Prioritization of policy initiatives to overcome Industry 4.0 transformation barriers based on a Pythagorean fuzzy multi-criteria decision making approach

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Abstract: Industry 4.0 (hereafter I4.0) transformation in manufacturing sectors is considerably gaining a lot of attention from both researchers and practitioners. To increase the success rate of I4.0 transformation, manufacturers and policymakers need to understand barriers and how to overcome them. This paper proposes an analytical framework to prioritize the policy initiatives to overcome I4.0 transformation barriers, which have so far been ignored in previous studies. Since the prioritization of policy initiatives involves many evaluating criteria, multi-criteria decision-making (MCDM) is an effective method to evaluate and rank the best alternatives. Notwithstanding, the uncertainty is a major issue in any decision-making process. One of the latest emerging tools in dealing with the uncertainties is Pythagorean fuzzy set (PFS). The use of PFS allows experts with a larger domain to determine both membership and non-membership degrees. In this study, TODIM (an acronym in Portuguese for Interactive Multi-Criteria Decision-Making) under PFS is employed to prioritize policy initiatives to overcome I4.0 barriers. The proposed framework presented herein is illustrated by the case of Thai food processing.
industry. The results of this study can help the policymakers aiming to drive I4.0 transformation to implement the policy initiative in a prioritize manner. Although the present work is focused on the food processing industry, the proposed framework can be further applied to other similar industries.

Subjects: Industrial Engineering & Manufacturing; Manufacturing Engineering; Engineering Management

Keywords: Industry 4.0; barriers to industry 4.0; multi-criteria decision making; Pythagorean fuzzy set; TODIM

1. Introduction

1.1. Background

The emergence of the fourth industrial revolution described as Industry 4.0 (I4.0) is currently taking place and acting as an economic game-changer, which poses a significant challenge to entire industries. This causes the changes in the way the products are designed, manufactured, and delivered (Hofmann & Rüsch, 2017). The I4.0 concept was originally developed in Germany and later developed in other countries with advanced economies, including United States, Japan, France, South Korea, Taiwan, and Singapore. The advanced countries, like China and India, have also launched their industrial program policies related to I4.0 transformation. Similarly, Thailand needs to build a new era of I4.0 paradigm for a similar scheme to realize its aspiration. The I4.0 implementation can be viewed as end-to-end digital connection among physical assets and integration into digital ecosystems with value chain partners. This concept is based on cyber-physical system (CPS), enabling an interaction between the real and the virtual worlds along core value chain of manufacturing. It also allows firms to collect, transmit, and exchange a large amount of data between physical and cyber worlds (Bangemann et al., 2016). I4.0 and related technologies are being driven by disruptive innovation, which promises to bring innumerable new value creation opportunities over every main market. Taking advantage of I4.0 adoption should be significantly considered to improve business sustainability.

According to Y. Liao et al. (2017), the benefits of I4.0 adoption to manufacturers are vertical integration, horizontal integration, and end-to-end engineering. This high level of integration can provide greater efficiency, flexibility, and productivity. Also, it creates more agile and responsive supply chains across the whole value chain. Haddud et al. (2017) emphasized that I4.0 adoption is a complex process. It provided a myriad of competitive advantages and enabled supply chain process to improve productivity, flexibility and scalability (Hahn, 2020). This could shift economics and foster industrial growth.

Nevertheless, several manufacturing sectors across different countries have encountered the different obstacles. Recently, researchers have studied the driving forces and barriers to I4.0 adoption. Kamble et al. (2018) have studied the significant barriers to I4.0 adoption of Indian manufacturers and analyzed their inter-relationships. Horváth and Szabó (2019) explored both driving forces and main barriers of I4.0 adoption on SMEs and multinational enterprises in various industrial sectors. Raj et al. (2020) examined the cause and effect relationship among barriers to I4.0 adoption in the manufacturing sector in both developed and developing countries. In response to I4.0 challenges, the industrial policy initiatives made by state government should play a major role in fostering and accelerating manufacturers to I4.0 adoption (Schneider, 2018). Thereafter, industrial policies have been normally designed and implemented to take advantage of new technologies. The benefits of I4.0 depend on policymakers to respond to the relevant opportunities and challenges. There are also many challenges that are required to be resoved to improve I4.0 applicable (Xu et al., 2018). In this regard, government should encourage I4.0 innovation and implementation by creating an environment and effective
regulatory policies while obstacles in I4.0 adoption are removed. However, policy research on I4.0 is very rare and limited as it is still in the early stage development (Lee & Lee, 2015). Although previous researches have mainly made a remarkable contribution to analyzing the barriers to I4.0 adoption (Raj et al., 2020) and examining the driving forces and barrier of I4.0 (Kamble et al., 2018), however, few researches have focused on policies to overcome I4.0 barriers.

This study attempts to bridge the gap by proposing a framework to prioritization of policy initiatives to overcome Industry 4.0 transformation barriers. Thai food processing industry is used as a case study. To accomplish this, the following three research questions are addressed in this study:

RQ1. What are the key barriers in transforming into I4.0 and what are the significant policy initiatives to overcome them?

RQ2. How is the PFS application used to prioritize the policy initiatives to overcome I4.0 transformation barriers?

RQ3. What are the most important policy initiatives that help Thai food processing industry to overcome I4.0 transformation barriers?

1.2. **Motivation to use multi-criteria decision making (MCDM)**

The prioritization of policy initiatives to overcome I4.0 transformation barriers is an important strategic decision. Since it involves many evaluating criteria, the prioritization of these policies is a complex decision based on the experiences and knowledge of experts in the fields. MCDM is then the most widely used method to evaluate and rank the best alternatives with respect to criteria through data analysis (Ilbahar et al., 2018). However, the input data for MCDM rely on human judgment, which is often imprecise and vague. Hence, Fuzzy sets theory proposed by Zadeh (1965), as an effective approach, is used to deal with uncertainty and ambiguity in decision-making processes. This is the motivation that the present paper proposes MCDM under a fuzzy condition as an analysis framework.

Throughout the years, MCDM techniques have been progressively developed to help academicians and practitioners to solve numerous real-world problems. Atanassov (1986) introduced the Instinctive Fuzzy Set (IFS) to be more effective in resolving MCDM under uncertain circumstances. IFS utilizes a membership degree and a non-membership degree with the sum between such two degrees less than or equal to 1. IFS significantly provides the ability to evaluate information by taking consideration of both positive and negative views, simultaneously. Yager (2014) pioneered the concept of Pythagorean fuzzy sets (PFSs) to portray the uncertainty in the decision-making process. PFS allows a sum of a membership degree and a non-membership degree to be more than 1, but the sum of squares between such two degrees is less than or equal to 1. This caused PFS to be more flexible than IFS. PFS can solve some types of problems, while IFS cannot. For instance, if a decision maker gives the membership degree and the non-membership degree to be 0.7 and 0.4, respectively, then it cannot be handled by IFS (since 0.7 +0.5 >1). On the other hand, PFS is able to cope with such a situation, since \((0.7)^2 + (0.5)^2 \leq 1\). PFS seems to be superior to IFS, as it can accommodate higher degrees of uncertainties. Recently, numerous studies have utilized PFS to solve many different decision-making problems such as ranking the performance outcomes of circular supply chain (Lahane & Kant, 2021), prioritizing risks in self-driving vehicles (Bakioglu & Atahan, 2021), assessing the medical waste treatment technology (Liu et al., 2021), evaluating the enablers of sustainable supply chain innovation (Shete et al., 2020), evaluating internet banking website quality (Liang et al., 2019), and evaluating renewable energy
technologies (Rani et al., 2019). Therefore, PFS is used in this study in order to cope with the uncertainty issue.

In addition, literature reports that MCDM has several popular ranking techniques, including VIKOR, PROMETHEE, ELECTRE and TOPSIS and TODIM. The different methods have their own characteristics as shown in Table 1. According to Table 1, as compared to others, TODIM is very simple to use. It takes much less time to calculate and has good stability. It is also the only technique that takes into account the psychological behavior and risk attitude of decision makers. In this study, the different decision makers have diverse attitudes towards policy initiatives (alternatives), which can affect the final result. Hence, the risk attitudes of decision makers should be considered in the analysis process. Therefore, TODIM is an appropriate ranking method in this study.

