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Improving Mobile Commerce Adoption Using a New Hybrid Fuzzy MADM Model

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Abstract As mobile commerce (m-commerce) has continued to grow via advancements in wireless and mobile technology, the issue of m-commerce has become more significant. To improve m-commerce adoption, companies should establish a perfect m-commerce environment and learn to understand consumer needs. This paper proposes an evaluation model for m-commerce that can explore and improve m-commerce adoption for uncertain information in a fuzzy environment. The model addresses the interdependence and feedback effects between criteria or dimensions, the best alternative selection and systematic improvement by adopting a new hybrid fuzzy MADM model, which uses the fuzzy DEMATEL technique to construct the fuzzy INRM and determine the fuzzy influential weights using the fuzzy DANP. It further combines the fuzzy VIKOR methods for creating the best improvement plan based on the fuzzy INRM. An empirical case for evaluating m-commerce adoption is used to verify the proposed planning model. The results reveal that the proposed planning model can help companies improve m-commerce adoption for enhancing consumer trust via integrity.

Keywords Mobile commerce adoption · Fuzzy MADM (fuzzy multiple attribute decision making) · Fuzzy DEMATEL (fuzzy decision making trial and evaluation laboratory) · Fuzzy INRM (fuzzy influential network relationship map) · Fuzzy DANP (fuzzy DEMATEL-based analytic network process) · Fuzzy VIKOR (fuzzy VlseKriterijumska Optimizacija I Kompromisno Resenje)

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1 Introduction

With the advancement of wireless and mobile technologies, business communities and industries for m-commerce are developing along with the expansion in the number of mobile phones. In particular, m-commerce can create business opportunities as a result of its rapid market development and the large number of mobile users [1]. Therefore, the issue of m-commerce has become significant. To improve m-commerce adoption to satisfy users' needs, companies should establish a perfect m-commerce environment and work to understand customers' needs. The multiple attribute decision-making (MADM) problem often exists to solve real-world situations in a fuzzy environment; decision makers need to conduct open-minded judgment responses by perception/feeling with natural language using linguistic variables and fuzzy numbers based on individual opinions. Fuzzy MADM methods can help decision makers conduct open-minded and vague measurements with value judgments that are not based on individual opinions; thus, the results of the hybrid fuzzy MADM model can more be reflective of real-world situations in the fuzzy environment [2–5]. Previous studies [6–8] have listed many fuzzy

MADM methods, but assumed independent criteria in a hierarchical structure to achieve relatively optimal results based on fixed current resources. There are many studies that address methods to resolve the m-commerce issue [9–11]; however, these studies assume that the criteria are constructed independently and hierarchically. In real-world problems, the relationships between the criteria or dimensions are often interdependent and sometimes provide feedback-like effects. To solve the above real-world situations, this study adopts a new hybrid fuzzy MADM model using the fuzzy DEMATEL (decision-making trial and evaluation laboratory) technique to construct the fuzzy INRM (influential network relationship map) and determine the fuzzy influential weights of fuzzy DANP (DEMATEL-based analytic network process), and then combines the fuzzy influential weights with the fuzzy VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje) method to explore and improve m-commerce adoption with uncertain information in fuzzy environments to create the best improvement plan. Therefore, our new hybrid fuzzy MADM model is used to address the interrelationship criteria with dependence and feedback problems using the fuzzy DEMATEL technique to determine how to reduce gaps and prioritize improvement in each alternative of each criterion, dimension, and overall performance using the hybrid fuzzy VIKOR method with the fuzzy influential weights of fuzzy DANP based on the fuzzy INRM. These three fuzzy stages are integrated in this hybrid fuzzy study to construct a fuzzy evaluation model for improving the criteria gap to achieve the aspiration level called for by the hybrid fuzzy MADM model. Simon incorporated this basic concept of the aspiration level in his work, receiving the Nobel Prize in Economics in 1978 [12]. Finally, an empirical case for evaluating m-commerce adoption is illustrated to verify the proposed new hybrid fuzzy MADM model that can be effective to create the best improvement plan. The results reveal that the proposed planning model can help companies' decision makers improve m-commerce adoption by enhancing consumer trust via integrity and satisfying customers' needs.

The remainder of this paper is organized as follows. Section 2 describes the research framework of m-commerce. In Sect. 3, a new hybrid fuzzy MADM model for exploring m-commerce adoption is developed. Section 4 presents an empirical case analysis to illustrate the proposed model, and Sect. 5 concludes.

2 Research Framework of M-commerce

M-commerce is defined as any transaction with a financial value that takes place via wireless communication technologies. In Business-to-Consumer (B2C) markets, m-commerce will create more business opportunities due to the characteristics of mobility [13]. M-commerce can be regarded as an extension of electronic commerce (e-commerce) and is developed by consumer behavior, technology acceptance, and the diffusion of its applications and services [14]. In this regard, this paper explores its evaluation attributes within the existing literatures and questionnaire responses and shows that the three dimensions of trust, attitude, and mobile services are keys for m-commerce adoption.

2.1 Trust

Trust has been considered as an activator for buyer–seller transactions that provides consumers with high expectations of satisfying business relationships; trust also encourages customers' business activity in online shopping [15, 16]. Based on prior conceptualizations of trust, we use four types of trust antecedents to examine trust in m-commerce. These antecedents include integrity, competence, benevolence, and familiarity. Integrity is the expectation that the other side can make good faith agreements, such as telling the truth and fulfilling promises. Competence is the belief that the other side will have the skills to do the bounden duty; the sufficient competence of the mobile vendor will secure the provision of goods and services to the consumers. Benevolence is the expectation that the other side will behave with good intentions; the benevolence of the mobile vendor will enhance service quality and customer satisfaction. Familiarity is an understanding generated from previous interactions and experiences; consumer familiarity will influence behavioral intentions via understanding the vendor [17–19].

2.2 Attitude

Attitude is defined as an individual's perceptions of or thoughts about performing certain behaviors [20]. In this study, attitude refers to customers' pre-service feelings about using m-commerce technologies to fulfill their needs. With regard to m-commerce use, the present study decomposes attitude into perceived usefulness, perceived ease of use, and compatibility [21]. Among these attributes, perceived usefulness, perceived ease of use, and compatibility are the most frequently identified factors in the adoption and diffusion of Internet-based technologies. Perceived usefulness is the degree to which a user thinks that using an information technology system will enhance his/her own performance. Perceived ease of use is the degree to which a user thinks that using an information technology system will be simple. Compatibility is the degree to which technology adoption fits the tasks, values, and needs of the user [21–25].

2.3 Mobile Services

Mobile services have been considered as a value-added service for electronic transactions that can provide consumers with significant added value in mobility, convenience, personalization, and location to enhance business relationships and encourage the usage of m-commerce [26, 27]. Based on prior conceptualizations of mobile services, we break it down into four types: mobile communication services (MCS), mobile information services (MIS), mobile entertainment services (MES), and mobile transaction services (MTS) in order to examine the usage intention of mobile services. MCS provide telecommunication services that will fulfill consumers' information, entertainment, or commerce needs via a mobile phone. MIS provide consumers with dynamic information services via a mobile phone. MES provide consumers with entertainment application services via a mobile phone, and MTS provide consumers with commerce and banking services via a mobile phone. Accordingly, these factors will influence the usage of mobile services, and can be a significant criterion in examining mobile commerce adoption [28–30].

Consequently, the research framework, which is based on the conceptualizations of the aforementioned literature and the investigation of pre-test questionnaires, has three dimensions and eleven criteria to be selected or adopted, as shown in Fig. 1.

3 Research Methodology

In this section, this study combines the fuzzy DEMATEL technique with the fuzzy DANP and fuzzy VIKOR methods (see Appendix in detail) into a new hybrid fuzzy MADM model to create the best improvement plan based on the fuzzy INRM for m-commerce adoption in complex real-world interaction problems, as shown in Fig. 2. The procedures/stages for the hybrid fuzzy MADM model are summarized as follows. First, the fuzzy DEMATEL technique is used to construct a fuzzy total influence matrix and the fuzzy INRM in the eleven criteria using experts' fuzzy questionnaires. We then determine the fuzzy influential weights of fuzzy DANP using a fuzzy total influence matrix based on the basic concept of ANP. Second, the fuzzy VIKOR method is used to calculate the overall fuzzy performance gaps in the eleven criteria and three dimensions using the fuzzy performance scores obtained from other experts' fuzzy questionnaires and the fuzzy influential weights of fuzzy DANP. Finally, we determine how to reduce the gaps and prioritize improvement for achieving the aspiration level by constructing a hybrid fuzzy MADM model based on the fuzzy INRM to create the best improvement plan for m-commerce adoption.

