A DATA-DRIVEN MADM MODEL FOR PERSONNEL SELECTION AND IMPROVEMENT

Yen-Ching CHUANG[1], Shu-Kung HU[2], James J. H. LIOU[1*],
Gwo-Hshiung TZENG[3, 4]

[1]Department of Industrial Engineering and Management, National Taipei University of Technology,
No. 1, Section 3, Chung-Hsiao East Road, Da'an District, 10608 Taipei City, Taiwan
[2]Department of Business and Entrepreneurial Management, Kainan University, No. 1,
Kainan Road, Luchu District, 33857 Taoyuan City, Taiwan
[3]Institute of Management of Technology, National Chiao Tung University, No. 1001,
Ta-Hsueh Road, 30010 Hsinchu City, Taiwan
[4]Graduate Institute of Urban Planning, College of Public Affairs, National Taipei University,
No. 151 University Road, San Shia District, 23741 New Taipei City, Taiwan

Abstract. Personnel selection and human resource improvement are characteristically multiple-attribute decision-making (MADM) problems. Previously developed MADM models have principally depended on experts' judgements as input for the derivation of solutions. However, the subjectivity of the experts' experience can have a negative influence on this type of decision-making process. With the arrival of today's data-based decision-making environment, we develop a data-driven MADM model, which integrates machine learning and MADM methods, to help managers select personnel more objectively and to support their competency improvement. First, RST, a machining learning tool, is applied to obtain the initial influential significance-relation matrix from real assessment data. Subsequently, the DANP method is used to derive an influential significance-network relation map and influential weights from the initial matrix. Finally, the PROMETHEE-AS method is applied to assess the gap between the aspiration and current levels for every candidate. An example was carried out using performance data with evaluation attributes obtained from the human resource department of a Chinese food company. The results revealed that the data-driven MADM model could enable human resource managers to resolve the issues of personnel selection and improvement simultaneously, and can actually be applied in the era of big data analytics in the future.

Keywords: human resource development, personnel selection and improvement, data-driven decision-making environment, data-driven multiple attribute decision-making (Data-driven MADM), rough set theory (RST), DEMATEL-based analytical network process (DANP), preference ranking organization method for enrichment evaluation with aspiration level (PROMETHEE-AS).

JEL Classification: C44, C53, C55, M12, M51.

*Corresponding author. E-mail: jamesjhliou@gmail.com

Introduction

Modern enterprises have to function in a highly competitive environment, and their future survival principally depends on the extent to which qualified employees are dedicated to their companies (Gungor et al., 2009; Sang et al., 2015; Chen et al., 2018). The qualities of an employee play a crucial role in the success of an enterprise; these competencies include knowledge, skills, and other abilities (Aarushi & Malik, 2016; Bohlouli et al., 2017). Futhermore, the placement of each employee in the right position and the improvement of their competency play an immensely critical role in the growth of any enterprise's competitiveness (Guest, 1997; Golec & Kahya, 2007; Chien & Chen, 2008; Bates, 2014; Koutra et al., 2017).

Multiple-attribute decision-making (MADM) methods are often applied in employee assessment models to assist with personnel evaluation, selection, and improvement issues which often involve both qualitative and quantitative factors (Afshari et al., 2013; Alguliyev et al., 2015; Heidary Dahooie et al., 2018). The methodolgoy includes the analytic hierarchy process (AHP) (Gibney & Shang, 2007; Fouladi & Jafari Navimipour, 2017; Chen et al., 2018), the analytic network process (ANP) (Boran et al., 2008; Celik et al., 2009; Liao & Chang, 2009), and the decision-making trial and evaluation laboratory (DEMATEL) (Aksakal & Dağdeviren, 2010). The afore-mentioned MADM studies have made valuable contributions to this field,attempting to establish various appropriate models (i.e., evaluation, selection, and improvement functions) in a crisp-based decision-making environment. However, embedded in past MADM studies is an obvious presupposition related to the utilization of expert opinion as the input data for various decision-making problems. The problem is that the results are affected by the differences in the experts' experiences and their limitations and complicate the MADM process itself, such as the computation times needed for the total number of pairwise comparisons for the well-known AHP, ANP, and DEMATEL-based ANP (DANP) methods, $(n^2 - n)/2$, $n((n^2 - n)/2)$, and $n^2 - n$, respectively.

To consider ambiguities in the decision-making processes, some have incoporated uncertainty methods (e.g., fuzzy, grey, and rough methods) as a data-processing technique into MADM models. For example, Capaldo and Zollo (2001) utilized a fuzzy logic method to solve personnel assessment, whereas Zhang and Liu (2011) used a grey relational analysis–based intuitionistic fuzzy set method for personnel selection. Manoharan, Muralidharan, and Deshmukh (2011) developed a fuzzy AHP and fuzzy quality function deployment (FQFD) model for employee appraisal, and Kabak (2013) proposed a fuzzy DEMATEL-ANP-based model for solving personnel selection. Alguliyev et al. (2015) integrated the worst-case and fuzzy vlsekriterijumska optimizacija i kompromisno resenje (FVIKOR) methods for solving personnel selection problems. Karabasevic, Zavadskas, Turskis, and Stanujkic (2016) developed an MADM evaluation framework for personnel selection by applying step-wise weight assessment ratio analysis (SWARA) and fuzzy additive ratio assessment (FARAS) methods. Although the contributions of these MADM studies should not be minimized, they are an extension of crisp-based to uncertainty-based models, dependent on experts' domain knowledge.

Along with the gradual maturation of information technology and grwoth of the data analysis environment, comes the accumulation of large amounts of data on human resource performance within the company. Some have attempted to take advantage of this, combining

machine learning with MADM methodologies to establish a new type of personnel decision-making model that is different from the earlier MADM models. For example, Li, Lai, and Kao (2011) established a qualitative recruitment system through the application of support vector machine (SVM) and technique for order preference by similarity to ideal solution (TOPSIS) approaches. Ozkan, Keskin, and Omurca (2014) constructed a performance appraisal system using a fuzzy c-means algorithm. Besides, Sang et al. (2015) developed an analytical solution with the Karnik–Mendel (KM) algorithm and Fuzzy TOPSIS methods. Shehu and Saeed (2016) proposed an adaptive personnel selection model for recruitment through the application of the decision tree algorithm, and Li, Kong, Ma, Gong, and Huai (2016) executed human performance modeling through the k-nearest neighbor (KNN) algorithm. Krishankumar, Ravichandran, and Bala (2017) established a personnel evaluation method using the expectation-maximization approach. Such studies have initiated new thinking and the incorporation of new modeling methods of data-driven decision-making (DDDM) into the conventional personnel management environment. These objective-based MADM models try to reduce or avoid subjective effects on the final decision-making process. However, such models cannot show how each employee can attain an aspiration level from a current level. Attempts have been made to integrate MADM methods and machine learning algorithms, to create a new decision-making model in a data-driven environment. This kind of modeling is a new trend using MADM for personnel selection or improvement.

One of the major shortcomings of the existing MADM models is their dependence on domain knowledge and the experience of experts for the initial input. Different conclusions can arise due to the variety of expert opinions. To solve this problem, we propose a data-driven MADM model, which integrates machine learning and MADM methods, to help managers to select personnel more objectively and to support their competency improvement. First, rough set theory (RST) is applied to estimate the degree of interdependence and significance-relation between attributes, to be merged into an initial influential significance-relation matrix. Then, using the DANP method, the initial matrix is used to obtain an influential significance-network relation map (ISNRM) and the influential significance weights among the attributes. Finally, the preference-ranking organization method for enrichment evaluation with the aspiration level (PROMETHEE-AS) method is used to obtain the ranking and the gaps to the aspiration for each candidate. The departmental manager must select suitable personnel from the pool of candidates to fill a position. The human resource (HR) manager can suggest appropriate training courses for improvement of each person according to the derived ISNRM.