1.3. Contributions of this study
The primary contributions of this study can be summarized as follows:

- Identifying the key barriers in transforming into I4.0, along with the significant policy initiatives to overcome these barriers through literature analysis and expert’s opinions, as existing researches on I4.0 policy level are still limited.
- Proposing a decision-making framework to prioritize policy initiatives to overcome I4.0 transformation barriers.
- Applying the conventional TODIM method under PFS to solve MCDM problems of prioritizing policy initiatives to overcome I4.0 transformation barriers. The use of PFS allows experts with a larger domain to determine both membership and non-membership degrees, while TODIM is able to address the psychological behavior and risk attitude of decision makers.
- Employing the proposed framework on a real case study of the Thai food processing industry. Managerial decisions are provided to guide the practitioners in implementing the initiative policies in a stepwise manner. Although the present work is carried out in the food processing industry, the proposed framework can be further applied to other similar industries.
- Conducting sensitivity analyses and making comparative study with another method reported in the literature to validate the proposed method.

The rest of the paper is organized as follows: Section 2 provides the literature on I4.0 and barriers to I4.0 transformation. Section 3 presents research methodology including Pythagorean
fuzzy sets, criteria weight determination, and Pythaorean fuzzy TODIM. The proposed research framework and results are shown in Section 4. Managerial implication is presented in Section 5. The sensitivity analysis and comparative analysis are displayed in Section 6 and Section 7, respectively. Conclusion is ended up in Section 8.

2. Literature review
This study conducted a review of relevant papers by selecting the articles from various academic databases including ScienceDirect, Taylor & Francis Group, Ebscohost, Emerald Insight, etc. Keywords used are “Industry 4.0 transformation”, “Smart factory”, “Industry 4.0 policy” and “Industry 4.0 with MCDM”. Then, the selected articles were reviewed through abstract and main concepts of the published works, including analysing their contributions for this study. The implementation of literature review is divided into three main parts. First, a brief overview of Industry 4.0 is presented in Section 2.1. Next, Industry 4.0 with fuzzy MCDM perspectives is presented in Section 2.2. Finally, the barriers to 4.0 transformation are reviewed in Section 2.3.

2.1. Industry 4.0
In 2011, the terminology of Industry 4.0 (I4.0) originated for the first time at the Hanover Fair. Subsequently, in 2013, German government used it as a strategic initiative for revolution of the manufacturing industry. The term I4.0 was first adopted in 2011, when a combination of representatives from the business, political, and educational institutions of Germany is present. This event is to support the German manufacturing industry getting more competition (Hahn, 2020). In the concept of I4.0, it is important to adopt IoT and service into the production process and to embed systems, IoT, data integration, and new ICT-driven technological evolution (Xu et al., 2018). Based on the fast transformation, the use of internet communication between machines and human for smart products and services is immediately processed for adaptability, interconnectivity, efficiency, and ergonomics (Losi et al., 2014). I4.0 has recently been gaining attention due to many benefits for manufacturing organizations (Dalenogare et al., 2018). However, research on I4.0 is still in the early stages (Horváth & Szabó, 2019). Many scholars have reviewed literatures to extend to future researches.

Regarding I4.0 opportunities in logistics context, Hofmann and Rüsch (2017) argued that management had encountered the challenges of I4.0 adaptation since organizations might not perceive short-term financial returns after I4.0 implementation. Haddud et al. (2017) have expanded the concept of I4.0 from logistics to the supply chain. They analyzed the challenges and benefits that might occur from I4.0 integration into supply chain. The simultaneous integration of several technologies across the supply chain for I4.0 implementation has been highly essential. Despite facing obstacles, I4.0 implementation has been recently applied across various developed and developing countries. Many researchers attempt to study contexts related to this issue, for example, Li (2018) identified factors for technology drivers of I4.0 across the supply chain; Dalenogare et al. (2018) investigated the impact of technology I4.0 on Brazilian industries; Lee and Lee (2015) studied the challenges, applications, and investment of IoT for firms.

2.2. Industry 4.0 with fuzzy MCDM perspective
Recently, literature reported on the use of various fuzzy MCDM applications in the context of I4.0; such as Bakhtari et al. (2021) used the fuzzy analytic hierarchy process (FAHP) to evaluate I4.0 implementation. Shayanmehr et al. (2021) applied the fuzzy Delphi method (FDM) and Interval-valued fuzzy analytical hierarchy process (IVF-AHP) to analyze I4.0 enablers for cleaner production and circular economy in a developing country. Çalık (2021) combined Pythagorean fuzzy AHP (PFAHP) and Pythagorean fuzzy TOPSIS (PFTOPSIS) approach to select green supplier in the industry 4.0 era in the agricultural tools and machinery industry. Abdul-Hamid et al. (2020) applied FDM to study Impeding challenges on industry 4.0 in circular economy in palm oil industry in Malaysia. Kaya et al. (2020) employed AHP and TOPSIS under Interval valued intuitionistic fuzzy (IVIF) to create a road map for industry 4.0. Vinodh and Wankhede (2020) integrated fuzzy DEMATEL and
fuzzy CODAS to analyze workforce attributes pertaining to I4.0. The recent applications of fuzzy MCDM in I4.0 are summarized in Table 2.

### 2.3. Barriers to I4.0 transformation

In this section, main barriers to I4.0 transformation from extensive literature are presented. This study is based on the assumption that the organizations have no problems related to the operational issues such as production capabilities, supply chain operations and maintenances. The barriers discussed here are considered only in the business capabilities and resource-based perspective contexts as displayed in Table 3.

### 3. Research methodology

The research methodology contains three main sub-sections. The basic concept of Pythagorean fuzzy sets (PFSs) is presented in Section 3.1. Section 3.2 explains the step of criteria weight determination. Finally, the Pythagorean fuzzy TODIM procedure is illustrated in Section 3.3.

#### 3.1. Pythagorean fuzzy sets (PFSs)

Pythagorean fuzzy sets were introduced by Yager (2014) to fully capture uncertainty and imprecise and ambiguous information in decision-making process. The concept of PFSs was similar to Intuitionistic Fuzzy Sets (IFSs) in such a way that both IFSs and PFSs could be presented in the form of membership and non-membership function and hesitancy degree. Compared to IFSs, PFSs were more flexible and powerful in addressing uncertainty because PFSs allowed the sum of degrees of membership and non-membership values to be greater than 1, while sum of squares of both values did not exceed 1 (Peng & Selvachandran, 2017). Apparently, IFSs could not address such a circumstance.

A basic concept of PFSs consisted of four definitions, as follows (Zhang & Xu, 2014):

(1) Let $X$ be a finite nonempty set and $P$ is a PFS in $X$, then $P$ is presented as

$$P = \{x, P_\mu(x), P_\nu(x)\} | x \in X\}.$$  \hspace{1cm} (1)

where the function $\mu_P(x) : X \rightarrow [0, 1]$ shows the degree of membership and $\nu_P(x) : X \rightarrow [0, 1]$ represents the degree of non-membership of the element $x \in X$ to $P$, respectively. Also, the condition of

### Table 2. The recent applications of fuzzy MCDM in I4.0

| No. | Application of fuzzy MCDM | I4.0 area | References |
|-----|---------------------------|-----------|------------|
| 1   | FAHP                      | To evaluate I4.0 implementation. | Bakhtari et al. (2021) |
| 2   | FDM and IVFS-AHP          | To analyze I4.0 enablers for cleaner production and circular economy. | Shayganmehr et al. (2021) |
| 3   | PFAHP and PFTOPSIS        | To select green supplier in the industry 4.0 era. | Çalık (2021) |
| 4   | FDM                       | To study impeding challenges on industry 4.0 in circular economy. | Abdul-Hamid et al. (2020) |
| 5   | AHP and TOPSIS under IVIF | To create a road map for industry 4.0. | Kaya et al. (2020) |
| 6   | Fuzzy DEMATEL and Fuzzy CODAS | To analyze workforce attributes pertaining to I4.0 | Vinodh and Wankhede (2020) |
Since the cybersecurity is essential for CPS where a large amount of information flow is present, data exchanges of CPS via various devices and connected physical objects will make systems vulnerable to cyber-attack (Bruijn & Janssen, 2017). The cybersecurity treats have caused production downtimes, products destruction on damaged equipment and loss of financial and reputational security (Kamble et al., 2018). The fragmentation of security standards and initiatives is one of the key barriers to consider I4.0 adoption (Lee & Lee, 2015).
Table 3. (Continued)