3.1 Linguistic Variables and Fuzzy Numbers

The concept of a linguistic variable was proposed by Zadeh [31] to address words or sentences with composite

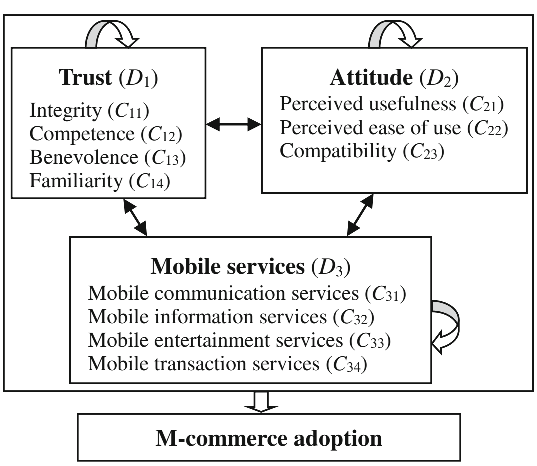

Fig. 1 Research framework of M-commerce adoption

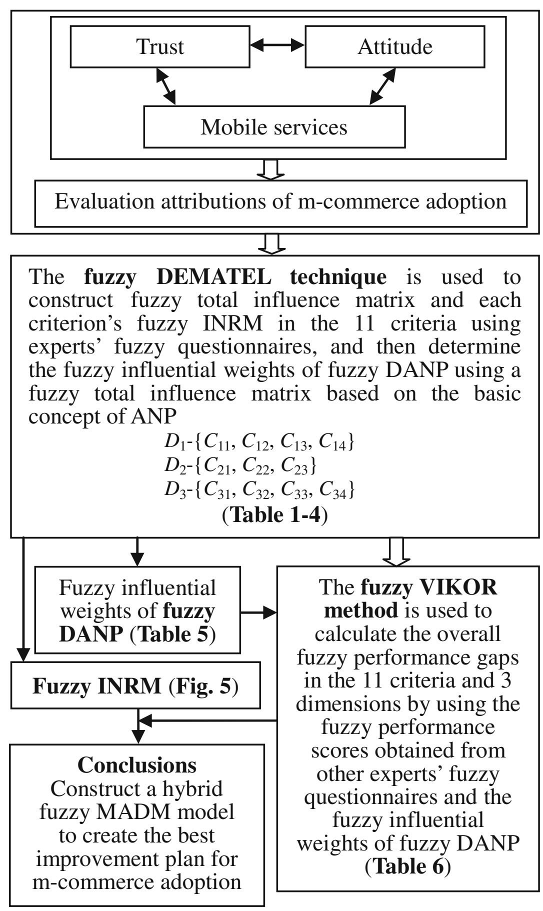

Fig. 2 The procedure for hybrid fuzzy MADM model

linguistic value in perception or feeling by a natural or artificial language. This study uses the linguistic variables to measure pairwise comparisons of the fuzzy DEMATEL questionnaire, including “no influence,” “low influence,” “medium influence,” “high influence,” and “very high influence” with respect to a fuzzy linguistic scale by experts’ perception/feeling; an example is shown in Fig. 3. Similarly, linguistic variables are used to measure the performance values for the fuzzy VIKOR questionnaire by fuzzy linguistics, such as “very bad,” “bad,” “normal,” “good,” and “very good.”

According to Dubois and Prade [32], fuzzy numbers are a fuzzy subset of real numbers representing the expansion of the idea of the confidence interval. According to the definition of Laarhoven and Pedrycz [33], a triangular fuzzy number should hold the following basic features: a fuzzy number $\tilde{B}$ on R to be a triangular fuzzy number when its membership function $\mu_{\tilde{B}}(x) : R \rightarrow [0, 1]$ is as follows:

$$\mu_{\tilde{B}}(x) = \begin{cases} (x-l)/(m-l), & l \leq x \leq m \\ (h-x)/(h-m), & m \leq x \leq h \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

where l and h are the lower and upper bounds of the fuzzy number $\tilde{B}$, respectively, and m is the modal value (see Fig. 4).

The triangular fuzzy number can be measured by $\tilde{B} = (l, m, h)$; Eq. (2) is the operational laws of two triangular fuzzy numbers $\tilde{B}_1 = (l_1, m_1, h_1)$ and $\tilde{B}_2 = (l_2, m_2, h_2)$.

$$\left.\begin{array}{r} \text{Addition:}\tilde{B}_1 \oplus \tilde{B}_2 = (l_1 + l_2, m_1 + m_2, h_1 + h_2) \\ \text{Subtraction}: \tilde{B}_1 \Theta \tilde{B}_2 = (l_1 - h_2, m_1 - m_2, h_1 - l_2) \\ \text{Multiplication}: \tilde{B}_1 \otimes \tilde{B}_2 \cong (l_1 \times l_2, m_1 \times m_2, h_1 \times h_2) \\ \text{Division}: \tilde{B}_1 \varnothing \tilde{B}_2 \cong (l_1/h_2, m_1/m_2, h_1/l_2) \\ \text{where } l_2, m_2, h_2 \neq 0 \\ \text{Scalar:}\lambda \odot \tilde{B} = \begin{cases} (\lambda l, \lambda m, \lambda h), \lambda \geq 0, \lambda \in R \\ (\lambda h, \lambda m, \lambda l), \lambda < 0, \lambda \in R \end{cases} \end{array}\right\}. \quad (2)$$

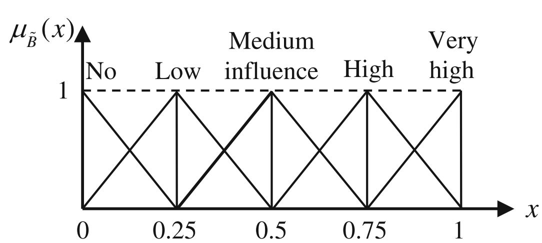

Fig. 3 Membership functions of fuzzy linguistic scale

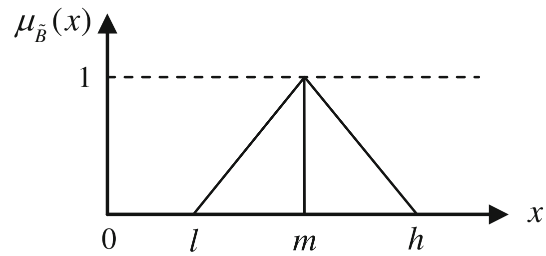

Fig. 4 Membership functions of triangular fuzzy number

3.2 The Fuzzy DEMATEL Technique

The procedure for constructing the fuzzy total influence matrix and fuzzy INRM using the fuzzy DEMATEL technique [34] (see Appendix 1) can be summarized as follows:

- *The first step* is to construct the fuzzy direct relation average matrix with expert questionnaires. A fuzzy direct relation matrix is generated by each questionnaire, after which a fuzzy direct relation average matrix $\tilde{A} = [\tilde{a}_{ij}]_{n \times n}$ can be obtained from the mean of the same criteria in the respective fuzzy direct relation matrices for all questionnaires. Questionnaires are required to represent the degree of influence of criterion i on criterion j, using the measurement scale $\tilde{0}$ to $\tilde{4}$ as linguistic perception shown by natural language (such as completely no influence ($\tilde{0}$), low influence ($\tilde{1}$), medium influence ($\tilde{2}$), high influence ($\tilde{3}$), and extremely high influence ($\tilde{4}$) for pairwise comparison of dimensions/criteria.
- *The second step* is to calculate the fuzzy initial influence matrix. The fuzzy initial influence matrix can be obtained by normalizing the fuzzy direct relation average matrix.
- *The third step* is to obtain the fuzzy total influence matrix. The fuzzy total influence matrix can be obtained by the infinite series of direct and indirect effects for the fuzzy initial influence matrix.
- *The fourth step* is to build a fuzzy INRM (as Fig. 5) based on the fuzzy total influence matrix.

3.3 The Fuzzy DANP

The procedure for determining the fuzzy influential weights using the fuzzy DANP method [2] (see Appendix 2) can be summarized as follows:

- *The first step* is to construct the fuzzy un-weighted super-matrix with the fuzzy total influence matrix of criteria.

- *The second step* is to determine the fuzzy weighted super-matrix with the fuzzy un-weighted super-matrix and the fuzzy total influence matrix of dimensions.
- *The third step* is to calculate the fuzzy influential weights with the limit fuzzy weighted super-matrix.

3.4 The Fuzzy VIKOR

The procedure for evaluating the fuzzy performance gaps using the fuzzy VIKOR method (see Appendix 3) can be summarized as follows:

- *The first step* is to set the best (i.e., the aspiration level) and worst levels in the fuzzy performance matrix $[\tilde{f}_{kj}]_{K\times n}$.
- *The second step* is to calculate the group utility (i.e., total average gap) based on the sum of all individual criterion gaps and calculate the individual maximum regret/gap of an individual criterion for priority improvement.
- *The third step* is to calculate the comprehensive indicators based on the view-points for various options.

3.5 Defuzzification for Ranking and Selection

The result of the fuzzy comprehensive decision achieved by each alternative is a fuzzy number. Therefore, it is necessary to use a non-fuzzy ranking method for fuzzy numbers to compare the best plan for each alternative. In this paper, we choose the defuzzified version of the center of area method (COA) to determine the best non-fuzzy performance (BNP) value of fuzzy numbers because it is simple and practical. The BNP value of the triangular fuzzy number $\tilde{P}_k = (lP_k, mP_k, hP_k)$ for k alternative can be calculated as shown in Eq. (3).

$$BNP_k = lP_k + [(hP_k - lP_k) + (mP_k - lP_k)]/3. \quad (3)$$

According to the value of the derived BNP for each of the alternatives, the ranking of the best plan of each of the alternatives can be determined [35].

4 An Empirical Case for Improving M-commerce Adoption

This section presents an empirical case study to verify the proposed model for improving m-commerce adoption and thereby enhancing consumer trust via integrity based on the new hybrid fuzzy MADM model.