The main contributions of our proposed data-driven MADM model are summarized below. (1) There is no need to rely upon the experts' judgements. Rather, the initial matrix for the DANP method is derived from real data by using rough set theory. Our proposed rough set-based DANP method (called the RST-DANP method in our study) overcomes the methodological limitation of the DANP requirement of time-consuming $n^2 - n$ pairwise comparisons. (2) The positive and negative ideal points (i.e., the concept of the relative good) of the original PROMETHEE method are replaced in the new method (which we call PROMETHEE-AS) by the application of the aspiration level as the benchmark, to more effectively reflect real-world situations. Thus PROMETHEE-AS can avoid the problem of having

to "pick the best apple from a barrel of rotten apples" often encountered in the decision-making environment. (3) All the input data are extracted from the case company's long-term database. Hence, the results derived with our proposed model (i.e., network strength relation map, weights, and gap analysis) accurately reflect the real situation in terms of personnel evaluation, selection, and improvement. The data-driven MADM model can help decision-makers or HR managers to propose an appropriate strategy for performance improvement from a systemic perspective, based on the behavior patterns mined from real-data. Therefore, these new concepts will help with the application of MADM methods actually in the decision-making environment in the future era of big data analysis. In this study, empirical data on employee performance and evaluation attributes were obtained from the HR department of a Chinese food company. The results show that our model can more accurately reflect the operating environment for the case company.

The remainder of this article is organized as follows. In Section 1, we discuss the modeling within the context of personnel evaluation and selection. Subsequently, the new data-driven model combining RST with DANP and PROMETHEE-AS is described in Section 2. In Section 3, an empirical case is presented to illustrate our proposed model, and the results are discussed in Section 4. On the basis of the findings, conclusions and remarks are provided in last section.

1. MADM modelling for personnel evaluation and selection

MADM is a special-purpose modeling methodology for solving qualitative and quantitative factors within a decision-making environment. In the field of personnel evaluation and selection, MADM models can be roughly divided into the following categories: (1) crisp-based MADM, (2) uncertainty-based MADM, and (3) objectivity-based MADM models. Gaps in the research and key points in the proposed model are summarized at the end of this section.

1.1. Crisp-based MADM models

Such models are principally aimed at establishing various major decision functions (e.g., evaluation, selection, or improvement) in a multifactor environment based on crisp data. For example, Afshari, Mojahed, Yusuff, Hong, and Ismail (2010) developed a systemic model to solve personnel selection problems by using AHP and ELECTRE methods. Fouladi and Jafari Navimipour (2017) employed the AHP method for the personnel selection problem, and Chen et al. (2018) used the AHP method to evaluate personnel performance. However, the AHP involves the precondition that attributes have an independent relationship, although this assumption is inconsistent with real-world operational situations. To solve this problem, Boran et al. (2008) employed the ANP method to measure the performance of personnel selection, and Celik et al. (2009) applied the ANP method. Aksakal and Dağdeviren (2010) integrated a network-based MADM model to solve the personnel selection problem by using DEMATEL and ANP methods. In addition, Ishizaka and Pereira (2016) developed an appraisal system to measure employee performance through a combination of the ANP and PROMETHEE approaches. These models provide a complete decision-making function that

helps departmental managers to easily assess and select suitable personnel from a group of candidates. Although these models satisfy the selection requirement function within a MADM environment, their strategies are highly dependent on the experts' domain knowledge which comes from different sources, and this affects the final decision-making results.

1.2. Uncertainty-based MADM models

To reduce the sensitivity of the results to differences in the source of experts' domain knowledge, and to address the problems of incomplete information and human cognitive ambiguity in the decision-making environment researchers have combined MADM methods with fuzzy or grey methods. For example, Zolfani and Antucheviciene (2012) prepared a grey MADM model to solve the team-member selection problem by using the AHP and grey TOPSIS methods. Kabak, Burmaoglu, and Kazancoglu (2012) proposed a fuzzy hybrid multiple-criteria decision-making (MCDM) model for professional selection via fuzzy ANP, fuzzy TOPSIS, and fuzzy ELECTRE methods. Wan, Wang, and Dong (2013) developed a multiple-attribute group decision-making (MAGDM) model for personnel selection problems through a triangular intuitionistic fuzzy set VIKOR (TIFS-VIKOR) method. Alguliyev et al. (2015) proposed a fuzzy VIKOR method for solving personnel selection, and Liu, Qin, Mao, and Zhang (2015) used an interval 2-tuple linguistic VIKOR method to solve personnel selection. Ji, Zhang, and Wang (2016) proposed a fuzzy acronym in portuguese of interactive and multi-criteria decision making method (fuzzy TODIM) method for personnel selection. Moreover, Heidary Dahooie et al. (2018) proposed a hybrid SWARA and ARAS-G model to solve this problem. Kazancoglu and Ozkan-Ozen (2018) used a fuzzy DEMATEL method for personnel selection in Industry 4.0. Nabeeh, Smarandache, Abdel-Basset, El-Ghareeb, and Aboelfetouh (2019) developed an integrated neutrosophic-TOPSIS approach and applied it to personnel selection. Krishankumar et al. (2019) developed a novel extension of the VIKOR method in an intuitionistic fuzzy context for solving personnel selection problem. These models consider the various degrees of uncertainty in the real world. Therefore, they can render an improved result for helping managers to select suitable personnel from a pool of candidates. However, such models have been extended from crisp-based to uncertainty-based models; thus, they are also dependent on experts' domain knowledge.

1.3. Objectivity-based MADM models

Others have used mathematical programming or machine-learning algorithms to develop decision-making models, known as objectivity-based MADM models. For instance, Lin (2010) combined ANP with fuzzy data envelopment analysis (Fuzzy DEA) approaches to solve personnel selection problems. Choobdari Namin, Baradaran Jamili, and Allah Kalvandi (2013) used a combinational model of DEA and an artificial neural network (ANN) for efficiency analysis and ranking of each person. In addition, Ozkan et al. (2014) constructed an appraisal system through a fuzzy c-means algorithm for evaluating personnel performance, while Sang et al. (2015) developed an analytical solution through the KM algorithm and Fuzzy TOPSIS method for personnel selection. Shehu and Saeed (2016) proposed an adaptive personnel selection model for solving the personnel selection problem by using a deci-

sion tree algorithm. Moreover, Li et al. (2016) used an improved KNN algorithm in human performance modeling. Krishankumar et al. (2017) employed an expectation-maximization approach in personnel evaluation, and Bello et al. (2018) adopted an ant colony optimization (ACO) algorithm for solving a team selection problem between two decision-makers. Petrović, Puharić, and Kastratović (2018) combined genetic algorithm (GA) and ANN to define the necessary number of employees. Young, Glerum, Wang, and Joseph (2018) used meta-analysis of personality and employee engagement, using personality assessment to select and engage employees. Nguyen et al. (2018) developed a linguistic multi-criteria decision-aiding system to support university career services. Cho (2018) used a basic statistical method to select candidates for pharmacy residencies. Petridis, Drogalas, and Zografidou (2019) developed a TOPSIS/non-linear programming model for internal auditor selection. These models suggest a new perspective on data-driven decision-making, differing from that of the crisp-based and uncertainty-based MADM models. Objectivity-based MADM models integrate mathematical programming or machine-learning algorithms as a modeling technique to reduce or avoid subjective effects on the final decision-making processes. However, such models are of no help to direct personnel how to reach an aspiration level relative to the current performance level.