| I4.0 transformation barriers | Description |
|------------------------------|-------------|
| Lack of digital business plan (B06) | Manufacturing firms operate in a highly uncertain business environment when transforming to I4.0 system (Hasselblatt et al., 2018). Frank et al. (2019) implied that manufacturers need to develop new digital business models to deal with the uncertainties. Without a proper digital business development, manufacturers are unable to generate revenues and profits and take advantages of I4.0 adoption. |
| Lack of knowledgeable workforces (B07) | I4.0 transformation requires both various technical and non-technical disciplines. IT and digital knowledge development of qualified staffs is important for organizations to I4.0 implementation. The qualified staff recruitments are difficult to acquire because digital skilled labors are valuable and rare assets in the workforce industry. |
| Organizational culture resistance to change (B08) | An increase in I4.0 automated production implementation will lead to a substantial reduction of employees. New sets of knowledge and skills of employees are essentially required under I4.0 circumstance. These changes caused employees to be afraid of unemployment and getting more resistant or against I4.0 (Haddud et al., 2017). The roles and tasks of employees will radically change when manufacturers shift to the I4.0 environment. Thus, employees seem to be hesitant to move out of their comfort zone (Vey et al., 2017). |
| Lack of data management system (B09) | One of the foundations for manufacturers to shift towards I4.0 is data quality management. A large amount of heterogeneous data from sensors and devices would be generated, interconnected, exchanged, analyzed and visualized along with internal and external boundaries of enterprises. Alharthi et al. (2017) stressed that enterprises are unable to fully realize I4.0 benefits if an effective data management system is lacking. |
| Lack of value-chain network integration (B10) | The successful implementation of I4.0 requires the establishment of value-chain network across the enterprises’ boundaries (Y. Liao et al., 2017). But most manufacturers encounter obstacles for both internal and external value-chain integration. Barriers among various departments are hindered to obtain vertical integration. The horizontal integration needs fostering trust, openness, and willingness to cooperate and implement compatible technologies with partners along value-chain (Breunig et al., 2016). |
| Lack of awareness and knowledge (B11) | The lack of I4.0 awareness is one of main obstacles among manufacturers. Several manufacturers consider the process of I4.0 adoption be complicated, expensive exercise and time-consume (Harváth & Szabó, 2019). Furthermore, the successful I4.0 adoption requires several new specific knowledge pertained to industrial automation, intelligent vertical and horizontal networking, data analytics, man-machine interaction, and software engineering (Breunig et al., 2016). The deficit knowledge undermined the capabilities of manufacturers for I4.0 adoption (Kamble et al., 2018). |

(Continued)
Several applications and supporting technologies to I4.0 are under developing with their own proprietary technologies. These different proprietary standards and platforms made it difficult to implement, to connect and to exchange data throughout supply chains (Horváth & Szabo, 2019). In 2017, British Standards Online (BSOL) introduced the I4.0 architecture as and international standard platform. It is essential that the organizations develop their capabilities to be able to adopt the existing standards and reference platform.

| I4.0 transformation barriers | Description |
|------------------------------|-------------|
| Lack of capability to adopt standards and reference platform (B12) | Several applications and supporting technologies to I4.0 are under developing with their own proprietary technologies. These different proprietary standards and platforms made it difficult to implement, to connect and to exchange data throughout supply chains (Horváth & Szabo, 2019). In 2017, British Standards Online (BSOL) introduced the I4.0 architecture as and international standard platform. It is essential that the organizations develop their capabilities to be able to adopt the existing standards and reference platform. |

\[
0 \leq (\mu_p(x))^2 + (\nu_p(x))^2 \leq 1 \text{ is satisfied. For any PFS, } P \text{ and } x \in X, \text{ the degree of indeterminacy of } x \text{ to } P \text{ is defined as } \pi_p(x) = \sqrt{1 - (\mu^2_p(x))^2 - (\nu^2_p(x))^2}. \text{The pair } P(\mu_p(x), \nu_p(x)) \text{ is determined as a Pythagorean Fuzzy Number (PFN), denoted by } A_\pi = P(\mu_\pi, \nu_\pi) \text{ where } \mu_\pi, \nu_\pi \in [0, 1], \pi_\pi = \sqrt{1 - (\mu_\pi)^2 - (\nu_\pi)^2} \text{and } (\mu_\pi)^2 + (\nu_\pi)^2 \leq 1. \text{ The small value of } \pi_\pi \text{ implies that knowledge on } A \text{ is more confident.} |
\]

(2) Let \( A = P(\mu_a, \nu_a) \) and \( B = P(\mu_p, \nu_p) \) be two PFNs, and \( \lambda > 0 \); then, operations on these two PFNs are as follows:

\[
A \oplus B = P(\mu_a^2 + \mu_p^2 - \mu_a^2 \mu_p^2, \nu_a^2 \nu_p^2) 
\]  
\[
A \odot B = P(\mu_a \mu_p, \sqrt{\nu_a^2 + \nu_p^2 - \nu_a^2 \nu_p^2}) 
\]  
\[
\lambda A = P(\sqrt{1 - (\mu_a^2)^2}, \nu_a^2), \lambda > 0. 
\]  
\[
A^\lambda = P(\mu_a^4, \sqrt{1 - (\nu_a^2)^2}), \lambda > 0. 
\]

(3) Let \( A = P(\mu_a, \nu_a) \) be a PFN. The score function of \( A \) is as follows:

\[
s(A) = (\mu_a)^2 - (\nu_a)^2. \]

where \( -1 \leq s(A) \leq 1 \), to compare indispensabiliy of two PFNs; the larger the score value is, the better the PFN is.

(4) Let \( A = P(\mu_a, \nu_a) \) and \( B = P(\mu_p, \nu_p) \) be two PFNs. The distance between \( A \) and \( B \) is obtained as follows:

\[
d(A, B) = \frac{1}{2} \left( |(\mu_a)^2 - (\mu_p)^2| + |(\nu_a)^2 - (\nu_p)^2| + |(\pi_a)^2 - (\pi_p)^2| \right). \]


3.2. Criteria weight determination

3.2.1. Calculate the subjective weight \( (a_{ij}^s) \) for each criterion

**Step 1 Evaluate the significant degree of experts**

Let \( E_k = P(\mu_k, \nu_k, \pi_k) \) be a PFN of the evaluation of significant degree of the expert \( k^{th} \) based on his/her qualifications, and the relative importance weight of the \( k^{th} \) expert \( (A_k) \) is obtained as follows (Boran et al., 2009):

\[
\lambda_k = \left( \frac{\mu_k^2 + \nu_k^2 (\frac{\mu_k^2}{\nu_k^2} + \frac{\nu_k^2}{\mu_k^2})}{\sum_{k=1}^{\lambda} (\mu_k^2 + \nu_k^2 (\frac{\mu_k^2}{\nu_k^2} + \frac{\nu_k^2}{\mu_k^2}))} \right), k = 1, 2, \ldots, l. \tag{8}
\]

**Step 2 Aggregate the preference weights of experts**

Let \( a_{ijk}^s = (P_{jk}) \) be the preference weight value given by the \( k^{th} \) expert, where \( P_{jk} = (\mu_{jk}, \nu_{jk}), k = 1, 2, \ldots, l \) is a PFN. Each aggregated preference weight \( (a_{ij}^s) \) of criterion is calculated as follows:

\[
a_{ij}^s = \left[ 1 - \prod_{k=1}^{l} (1 - \mu_{jk}^s)^{\lambda_k} \right] \prod_{k=1}^{l} (\nu_{jk}^s)^{\lambda_k}. \tag{9}
\]

Here, \( a_{ij}^s = (\mu_{jk}, \nu_{jk}) \) is a PFN.