4.1 Problem Description

Mobile phone usage has continued to grow due to the advancement in mobile marketing. Commercial

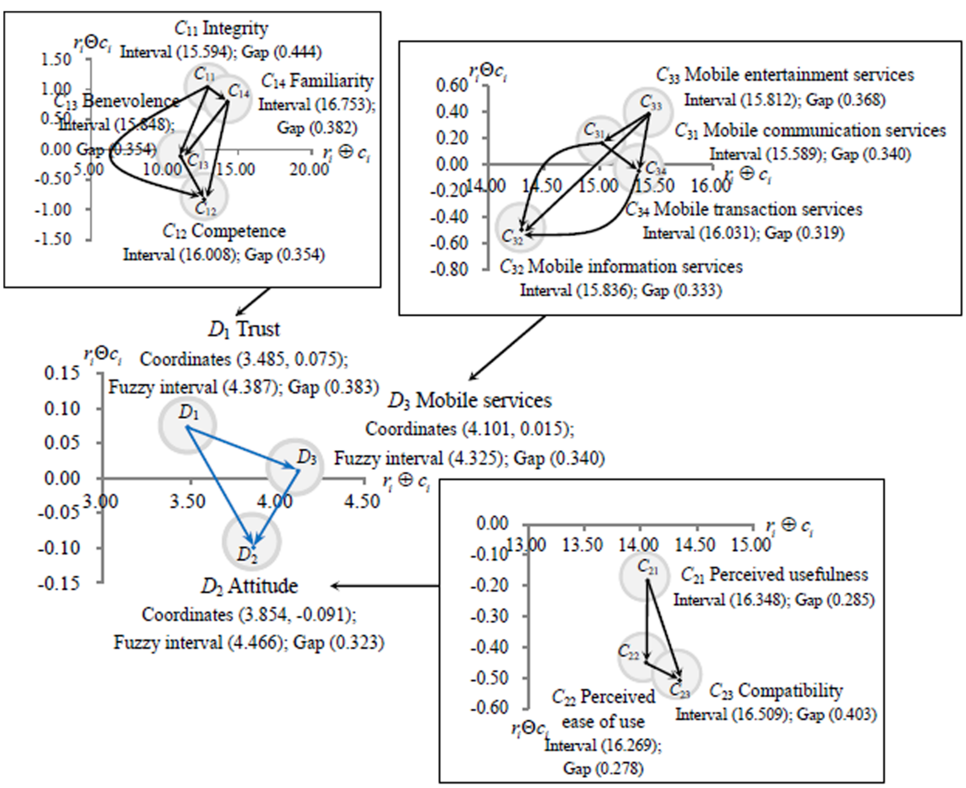

Fig. 5 The fuzzy INRM for systematic improvement

Table 1 The fuzzy direct relation average matrix $\tilde{A}$

Criteria	C_{11}	C_{12}	C_{13}	C_{14}	C_{21}	C_{22}
C_{11}	(0.000,0.000,0.000)	(0.271,0.521,0.729)	(0.396,0.646,0.854)	(0.375,0.625,0.833)	(0.188,0.438,0.667)	(0.188,0.438,0.667)
C_{12}	(0.250,0.505,0.750)	(0.000,0.000,0.000)	(0.125,0.375,0.625)	(0.292,0.542,0.792)	(0.250,0.500,0.729)	(0.208,0.458,0.688)
C_{13}	(0.229,0.479,0.729)	(0.125,0.375,0.625)	(0.000,0.000,0.000)	(0.271,0.521,0.771)	(0.104,0.354,0.604)	(0.104,0.354,0.604)
C_{14}	(0.313,0.563,0.813)	(0.292,0.542,0.792)	(0.292,0.542,0.792)	(0.000,0.000,0.000)	(0.458,0.708,0.958)	(0.438,0.688,0.938)
C_{21}	(0.188,0.438,0.688)	(0.396,0.646,0.875)	(0.146,0.396,0.646)	(0.316,0.563,0.792)	(0.000,0.000,0.000)	(0.479,0.729,0.958)
C_{22}	(0.167,0.417,0.646)	(0.333,0.583,0.813)	(0.146,0.396,0.646)	(0.292,0.542,0.792)	(0.458,0.708,0.938)	(0.000,0.000,0.000)
C_{23}	(0.146,0.396,0.646)	(0.333,0.583,0.813)	(0.125,0.375,0.625)	(0.354,0.604,0.854)	(0.479,0.729,0.958)	(0.479,0.729,0.958)
C_{31}	(0.208,0.396,0.625)	(0.313,0.563,0.792)	(0.125,0.354,0.604)	(0.167,0.417,0.667)	(0.354,0.604,0.833)	(0.354,0.604,0.833)
C_{32}	(0.229,0.479,0.708)	(0.167,0.417,0.667)	(0.125,0.375,0.625)	(0.292,0.542,0.792)	(0.313,0.563,0.771)	(0.271,0.521,0.729)
C_{33}	(0.354,0.604,0.972)	(0.396,0.646,0.833)	(0.354,0.604,0.833)	(0.396,0.646,0.854)	(0.438,0.688,0.875)	(0.458,0.708,0.875)
C_{34}	(0.313,0.563,0.813)	(0.417,0.667,0.896)	(0.188,0.438,0.688)	(0.292,0.542,0.792)	(0.313,0.563,0.813)	(0.500,0.750,0.958)

Criteria	C_{23}	C_{31}	C_{32}	C_{33}	C_{34}
C_{11}	(0.167,0.417,0.646)	(0.438,0.688,0.854)	(0.375,0.625,0.833)	(0.438,0.688,0.854)	(0.583,0.833,0.979)
C_{12}	(0.229,0.479,0.729)	(0.208,0.458,0.708)	(0.208,0.458,0.708)	(0.208,0.458,0.708)	(0.313,0.563,0.792)
C_{13}	(0.208,0.458,0.708)	(0.188,0.438,0.688)	(0.188,0.438,0.688)	(0.188,0.438,0.688)	(0.250,0.500,0.750)
C_{14}	(0.333,0.583,0.833)	(0.417,0.667,0.917)	(0.417,0.667,0.917)	(0.375,0.625,0.875)	(0.417,0.667,0.917)
C_{21}	(0.500,0.750,0.979)	(0.313,0.563,0.813)	(0.271,0.521,0.771)	(0.313,0.563,0.792)	(0.313,0.563,0.792)
C_{22}	(0.479,0.729,0.958)	(0.333,0.583,0.833)	(0.313,0.563,0.792)	(0.292,0.542,0.792)	(0.271,0.521,0.771)
C_{23}	(0.000,0.000,0.000)	(0.333,0.583,0.833)	(0.292,0.542,0.792)	(0.333,0.583,0.833)	(0.292,0.542,0.792)
C_{31}	(0.438,0.688,0.938)	(0.000,0.000,0.000)	(0.667,0.917,0.979)	(0.729,0.979,1.000)	(0.688,0.938,1.000)
C_{32}	(0.458,0.708,0.938)	(0.333,0.583,0.813)	(0.000,0.000,0.000)	(0.521,0.771,0.938)	(0.479,0.729,0.917)
C_{33}	(0.438,0.688,0.875)	(0.583,0.833,0.979)	(0.458,0.708,0.896)	(0.000,0.000,0.000)	(0.458,0.708,0.917)
C_{34}	(0.375,0.625,0.833)	(0.583,0.833,0.938)	(0.542,0.792,0.917)	(0.500,0.750,0.875)	(0.000,0.000,0.000)

The average sample gap $= \frac{1}{n(n-1)}\sum_{i=1}^{n}\sum_{j=1}^{n}(|a_{ij}^{P} - a_{ij}^{P-1}|/a_{ij}^{P}) \times 100\,\% = 2.2\,\% < 5\,\%$, where n is the number of criteria, p is the sample of 14 experts and significant confidence is 97.8 %

m-commerce is being popularized by the expansion in the number of mobile phones [36], and finding ways to improve strategies for promoting m-commerce adoption in Taiwan are growing in significance. Many previous studies assumed independent criteria in a hierarchical structure to achieve the relatively optimal result. This study aims to develop a new hybrid fuzzy MADM model to handle the complex real-world interaction problems to identify the sources of the problem for systematic improvement to avoid "choosing the best among inferior choices/alternatives." In other words, the relatively best result from the existing alternatives is replaced by the aspiration level to provide the improved direction.

4.2 Analysis of Results

This study constructed the structure of influential relationships in the decision-making problem using the fuzzy DEMATEL technique and examined three dimensions with eleven criteria to create the best improvement plan for promoting m-commerce adoption in Taiwan. Based on expert questionnaires, the fuzzy direct relation average matrix $\tilde{\boldsymbol{A}}$ can be obtained, as shown in Table 1. With significant confidence, the average sample gap equals only 2.2 % and is smaller than 5 % (i.e., the significant confidence is 97.8 %, exceeding 95 %). The fuzzy initial influence matrix $\tilde{\boldsymbol{E}}$ can be obtained by normalizing the fuzzy matrix $\tilde{\boldsymbol{A}}$. The fuzzy total influence matrix $\tilde{\boldsymbol{T}}$ can be obtained by the infinite series of direct and indirect effects for the fuzzy matrix $\tilde{\boldsymbol{E}}$, as shown in Table 2. Table 2 reveals that all criteria have an interactive relationship. The fuzzy matrix $\tilde{\boldsymbol{T}}$ can be divided into the fuzzy total influence matrix by dimensions $\tilde{\boldsymbol{T}}_D$ and the total influence matrix by criteria $\tilde{\boldsymbol{T}}_C$, as shown in Tables 3 and 4, respectively. Tables 3 and 4 show that the relationship of the three dimensions and eleven criteria is based on expert cognition in perception/feeling, and the sum of the influence given and received for each dimension and criterion, respectively. As shown in Table 3, trust has the largest positive value $(\tilde{r}_1^D \Theta \tilde{c}_1^D)$, meaning that it is the most influential dimension. Trust plays a major role in the evaluation