1.4. Gaps in the literature

Previous MADM studies indicate a trend away from modeling perspectives that rely on using experts' judgements to uncovering behavioral patterns from real database. The main reason this is possible now is that companies have accumulated an immense amount of human resource-related data in their information system and computing speeds are faster. In practice, each company establishes standards/attributes for various positions and each has its unique operating environment. The criteria applied in this study were based on the requirements of the case company to help managers select suitable personnel and to support such personnel in improving their performance. The developed strategies originate with the analysis of a real database, not experts' opinions. Our developed data-driven MADM model is described in detail in the next section. A comparative analysis of various MADM models is shown in Table 1.

2. Data-driven MADM model and corresponding methods

The three steps included in the data-driven MADM model, based on a machine-learning algorithm and MADM methods are outlined below three steps.

In the first step, the rough set theory-based machine learning tool is applied to derive the initial influence matrix (Pawlak, 1997, 1998; Moshkov, & Zielosko, 2011; Mahajan et al., 2012; Bello & Falcon, 2017). Pawlak developed the rough set theory in the early 1980s, including a specialized algorithm for dealing with vagueness and uncertainty in a dataset (Pawlak, 1982; Pawlak et al., 1995; Bai & Sarkis, 2010). The basic component ideas of rough set theory include: (1) data table; (2) indiscernibility relation; (3) reducts; (4) functional dependence; (5) definable and rough concepts/sets; (6) rough membership functions, and decision systems and rules (Pawlak et al., 2005). Rough set theory has several practical advantages in big data analytics: (1) it does not require any preliminary or additional information about the data,

Table 1. Comparative analysis of various MADM models

Categories	Advantages	Limitations
Crisp-based MADM models	These models provide a complete decision-making function that helps departmental managers to easily assess and select suitable personnel from a group of candidates.	– The decisions in these models are highly dependent on the experts' domain knowledge. – The decision-making does not consider the uncertainty of knowledge sources for different fields. – The methodologies, such as AHP, ANP, and DANP require time-consuming pairwise comparisons (i.e., number of pairwise comparisons $(n^2 - n)/2$), $(n\,(n^2 - n)/2)$, and $(n^2 - n)$, respectively).
Uncertainty-based MADM models	These models consider the various degrees of uncertainty in the real world. Therefore, they can render an improved result with various uncertainty characteristics to help managers select suitable personnel from a group of candidates.	– The models were extended from crisp-based to uncertainty-based models; thus, they are also dependent on experts' domain knowledge.
Objectivity-based MADM models	These models suggest another perspective on data-driven decision-making which differs from crisp-based and uncertainty-based MADM models. Objectivity-based MADM models integrate mathematical programming or machine-learning algorithms as a modelling technique to reduce or avoid subjective effects on the final decision-making processes.	– These models use real data as input, but do not consider the concept of the aspiration level; thus, the problem of having to "pick the best apple from a barrel of rotten apples" cannot be avoided in the decision-making environment.

such as the probability distribution in statistics (Liou et al., 2016); (2) it can handle both quantitative and qualitative attributes in the dataset (Rossi et al., 1999); (3) it can discover associative patterns hidden in the data and can represent them in the form of decision rules (Chen & Cheng, 2010). For these reasons, rough set theory can give a clear interpretation of the results and can identify and characterize uncertain systems (Bal, 2013). There are two kinds of application modes in rough set theory (Bello & Falcon, 2017): (1) the analysis of the attributes, such as feature selection, inter-attribute dependency characterization, feature reduction, and feature weighting; (2) the formulation of discovered knowledge, such as the discovery of decision rules, and quantification of the uncertainty in the decision rules. Moreover, the method estimates the degree of influence (called the significance degree in data mining; see Eqs (A4)–(A8)) of attributes as a basis for determining which are the most essential (Pawlak, 1991; Modrzejewski, 1993; Swiniarski & Skowron, 2003; Hu et al., 2003). The derived rules are based on facts; no assumptions are needed.

In the second step, the input data for the original DANP method are obtained from a pairwise comparison questionnaire administered to find experts' domain knowledge. Our novel model uses an RST algorithm to obtain the degree of influence among the attributes. Lee, Tzeng, and Cheng (2009) developed a DANP for derivation of the influential weights of attributes from an influential relation matrix. The DANP integrates the DEMATEL technique

(Gabus & Fontela, 1972; Fontela & Gabus, 1976) and ANP procedures (Saaty, 1996, 2001). Consequently, the weight is a synthetic ratio indicating the influential relationship between attributes in the evaluation system. Therefore, the influential significance-network relation map (ISNRM) and influential weights are derived through the DANP calculation process. The derived ISNRM has proven to be an effective tool to explore the cause and effect relations (see Tseng, 2009; Si et al., 2018; Kiani Mavi & Standing, 2018; Ding et al., 2019; Liou et al., 2019).

In the last step, the PROMETHEE-AS method a combination of the original PROMETHEE (Brans & Vincke, 1985; Brans & Mareschal, 1995) and the aspiration level concept is used (Tzeng & Shen, 2017). The method can not only provide rankings for all candidates for selection but also provide the gaps between the current level and aspiration level for each individual. This method can thus avoid the problem of having to "pick the best apple from a barrel of rotten apples" in the decision-making environment (Liou et al., 2014, 2017). This integrated DANP and PROMETHEE model has been successfully applied to several different studies (Govindan et al., 2015; Tsui et al., 2015; Hu & Tzeng, 2019). The modeling process of the data-driven MADM model is illustrated in Figure 1.

In this study, the critical factors are gleaned from analysis of the company's long-term audit data, thereby more accurately reflecting its real-world operating environment. The data set is comprised of n variables ($x_1, x_2,\ldots, x_n$) representing personnel evaluation attributes and performance results. The three phases of the data-driven MADM modeling process are described below:

The first stage entails applying RST to derive a direct influential and significance relation matrix. A dataset with n attributes ($x_1, x_2,\ldots, x_n$) is prepared, representing the personnel with the relevant attributes and their evaluation results. Subsequently, n attributes are condensed into one attribute (decision attribute x_1) and $n - 1$ attributes (condition attributes $x_2, x_3,\ldots, x_n$). For instance, when x_1 is a decision attribute, then $x_2, x_3,\ldots, x_n$ are condition attributes (i.e., condition attributes do not include decision attributes). Therefore, we can obtain n different data sets (i.e., a decision attribute and a corresponding set of condition attributes). Subsequently, for each data set, RST is applied to retrieve the influential significance-relation degrees between the condition attributes (e.g., $x_2, x_3,\ldots, x_n$) and a decision attribute (e.g., x_1) using Eqs. (A1)–(A8). Finally, the influential significance-relation degrees of n different data sets are integrated. Consequently, we can obtain a matrix $\boldsymbol{E} = [e_{io}]_{n \times n}$, $i, o \in \{1, 2,\ldots, n\}$, where e_{io} represents an influential significance degree of attribute (condition attribute) i on another attribute (decision attribute) o and the diagonal elements are equal to zero ($e_{io} = 0$). The detailed definitions are shown in Appendix A.