**Step 3 Calculate the crisp aggregated preference weight of each criterion**

Each \( \tilde{a}_{ij}^s = (\mu_{jk}, \nu_{jk}) \) is converted to crisp aggregated preference weight for each criterion \( \tilde{a}_{ij}^s \) as follows (Rani et al., 2019):

\[
\hat{a}_{ij}^s = \frac{1}{2} ((\mu_{jk})^2 - (\nu_{jk})^2 + 1). \tag{10}
\]

**Step 4 Obtain the final subjective weights of each criterion**

By normalizing the crisp aggregated preference weight of each criterion, the final subjective weight denoted as \( a_{ij}^s \) can be obtained as

\[
a_{ij}^s = \frac{\hat{a}_{ij}^s}{\sum_{j=1}^{l} \hat{a}_{ij}^s}. \tag{11}
\]

3.2.2. Calculate the objective weight \( (a_{ij}^o) \) for each criterion

**Step 1 Establish the Pythagorean fuzzy decision matrix \( Z \)**

Let \( A = \{A_i | i \in M \} \) be a finite set of alternatives, \( C = \{C_j | j \in N \} \) be a set of criterion and \( E = \{E_k | k \in L \} \) be a set of experts. The evaluation score of the alternative \( A_i \) with respect to criterion \( C_j \) by the expert \( k^{th} \) is expressed in terms of a PFN as \( z_{ij}^k = P\left(\mu_i^k, \nu_i^k\right) \). Then, the Pythagorean fuzzy (PF) decision
matrix is constructed as \( Z^k = (z^k_{ij})_{mn} \), where \( \mu^k_i \) and \( \nu^k_i \) denote the \( k \)th expert evaluating the degree that \( A_i \) is satisfied and dissatisfied by \( C_j \), respectively. The PF decision matrix is as follows:

\[
\begin{pmatrix}
0 & C_1 & \ldots & C_n \\
A_1 & P(\mu_{11}^k, \nu_{11}^k) & \ldots & P(\mu_{1n}^k, \nu_{1n}^k) \\
\vdots & \vdots & \ddots & \vdots \\
A_m & P(\mu_{m1}^k, \nu_{m1}^k) & \ldots & P(\mu_{mn}^k, \nu_{mn}^k)
\end{pmatrix}
\]  \hspace{1cm} (12)

**Step 2 Construct the group aggregate PFS-decision matrix \( R \)**

To construct the aggregate PFS-decision matrix denoted as \( R = (r_{ij})_{mn} \), all individual PF decision matrices \( Z^k \) are aggregated into one group based on the significant degree of experts. Each element in the aggregated PFS decision matrix is calculated by applying the Pythagorean Fuzzy Weighted Averaging Operator (PFWAO) developed by Yager (2014), as follows:

\[
r_{ij} = PF\text{FWAO}(z^{(1)}_{ij}, z^{(2)}_{ij}, \ldots, z^{(m)}_{ij}) = \left(1 - \frac{1}{\sum_{k=1}^{m} (1 - \mu^k_{ij})^2 + \sum_{k=1}^{m} (\nu^k_{ij})^2}\right),
\]  \hspace{1cm} (13)

where \( \lambda_k \) is the relative importance weight of the expert \( k \)th.

**Step 3 Determine the normalized PF decision matrix \( V \)**

Based on the aggregated PFS-decision matrix \( R \), the normalized PF decision matrix denoted as \( V = (v_{ij})_{mn} \) is computed as

\[
v_{ij} = \begin{cases} v_{ij} & \text{for the benefit criterion} \\ (v_{ij})^c & \text{for the cost criterion}, \end{cases}
\]  \hspace{1cm} (14)

where \((v_{ij})^c\) is the complement of \( v_{ij} \). For \((v_{ij})^c = P(v_{ij}, \mu_{ij})\), \( i = 1, 2, \ldots, m; j = 1, 2, \ldots, n \).

**Step 4 Compute the PFS entropy measurement for each criterion**

By exploiting the entropy measure method theory (Dharmarajan, 2017), the entropy of PFS denoted as \( e_j \) is computed as

\[
e_j = -\frac{1}{\ln 2} \sum_{i=1}^{m} \mu^k_{ij} \ln(\mu^k_{ij}) + \nu^k_{ij} \ln(\nu^k_{ij}) - (1 - \mu^k_{ij}) \ln(1 - \mu^k_{ij}) - \sigma^k_{ij} \ln 2,
\]  \hspace{1cm} (15)

where \( 0 \leq e_j \leq 1 \).

**Step 5 Compute the divergence value \( (d_j) \)**

The divergence value \( (d_j) \) is computed through Eq. (16). The larger the divergence value is, the more relatively important the criterion is,

\[
d_j = 1 - e_j, j = 1, 2, \ldots, n.
\]  \hspace{1cm} (16)
Step 6 Obtain the normalized $d_j$

The objective weight $\omega_j^o$ is obtained as below:

$$\omega_j^o = \frac{d_j}{\sum_{j=1}^{n} d_j}, \quad j = 1, 2, \ldots, n.$$  

(17)

3.2.3. Compute the combination weight of each criterion $w_j$

The objective weight ($\omega_j^o$) and subjective weight ($\omega_j^s$) are combined as follows:

$$w_j = \gamma \omega_j^s + (1 - \gamma) \omega_j^o.$$  

(18)

where $\gamma$ is the combined decision mechanism coefficient and $\gamma \in [0, 1]$. without loss of generality, here is 0.5.

3.3. Pythagorean fuzzy TODIM

The TODIM approach was introduced by Gomes and Lima (1992) to solve MCDM. The concept of TODIM was developed under prospect theory (Tversky & Kahneman, 1992) by taking into consideration human's psychological behavior under risk and uncertainty. To portray the complex decision-making problems including uncertainty, vagueness and ambiguity, TODIM has been extended to fuzzy information (Wang et al., 2018). The PFS TODIM procedure is as follows:

Step 1 Select the reference criterion

Based on the weights of criteria $w_j = (w_1, w_2, \ldots, w_n)^T$, the criterion with the largest weight is selected as reference criterion denoted as $w_r$.

$$w_r = \max \{w_j | j = 1, 2, n\}.$$  

(19)

Step 2 Calculate the relative weight ratio

The relative weight ratio for each criterion ($w_j$) is as follows:

$$w_{j}^{r} = \frac{w_j}{w_r}.$$  

(20)

where $w_j$ is the weight of the criterion $C_j$ and $0 \leq w_j \leq 1, \quad (j = 1, 2, \ldots, n)$.

Step 3 Construct the PF dominance matrix of alternative $A_i$ over alternative $A_j$

Let $A = \{A_i | i \in M\}$ be a finite set of alternatives and $C = \{C_j | j \in N\}$ be a set of criteria, the PF dominance matrix of $A_i$ over $A_j$ with respect to criterion $C_j$ is defined as $\phi_{ij} = [\phi_{ij}(A_i, A_j)]_{m \times m}$ as shown below:

$$\phi_{ij} = \begin{bmatrix} A_1 & A_2 & \cdots & A_m \\ 0 & \phi_j(A_1, A_2) & \cdots & \phi_j(A_1, A_m) \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \phi_j(A_m, A_2) & \cdots & 0 \end{bmatrix}_{m \times m}$$  

(21)
where the dominance degree of alternatives for each criterion is computed as:

$$
\phi_j(A_i, A_k) = \begin{cases} 
\frac{1}{\lambda} \sqrt{\frac{\sum_{j=1}^{n} w_j d(A_i, A_k)}{\sum_{j=1}^{n} w_j}}, & \text{if score}(A_i) > \text{score}(A_k) \\
\frac{1}{\lambda} \sqrt{\frac{\sum_{j=1}^{n} w_j d(A_k, A_i)}{\sum_{j=1}^{n} w_j}}, & \text{if score}(A_i) = \text{score}(A_k) \\
0, & \text{if score}(A_i) < \text{score}(A_k)
\end{cases} \tag{22}
$$

Here, the parameter $\theta$ represents the attenuation factor of the losses. The smaller the $\theta$ is, the better the loss aversion is. The distance measurement of $d(A_j, A_k)$ is as follows:

$$
d(A_j, A_k) = \frac{1}{2} \left| (\mu_{A_j})^2 - (\mu_{A_k})^2 \right| + \left| (\nu_{A_j})^2 - (\nu_{A_k})^2 \right| + \left| (\sigma_{A_j})^2 - (\sigma_{A_k})^2 \right|. \tag{23}
$$

**Step 4 Determine total dominance of the alternative concerning other alternatives**

Total dominance of alternative $(A_i)$ compared to other alternatives $(A_t)$, $(t = 1, 2, \ldots, m)$ respect to criterion $(C_j)$ is determined as follows:

$$
\delta_j(A_i) = \sum_{t=1}^{m} \phi_j(A_i, A_t). \tag{24}
$$

Under criterion $(C_j)$, total dominance for all alternatives can be expressed as below:

$$
\begin{bmatrix}
A_1 \\
A_2 \\
\vdots \\
A_m
\end{bmatrix}
\begin{bmatrix}
\sum_{t=1}^{m} \phi_j(A_1, A_t) \\
\sum_{t=1}^{m} \phi_j(A_2, A_t) \\
\vdots \\
\sum_{t=1}^{m} \phi_j(A_m, A_t)
\end{bmatrix}
\tag{25}
$$