Table 2 The fuzzy total influence matrix $\tilde{\boldsymbol{T}}$

Criteria	C_{11}	C_{12}	C_{13}	C_{14}	C_{21}	C_{22}
C_{11}	(0.194,0.398,0.866)	(0.304,0.525,1.016)	(0.245,0.456,0.923)	(0.318,0.534,1.033)	(0.312,0.539,1.045)	(0.325,0.551,1.053)
C_{12}	(0.186,0.394,0.876)	(0.169,0.373,0.864)	(0.137,0.354,0.834)	(0.226,0.442,0.954)	(0.241,0.462,0.974)	(0.240,0.465,0.977)
C_{13}	(0.158,0.363,0.835)	(0.165,0.392,0.889)	(0.090,0.276,0.731)	(0.192,0.408,0.910)	(0.176,0.409,0.918)	(0.182,0.417,0.925)
C_{14}	(0.273,0.491,1.034)	(0.329,0.550,1.112)	(0.233,0.459,0.997)	(0.257,0.471,1.037)	(0.390,0.597,1.168)	(0.398,0.606,1.174)
C_{21}	(0.218,0.442,0.957)	(0.314,0.525,1.050)	(0.178,0.409,0.920)	(0.289,0.510,1.050)	(0.257,0.464,0.997)	(0.366,0.571,1.103)
C_{22}	(0.207,0.431,0.941)	(0.293,0.508,1.032)	(0.172,0.401,0.909)	(0.276,0.497,1.037)	(0.342,0.547,1.080)	(0.256,0.464,0.991)
C_{23}	(0.209,0.434,0.955)	(0.300,0.515,1.046)	(0.172,0.404,0.920)	(0.295,0.512,1.058)	(0.355,0.558,1.097)	(0.365,0.568,1.105)
C_{31}	(0.276,0.490,0.971)	(0.363,0.574,1.064)	(0.217,0.452,0.935)	(0.324,0.550,1.059)	(0.403,0.607,1.105)	(0.418,0.620,1.113)
C_{32}	(0.234,0.451,0.942)	(0.276,0.500,1.012)	(0.181,0.410,0.902)	(0.293,0.511,1.031)	(0.331,0.544,1.058)	(0.336,0.550,1.062)
C_{33}	(0.310,0.531,1.029)	(0.386,0.603,1.113)	(0.268,0.499,0.998)	(0.376,0.597,1.123)	(0.426,0.637,1.156)	(0.444,0.652,1.165)
C_{34}	(0.289,0.509,1.011)	(0.374,0.586,1.097)	(0.224,0.462,0.964)	(0.339,0.565,1.095)	(0.385,0.602,1.128)	(0.434,0.636,1.150)

Criteria	C_{23}	C_{31}	C_{32}	C_{33}	C_{34}
C_{11}	(0.329,0.558,1.075)	(0.392,0.599,1.086)	(0.383,0.593,1.076)	(0.406,0.612,1.084)	(0.440,0.639,1.123)
C_{12}	(0.249,0.476,1.003)	(0.250,0.478,0.993)	(0.250,0.479,0.985)	(0.258,0.489,0.991)	(0.283,0.509,1.024)
C_{13}	(0.207,0.437,0.956)	(0.208,0.440,0.946)	(0.209,0.440,0.938)	(0.216,0.450,0.944)	(0.232,0.464,0.974)
C_{14}	(0.388,0.604,1.190)	(0.408,0.619,1.188)	(0.409,0.621,1.178)	(0.414,0.628,1.182)	(0.428,0.642,1.215)
C_{21}	(0.378,0.582,1.129)	(0.342,0.564,1.104)	(0.335,0.559,1.090)	(0.353,0.576,1.099)	(0.358,0.584,1.127)
C_{22}	(0.364,0.569,1.114)	(0.335,0.555,1.092)	(0.332,0.554,1.079)	(0.339,0.563,1.086)	(0.339,0.567,1.111)
C_{23}	(0.273,0.480,1.031)	(0.344,0.563,1.108)	(0.337,0.559,1.094)	(0.356,0.575,1.105)	(0.352,0.578,1.129)
C_{31}	(0.445,0.641,1.148)	(0.359,0.556,1.042)	(0.496,0.676,1.133)	(0.522,0.697,1.142)	(0.518,0.700,1.170)
C_{32}	(0.379,0.581,1.105)	(0.360,0.572,1.085)	(0.289,0.494,0.991)	(0.408,0.607,1.094)	(0.403,0.610,1.119)
C_{33}	(0.452,0.660,1.191)	(0.484,0.684,1.191)	(0.463,0.671,1.173)	(0.382,0.591,1.088)	(0.484,0.694,1.212)
C_{34}	(0.422,0.632,1.163)	(0.466,0.663,1.163)	(0.461,0.660,1.152)	(0.467,0.668,1.155)	(0.369,0.578,1.093)

system and has the greatest actual impact on other dimensions. Attitude has the least negative value $(\tilde{r}_2^D \Theta \tilde{c}_2^D)$ and is thus most easily affected by other dimensions. As a result, decision makers can manage trust as a core consideration in potential m-commerce activity. Mobile services have the highest strength of relationship $(\tilde{r}_3^D \oplus \tilde{c}_3^D)$ and are thus considered the most interactive dimension by experts, and also have the most significant relationship to other dimensions. As shown in Table 4, integrity has the largest degree of causality $(\tilde{r}_{11} \Theta \tilde{c}_{11})$ and thus most easily affects other criteria. Competence has the least degree of causality $(\tilde{r}_{12} \Theta \tilde{c}_{12})$ and is thus most easily affected by other criteria. In addition, mobile entertainment services have the most significant relationship $(\tilde{r}_{33} \oplus \tilde{c}_{33})$ to other criteria. Based on Tables 3 and 4, the influential network relationship can be illustrated by drawing a fuzzy INRM of the three dimensions and their criteria, as shown in Fig. 5. Based on Fig. 5, experts revealed that trust should be prioritized in improvement. Then, the aforementioned fuzzy DANP method is used to find the fuzzy influential weights based on Saaty's [37] basic concept of ANP [37]. The fuzzy DANP can obtain a fuzzy un-weighted super-matrix that reveals the degrees of influence among the relationships. Furthermore, we also consider the impacts of other dimensions to obtain the fuzzy weighted super-matrix, which reflects the degrees of influence exerted by other dimensions. The fuzzy weighted super-matrix is multiplied by itself multiple times to obtain the limit fuzzy weighted super-matrix. Then, the fuzzy influential weights (i.e., global weights) can be calculated using the infinite power of the limit fuzzy weighted super-matrix until the super-matrix has converged and become a steady-state super-matrix, as shown in Table 5. Finally, the fuzzy influential weights are used to weight the fuzzy VIKOR for integrating each criterion into each dimensional and overall performance. This allows us to evaluate the performance gaps and discover the priority improvements in creating the best improvement plan to reduce performance gaps and achieve m-commerce adoption based on the fuzzy INRM (see Fig. 5). An empirical case is illustrated to evaluate the performance gaps combining the fuzzy influential weights with fuzzy VIKOR method. The performance gaps can be obtained based on performance questionnaires, as shown in Table 6. Furthermore, the fuzzy comprehensive indicators

Table 3 The fuzzy total influence matrix $\tilde{\boldsymbol{T}}_D$ by dimensions, and the sum of influences given/received for dimensions

Dimensions	D_1	D_2	D_3	$\tilde{r}_i^D$	$\tilde{c}_i^D$	$\tilde{r}_i^D \Theta \tilde{c}_i^D$	$\tilde{r}_i^D \Theta \tilde{c}_i^D$
D_1	(0.217,0.430,0.932)	(0.286,0.510,1.038)	(0.324,0.544,1.058)	(0.828,1.484,3.028)	(0.757,1.414,2.943)	(1.584,2.899,5.972)	(−2.115,0.070,2.272)
D_2	(0.244,0.466,0.990)	(0.328,0.534,1.072)	(0.343,0.566,1.102)	(0.916,1.566,3.163)	(1.021,1.657,3.239)	(1.937,3.223,6.402)	(−2.323,−0.091,2.142)
D_3	(0.296,0.518,1.022)	(0.406,0.613,1.129)	(0.433,0.633,1.125)	(1.135,1.764,3.276)	(1.101,1.743,3.285)	(2.236,3.507,6.561)	(−2.150,0.021,2.175)

$\tilde{R}_k$ can also be obtained; the value of ν can indicate decisions by the experts that are adjusted as $v = 1$, $v = 0.5$ and $v = 0$ in this paper. The defuzzified results of the comprehensive indicators are 0.384 (the group utility), 0.414 (the majority of criteria), and 0.444 (individual maximum gap), revealing that the integrity criterion in trust is the first priority in terms of improvement.

4.3 Discussions and Implications

In some fields or problems (e.g., decision making, reasoning, and learning), traditional mathematical tools are not entirely suitable for establishing a model. Zadeh [38] proposed fuzzy set theory to address problems of vagueness or imprecision in human cognitive processes. Bellman and Zadeh [39] described the decision-making methods in fuzzy environments, and an increasing number of studies have dealt with uncertain fuzzy problems by applying fuzzy set theory. Zadeh [31] proposed the concept of a linguistic variable to address words or sentences with composite linguistic value in perception or feeling via natural language. Therefore, the notion of fuzzy theory is necessary in such situations (i.e., the application of fuzzy theory has been widely used in solving actual problems to evaluate different works). This study adopts a new hybrid fuzzy MADM model to explore and improve m-commerce adoption with uncertain information in a fuzzy environment to create the best improvement plan. The fuzzy influential analyses among dimensions and criteria are shown in Fig. 5, and the fuzzy/defuzzified performance gaps are shown in Table 6, which help decision makers to make actual decisions. According to Fig. 5, three dimensions and eleven criteria can be easily shown to influence each other. The results reveal that trust, which has the largest positive value $(\tilde{r}_1^D \Theta \tilde{c}_1^D)$, is the most influential dimension for priority improvement; this is the source of the problem, followed by mobile services and attitude. Similarly, integrity, with the largest positive value $(\tilde{r}_{11} \Theta \tilde{c}_{11})$, is the most influential criterion, followed by familiarity and mobile entertainment services. To solve the problem of conflicting criteria, fuzzy influential weights are used to weight the fuzzy VIKOR (the compromise ranking method) to evaluate fuzzy/defuzzified performance gaps and determine the priorities for improvement based on the fuzzy INRM. The fuzzy performance scores are replaced by the fuzzy performance gaps that represent the direction of improvement, which is more suitable in the current competitive environment. According to Table 6, trust, the dimension with the maximal gap value, should be prioritized in improvement, followed by mobile services and attitude; similarly, integrity, the criterion with the maximal gap value, should be prioritized in improvement,