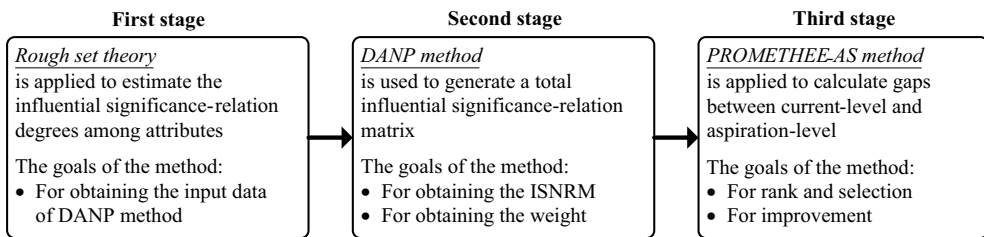| First stage	Second stage	Third stage
Rough set theory is applied to estimate the influential significance-relation degrees among attributes	*DANP method* is used to generate a total influential significance-relation matrix	*PROMETHEE-AS method* is applied to calculate gaps between current-level and aspiration-level
The goals of the method: • For obtaining the input data of DANP method	The goals of the method: • For obtaining the ISNRM • For obtaining the weight	The goals of the method: • For rank and selection • For improvement

Figure 1. The modelling process of the integrated data-driven MADM model

The second stage entails using the DANP method to obtain the ISNRM and influential significance weights. When the first stage is executed k times, we obtain k matrices from the audit assessment data for the direct influential significance-relation matrix. By averaging these k matrices, we can obtain an initial influence-significance relation matrix $Q = [q_{io}]_{n \times n} = [(\sum_{\varphi=1}^{k} e_{io}^{\varphi}) / k]_{n \times n}$. Using Eqs (B1) and (B2), a normalized matrix Z can be obtained from matrix Q. Subsequently, we can apply Eq. (B3) to obtain the total influential strength-relation matrix T from the normalized matrix Z. Based on matrix T, we use Eqs (B6) and (B7) to develop an ISNRM. Additionally, matrix T uses the ANP to obtain the unweighted supermatrix W^{∇} (i.e., Eqs (B8) and (B9)) and weighted supermatrix $W^{\ominus}$ (i.e., Eqs (B10) and (B11)). Finally, the global influential significance-weight of each attribute is derived using Eq. (B12). The calculations are shown in detail in Appendix B.

The third stage entails using the PROMETHEE-AS method to compare the aspiration gap, the gap between each the current level and the aspiration level for all personnel for each attribute. The performance of the eight candidates appears in a matrix F (i.e., Eq. (C1)). The normalized performance matrix F^{Φ} is derived from matrix F by using Eqs (C4)–(C6). Subsequently, using Eqs (C7)–(C11) we obtain the net flows for all personnel. A smaller value representative of the net flow ranking of each person is preferred. The calculations are shown in detail in Appendix C.

3. An illustration

We used real assessment data from the HR department of a Chinese food company to illustrate the modeling process for our proposed data-driven MADM model. This section first provides an overview of the case company and data. The computing process applied to evaluate and improve each person's competency performance is described. Finally, the results are discussed.

3.1. Background and data description

China is one of the world's largest, most important and competitive markets. Effective human resource management and development are critical because the foundation of the company's core competitiveness comes from the capabilities of its staff. The case examined here is a well-known company in the Chinese food industry whose business includes the manufacture of instant noodles and beverages. How to select the most suitable person for a position and how to improve their performance have always been concern for the case company. HR managers usually adopt a set of competency attributes based on expert knowledge which they use when selecting suitable personnel and when making decisions about providing training programs to improve an individual's abilities. However, decisions based on experts' knowledge are influence by the experts' subjective experience.

Consequently, this company needs to utilize a more objective decision-making model for selecting suitable personnel and improving their performance. To solve this problem, we developed a novel data-driven MADM model to explore patterns derived from a real assessment database. The proposed model can help managers systematically improve personnel performance ultimately improving the company's competitiveness. The data, comprising 390 employees' annual evaluation results, were obtained from the HR department of the case company in 2016. The data included the evaluation attributes of personnel divided into three

aspects, with the total number of attributes being 12 (Table 2). Managers typically evaluated their subordinates performance using a 6-point Likert-type scale. An analytical diagram of this empirical case is shown in Figure 2.

3.2. Constructing an initial influence-significance relation matrix through RST

RST was applied to obtain an influential significance-relation matrix by retrieving influential degrees among all attributes in the personnel assessment data. The assessment attributes were divided by setting one attribute as the decision attribute and the others as condition attributes. Consequently, we derived 12 combinational sets of attributes, with each set including 11 condition attributes and 1 decision attribute. On the basis of these sets, we applied RST to measure the influential significance relation between condition attribute i and decision attribute o. For example, to understand the influential significance relation between C_{11} and the other attributes (i.e., C_{12} to C_{34}), we assumed C_{11} to be the decision attribute and the other attributes (C_{12} to C_{34}) to be the condition attributes. RST (i.e., Eqs (A1)–(A8)) is then used to estimate the influential significance-relation degrees between condition attributes (C_{12} to C_{34}) and the decision attribute (C_{11}). The influential significance-relation degrees of other attributes can be obtained similarly by setting different decision attributes. In our case, 12 rough set models were created in our case. Applying these models, we generate one direct influential significance-relation matrix E. Next, by repeating the process k times (in this case, $k = 10$), we derive an average initial influential significance-relation matrix Q (Table 3).

Table 2. Personnel evaluation aspects and attributes

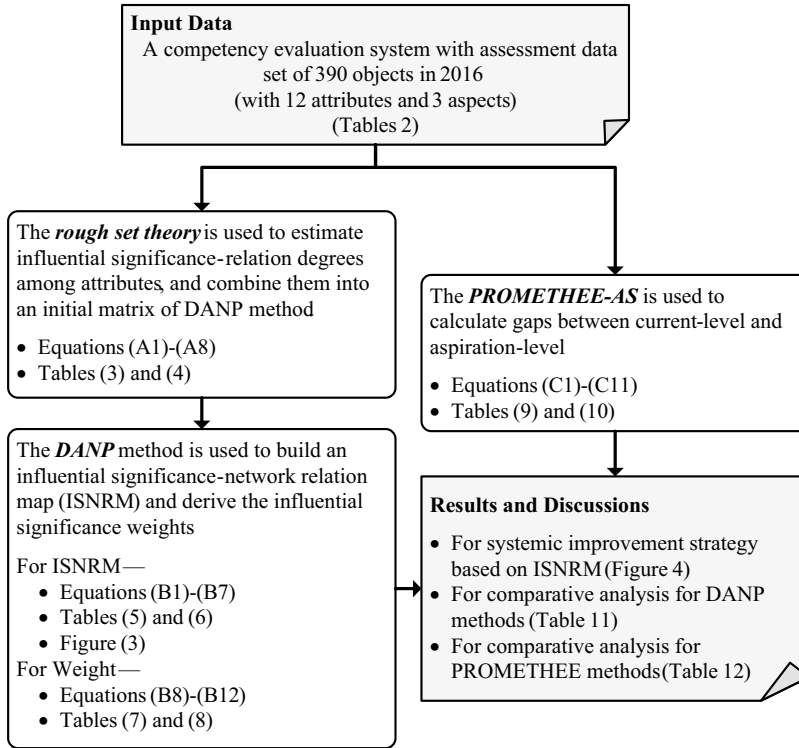| Aspect	Attribute	Definition
Personal (C_1)	Responsibility (C_{11})	Being able to complete tasks proactively and assume responsibilities
	Ethics and integrity (C_{12})	Being able to be a person of strict morality and to match his/her words with deeds
	Continuous learning (C_{13})	Being able to improve work performance by learning, innovation, and self-improvement
	Intelligence (C_{14})	Being able to think logically and know the scope of the work
Professional competency (C_2)	Innovative thinking (C_{21})	Being able to seek various solutions to solve problems
	Service orientation (C_{22})	Being able to manage relationships with customers and regard meeting customer needs as a priority
	Professional skills (C_{23})	Being able to identify problems and to seek effective solutions
	Teamwork (C_{24})	Being able to be a good team player
General competency (C_3)	Independence (C_{31})	Being able to complete tasks independently
	Problem prevention and improvement (C_{32})	Being able to identify potential problems and take preventive measures
	Work efficiency improvement (C_{33})	Being able to seek ways to improve efficiency
	Self-development (C_{34})	Being able to make a long-term learning plan to increase the required knowledge and acquire skills

Input Data
A competency evaluation system with assessment data set of 390 objects in 2016
(with 12 attributes and 3 aspects)
(Tables 2)