By considering a set of $n$ criteria, total dominance matrix $D = [d_{ij}]_{m \times n}$ is as below:

$$
D = [d_{ij}]_{m \times n} = 
\begin{bmatrix}
\sum_{t=1}^{m} \phi_j(A_1, A_t) & \sum_{t=1}^{m} \phi_j(A_1, A_t) & \cdots & \sum_{t=1}^{m} \phi_j(A_1, A_t) \\
\sum_{t=1}^{m} \phi_j(A_2, A_t) & \sum_{t=1}^{m} \phi_j(A_2, A_t) & \cdots & \sum_{t=1}^{m} \phi_j(A_2, A_t) \\
\vdots & \vdots & \ddots & \vdots \\
\sum_{t=1}^{m} \phi_j(A_m, A_t) & \sum_{t=1}^{m} \phi_j(A_m, A_t) & \cdots & \sum_{t=1}^{m} \phi_j(A_m, A_t)
\end{bmatrix}
\tag{26}
$$

**Step 5 Calculate the global prospect value ($\xi$) and rank the policy initiatives**

The global prospect value of the alternative ($\xi_j$) is calculated as follows:

$$
\xi_j = \frac{\sum \delta_j(A_i, A_i) - \min \sum \delta_j(A_i, A_i)}{\max \sum \delta_j(A_i, A_i) - \min \sum \delta_j(A_i, A_i)}. \tag{27}
$$
The ranking order of alternatives determines the global prospect value \( \xi \); the larger the \( \xi \) is, the better the alternative is.

4. Proposed research framework

This study proposes a six-phase MCDM framework to prioritize policy initiatives to overcome I4.0 barriers as illustrated in Figure 1. Phase I, extraction and validation of I4.0 transformation barriers is presented through an extensive literature review and experts' discussion. Phase II, the associated policy initiatives to overcome I4.0 barriers are identified. Phase III, the decision model to overcome barriers in I4.0 adoption is developed by using the outcomes from two previous phases. Phase IV, the rating of experts' relative importance weights is defined. Phase V, the relative importance weights of barriers are determined. Finally, the policy initiatives to overcome I4.0 barriers are prioritized in Phase VI.
Table 4. Policy initiatives to overcome I4.0 barrier transformation

| Policy                                                      | Description                                                                                                                                                                                                                                                                                                                                 |
|-------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Strengthening establishment of standards and reference architectures (A1) | According to Kamble et al. (2018), there are great diversities of I4.0 standards and reference architectures, which cause obstacles to enable smooth or seamless digital flows of manufacturing and supply chains. The wide development and implementation of standards and reference architecture are essential as they provide the fundamental interoperability and an increase in economies of scale (Haddud et al., 2017). This should also be flexible to support I4.0 applications in the future. In addition, the establishment of standards and reference architectures should be transparent, led by industry, consensus-based and global connection (Lee, 2019). |
| Enabling national ICT infrastructures (A2)                  | ICT infrastructure is a prerequisite to support I4.0 adoption (Kim, 2018). I4.0 requires the availability of ubiquitous broadband connectivity, bandwidth spectrum, wireless network connectivity and internet speed to connect the devices, transfer and exchange data (Chatfield & Reddick, 2019). ICT infrastructure is essential for industrial firms to gain benefits from I4.0 applications (Kim, 2018). Government should play a key role in promoting infrastructure investment of supply chain and manufacturing (Castelo-Branco et al., 2019). |
| Developing national cybersecurity frameworks (A3)            | Governments should play a leading role in recognizing secured I4.0 technology adoption (Lee, 2019). The regulations and cybersecurity policies, which are properly initiated and implemented, can bring the effective results to I4.0 securities (Brujin & Janssen, 2017). The I4.0 security rules should clearly define the responsibilities and accountabilities for cybersecurity solutions in order to prevent concerns of I4.0 vulnerabilities (Srinivas et al., 2019). |
| Enhancing capabilities of human capital (A4)                | Human capital readiness is essential to accelerate I4.0 adoption. The preparation of qualified and skilled workforces must be equipped with up-to-date digital skills. I4.0 adoption needs a variety of skill sets and technical professions such as entrepreneurs, programmers, robots, data miners, and researchers. Governments should help firms to improve staffs’ knowledge, skills and educations at all levelworkers. Also, the strong collaboration among government, industry, and educational institutions is required to improve staffs’ skills toward I4.0 (Ryan & Watson, 2017). |
| Promoting awareness campaigns and programs (A5)             | Most industries have not been recognized how I4.0 will affect their business’ opportunities. A greater understanding of I4.0 is so important for industrial operators to make decisions on investment and I4.0 adoption (Clausen & Rasmussen, 2015). Government also plays a crucial role in actively increasing campaigns to urge knowledge transfer to enhance benefits and chances for I4.0 technological transformation (Schneider, 2018). |

(Continued)
4.1. Problem description

Thailand has been designated as “Kitchen of the World” due to its various biodiversity and natural agricultural products. Moreover, it is recognized as a strategic center for food production in both Asia and around the world. The country is also a main producer and exporter for food processing, canned tuna, frozen seafood, shrimp, and chicken. Food processing industry in Thailand provides large contributions to nation’s economic benefits, accounting for 23% of country’s GDP. The government also promotes a global food innovation center to support R&D and innovation, known as Food Innopolis. Then, government stimulates Thai enterprises to adopt the advanced manufacturing technologies enabled by connectivity, robotics, IoT, and data integration. Although three are approximately 9,000 food processing operators in Thailand, most of them are sluggish to accept automation and digitalization. Only a few food processing firms are ready to transform toward I4.0. Due to time and resource limitations, it is necessary to investigate the prioritization of relevant barriers and their policy-related solutions to increase I4.0 transformation rate. In such a case, all stakeholders should concentrate to rank barriers and advanced policy initiatives to be implemented step by step.

4.2. Result

**Phase 1: Extract and validate I4.0 transformation barriers**

Twelve I4.0 transformation barriers were extracted through comprehensive literature review, shown in Table 1. A qualified panel of six experts is invited for workshop participation. They are one academician, one director of National Industrial Promotion Agency, one head department of National Science Technology and the Innovation Policy Office and three remaining executive officers from different leading enterprises in Thai food processing industry. Based on experts’ discussions and consensus, such twelve barriers from literature reviews are recognized to be applicable for Thai food processing industry. These barriers are also validated and confirmed to appropriately apply in this research.
**Phase II: Identify and confirm the policies overcoming barriers**

According to Thailand’s 20-Year National Strategy, it is considered that most policies related to I4.0 adoption are initiative conceptually and widely addressed as guidelines. The fact that such policies may not be directed and cascaded to comprehensive strategies is taken into consideration, especially for the food processing industry. After exploring literature review, the six policy initiatives are identified and validated by experts, i.e. Strengthening establishment of standards and reference architectures ($A_1$), Enabling national ICT Infrastructures ($A_2$), Developing national cybersecurity frameworks ($A_3$), Enhance capabilities of human capital ($A_4$), Promote awareness campaigns and programs ($A_5$), Financial instruments ($A_6$), and Cultivate the collaboration, and best practices sharing ($A_7$).
Developing national cybersecurity frameworks (\(A_2\)), Enhancing capabilities of human capital (\(A_4\)), Promoting awareness campaigns and programs (\(A_5\)), and Financial instrument (\(A_6\)). Another one is added by experts, i.e. Cultivating the collaboration and best practices sharing (\(A_7\)). Their descriptions are presented in Table 4.

**Phase III: Develop a decision model to overcome barriers for 4.0 adoption**

The results for barriers and policy initiative were used to develop the decision model, as displayed in Figure 2.