Table 4 The fuzzy total influence matrix $\tilde{\boldsymbol{T}}_C$ by criteria, and the sum of influences given/received for criteria

Criteria	C_{11}	C_{12}	C_{13}	C_{14}	C_{21}	C_{22}	C_{23}
C_{11}	(0.194,0.398,0.866)	(0.304,0.525,1.016)	(0.245,0.456,0.923)	(0.318,0.534,1.033)	(0.312,0.539,1.045)	(0.325,0.551,1.053)	(0.329,0.558,1.075)
C_{12}	(0.186,0.394,0.876)	(0.169,0.373,0.864)	(0.137,0.354,0.834)	(0.226,0.442,0.954)	(0.241,0.462,0.974)	(0.240,0.465,0.977)	(0.249,0.476,1.003)
C_{13}	(0.158,0.363,0.835)	(0.165,0.392,0.889)	(0.090,0.276,0.731)	(0.192,0.408,0.910)	(0.176,0.409,0.918)	(0.182,0.417,0.925)	(0.207,0.437,0.956)
C_{14}	(0.273,0.491,1.034)	(0.329,0.550,1.112)	(0.233,0.459,0.997)	(0.257,0.471,1.037)	(0.390,0.597,1.168)	(0.398,0.606,1.174)	(0.388,0.604,1.190)
C_{21}	(0.218,0.442,0.957)	(0.314,0.525,1.050)	(0.178,0.409,0.920)	(0.289,0.510,1.050)	(0.257,0.464,0.997)	(0.366,0.571,1.103)	(0.378,0.582,1.129)
C_{22}	(0.207,0.431,0.941)	(0.293,0.508,1.032)	(0.172,0.401,0.909)	(0.276,0.497,1.037)	(0.342,0.547,1.080)	(0.256,0.464,0.991)	(0.364,0.569,1.114)
C_{23}	(0.209,0.434,0.955)	(0.300,0.515,1.046)	(0.172,0.404,0.920)	(0.295,0.512,1.058)	(0.355,0.558,1.097)	(0.365,0.568,1.105)	(0.273,0.480,1.031)
C_{31}	(0.276,0.490,0.971)	(0.363,0.574,1.064)	(0.217,0.452,0.935)	(0.324,0.550,1.059)	(0.403,0.607,1.105)	(0.418,0.620,1.113)	(0.445,0.641,1.148)
C_{32}	(0.234,0.451,0.942)	(0.276,0.500,1.012)	(0.181,0.410,0.902)	(0.293,0.511,1.031)	(0.331,0.544,1.058)	(0.336,0.550,1.062)	(0.379,0.581,1.105)
C_{33}	(0.310,0.531,1.029)	(0.386,0.603,1.113)	(0.268,0.499,0.998)	(0.376,0.597,1.123)	(0.426,0.637,1.156)	(0.444,0.652,1.165)	(0.452,0.660,1.191)
C_{34}	(0.289,0.509,1.011)	(0.374,0.586,1.097)	(0.224,0.462,0.964)	(0.339,0.565,1.095)	(0.385,0.602,1.128)	(0.434,0.636,1.150)	(0.422,0.632,1.163)

Criteria	C_{31}	C_{32}	C_{33}	C_{34}	$\tilde{r}_{ij}$	$\tilde{c}_{ij}$	$\tilde{r}_{ij} \Theta \tilde{c}_{ij}$	$\tilde{r}_{ij} \Theta \tilde{c}_{ij}$
C_{11}	(0.392,0.599,1.086)	(0.383,0.593,1.076)	(0.406,0.612,1.084)	(0.440,0.639,1.123)	(3.648,6.004,11.381)	(2.555,4.935,10.417)	(6.203,10.939,21.798)	(−6.796,1.069,8.825)
C_{12}	(0.250,0.478,0.993)	(0.250,0.479,0.985)	(0.258,0.489,0.991)	(0.283,0.509,1.024)	(2.489,4.920,10.476)	(3.274,5.651,11.295)	(5.763,10.571,21.771)	(−8.806,−0.731,7.202)
C_{13}	(0.208,0.440,0.946)	(0.209,0.440,0.938)	(0.216,0.450,0.944)	(0.232,0.464,0.974)	(2.036,4.496,9.967)	(2.116,4.582,10.033)	(4.152,9.079,20.000)	(−7.998,−0.086,7.851)
C_{14}	(0.408,0.619,1.188)	(0.409,0.621,1.178)	(0.414,0.628,1.182)	(0.428,0.642,1.215)	(3.926,6.288,12.476)	(3.186,5.598,11.388)	(7.111,11.886,23.864)	(−7.462,0.690,9.290)
C_{21}	(0.342,0.564,1.104)	(0.335,0.559,1.090)	(0.353,0.576,1.099)	(0.358,0.584,1.127)	(3.389,5.786,11.627)	(3.617,5.965,11.727)	(7.006,11.752,23.354)	(−8.338,−0.179,8.009)
C_{22}	(0.335,0.555,1.092)	(0.332,0.554,1.079)	(0.339,0.563,1.086)	(0.339,0.567,1.111)	(3.257,5.656,11.471)	(3.765,6.098,11.819)	(7.022,11.754,23.291)	(−8.562,−0.442,7.707)
C_{23}	(0.344,0.563,1.108)	(0.337,0.559,1.094)	(0.356,0.575,1.105)	(0.352,0.578,1.129)	(3.357,5.746,11.648)	(3.886,6.221,12.105)	(7.244,11.967,23.753)	(−8.748,−0.476,7.761)
C_{31}	(0.359,0.556,1.042)	(0.496,0.676,1.133)	(0.522,0.697,1.142)	(0.518,0.700,1.170)	(4.341,6.564,11.881)	(3.949,6.295,11.998)	(8.290,12.859,23.879)	(−7.657,0.268,7.932)
C_{32}	(0.360,0.572,1.085)	(0.289,0.494,0.991)	(0.408,0.607,1.094)	(0.403,0.610,1.119)	(3.490,5.831,11.402)	(3.965,6.305,11.889)	(7.455,12.137,23.291)	(−8.399,−0.474,7.437)
C_{33}	(0.484,0.684,1.191)	(0.463,0.671,1.173)	(0.382,0.591,1.088)	(0.484,0.694,1.212)	(4.477,6.819,12.439)	(4.121,6.456,11.971)	(8.598,13.275,24.410)	(−7.494,0.363,8.318)
C_{34}	(0.466,0.663,1.163)	(0.461,0.660,1.152)	(0.467,0.668,1.155)	(0.369,0.578,1.093)	(4.230,6.562,12.172)	(4.205,6.546,12.295)	(8.435,13.125,24.466)	(−8.064,−0.002,7.967)

Table 5 The steady-state super-matrix with the fuzzy influential weights of fuzzy DANP

Criteria	C_{11}	C_{12}	C_{13}	C_{14}	C_{21}	C_{22}	C_{23}
Fuzzy influential weights	(0.043,0.070,0.096)	(0.055,0.080,0.105)	(0.035,0.065,0.093)	(0.054,0.079,0.106)	(0.089,0.112,0.139)	(0.092,0.115,0.140)	(0.095,0.117,0.144)
Criteria	C_{31}	C_{32}	C_{33}	C_{34}			
Fuzzy influential weights	(0.077,0.089,0.101)	(0.077,0.089,0.100)	(0.080,0.091,0.101)	(0.081,0.093,0.103)			

followed by compatibility and familiarity. The results revealed that the proposed model can improve the problems of m-commerce according to the fuzzy INRM and can reduce these gaps to achieve the aspiration level, based on real-world interrelationships of dependence and the feedback problem. The following recommendations are proposed to improve m-commerce adoption in Taiwan. Decision makers should consider how to request companies to improve consumer trust (D_1) as a priority improvement. Another option for decision makers is to reference D_1 to advise their companies to prioritize the improvement of integrity (C_{11}), followed by familiarity (C_{14}) in order to improve consumer trust. In other words, decision makers can reference the fuzzy INRM of the fuzzy DEMATEL technique and the fuzzy/defuzzified performance gaps of the fuzzy VIKOR to improve their priority dimensions and criteria to evaluate and improve m-commerce. The results revealed that trust (D_1) best predicts consumer needs, and decision makers should provide an optimal interactive environment to enhance consumer trust.