The **rough set theory** is used to estimate influential significance-relation degrees among attributes, and combine them into an initial matrix of DANP method

- Equations (A1)-(A8)
- Tables (3) and (4)

The **PROMETHEE-AS** is used to calculate gaps between current-level and aspiration-level

- Equations (C1)-(C11)
- Tables (9) and (10)

The **DANP** method is used to build an influential significance-network relation map (ISNRM) and derive the influential significance weights

For ISNRM—
- Equations (B1)-(B7)
- Tables (5) and (6)
- Figure (3)
For Weight—
- Equations (B8)-(B12)
- Tables (7) and (8)

Results and Discussions

- For systemic improvement strategy based on ISNRM (Figure 4)
- For comparative analysis for DANP methods (Table 11)
- For comparative analysis for PROMETHEE methods (Table 12)

Figure 2. Analytical diagram of the empirical case

Table 3. Initial influential significance-relation matrix

Q	C_{11}	C_{12}	C_{13}	C_{14}	C_{21}	C_{22}	C_{23}	C_{24}	C_{31}	C_{32}	C_{33}	C_{34}
C_{11}	–	0.077	0.018	0.033	0.038	0.031	0.043	0.093	0.055	0.015	0.076	0.035
C_{12}	0.058	–	0.074	0.067	0.024	0.043	0.060	0.095	0.054	0.017	0.029	0.056
C_{13}	0.026	0.050	–	0.043	0.025	0.017	0.028	0.038	0.052	0.016	0.025	0.040
C_{14}	0.031	0.038	0.038	–	0.035	0.015	0.009	0.101	0.024	0.008	0.017	0.042
C_{21}	0.030	0.041	0.023	0.032	–	0.017	0.027	0.071	0.037	0.028	0.079	0.029
C_{22}	0.030	0.039	0.018	0.014	0.014	–	0.046	0.044	0.051	0.016	0.028	0.020
C_{23}	0.043	0.051	0.027	0.010	0.029	0.043	–	0.030	0.059	0.024	0.028	0.020
C_{24}	0.041	0.061	0.037	0.098	0.036	0.049	0.034	–	0.031	0.035	0.023	0.016
C_{31}	0.037	0.048	0.076	0.039	0.030	0.052	0.105	0.040	–	0.027	0.085	0.066
C_{32}	0.011	0.018	0.013	0.008	0.027	0.016	0.023	0.027	0.026	–	0.044	0.010
C_{33}	0.027	0.022	0.025	0.024	0.022	0.021	0.028	0.023	0.066	0.046	–	0.105
C_{34}	0.030	0.024	0.036	0.044	0.029	0.019	0.019	0.016	0.040	0.011	0.103	–

3.3. Obtaining ISNRM and influential significance weight through the DANP method

The initial matrix Q (Table 3) was assumed to affect the ISNRM results (Figure 3) and the influential significance weights. Therefore, to ensure the reliability of these results, we applied a *k*-fold cross-validation method to calculate the confidence level in the *k* matrices (Table 4); in this case, $k = 10$. Table 3 shows that the average *k*-fold variance was 0.13% (below 5%) in the consensus. Specifically, the significant confidence reached 99.87% (over 95%); accordingly, RST determined that the influential significance-relation degrees of the attributes were satisfactory.

By using Eqs (B1) and (B2), we obtained the normalized matrix Z, which was then transformed into the total influential significance-relation matrix T (Table 5) through Eq. (B3).

Table 4. Variance of the *k*-fold cross-validation (in this case, $k = 10$)

Number of matrices	No. 1	No. 2	No. 3	No. 4	No. 5	No. 6
Gap	0.0014	0.0015	0.0012	0.0012	0.0016	0.0012
Gap (%)	0.14%	0.15%	0.12%	0.12%	0.16%	0.12%
Number of matrices	No. 7	No. 8	No. 9	No. 10	Average	
Gap	0.0015	0.0015	0.0012	0.0011	0.0013	
Gap (%)	0.15%	0.15%	0.12%	0.11%	0.13%	

Note: The significant confidence equation is $\dfrac{1}{n(n-1)}\sum\limits_{i=1}^{\varphi}\sum\limits_{o=1}^{\varphi}\dfrac{\left|e_{io}^{\varphi}-e_{io}^{\varphi-1}\right|}{e_{io}^{\varphi}}\times 100\% = 0.13\% < 5\%$, i.e., significant confidence is 99.87%, where $\varphi = 10$ denotes the number of influential strength matrixes and e_{io}^{φ} is the average influence-significance degree of *i* indicator on *o*; and *n* denotes the number of indicators, where $n = 12$.

Table 5. Total influence significance-relation matrix

T	C_{11}	C_{12}	C_{13}	C_{14}	C_{21}	C_{22}	C_{23}	C_{24}	C_{31}	C_{32}	C_{33}	C_{34}
C_{11}	0.162	0.315	0.205	0.244	0.192	0.196	0.250	0.375	0.292	0.136	0.329	0.252
C_{12}	0.262	0.218	0.298	0.308	0.183	0.222	0.284	0.399	0.304	0.142	0.276	0.288
C_{13}	0.154	0.216	0.125	0.200	0.134	0.130	0.173	0.227	0.225	0.101	0.194	0.199
C_{14}	0.162	0.201	0.181	0.143	0.149	0.126	0.140	0.320	0.180	0.089	0.178	0.195
C_{21}	0.173	0.219	0.172	0.201	0.105	0.142	0.185	0.292	0.222	0.132	0.290	0.204
C_{22}	0.151	0.188	0.141	0.141	0.107	0.095	0.191	0.217	0.211	0.095	0.182	0.155
C_{23}	0.183	0.222	0.168	0.150	0.141	0.172	0.137	0.217	0.240	0.115	0.203	0.172
C_{24}	0.202	0.264	0.206	0.307	0.171	0.197	0.205	0.216	0.223	0.144	0.216	0.189
C_{31}	0.231	0.289	0.300	0.256	0.191	0.236	0.353	0.311	0.232	0.162	0.364	0.315
C_{32}	0.088	0.113	0.096	0.092	0.101	0.089	0.117	0.142	0.132	0.049	0.164	0.103
C_{33}	0.161	0.181	0.171	0.175	0.137	0.141	0.183	0.206	0.257	0.152	0.181	0.308
C_{34}	0.158	0.174	0.177	0.196	0.139	0.129	0.157	0.190	0.212	0.098	0.312	0.151

Note: The values were computed by Eq. (B3).

Subsequently, matrix **T** was calculated by applying Eqs (B6) and (B7) to obtain the "influence given (g_i)" and the "influence received (r_i)" for each attribute; these values were compounded to produce the "prominence ($g_i + r_i$)" and "relation ($g_i - r_i$)" indicators, respectively. The indicator "prominence ($g_i + r_i$)" represents the influential strength of the ith attribute within the entire evaluation system; a higher value indicates a higher importance of the attribute. For "relation ($g_i - r_i$)", a positive value indicates that the ith attribute belongs to the causal group, whereas a negative value indicates that the ith attribute belongs to the affected group. The results obtained for the attributes and aspects are summarized in Table 6.