**Phase IV: Rate the experts' relative importance weights**
| Barrier code | E1  | E2  | E3  | E4  | E5  | E6  | Aggregated experts preference | Crisp subjective weight | Final subject weight (ωs) |
|-------------|-----|-----|-----|-----|-----|-----|-------------------------------|-------------------------|--------------------------|
| B01         | ML  | H   | H   | MH  | MH  | H   | P(0.702, 0.030)               | 2.804                   | 0.0812                   |
| B02         | H   | MH  | MH  | A   | A   | MH  | P(0.663, 0.338)               | 2.650                   | 0.0768                   |
| B03         | H   | H   | VH  | H   | H   | VH  | P(0.804, 0.197)               | 3.214                   | 0.0931                   |
| B04         | A   | A   | ML  | ML  | A   | A   | P(0.608, 0.398)               | 2.423                   | 0.0713                   |
| B05         | VH  | VH  | H   | VH  | VH  | MH  | P(0.796, 0.036)               | 3.183                   | 0.0922                   |
| B06         | H   | H   | H   | A   | MH  | H   | P(0.732, 0.268)               | 2.929                   | 0.0849                   |
| B07         | H   | H   | MH  | MH  | H   | MH  | P(0.732, 0.302)               | 2.890                   | 0.0837                   |
| B08         | H   | MH  | MH  | A   | H   | MH  | P(0.675, 0.326)               | 2.697                   | 0.0782                   |
| B09         | H   | H   | MH  | A   | H   | MH  | P(0.698, 0.303)               | 2.792                   | 0.0809                   |
| B10         | MH  | H   | H   | MH  | MH  | H   | P(0.723, 0.278)               | 2.891                   | 0.0839                   |
| B11         | MH  | H   | H   | MH  | MH  | MH  | P(0.723, 0.278)               | 2.891                   | 0.0811                   |
| B12         | VH  | H   | VH  | H   | H   | VH  | P(0.800, 0.202)               | 3.200                   | 0.0927                   |
|   | B01 | B02 | B03 | B04 | B05 | B06 |
|---|-----|-----|-----|-----|-----|-----|
| A1 | 0.561 | 0.562 | 0.471 | 0.252 | 0.880 | 0.411 | 0.690 | 0.561 | 0.562 | 0.628 | 0.454 |
| A2 | 0.378 | 0.315 | 0.309 | 0.834 | 0.557 | 0.516 | 0.581 | 0.567 | 0.742 | 0.383 |
| A3 | 0.381 | 0.816 | 0.576 | 0.524 | 0.469 | 0.622 | 0.300 | 0.918 | 0.291 | 0.931 | 0.439 | 0.661 |
| A4 | 0.416 | 0.669 | 0.773 | 0.350 | 0.422 | 0.678 | 0.482 | 0.590 | 0.259 | 0.953 | 0.444 | 0.649 |
| A5 | 0.446 | 0.617 | 0.432 | 0.668 | 0.387 | 0.778 | 0.428 | 0.651 | 0.491 | 0.594 | 0.683 | 0.572 |
| A6 | 0.272 | 0.945 | 0.383 | 0.775 | 0.427 | 0.674 | 0.666 | 0.429 | 0.731 | 0.387 | 0.647 | 0.628 |
| A7 | 0.610 | 0.482 | 0.614 | 0.504 | 0.583 | 0.492 | 0.504 | 0.575 | 0.421 | 0.680 | 0.416 | 0.685 |
| B07 | 0.603 | 0.486 | 0.608 | 0.540 | 0.755 | 0.366 | 0.533 | 0.653 | 0.650 | 0.480 | 0.389 | 0.750 |
| B08 | 0.628 | 0.522 | 0.812 | 0.082 | 0.733 | 0.373 | 0.400 | 0.700 | 0.762 | 0.355 | 0.465 | 0.623 |
| B09 | 0.515 | 0.555 | 0.400 | 0.260 | 0.466 | 0.621 | 0.422 | 0.678 | 0.520 | 0.589 | 0.665 | 0.430 |
| B10 | 0.291 | 0.931 | 0.400 | 0.260 | 0.366 | 0.831 | 0.461 | 0.608 | 0.688 | 0.421 | 0.708 | 0.407 |
| B11 | 0.799 | 0.338 | 0.659 | 0.260 | 0.545 | 0.542 | 0.471 | 0.617 | 0.574 | 0.543 | 0.491 | 0.594 |
| B12 | 0.815 | 0.390 | 0.822 | 0.120 | 0.754 | 0.420 | 0.606 | 0.507 | 0.721 | 0.392 | 0.798 | 0.366 |
| B0 | 0.445 | 0.656 | 0.405 | 0.236 | 0.421 | 0.680 | 0.383 | 0.775 | 0.433 | 0.668 | 0.481 | 0.609 |
Each expert defines the ratings of relative importance weight based on his/her experiences and knowledge on 14.0 contexts. The relative importance weight process is evaluated by using linguistic variables, as presented in Table 5. Linguistic variables are then converted to corresponding PFNs and computed using Eq. (8). The relative importance weights of six experts (j) are depicted in Table 6.

**Phase V: Determine the relative importance weights of barriers**

This study integrates both subjective and objective approaches to determine the relative importance weights of barriers. The subjective method can deliver the preference and risk attitude of experts in the decision-making process, but it fails to capture the objective information. Although the objective approach can enhance reliability of experts' judgment, the objective approach also ignores the preference of experts into consideration. The process of relative importance weights is calculated as follows:

**Step 1 Calculate the subjective weights (ω^s_j) for each barrier**

According to Table 7, the group of experts expressed their preferences toward the important weight of each barrier by using linguistic terms. Then, the linguistic terms were converted to corresponding PFNs. Based on the rating results of experts' relative importance weights in Phase IV, the aggregation of experts' preference of each barrier was calculated using Eq. (9). Next, each aggregated value of each barrier was converted to crisp subjective weight by using Eq. (10). Then, the final subject weight (ω^s_j) was calculated by using Eq. (11). The calculation results of subjective weights are ω^s_j = (0.0812, 0.0768, 0.0931, 0.0713, 0.0922, 0.0849, 0.0837, 0.0782, 0.0809, 0.0839, 0.0811, 0.0927), as presented in Table 8.

**Step 2 Calculate the objective weights (ω^o_j) for each barrier**

Each expert provided his/her assessment, regarding the impact of policy initiatives, with respect to transformation barriers in linguistic terms by using Table 7. Hereafter, the linguistic terms were converted to their corresponding PFNs. A decision matrix in PFS of each expert was constructed by using Eq. (12). A group of aggregated PFS decision matrices was computed by using Eq. (13). Then, this aggregated PFS decision matrix was normalized by Eq. (14) to ensure the comparability amongst barriers criteria, as shown in Table 9. Then, the entropy-based PFS approach was applied to compound the objective weights (ω^o_j) by utilizing Eqs. (15)-(17), giving ω^o_j = (0.0827, 0.0830, 0.0846, 0.0841, 0.0800, 0.0861, 0.0816, 0.0794, 0.0829, 0.0858, 0.0852, 0.0845), as shown in Table 9.

**Step 3 Calculate the integrated subjective and objective weights**

According to Table 7 and 10, the integrated subjective and objective weights were obtained by using Eq. (18). Without loss of generality, this study took γ = 0.5 in the calculation of the integrated subjective and objective weights. The results were w_j = (0.082, 0.079, 0.091, 0.074, 0.088, 0.084, 0.082, 0.079, 0.081, 0.084, 0.084, 0.090), as shown in Table 11.

**Phase VI: Prioritize the policy initiatives**

The PFS-based TODIM approach was deployed to prioritize the policy initiatives to overcome barriers as follows:

**Step 1 Select the reference barrier**
Table 10. The objective weights of barriers ($\omega_o$) derived by the entropy-based PFS approach

|     | B01   | B02   | B03   | B04   | B05   | B06   | B07   | B08   | B09   | B10   | B11   | B12   |
|-----|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| e   | -0.8554 | -0.8626 | -0.8992 | -0.8865 | -0.7948 | -0.9325 | -0.8317 | -0.7829 | -0.8611 | -0.9245 | -0.9128 | -0.8972 |
| d   | 1.8554 | 1.8626 | 1.8992 | 1.8865 | 1.7948 | 1.9325 | 1.8317 | 1.7829 | 1.8611 | 1.9245 | 1.9128 | 1.8972 |
| $\omega_o$ | 0.0827 | 0.0830 | 0.0846 | 0.0841 | 0.0800 | 0.0861 | 0.0816 | 0.0794 | 0.0829 | 0.0858 | 0.0852 | 0.0845 |
Based on Table 11 and Eq. (19), it is found that barrier B03 gained the highest important weight value of 0.091. Hence, it was selected as the reference barrier.