5 Conclusions

This study developed a new hybrid fuzzy MADM model adopting the fuzzy DEMATEL technique and the fuzzy DANP method to construct the fuzzy INRM and determine the fuzzy influential weights by fuzzy DANP, and it then combined the fuzzy influential weights with the fuzzy VIKOR method to explore and improve m-commerce adoption with uncertain information in a fuzzy environment to create the best improvement plan. After an empirical case study, several main contributions are described as follows. First, this study can construct an improvement model for the decision-making problem of m-commerce, and can provide decision makers with a deeper understanding of m-commerce adoption via the proposed model. Second, the fuzzy DEMATEL technique can construct a fuzzy INRM to solve interactive relationships in the real world and overcome independent assumptions in a hierarchical structure. The fuzzy DANP method can derive the fuzzy influential weights and overcome the problems of dependence and feedback. Third, the relatively optimal result is replaced by the aspiration level to avoid "picking the best apple from a barrel of rotten apples." The fuzzy VIKOR method can transform the fuzzy performance scores into fuzzy performance gaps by setting the aspiration level based on the fuzzy influence weights. The fuzzy/defuzzified performance gaps enable the decision maker to reduce the gaps in each dimension and criterion to improve the decision-making problem and achieve his/her the aspiration level

Table 6 The performance gap evaluation of the case study using the fuzzy VIKOR

Dimensions/ criteria	Global weights (fuzzy numbers and BNP values)	Local weights (fuzzy numbers and BNP values)	Case study	
			Score (fuzzy performances and BNP values)	Gap (fuzzy gaps and BNP values)
Trust(D_1)		**(0.186,0.294,0.399), 0.293**	**(1.483,2.482,3.4389), 2.468**	**(0.140,0.380,0.630), 0.383**
Integrity (C_{11})	(0.043,0.070,0.090), 0.070	(0.230,0.238,0.242), 0.238	(1.250,2.250,3.167), 2.222	(0.208,0.438,0.688), 0.444
Competence (C_{12})	(0.055,0.080,0.105), 0.080	(0.295,0.272,0.262), 0.272	(1.583,2.583,3.583), 2.583	(0.104,0.354,0.604), 0.354
Benevolence (C_{13})	(0.035,0.065,0.093), 0.064	(0.187,0.220,0.232), 0.219	(1.583,2.583,3.583), 2.583	(0.104,0.354,0.604), 0.354
Familiarity (C_{14})	(0.054,0.079,0.106), 0.079	(0.288,0.270,0.264) 0.271	(1.500,2.500,3.417), 2.472	(0.146,0.375,0.625), 0.382
Attitude (D_2)		**(0.276,0.344,0.424), 0.347**	**(1.744,2.747,3.636), 2.709**	**(0.091,0.313,0.563), 0.323**
Perceived usefulness (C_{21})	(0.089,0.112,0.139), 0.113	(0.322,0.326,0.329), 0.326	(1.917,2.917,3.750), 2.861	(0.063,0.271,0.521), 0.285
Perceived ease of use (C_{22})	(0.092,0.115,0.140), 0.116	(0.333,0.333,0.332), 0.333	(1.917,2.917,3.833), 2.889	(0.042,0.271,0.521), 0.278
Compatibility (C_{23})	(0.095,0.117,0.144), 0.118	(0.345,0.340,0.340), 0.341	(1.417,2.417,3.333), 2.389	(0.167,0.396,0.646), 0.403
Mobile services (D_3)		**(0.315,0.362,0.405), 0.360**	**(1.667,2.667,3.584), 2.639**	**(0.104,0.333,0.583), 0.340**
MCS (C_{31})	(0.077,0.089,0.101), 0.089	(0.244,0.246,0.249), 0.247	(1.667,2.667,3.583), 2.639	(0.104,0.333,0.583), 0.340
MIS (C_{32})	(0.077,0.089,0.100), 0.088	(0.243,0.246,0.247), 0.246	(1.667,2.667,3.667), 2.667	(0.083,0.333,0.583), 0.333
MES (C_{33})	(0.080,0.091,0.101), 0.091	(0.254,0.252,0.249), 0.251	(1.583,2.583,3.417), 2.528	(0.146,0.354,0.604), 0.368
MTS (C_{34})	(0.081,0.093,0.103), 0.092	(0.258,0.256,0.255), 0.256	(1.750,2.750,3.667), 2.722	(0.083,0.313,0.563), 0.319
Total average performance			**(1.283,2.640,4.365), 2.763**	
Total average gap				**(0.084,0.340,0.726), 0.384**

Table 7 Membership functions for fuzzy DEMATEL questionnaire as example

Linguistic scales of fuzzy number $\tilde{a}_{ij}$	Corresponding triangular fuzzy numbers $(a_{ij}^l, a_{ij}^m, a_{ij}^h)$
No influence ($\tilde{0}$)	(0,0,0.25)
Low influence ($\tilde{1}$)	(0,0.25,0.5)
Medium influence ($\tilde{2}$)	(0.25,0.5,0.75)
High influence ($\tilde{3}$)	(0.5,0.75,1)
Very high influence ($\tilde{4}$)	(0.75,1,1)

based on the fuzzy INRM. Fourth, the proposed model can be used for not only "ranking and selecting," but also for "improvement" in achieving the aspiration level (reducing gaps to zero). Finally, the empirical case reveals that the proposed model is effective.

Appendix: Hybrid Fuzzy MADM Model Based on the Fuzzy DANP and Fuzzy VIKOR

Appendix 1: The Fuzzy DEMATEL Technique

The technique is described as follows:

Step 1 Calculate the fuzzy direct relation average matrix.

The fuzzy direct relation average matrix $\tilde{\boldsymbol{A}}$ is given by Eq. (4), and membership functions of the linguistic scale in this paper are constructed using triangular fuzzy numbers, as shown in Table 7, where $\tilde{\boldsymbol{A}} = [\tilde{a}_{ij}]_{n\times n} = [(a_{ij}^l, a_{ij}^m, a_{ij}^h)]_{n\times n}$, $\tilde{a}_{ij}$ represents the fuzzy degree of direct influence of criterion i on criterion j.

$$\tilde{\boldsymbol{A}} = \begin{bmatrix} \tilde{a}_{11} & \cdots & \tilde{a}_{1j} & \cdots & \tilde{a}_{1n} \\ \vdots & & & & \vdots \\ \tilde{a}_{i1} & \cdots & \tilde{a}_{ij} & \cdots & \tilde{a}_{in} \\ \vdots & & & & \vdots \\ \tilde{a}_{n1} & \cdots & \tilde{a}_{nj} & \cdots & \tilde{a}_{nn} \end{bmatrix}. \tag{4}$$

Step 2 Calculate the fuzzy initial influence matrix.

The fuzzy initial influence matrix $\tilde{\boldsymbol{E}}$ can be obtained by normalizing matrix $\tilde{\boldsymbol{A}}$. In addition, matrix $\tilde{\boldsymbol{E}}$ can be obtained by Eqs. (5) and (6), in which the main diagonal criteria are equal to zero.

$$\tilde{E} = \tilde{A}/s \tag{5}$$

$$s = \max_{ij}\{\max_{1\le i\le n}\sum_{j=1}^{n} a_{ij}^h, \max_{1\le j\le n}\sum_{i=1}^{n} a_{ij}^h\}, \tag{6}$$

where $\tilde{\boldsymbol{E}} = [\tilde{e}_{ij}]_{n\times n} = [(e^l_{ij}, e^m_{ij}, e^h_{ij})]_{n\times n}$, $(0,0,0) \le \tilde{e}_{ij} < (1,1,1)$, $(0,0,0) < \sum_{j=1}^n \tilde{e}_{ij}, \sum_{i=1}^n \tilde{e}_{ij} \le (1,1,1)$, and $i,j = 1,2,\ldots,n$; If at least one row or column of summation is equal to 1 (but not all) in $\sum_{j=1}^n \tilde{e}_{ij}$ and $\sum_{i=1}^n \tilde{e}_{ij}$, we can guarantee $\lim_{x\to\infty} \tilde{\boldsymbol{E}}^x = [\tilde{0}]_{n\times n} = [(0,0,0)]_{n\times n}$.

Step 3 Calculate the fuzzy total influence matrix.

The fuzzy total influence matrix $\tilde{T}$ can be obtained by the infinite series of direct and indirect effects for matrix $\tilde{E}$. In addition, matrix $\tilde{T}$ can be obtained by Eq. (A4), in which I is an identity matrix.

$$\begin{aligned}\tilde{T} &= \tilde{E} \oplus \tilde{E}^2 \oplus \tilde{E}^3 \oplus \ldots \oplus \tilde{E}^x \\ &= \tilde{E} \otimes (I \otimes \tilde{E} \otimes \tilde{E}^2 \oplus \ldots \otimes \tilde{E}^{x-1}) \\ &\quad \otimes (I \,\Theta\, \tilde{E}) \otimes (I \,\Theta\, \tilde{E})^{-1} \\ &= \tilde{E} \otimes (I \,\Theta\, \tilde{E}^x) \otimes (I \,\Theta\, \tilde{E})^{-1}, \text{ then} \\ \tilde{T} &= \tilde{E} \otimes (I \,\Theta\, \tilde{E})^{-1}, \text{ when } \lim_{x\to\infty} \tilde{\boldsymbol{E}}^x \\ &= [\tilde{0}]_{n\times n} = [0,0,0]_{n\times n}\end{aligned}, \tag{7}$$

where $\tilde{\boldsymbol{T}} = [\tilde{t}_{ij}]_{n\times n} = [t^l_{ij}, t^m_{ij}, t^h_{ij}]_{n\times n}$, $i,j = 1,2,\ldots,n$ and $\boldsymbol{I} = (\boldsymbol{I}\Theta\tilde{\boldsymbol{E}}) \otimes (\boldsymbol{I}\Theta\tilde{\boldsymbol{E}})^{-1}$.

Step 4 Construct the fuzzy INRM.

According to Eqs. (8) and (9), the sum of each row and column for matrix $\tilde{T}$ can be obtained, where $\tilde{r}_i$ denotes the sum of the ith row of matrix $\tilde{T}$ and shows the sum of the direct and indirect effects that criterion i influences other criteria, and $\tilde{c}_j$ denotes the sum of the jth column of the matrix $\tilde{T}$ and shows the sum of the direct and indirect effects that criterion j is influenced by other criteria. When i equals j, $\tilde{r}_i \oplus \tilde{c}_i$ represents an index of the strength of influence given and received and shows the degree of the central role that criterion i plays in the problem. In addition, $\tilde{r}_i \Theta \tilde{c}_i$ represents the degree of causality among criteria. Based on matrix $\tilde{T}$, the fuzzy INRM can be constructed by the fuzzy degrees of influence and causality.

$$\begin{aligned}\tilde{\boldsymbol{r}} = [\tilde{r}_i]_{n\times 1} &= \left[\sum_{j=1}^n \tilde{t}_{ij}\right]_{n\times 1} = [\tilde{r}_1, \ldots, \tilde{r}_i, \ldots, \tilde{r}_n]_{n\times 1} \\ &= \left[(r^l_1, r^m_1, r^h_1), \ldots, (r^l_i, r^m_i, r^h_i), \ldots, (r^l_n, r^m_n, r^h_n)\right]_{n\times 1}\end{aligned} \tag{8}$$

$$\begin{aligned}\tilde{\boldsymbol{c}} = [\tilde{c}_j]'_{1\times n} &= \left[\sum_{i=1}^n \tilde{t}_{ij}\right]'_{1\times n} = [\tilde{c}_1, \ldots, \tilde{c}_j, \ldots, \tilde{c}_n]_{n\times 1} \\ &= \left[(c^l_1, c^m_1, c^h_1), \ldots, (c^l_j, c^m_j, c^h_j), \ldots, (c^l_n, c^m_n, c^h_n)\right]_{n\times 1}\end{aligned}, \tag{9}$$

where vector $\tilde{\boldsymbol{r}}$ and $\tilde{\boldsymbol{c}}$ denote the sum of vector row and column, respectively, $i,j \in \{1,2,\ldots,n\}$.