Table 6. Sum of given and received influence degree

Aspects	g_i	r_i	$g_i + r_i$	$g_i - r_i$	Attributes	g_i	r_i	$g_i + r_i$	$g_i - r_i$
C_1	0.642	0.584	1.226 (1)	0.059 (+)	C_{11}	2.949	2.086	5.034 (2)	0.863 (+)
					C_{12}	3.184	2.600	5.784 (1)	0.584 (+)
					C_{13}	2.080	2.239	4.319 (4)	−0.160 (−)
					C_{14}	2.064	2.413	4.477 (3)	−0.348 (−)
C_2	0.554	0.570	1.124 (3)	−0.015 (−)	C_{21}	2.338	1.751	4.089 (3)	0.587 (+)
					C_{22}	1.873	1.877	3.749 (4)	−0.004 (−)
					C_{23}	2.118	2.376	4.494 (2)	−0.258 (−)
					C_{24}	2.542	3.110	5.652 (1)	−0.569 (−)
C_3	0.554	0.598	1.152 (2)	−0.043 (−)	C_{31}	3.241	2.731	5.972 (1)	0.511 (+)
					C_{32}	1.285	1.416	2.701 (4)	−0.131 (−)
					C_{33}	2.253	2.889	5.141 (2)	−0.636 (−)
					C_{34}	2.092	2.531	4.623 (3)	−0.439 (−)

Note:
1. The influential values given and received were calculated through Eqs. (B6) and (B7).
2. The value of () in "prominence (g_i+r_i)" is the ranking, where a smaller value is better.
3. The value of () in "relation (g_i-r_i)" is a symbol, with "+" indicating that the attribute belongs to the cause group and "−" indicating that it belongs to the affected group.

Table 6 shows two features of information on attributes or aspects: "prominence ($g_i + r_i$)" and "relation ($g_i - r_i$)." From the preceding analysis, the ranking in all aspects was $C_1 \succ C_3 \succ C_2$. The detailed rankings of attributes in their corresponding aspects were as follows: $C_{12} \succ C_{11} \succ C_{14} \succ C_{13}$ (in aspect C_1); $C_{31} \succ C_{33} \succ C_{34} \succ C_{32}$ (in aspect C_3); and $C_{24} \succ C_{23} \succ C_{21} \succ C_{22}$ (in aspect C_2). These results show that "ethics and integrity (C_{12}) (5.784)", "independence (C_{31}) (5.972)," and "teamwork (C_{24}) (5.652)" respectively had the greatest priorities in their aspects.

As shown in Table 6, "responsibility (C_{11})," "ethics and integrity (C_{12})," "innovative thinking (C_{21})," and "independence (C_{31})" belonged to the cause group with positive relation (g_i-r_i) values. By contrast, "continuous learning (C_{13})," "intelligence (C_{14})," "service orientation (C_{22})," "professional skills (C_{23})," "teamwork (C_{24})," "problem prevention and improvement (C_{32})," "work efficiency improvement (C_{33})," and "self-development (C_{34})" belonged to the affected group with negative values. Finally, "prominence ($g_i + r_i$)" and "relation ($g_i - r_i$)" were combined to create an ISNRM. Figure 3 depicts the ISNRM of all mutually interdependent

aspects and attributes, which can help managers to comprehensively understand the systemic relationships between all aspects and attributes.

An unweighted supermatrix W^∇ could be obtained through matrix T by using Eqs (B8) and (B9), as shown in Table 7. Finally, by using matrix W^∇, we applied Eqs (B10)–(B12) to derive the weights (i.e., global weights) of aspects and attributes, as shown in Table 8.

As indicated by the local weights in Table 8, the ranking of aspects was $C_3 \succ C_1 \succ C_2$. The ranking of attributes in the C_3 aspect was $C_{33} \succ C_{31} \succ C_{34} \succ C_{32}$. In addition, the ranking of attributes in the C_1 aspect was $C_{12} \succ C_{14} \succ C_{13} \succ C_{11}$. The ranking of attributes in the C_2 aspect was $C_{24} \succ C_{23} \succ C_{22} \succ C_{21}$. The top three attributes for the global weights were "teamwork (C_{24}) (0.110)," "work efficiency improvement (C_{33}) (0.103)," and "independence (C_{31}) (0.098)." These attributes were crucial in the competency evaluation system because they had greater influential significance weights for competency and were ranked among the top three attributes.
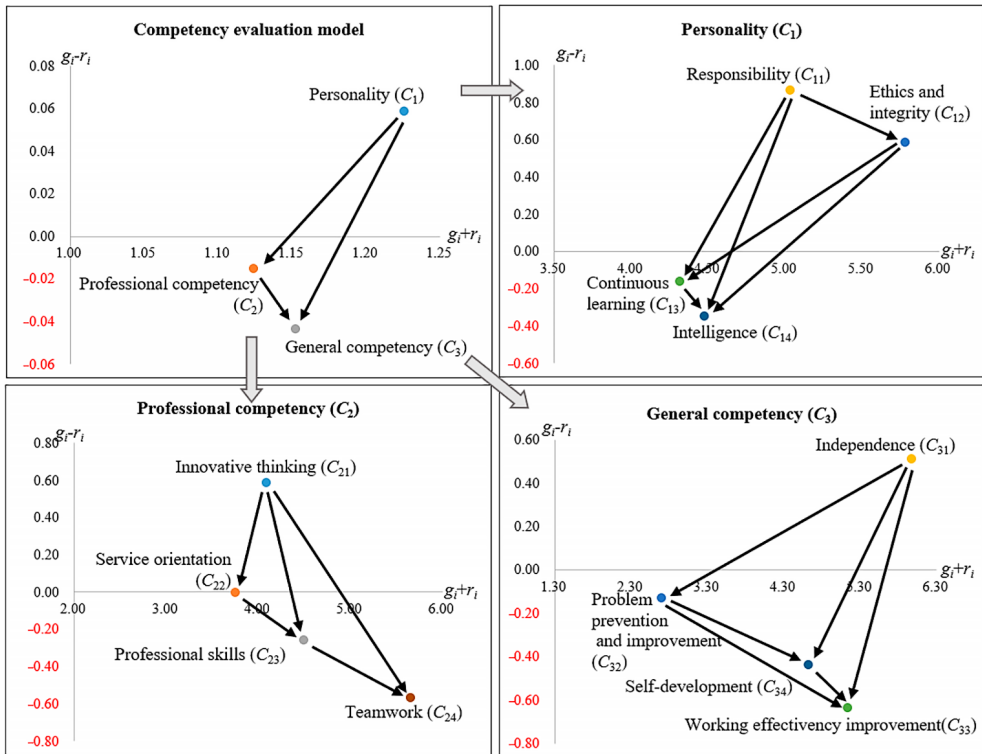

Figure 3. Influential significance-network relation map (ISNRM)

Table 7. Unweighted supermatrix

W^{∇}	C_{11}	C_{12}	C_{13}	C_{14}	C_{21}	C_{22}	C_{23}	C_{24}	C_{31}	C_{32}	C_{33}	C_{34}
C_{11}	0.175	0.241	0.222	0.236	0.227	0.243	0.253	0.206	0.215	0.226	0.233	0.224
C_{12}	0.340	0.201	0.310	0.293	0.286	0.304	0.307	0.270	0.268	0.291	0.263	0.247
C_{13}	0.222	0.274	0.180	0.263	0.225	0.226	0.233	0.210	0.279	0.246	0.249	0.251
C_{14}	0.264	0.284	0.288	0.208	0.263	0.227	0.207	0.313	0.238	0.237	0.255	0.278
C_{21}	0.190	0.168	0.201	0.203	0.145	0.176	0.211	0.217	0.175	0.225	0.205	0.226
C_{22}	0.194	0.204	0.196	0.172	0.196	0.155	0.258	0.250	0.217	0.199	0.211	0.210
C_{23}	0.246	0.261	0.261	0.191	0.255	0.313	0.206	0.260	0.323	0.260	0.275	0.256
C_{24}	0.370	0.366	0.342	0.435	0.403	0.355	0.325	0.273	0.285	0.316	0.308	0.308
C_{31}	0.290	0.301	0.313	0.281	0.261	0.328	0.329	0.289	0.217	0.295	0.286	0.274
C_{32}	0.134	0.140	0.141	0.139	0.156	0.147	0.158	0.186	0.151	0.110	0.169	0.127
C_{33}	0.326	0.274	0.270	0.277	0.342	0.283	0.278	0.280	0.339	0.365	0.201	0.404
C_{34}	0.250	0.285	0.277	0.304	0.241	0.241	0.235	0.245	0.293	0.230	0.343	0.195

Note: The values were calculated through Eqs (B8) and (B9).

