining these sophisticated techniques. It provides a distinctive analytical framework that enhances both the precision and relevance of strategic prioritization, distinguishing it from conventional models in the field.
- Sectoral importance: The IIoT is crucial for the agro-food processing industry, enhancing efficiency, productivity, and sustainability through real-time monitoring, advanced sensors, data analytics, and automation. It optimizes resource use, reduces waste, and improves traceability and quality control from farm to table. IIoT also enables predictive maintenance, minimizing downtime and extending equipment lifespan. Overall, IIoT adoption drives innovation, increases competitiveness, and strengthens the industry's contribution to the national economy.
- Practical Applicability: The findings of this study provide valuable insights for scholars and practitioners in the IIoT implementation field, highlighting the critical barriers to IIoT adoption in the agro-food processing sector and the prioritization of overcoming these barriers under THM pragmatic strategies. These insights can effectively guide policymakers, academics, and industry leaders in addressing the evolving needs within the sector. Furthermore, the study underlines the potential of the integrated framework to serve as a foundational guide for future research endeavors across diverse industries, demonstrating its adaptability and broad relevance beyond agro-food processing.

11. Suggestions for future research

This study suggests several key directions for future research into the IIoT. Firstly, a critical area for investigation is the economic and environmental impacts of IIoT adoption. Scholars should conduct comprehensive cost-benefit analyses, assess the return on investment, and evaluate the potential of IIoT to support sustainable manufacturing practices. Such research would provide practical guidelines for businesses, enabling them to justify their IIoT investments more effectively.

To gain a thorough understanding of the long-term effects of IIoT adoption, it is recommended that researchers consider employing a longitudinal study approach. This method would involve tracking the evolution of IIoT implementation over time and analyzing trends, challenges, and outcomes at different stages. Such an approach would offer a more comprehensive view of the technology's effectiveness and its contributions to sustainability.

Additionally, detailed case studies of successful IIoT implementations across various manufacturing settings can offer valuable insights. Researchers should systematically analyze these case studies to identify best practices and common pitfalls, thereby creating a roadmap that other enterprises can follow. These insights will be crucial for guiding future IIoT adoption efforts.

Furthermore, exploring the integration of IIoT with emerging technologies such as Artificial Intelligence (AI), Machine Learning (ML), and Blockchain is essential. Investigating these synergies could uncover new methods for enhancing manufacturing processes, advancing predictive maintenance, and improving data security. Such studies could reveal innovative approaches to leveraging IIoT in conjunction with other cutting-edge technologies.

Examining the role of policy and regulatory frameworks in IIoT adoption is vital. This involves analyzing existing regulations, identifying regulatory gaps, and proposing new policies to facilitate broader IIoT adoption while ensuring compliance with safety and privacy standards. Addressing these regulatory aspects will be crucial for fostering a supportive environment for IIoT implementation.

Regarding further research methodologies, the combination of subjective and objective weighting methods, such as BWM integrated with IDOCRIW, LBWA combined with LOPCOW, should be further examined. Exploring these hybrid methods can provide a more balanced and accurate assessment of factors influencing IIoT adoption. Additionally, various types of fuzzy aggregation operators, such as fuzzy Einstein, fuzzy Dombi, and fuzzy Aczel-Alsina, warrant further investigation. These operators can enhance the decision-making process by handling uncertainty and imprecision more effectively, leading to more robust and reliable IIoT adoption strategies.

Data availability

Data will be made available on request.

CRediT authorship contribution statement

Detcharat Sumrit: Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Data curation, Conceptualization, Formal analysis, Project administration, Validation, Visualization, Funding acquisition.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:Dr. Detcharat Sumrit reports article publishing charges was provided by Mahidol University. Dr. Detcharat Sumrit reports was provided by Mahidol University. Detcharat Sumrit reports a relationship with Mahidol University that includes: employment. No any a conflict of interest. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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