Appendix 2: The Fuzzy DANP Method

The method is described as follows:

Step 1 Construct the fuzzy un-weighted super-matrix.

The fuzzy total influence matrix can be measured by criteria, as shown in matrix $\tilde{\boldsymbol{T}}_C$ in Eq. (10). Matrix $\tilde{\boldsymbol{T}}^\alpha_C$ can be obtained from a normalized matrix $\tilde{\boldsymbol{T}}_C$ with the total degree of effect of dimensions, as shown in Eq. (11). Next, the fuzzy un-weighted super-matrix $\tilde{\boldsymbol{W}}$ can be obtained by transposing matrix $\tilde{\boldsymbol{T}}^\alpha_C$, as shown in Eq. (12).

$$\tilde{\boldsymbol{T}}_C = \begin{array}{cc} & \begin{array}{ccccc} D_1 & \cdots & D_j & \cdots & D_n \\ c_{11}\cdots c_{1m_1} & & c_{j1}\cdots c_{jm_j} & & c_{n1}\cdots c_{nm_n} \end{array} \\ \begin{array}{cc} D_1 & \begin{array}{c} c_{11} \\ \vdots \\ c_{1m_1} \end{array} \\ \vdots & \\ D_i & \begin{array}{c} c_{i1} \\ \vdots \\ c_{im_i} \end{array} \\ \vdots & \\ D_n & \begin{array}{c} c_{n1} \\ \vdots \\ c_{nm_n} \end{array} \end{array} & \begin{bmatrix} \tilde{\boldsymbol{T}}^{11}_C & \cdots & \tilde{\boldsymbol{T}}^{1j}_C & \cdots & \tilde{\boldsymbol{T}}^{1n}_C \\ \vdots & & \vdots & & \vdots \\ \tilde{\boldsymbol{T}}^{i1}_C & \cdots & \tilde{\boldsymbol{T}}^{ij}_C & \cdots & \tilde{\boldsymbol{T}}^{in}_C \\ \vdots & & \vdots & & \vdots \\ \tilde{\boldsymbol{T}}^{n1}_C & \cdots & \tilde{\boldsymbol{T}}^{nj}_C & \cdots & \tilde{\boldsymbol{T}}^{nn}_C \end{bmatrix} \end{array} = (\boldsymbol{T}^l_C, \boldsymbol{T}^m_C, \boldsymbol{T}^h_C) \tag{10}$$

$$\tilde{\boldsymbol{T}}^\alpha_C = \begin{array}{cc} & \begin{array}{ccccc} D_1 & \cdots & D_j & \cdots & D_n \\ c_{11}\cdots c_{1m_1} & & c_{j1}\cdots c_{jm_j} & & c_{n1}\cdots c_{nm_n} \end{array} \\ \begin{array}{cc} D_1 & \begin{array}{c} c_{11} \\ \vdots \\ c_{1m_1} \end{array} \\ \vdots & \\ D_i & \begin{array}{c} c_{i1} \\ \vdots \\ c_{im_i} \end{array} \\ \vdots & \\ D_n & \begin{array}{c} c_{n1} \\ \vdots \\ c_{nm_n} \end{array} \end{array} & \begin{bmatrix} \tilde{\boldsymbol{T}}^{\alpha 11}_C & \cdots & \tilde{\boldsymbol{T}}^{\alpha 1j}_C & \cdots & \tilde{\boldsymbol{T}}^{\alpha 1n}_C \\ \vdots & & \vdots & & \vdots \\ \tilde{\boldsymbol{T}}^{\alpha i1}_C & \cdots & \tilde{\boldsymbol{T}}^{\alpha ij}_C & \cdots & \tilde{\boldsymbol{T}}^{\alpha in}_C \\ \vdots & & \vdots & & \vdots \\ \tilde{\boldsymbol{T}}^{\alpha n1}_C & \cdots & \tilde{\boldsymbol{T}}^{\alpha nj}_C & \cdots & \tilde{\boldsymbol{T}}^{\alpha nn}_C \end{bmatrix} \end{array} = (\boldsymbol{T}^{\alpha l}_C, \boldsymbol{T}^{\alpha m}_C, \boldsymbol{T}^{\alpha h}_C) \tag{11}$$

$$\tilde{\boldsymbol{W}} = (\tilde{\boldsymbol{T}}^\alpha_C)' = \begin{array}{cc} & \begin{array}{ccccc} D_1 & \cdots & D_i & \cdots & D_n \\ c_{11}\cdots c_{1m_1} & & c_{i1}\cdots c_{im_i} & & c_{n1}\cdots c_{nm_n} \end{array} \\ \begin{array}{cc} D_1 & \begin{array}{c} c_{11} \\ \vdots \\ c_{1m_1} \end{array} \\ \vdots & \\ D_j & \begin{array}{c} c_{j1} \\ \vdots \\ c_{jm_j} \end{array} \\ \vdots & \\ D_n & \begin{array}{c} c_{n1} \\ \vdots \\ c_{nm_n} \end{array} \end{array} & \begin{bmatrix} \tilde{\boldsymbol{W}}^{11} & \cdots & \tilde{\boldsymbol{W}}^{i1} & \cdots & \tilde{\boldsymbol{W}}^{n1} \\ \vdots & & \vdots & & \vdots \\ \tilde{\boldsymbol{W}}^{1j} & \cdots & \tilde{\boldsymbol{W}}^{ij} & \cdots & \tilde{\boldsymbol{W}}^{nj} \\ \vdots & & \vdots & & \vdots \\ \tilde{\boldsymbol{W}}^{1n} & \cdots & \tilde{\boldsymbol{W}}^{in} & \cdots & \tilde{\boldsymbol{W}}^{nn} \end{bmatrix} \end{array} = (\boldsymbol{W}^l, \boldsymbol{W}^m, \boldsymbol{W}^h) \tag{12}$$

Step 2 Determine the fuzzy weighted super-matrix matrix.

The fuzzy total influence matrix can be measured by dimension, as shown in matrix $\tilde{\boldsymbol{T}}_D$ in Eq. (13). Matrix $\tilde{\boldsymbol{T}}^\alpha_D$ can be obtained from a normalized matrix $\tilde{\boldsymbol{T}}_D$ with the total degree of effect, as shown Eq. (14). The normalized matrix $\tilde{\boldsymbol{T}}^\alpha_D$ and the un-weighted super-matrix $\tilde{\boldsymbol{W}}$ are used to yield the weighted super-matrix $\tilde{\boldsymbol{W}}^\alpha$, as shown Eq. (15).

Step 3 Calculate the fuzzy influential weights.

The fuzzy weighted super-matrix $\tilde{\boldsymbol{W}}^\alpha$ is multiplied by itself multiple times to obtain the fuzzy limit weighted super-matrix $\lim_{\beta\to\infty}(\tilde{\mathbf{W}}^\alpha)^\beta$. Then, the fuzzy influential weights can be calculated with $\lim_{\beta\to\infty}(\tilde{\mathbf{W}}^\alpha)^\beta$ until the super-matrix has converged and become a stable super-matrix, where β represents a positive integer number.

$$\tilde{\boldsymbol{T}}_D = \begin{bmatrix} \boxed{\tilde{t}_{11}^{D_{11}} \cdots \tilde{t}_{1j}^{D_{1j}} \cdots \tilde{t}_{1m}^{D_{1m}}} \\ \vdots \\ \boxed{\tilde{t}_{i1}^{D_{i1}} \cdots \tilde{t}_{ij}^{D_{ij}} \cdots \tilde{t}_{im}^{D_{im}}} \\ \vdots \\ \boxed{\tilde{t}_{m1}^{D_{m1}} \cdots \tilde{t}_{mj}^{D_{mj}} \cdots \tilde{t}_{mm}^{D_{mm}}} \end{bmatrix} \begin{matrix} \rightarrow \tilde{d}_1 = \sum_{j=1}^{m} \tilde{t}_{1j}^{D_{1j}} \\ \\ \rightarrow \tilde{d}_i = \sum_{j=1}^{m} \tilde{t}_{ij}^{D_{ij}} \\ \\ \rightarrow \tilde{d}_m = \sum_{j=1}^{m} \tilde{t}_{mj}^{D_{mj}} \end{matrix}$$
$$= (\boldsymbol{T}_D^l, \boldsymbol{T}_D^m, \boldsymbol{T}_D^h) \tag{13}$$