Table 8. Influential significance weight on aspects and attributes

Aspect	Local weight	Rank	Attribute	Local weight	Rank	Global weight	Rank
C_1	0.333	2	C_{11}	0.225	4	0.075	9
			C_{12}	0.279	1	0.093	4
			C_{13}	0.239	3	0.080	8
			C_{14}	0.257	2	0.086	6
C_2	0.325	3	C_{21}	0.196	4	0.064	11
			C_{22}	0.207	3	0.067	10
			C_{23}	0.259	2	0.084	7
			C_{24}	0.338	1	0.110	1
C_3	0.342	1	C_{31}	0.287	2	0.098	3
			C_{32}	0.149	4	0.051	12
			C_{33}	0.300	1	0.103	2
			C_{34}	0.265	3	0.091	5

3.4. Obtaining the aspiration gap and ranking of eight personnel through the PROMETHEE-AS method

Currently, the case company has a managerial position and considers eight potential senior staff members. To understand the gap between the aspired levels and the current levels of performance of these eight staff members with respect to each attribute, we evaluated the data on a scale ranging from 0 to 6 (with a higher score indicating better performance for all attributes). Furthermore, the aspiration level could be considered to represent the presumed

future accomplishments of these eight candidates. Therefore, the values for the aspired and worst levels were set to 6 and 0, respectively. The performance matrix derived from the eight staff members is presented in Table 9.

The gaps between the current and aspired performance levels could be calculated through Eqs (C1)–(C11). Subsequently, the final net flow and each candidate's ranking were obtained, as summarized in Table 10. Clearly, the comparative ranking of the staff members was "F_4" $\succ$ "F_3" $\succ$ "F_8" $\succ$ "F_7" $\succ$ "F_1" $\succ$ "F_5" $\succ$ "F_2" $\succ$ "F_6". According to the results obtained using the PROMETHEE-AS method, "F_4" had the smallest aspiration gap between the aspiration levels and was thus regarded as the first choice. Furthermore, the results indicated that "F_6" had the worst performance value and the largest aspiration gap. These results indicate that departmental managers can understand that "F_4" is the most appropriate employee in personnel selection.

Table 9. Performance score on eight personnel

Attributes	F_1	F_2	F_3	F_4	F_5	F_6	F_7	F_8
Responsibility (C_{11})	4	4	5	5	5	5	5	5
Ethics and integrity (C_{12})	5	4	5	4	5	4	5	5
Continuous learning (C_{13})	4	3	4	5	4	4	4	4
Intelligence (C_{14})	4	4	4	4	3	3	4	4
Innovative thinking (C_{21})	4	4	4	5	4	4	4	4
Service orientation (C_{22})	4	4	6	5	4	4	4	5
Professional skills (C_{23})	4	4	4	4	3	3	4	4
Teamwork (C_{24})	4	4	5	4	4	4	4	4
Independence (C_{31})	4	4	5	4	4	4	5	5
Problem prevention and improvement (C_{32})	4	4	5	5	4	4	4	4
Work efficiency improvement (C_{33})	3	3	4	5	4	3	4	4
Self-development (C_{34})	4	4	3	5	3	4	4	4

Table 10. Aspiration gaps and ranking for eight personnel in the PROMETHEE-AS method

Aspects /Attributes	Weight	F_1	F_2	F_3	F_4	F_5	F_6	F_7	F_8
Personal (C_1)	0.333	0.287	0.287	0.249	0.249	0.249	0.249	0.249	0.249
Responsibility (C_{11})	0.225	0.333	0.333	0.167	0.167	0.167	0.167	0.167	0.167
Ethics and integrity (C_{12})	0.279	0.167	0.333	0.167	0.333	0.167	0.333	0.167	0.167
Continuous learning (C_{13})	0.239	0.333	0.500	0.333	0.167	0.333	0.333	0.333	0.333
Intelligence (C_{14})	0.257	0.333	0.333	0.333	0.333	0.500	0.500	0.333	0.333
Professional competency (C_2)	0.325	0.333	0.333	0.333	0.301	0.333	0.333	0.333	0.333
Innovative thinking (C_{21})	0.196	0.333	0.333	0.333	0.167	0.333	0.333	0.333	0.333
Service orientation (C_{22})	0.207	0.333	0.333	0.000	0.167	0.333	0.333	0.333	0.167
Professional skills (C_{23})	0.259	0.333	0.333	0.333	0.333	0.500	0.500	0.333	0.333

Aspects /Attributes	Weight	F_1	F_2	F_3	F_4	F_5	F_6	F_7	F_8
Teamwork (C_{24})	0.338	0.333	0.333	0.167	0.333	0.333	0.333	0.333	0.333
General competency (C_3)	0.342	0.383	0.383	0.336	0.383	0.383	0.383	0.336	0.336
Independence (C_{31})	0.287	0.333	0.333	0.167	0.333	0.333	0.333	0.167	0.167
Problem prevention and improvement (C_{32})	0.149	0.333	0.333	0.167	0.167	0.333	0.333	0.333	0.333
Work efficiency improvement (C_{33})	0.300	0.500	0.500	0.333	0.167	0.333	0.500	0.333	0.333
Self-development (C_{34})	0.265	0.333	0.333	0.500	0.167	0.500	0.333	0.333	0.333
Total in-flow		0.346	0.516	0.147	0.156	0.446	0.518	0.136	0.103
Total out-flow		0.147	0.087	0.588	0.676	0.136	0.068	0.305	0.361
Total net flow		0.199	0.429	–0.441	–0.520	0.310	0.449	–0.168	–0.258
Rank		5	7	2	1	6	8	4	3

Note:
1. The values of the normalized aspiration gap represent real aspiration gaps of each attribute or aspect.
2. All values of three flows were weighted (based on systemic influential relation).
3. Smaller net flow values were preferable.

4. Discussion

This study proposes a novel data-driven MADM model for solving personnel selection and improvement problems. An ISNRM and influential significance weights were obtained by using machine learning and MADM methods for real assessment data for the case company. On the basis of the results obtained for the case company, some management implications are provided.

4.1. Systemic improvement strategy based on ISNRM

To demonstrate how to apply this systemic analytical framework for improving the competencies of any employee, consider the following example. First, the ISNRM and aspiration gaps derived for personnel (F_3) are combined, as shown in Figure 4. As can be seen in this figure the largest gap obtained was for "general competency (C_3)" (0.336) and which should be improved to achieve the aspiration level (i.e., gap = 0). The worst performance was for "self-development (C_{34})" because it had the largest gap (0.500). An HR manager would assume that personnel (F_3) is not able to develop long-term learning plans to enhance their knowledge and skills. Therefore, based on this information, they would provide training courses on topics such as communication or management skills to help close the gap for "self-development (C_{34})".