Step 2 Calculate the relative weight ratios

By using Eq. (20), the relative weight ratio for each barrier \((w_r)\) is shown in Table 12.

**Step 3 Obtain the PF dominance degree matrix of policy initiatives \(A_i\) over all others \(A_j\)**

According to the normalized PF decision matrix in Table 8, the dominance degree matrix of the policy initiatives \(A_i\) over each policy \(A_j\) with respect to the barrier \(j\)th, denoted \(\phi_j(A_i,A_j)\), was obtained using Eqs. (21)—(22). In this study, the attenuation factor of the losses \(\delta\) was assigned to 2.500 (Liang et al., 2019) and \(d(A_i,A_j)\) was computed using Eq. (23). The small example that how the dominant matrix under B01(\(\delta_i\)) is obtained is as follows:

\[
\phi_1 = \begin{bmatrix}
A_1 & A_2 & A_3 & A_4 & A_5 & A_6 & A_7 \\
A_1 & 0.000 & 0.166 & 0.157 & 0.106 & 0.091 & 0.203 & 0.078 \\
A_2 & 0.166 & 0.000 & 0.215 & 0.172 & 0.160 & 0.249 & 0.161 \\
A_3 & -0.770 & -1.054 & 0.000 & -0.518 & 0.580 & 0.104 & -0.727 \\
A_4 & -0.518 & -0.844 & 0.130 & 0.000 & -0.337 & 0.182 & -0.638 \\
A_5 & -0.455 & -0.783 & 0.146 & 0.069 & 0.000 & 0.194 & -0.564 \\
A_6 & -0.991 & -1.221 & -0.628 & -0.890 & -0.951 & 0.000 & -1.059 \\
A_7 & 0.078 & -0.789 & 0.175 & 0.130 & 0.115 & 0.216 & 0.000 
\end{bmatrix}
\]

**Step 4 Determine total dominance of each policy initiatives over others**

Total dominance degree of each policy initiatives is determined by Eqs. (24)—(26), as presented in matrix below:

\[
\delta_j(A_i) = \begin{bmatrix}
A_1 & A_2 & A_3 & A_4 & A_5 & A_6 & A_7 \\
A_1 & 0.000 & 0.520 & -0.584 & 0.226 & 0.239 & 0.666 & 0.390 \\
A_2 & -4.236 & 0.000 & -6.684 & -6.219 & -3.701 & -1.375 & -4.359 \\
A_3 & -1.610 & -0.243 & 0.000 & -1.893 & -0.281 & -0.018 & -1.545 \\
A_4 & -3.873 & -1.581 & -4.085 & 0.000 & -3.059 & -2.172 & -2.674 \\
A_5 & -1.729 & -0.864 & -5.613 & -4.149 & 0.000 & -1.414 & -3.915 \\
A_6 & -3.785 & -1.673 & -5.347 & -4.621 & -4.308 & 0.000 & -4.716 \\
A_7 & -2.422 & -1.265 & -3.187 & -3.463 & -1.550 & -1.310 & 0.000 
\end{bmatrix}
\]

**Step 5: Calculate the global prospect value \((\zeta)\) and rank the policy initiatives**

By using Eq. (27), the \(\zeta\) was calculated as shown in Table 13.

According to Table 13, all policy initiatives were prioritized according to global prospect values \((\zeta)\). The result indicates that \(A_1\) has the greatest global prospect value of 1.117, followed by \(A_3\) (0.834), \(A_7\) (0.529), \(A_4\) (0.358), \(A_5\) (0.349), \(A_6\) (0.077) and \(A_2\) (0.000).

5. Managerial implication

5.1. Role of manufacturing enterprises

Based on the relative importance weights shown in Table 11, the top three most important barriers to transformation are as follows: (i) lack of a strategic technology plan (B03), (ii) lack of standards and reference platform (B02), and (iii) cybersecurity issue (B05). Therefore, it is recommended for Thai food processing industry to pay more attention to solve their internal
problems and obstacles. First, lack of a strategic technology plan (B03) is the most important barrier to restrict I4.0 transformation. This finding is consistent with Raj et al. (2020) stating that the lack of digital strategies along with resource shortages was the most important barrier to adopt I4.0 by both Indian and France enterprises. Horváth and Szabó (2019) also supported that adoption in I4.0 cannot be achieved without a strategic technology plan. Y. Liao et al. (2017) emphasized that only a few manufacturers have sufficient knowledge to create a clear technology plan. The development of a digital strategy for I4.0 adoption seems to be difficult because it would depend on decisions made by top executives. To tackle with this barrier, Raj et al. (2020) recommended that top management should make a concrete plan and systematically transform their organizations to I4.0. This research suggests that top management should support commitment and strategic technology programs to ensure effective implementation.

Next, lack of capability to adopt standards and reference platform (B12) is the second most significant barrier to I4.0 transformation. This finding is in conformance with the studies of Raj et al. (2020) for investigation of Indian manufacturing enterprise cases. They defined that the lack of standards, regulations, and forms of certification was the most critical barrier among I4.0 non-adoption in Indian enterprises. Horváth and Szabó (2019) also elucidated that the fragmentation of standards and reference platform may affect inter-organizational interfacing as well as the interoperability of tools and systems inside manufacturing enterprises. To mitigate this barrier, Breunig et al. (2016) addressed that the standards and reference platform

| Table 11. The integrated subjective and objective weights ($w$) |
|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|
|                             | B01 | B02 | B03 | B04 | B05 | B06 | B07 | B08 | B09 | B10 | B11 | B12 |
| $w_j$                       | 0.0812 | 0.0768 | 0.0931 | 0.0711 | 0.0922 | 0.0849 | 0.0837 | 0.0782 | 0.0809 | 0.0839 | 0.0811 | 0.0927 |
| $w^s$                       | 0.0827 | 0.0830 | 0.0846 | 0.084 | 0.0880 | 0.0861 | 0.0816 | 0.0794 | 0.0829 | 0.0858 | 0.0852 | 0.0845 |
| $w_j = 0.5w^s + (1 - 0.5)w^o$ | 0.0819 | 0.0799 | 0.0889 | 0.0777 | 0.0861 | 0.0855 | 0.0827 | 0.0784 | 0.0819 | 0.0848 | 0.0832 | 0.0886 |
| Rank                        | 8     | 9    | 1    | 11   | 3    | 4    | 7    | 10   | 8    | 5   | 6   | 2   |

| Table 12. The relative weight ratio |
|-------------------------------------|
| B01 | B02 | B03 | B04 | B05 | B06 | B07 | B08 | B09 | B10 | B11 | B12 |
| $w_j$                  | 0.0819 | 0.0799 | 0.0889 | 0.0777 | 0.0861 | 0.0855 | 0.0827 | 0.0784 | 0.0819 | 0.0848 | 0.0832 |
| $w^o$                  | 0.0886 | 0.090 | 0.868 | 1.000 | 0.813 | 0.967 | 0.923 | 0.901 | 0.868 | 0.890 | |
| $0.923$                | 0.923 | 0.989 | |

| Table 13. Ranking results of policy initiatives in overcoming barriers |
|---------------------------------------------------------------|
| $A_1$  | $A_2$  | $A_3$  | $A_4$  | $A_5$  | $A_6$  | $A_7$  |
| $\zeta_i$ | 1.117 | 0.000 | 0.834 | 0.358 | 0.349 | 0.077 | 0.529 |
| Ranking  | 1     | 7     | 2     | 4     | 5     | 6     | 3     |


may be varied from industry to industry. Hence, the cooperation among cross-industrial sectors was required to establish qualification and to select the standards and reference platform of industry.

Finally, cybersecurity issue (BO5) posed the third most significant barrier to I4.0 transformation. This finding is supported by Lee and Lee (2015), stating that cybersecurity vulnerabilities are overwhelmingly perceived as the major drawback to the IoT wider adoption. The threats of cybersecurity and data ownership also involved in I4.0 adoption. Breunig et al. (2016) discussed that the manufacturing enterprises are hesitant to adopt I4.0 due to fear to lose their data to third-party software and service providers. To conquer such a barrier, Waslo et al. (2017) advised that the cybersecurity strategies need to be collaboratively initiated and fully integrated through the entire manufacturing value chain. Similar to the study of Corallo et al. (2020), it was emphasized that the cybersecurity standards and guidelines can help manufacturers to create a common understanding to generate the effective industry security controls. Besides, this paper recommends that building trust and mutual understanding among supply chain partners can enable confidence in data sharing and governance.