$$\tilde{\boldsymbol{T}}_D^\alpha = \begin{bmatrix} \tilde{t}_{11}^{D_{11}} \oslash \tilde{d}_1 & \cdots & \tilde{t}_{1j}^{D_{1j}} \oslash \tilde{d}_1 & \cdots & \tilde{t}_{1m}^{D_{1m}} \oslash \tilde{d}_1 \\ \vdots & & \vdots & & \vdots \\ \tilde{t}_{i1}^{D_{i1}} \oslash \tilde{d}_i & \cdots & \tilde{t}_{ij}^{D_{ij}} \oslash \tilde{d}_i & \cdots & \tilde{t}_{im}^{D_{im}} \oslash \tilde{d}_i \\ \vdots & & \vdots & & \vdots \\ \tilde{t}_{m1}^{D_{m1}} \oslash \tilde{d}_m & \cdots & \tilde{t}_{mj}^{D_{mj}} \oslash \tilde{d}_m & \cdots & \tilde{t}_{mm}^{D_{mm}} \oslash \tilde{d}_m \end{bmatrix}$$
$$= \begin{bmatrix} \tilde{t}_{11}^{\alpha_{11}} & \cdots & \tilde{t}_{1j}^{\alpha_{1j}} & \cdots & \tilde{t}_{1m}^{\alpha_{1m}} \\ \vdots & & \vdots & & \vdots \\ \tilde{t}_{i1}^{\alpha_{i1}} & \cdots & \tilde{t}_{ij}^{\alpha_{ij}} & \cdots & \tilde{t}_{im}^{\alpha_{im}} \\ \vdots & & \vdots & & \vdots \\ \tilde{t}_{m1}^{\alpha_{m1}} & \cdots & \tilde{t}_{mj}^{\alpha_{mj}} & \cdots & \tilde{t}_{mm}^{\alpha_{mm}} \end{bmatrix} = (\boldsymbol{T}_D^{\alpha l}, \boldsymbol{T}_D^{\alpha m}, \boldsymbol{T}_D^{\alpha h}) \tag{14}$$

$$\tilde{\boldsymbol{W}}^\alpha = \tilde{\boldsymbol{T}}_D^\alpha \otimes \tilde{\boldsymbol{W}}$$
$$= \begin{bmatrix} \tilde{t}_{11}^{\alpha_{11}} \odot \tilde{\boldsymbol{W}}^{11} & \cdots & \tilde{t}_{1j}^{\alpha_{1j}} \odot \tilde{\boldsymbol{W}}^{i1} & \cdots & \tilde{t}_{1m}^{\alpha_{1m}} \odot \tilde{\boldsymbol{W}}^{n1} \\ \vdots & & \vdots & & \vdots \\ \tilde{t}_{i1}^{\alpha_{i1}} \odot \tilde{\boldsymbol{W}}^{1j} & \cdots & \tilde{t}_{ij}^{\alpha_{ij}} \odot \tilde{\boldsymbol{W}}^{ij} & \cdots & \tilde{t}_{im}^{\alpha_{im}} \odot \tilde{\boldsymbol{W}}^{nj} \\ \vdots & & \vdots & & \vdots \\ \tilde{t}_{m1}^{\alpha_{m1}} \odot \tilde{\boldsymbol{W}}^{1n} & \cdots & \tilde{t}_{mj}^{\alpha_{mj}} \odot \tilde{\boldsymbol{W}}^{in} & \cdots & \tilde{t}_{mm}^{\alpha_{mm}} \odot \tilde{\boldsymbol{W}}^{nn} \end{bmatrix}.$$
$$= (\boldsymbol{W}^{\alpha l}, \boldsymbol{W}^{\alpha m}, \boldsymbol{W}^{\alpha h}) \tag{15}$$

Appendix 3: The Fuzzy VIKOR Method

The expansion of the fuzzy VIKOR method began with the following form of the $\tilde{L}_k^p$ metric:

$$\tilde{L}_k^p = \left\{ \sum_{j=1}^{n} \left[\tilde{w}_j \otimes \left(\left| \tilde{f}_j^* \Theta \tilde{f}_{kj} \right| \varnothing \left| \tilde{f}_j^* \Theta \tilde{f}_j^- \right| \right) \right]^p \right\}^{1/p} \tag{16}$$

$$\tilde{r}_{kj} = \left| \tilde{f}_j^* \Theta \tilde{f}_{kj} \right| \varnothing \left| \tilde{f}_j^* \Theta \tilde{f}_j^- \right|, \tag{17}$$

where $\tilde{r}_{kj}$ is the fuzzy gap (i.e., fuzzy degrees of regret) of the jth criterion in the kth alternative, $\tilde{w}_j$ is the influential weight of the jth criterion, $\tilde{f}_{kj}$ is the performance score of the jth criterion in the kth alternative, $\tilde{f}_j^*$ is the best value (i.e., the aspiration level), and $\tilde{f}_j^-$ is the worst level, $1 \le p \le \infty$, $j = 1, 2, \ldots, n$, $k = 1, 2, \ldots, K$. The method is described as follows:

Step 1 Set the fuzzy aspiration level and worst level.

The proposed approach for improvement is given the fuzzy aspiration and worst level, as shown in Eqs. (18) and (19).

The fuzzy aspiration levels:

$$\tilde{f}_j^* = (\tilde{f}_1^*, \ldots, \tilde{f}_j^*, \ldots, \tilde{f}_n^*). \tag{18}$$

The fuzzy worst levels:

$$\tilde{f}_j^- = (\tilde{f}_1^-, \ldots, \tilde{f}_j^-, \ldots, \tilde{f}_n^-). \tag{19}$$

In this study, questionnaires use the measuring scores $\tilde{0}$ to $\tilde{4}$ (very bad $\leftarrow \tilde{0}, \tilde{1}, \tilde{2}, \tilde{3}, \tilde{4} \rightarrow$ very good) to evaluate the performances; therefore, the fuzzy aspiration level can be set at score $\tilde{f}_j^* = (f_j^{*l}, f_j^{*m}, f_j^{*h}) = (4, 4, 4)$ and the fuzzy worst level, at score $\tilde{f}_j^- = (f_j^{-l}, f_j^{-m}, f_j^{-h}) = (0, 0, 0)$. This approach can avoid "picking the best apple from a barrel of rotten apples." Membership functions of linguistic scale for questionnaires are constructed using triangular fuzzy numbers, as shown in Table 8.

Step 2 Calculate the fuzzy group utility and individual maximum regret.

The fuzzy group utility $\tilde{G}_k$ and individual maximum regret $\tilde{M}_k$ for gap measures can be formulated using the concept ($\tilde{L}_k^{p=1}$ and $\tilde{L}_k^{p=\infty}$) of the fuzzy VIKOR method, respectively, as shown in Eqs. (20) and (21). The compromise solution $\min_k \tilde{L}_k^p$ (i.e., $\min_k \tilde{G}_k$) minimizes the integrating gap (i.e., the average gap), which will be improved to ensure a value closest to the aspiration level. In addition, the fuzzy group utility is emphasized to make p small (e.g., $p = 1$); if p tends toward infinity, the fuzzy individual maximum regrets/gaps receive a greater priority in the improvement of each dimension/criterion.

$$\tilde{G}_k = \tilde{L}_k^{p=1} = \sum_{j=1}^{n} \tilde{w}_j \otimes \tilde{r}_{kj}$$
$$= \sum_{j=1}^{n} \tilde{w}_j \otimes \left(\left| \tilde{f}_j^* \Theta \tilde{f}_{kj} \right| \varnothing \left| \tilde{f}_j^* \Theta \tilde{f}_j^- \right| \right) \tag{20}$$

$$\tilde{M}_k = \tilde{L}_k^{p=\infty} = \max_j \{ \tilde{r}_{kj} | j = 1, 2, \ldots, n \}$$
$$= \max_j \left\{ \left| \tilde{f}_j^* \Theta \tilde{f}_{kj} \right| \varnothing \left| \tilde{f}_j^* \Theta \tilde{f}_j^- \right| \middle| j = 1, 2, \ldots, n \right\}. \tag{21}$$

Step 3 Calculate the fuzzy comprehensive indicators.

The fuzzy comprehensive indicators $\tilde{R}_k$ for improving and ranking the results can be obtained with Eq. (22). Therefore, $\tilde{R}_k$ can be considered the basis of the ranking/

Table 8 Membership functions for fuzzy VIKOR questionnaire as example

Linguistic scales of fuzzy number ($\tilde{f}_{kj}$)	Corresponding triangular fuzzy numbers ($f_{kj}^{l}, f_{kj}^{m}, f_{kj}^{h}$)
Very bad ($\tilde{0}$)	(0,0,1)
Bad ($\tilde{1}$)	(0,1,2)
Normal ($\tilde{2}$)	(1,2,3)
Good ($\tilde{3}$)	(2,3,4)
Very good ($\tilde{4}$)	(3,4,4)

improving alternatives when $\tilde{R}_k$ is close to zero (i.e., close to the aspiration level).

$$\tilde{R}_k = v \odot \left(\tilde{G}_k \Theta \tilde{G}^*\right) \varnothing \left(\tilde{G}^- \Theta \tilde{G}^*\right) \oplus (1-v) \odot \left(\tilde{M}_k \Theta \tilde{M}^*\right) \varnothing \left(\tilde{M}^- \Theta \tilde{M}^*\right), \tag{22}$$

where v represents the weight of the strategy. Generally, $v = 0.5$, which can be adjusted depending on the case under consideration from the view-points for various options; $v = 1$ indicates that only the average gap is considered, and $v = 0$ indicates that only the fuzzy individual maximum regret/gap is prioritized for improvement. Eq. (22) also can be rewritten as $\tilde{R}_k = v \odot \tilde{G}_k \oplus (1-v) \odot \tilde{M}_k$, when the fuzzy best gap is $\tilde{G}^* = (0,0,0)$ and the fuzzy worst gap $\tilde{G}^- = (1,1,1)$ in the average gap, and the fuzzy best gap is $\tilde{M}^* = (0,0,0)$ and the fuzzy worst gap $\tilde{M}^- = (1,1,1)$ in the individual maximum gap.

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