5.2. Role of policy makers
This study presents that top three policy initiatives of Thai food processing industry are prioritized, i.e. strengthening establishment standards and reference architecture (A1), developing national cybersecurity frameworks (A3), and cultivating the collaboration and best practices sharing (A7), respectively. To overcome I4.0 transformation barriers, it is recommended that the responsible policymakers should apply above three policies on the prioritization basis. Notwithstanding, according to policy “strengthening establishment standards and reference architectures”(A1), Clausen and Rasmussen (2015) pointed that policymakers should play a constructive role in facilitating the licensing model for encouraging other companies to use standards and integrate in value chains. Also, the adoption of standards and reference architectures by using the top-down policy approach may not be successful. The standards and reference architecture policy should be started by organizations. Furthermore, the study of Lee (2019) suggested that policymakers should engage in multinational regulatory agencies together with industries to facilitate the implementation of standards and reference architectures at both national and global levels. Policy “developing national cybersecurity frameworks” (A3) is given the second highest priority. As recommended by Corallo et al. (2020), policymakers should collaborate with industry agencies and businesses to develop cybersecurity frameworks. These frameworks should form the basis for all sectors and drive them into an industry standard for self-regulation. Regarding policy “cultivating collaboration and best practices sharing” (A7), it is ranked as the third highest priority. Lee (2019) suggested that policymakers should strengthen institutional coordination among government agencies, industrial chambers and academic to share and exchange the best practices in I4.0 areas.

6. Sensitivity analysis
The sensitivity analysis is performed to test the stability of the prioritizing orders by using the various parameter $\theta$ (the attenuation factor of the losses) in the Pythagorean TODIM procedure including recalculating the final rankings of policy initiatives with different values of $\theta$. The smaller the $\theta$ value represents, the higher the risk aversion psychology of decision makers is taken. The experiments were made by alternating $\theta$ values to 0.5, 0.75, 1, 1.25, 1.5, 2 and 2.5, respectively. The global prospect values are computed to prioritize policies, as illustrated in Table 12 and Figure 3 and 4. Based on Table 14, the prioritization of policy initiatives presents $A_1 \succ A_3 \succ A_7 \succ A_6 \succ A_5 \succ A_2$. This result is also consistent with such sensitivity, which can indicate the stability of the policy ranking in this study.
7. Comparative analysis
In order to validate ranking outcomes, this study conducts a comparative study with another novel MCDM reported from the literature. Since MOORA has been widely used to solve a wide range of complex MCDM problems and can be used with unknown data, the MOORA under PFS method (PFMOORA) proposed by Pérez-Domínguez et al. (2018) is used for comparison. The same input parameters (expert’s weights and criteria weights) are used. The comparison results between PFTODIM and PFMOORA are shown in Table 15.

According to the results in Table 15, the ranking report by PFMOORA is A1 (2.510) > A3 (1.919) > A7(1.640) > A4(1.636) > A6(1.369) > A5(1.292) > A2(1.125) and the result acquired by PFTODIM is A1(1.117) > A3(0.834) > A7(0.529) > A4(0.358) > A5(0.349) > A6(0.077) > A2(0.000). The results obtained from the two approaches differ slightly, with only A5 and A6 ranks. However, the top four
| ζ   | Rank | ζ   | Rank | ζ   | Rank | ζ   | Rank | ζ   | Rank | ζ   | Rank |
|-----|------|-----|------|-----|------|-----|------|-----|------|-----|------|
| A₁  | 0.810| 1   | 0.845| 1   | 0.882| 1   | 0.921| 1   | 0.962| 1   | 1.052| 1   |
| A₂  | 0.000| 7   | 0.000| 7   | 0.000| 7   | 0.000| 7   | 0.000| 7   | 0.000| 7   |
| A₃  | 0.583| 2   | 0.612| 2   | 0.637| 2   | 0.664| 2   | 0.691| 2   | 0.750| 2   |
| A₄  | 0.361| 4   | 0.374| 4   | 0.388| 4   | 0.403| 4   | 0.419| 4   | 0.439| 4   |
| A₅  | 0.316| 5   | 0.327| 5   | 0.357| 5   | 0.352| 5   | 0.365| 5   | 0.394| 5   |
| A₆  | 0.168| 6   | 0.174| 6   | 0.179| 6   | 0.185| 6   | 0.192| 6   | 0.222| 6   |
| A₇  | 0.443| 3   | 0.461| 3   | 0.476| 3   | 0.501| 3   | 0.522| 3   | 0.568| 3   |

Table 14. Ranking results under the different recession coefficients
alternative rankings (A1, A3, A7, and A4) and the final alternative ranking (A2) obtained from two approaches are of the same order. In addition, a Spearman rank-order correlation coefficient \( R_s \) to measure the correlation between two approaches is computed using Eq. 28. The result is \( R_s = 0.964 \), indicating that the two approaches provided high consistent results.

\[
R_s = 1 - 6 \frac{\sum_{i=1}^{m} D_i^2}{m(m^2 - 1)}.
\]

Where \( D_i \) is the difference in ranking between alternatives obtained using two different MCDM approaches and \( m \) is the number of alternatives.

### 8. Conclusions

The adoption rate of I4.0 in Thai enterprises is relatively low due to many barriers. A profound understanding of problems and barriers from production managers, industrialists and policymakers can improve the implementation of the action plan to overcome these barriers. In addition, government plays an important role in encouraging the manufacturing sector to use I4.0 through policy implementation. In fact, it is difficult to put all policy initiatives at the same time due to time and resource limitations. Therefore, it is important to prioritize policies and implement procedures in a stepwise manner. This study proposes a comprehensive MCDM model framework to prioritize policy initiatives to overcome barriers to I4.0 adoption. The PFS approach is used to deal with the ambiguity and imprecise information of experts’ decision-making processes. The empirical case study was conducted in Thai food processing industry.

Through an exhaustive literature review and experts’ opinions, total twelve barriers and seven policy initiatives were prioritized. In a PFS environment, a combination of weighting methods both subjective and objective approaches was used to determine the relative importance weights of barriers. Given a case study, the result presents top three most important barriers for I4.0 transformation based on the relative importance weights, i.e. lack of strategic technology plan, lack of capability to adopt standards and reference platform, and cybersecurity issues, respectively. The corresponding policy initiatives were then prioritized by applying PF TODIM. Finally, it was indicated that ‘strengthening establishment of standards and reference architectures’ policy was first prioritized due to the highest impact on overcoming obstacles for I4.0 transformation.
followed by policy “developing national cybersecurity frameworks” throughout countries and policy “cultivating the collaboration and best practices sharing”, respectively. This research also provides insights to academics, industrialists, and policymakers in order to prioritize the overcoming plan to increase 4.0 transformation rate. The framework of this study can be further improved and extended for other industrial explorations that plan to adopt 4.0.

Funding
The author received no direct funding for this research.

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

Citation information
Cite this article as: Prioritization of policy initiatives to overcome Industry 4.0 transformation barriers based on a Pythagorean fuzzy multi-criteria decision making approach, Detcharat Sumrit, Cogent Engineering (2021), 8: 1979712.

Nomenclature

| CODAS | Combinative Distance-based Assessment | MCDM | Multi-criteria decision-making |
|-------|-------------------------------------|------|-----------------------------|
| I4.0  | Industry 4.0                        | PFN  | Pythagorean Fuzzy Number    |
| DEMATEL | Decision-Making Trial and Evaluation Laboratory | PFWAO | Pythagorean Fuzzy Weighted Averaging Operator |
| DM    | Decision maker                      | PFS  | Pythagorean Fuzzy Set       |
| FAHP  | Fuzzy Analytic Hierarchy Process    | FDM  | Fuzzy Delphi method         |
| IVF-AHP | Interval-valued Fuzzy Analytic Hierarchy Process | TOPSIS | Technique for Order Performance by Similarity to Ideal Solution |
| PROMETHEE | Preference Ranking Organization METHod for Enrichment of Evaluations | TODIM | an acronym in Portuguese for Interactive Multi-Criteria Decision-Making |
| IVIF  | Interval-valued intuitionistic fuzzy | VIKOR| VisleKriterijumska Optimizacija I Kompromisno Resenje |

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