However, by observing the direction of influence from all aspects, the HR manager is able to see that "general competency (C_3)" is affected by both "personality (C_1)" and "professional competency (C_2)" simultaneously. Specifically, "personality (C_1)" and "professional competency (C_2)" are the causal aspects, so should be improved first. Through further analysis of

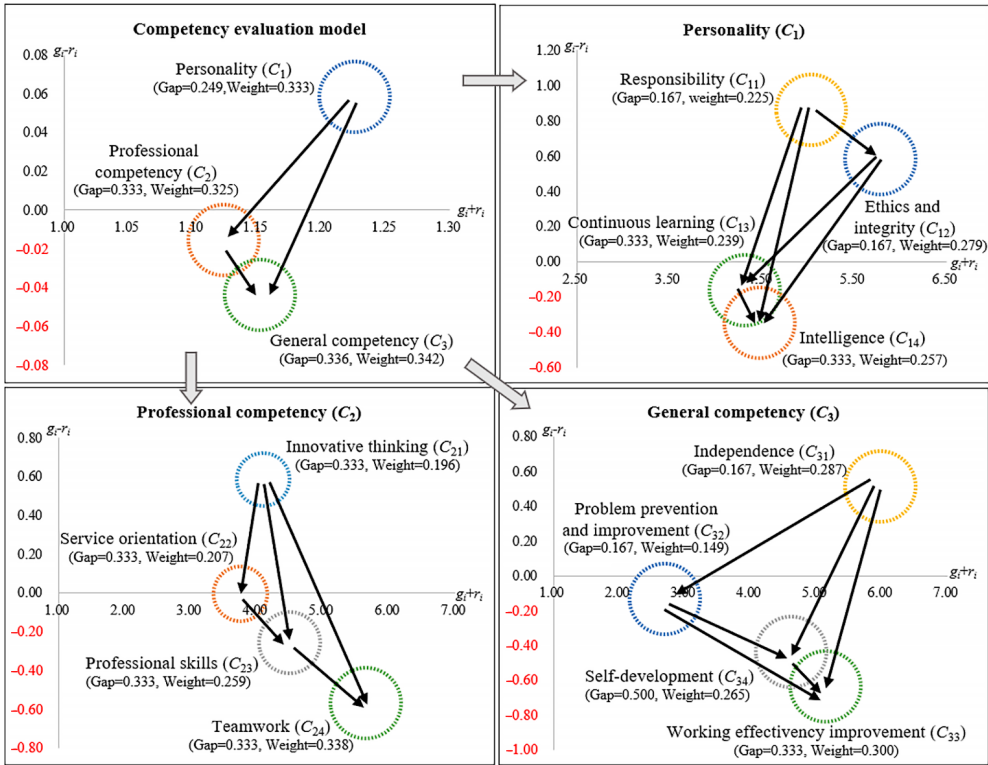Figure 4. Data-driven ISNRM for improving F_3

these three aspects, the manager can categorize "responsibility (C_{11})," "innovative thinking (C_{21})", and "independence (C_{31})" as causal factors in their corresponding aspects. Therefore, to reduce the gaps for personnel (F_3), the HR manager should suggest relevant courses to improve this individual's "responsibility (C_{11})", "innovative thinking (C_{21})", and "independence (C_{31})" rather than "self-development (C_{34})".

The preceding analysis shows that the worst attribute is not the source of the problem. To understand the problem, we need a systematic analytical tool, a requirement that can be satisfied by our model's data-driven ISNRM. A manager's personal preferences could lead to biases in personnel selection, which might have undesired side effects within an organization, could lower morale and even damage company performance. Our model can effectively select the most appropriate person based on long-term survey data, not the managers' personal preferences.

4.2. Comparative analysis of expert-based knowledge and data-driven pattern in DANP method

This study proposes a novel modelling concept that allows decision-making to be based on behavior patterns mined from large real datasets. Compared with the original DANP method, the weights derived with this novel data-driven DANP method are more robust. There

are two reasons for this: (i) behavior patterns are derived from a large number of collective behaviors, rather than a small number of expert opinions; (ii) the reliability of the weights is based on k-fold cross-validation calculated using the data-mining algorithms. The weight rankings of the aspects/attributes for the original DANP (i.e., expert-based knowledge) and data-driven DANP (i.e., data-driven collective pattern) models are shown in Table 11.

The ranks of the aspect level for original DANP method are "general competency (C_3)" ≻ "professional competency (C_2)" ≻ "personal (C_1)". With the data-driven DANP method, the aspects are ranked as follows: "general competency (C_3)" ≻ "personal (C_1)" ≻ "professional competency (C_2)". It can be seen that "general competency (C_3)" is ranked the same by both methods. In other words, both models deem this aspect to be crucial and therefore to be emphasized when conducting personnel evaluations. However, the "personal (C_1)" and "professional competency (C_2)" are ranked differently. Further analysis at the attribute level by the expert-based model shows "continuous learning (C_{13})," "professional skills (C_{23})", and "work efficiency improvement (C_{33})" to be the most important attributes, while the data-driven knowledge model found "ethics and integrity (C_{12})", "teamwork (C_{24})", and "work efficiency improvement (C_{33})" to be the most important attributes.

Some management implications can be derived from the above results. Both methods indicated that an employee's evaluation should focus on "work efficiency improvement (C_{33})". Employee's work efficiency will directly affect the company production and profit. The company should provide a work environment where employees can improve their work efficiency, such as brighter workspace, cleaner air, being equipped with the necessary tools, flexible

Table 11. Comparison between the domain-knowledge and the data-driven knowledge models

Aspects/Attributes	Expert-based		Data-driven	
	Local weight	Rank	Local weight	Rank
Personal (C_1)	0.270	3	0.333	2
Responsibility (C_{11})	0.278	2	0.225	4
Ethics and integrity (C_{12})	0.131	4	0.279	1
Continuous learning (C_{13})	0.321	1	0.239	3
Intelligence (C_{14})	0.270	3	0.257	2
Professional competency (C_2)	0.359	2	0.325	3
Innovative thinking (C_{21})	0.248	3	0.196	4
Service orientation (C_{22})	0.240	4	0.207	3
Professional skills (C_{23})	0.261	1	0.259	2
Teamwork (C_{24})	0.251	2	0.338	1
General competency (C_3)	0.371	1	0.342	1
Independence (C_{31})	0.245	3	0.287	2
Problem prevention and improvement (C_{32})	0.250	2	0.149	4
Work efficiency improvement (C_{33})	0.275	1	0.300	1
Self-development (C_{34})	0.230	4	0.265	3

working hours etc. On the other hand, employees should strengthen their professional skills to face the various challenges in today's complex working environment. The person with T-shaped skills is necessary for the future job market. The vertical part of the T represents the person's expertise in a single field and the horizontal bar indicates their ability to collaborate with others in other fields. Having a larger number of employees with T-shaped skills will obviously help with company growth and raise its production efficiency. The results also point out the importance of the teamwork and ethics; the workforce suffers in there is poor communication and lack of employee ethics. Good communication is the key to establish solid teamwork. For example, managers can encourage their team members to share ideas, brainstorm together and accept differing opinions. Also, employee recognition and appropriate rewards can encourage a positive teamwork culture. Ethics are vital for a company because it helps to improve corporate image and avoid legal problems. The first step to improve ethics is to develop clear policies and procedures to train employees and facilitate understanding of the company's expectations. In addition, organizational leaders should display the highest degree of ethical behaviour in their daily activities or decisions. Our results suggest that good teamwork, high standards of ethics and excellent work efficiency will help companies to increase their production performance and improve their corporate image.

4.3. Comparative analysis of the original and aspiration gap in the PROMETHEE method

To obtain a better understanding of the difference between the proposed PROMETHEE-AS method and the original PROMETHEE method, we also calculated the gaps and rankings for the eight candidates using the original PROMETHEE method, see Table 12. We found differences in the order of the rankings for these eight candidates from those obtained using the proposed model. In the original PROMETHEE method, the eight candidates were ranked as follows: "F_3" $\succ$ "F_4" $\succ$ "F_8" $\succ$ "F_7" $\succ$ "F_1" $\succ$ "F_5" $\succ$ "F_2" $\succ$ "F_6". In contrast, in the PROMETHEE-AS method, the eight candidates' rankings were as follows: "F_4" $\succ$ "F_3" $\succ$ "F_8" $\succ$ "F_7" $\succ$ "F_1" $\succ$ "F_5" $\succ$ "F_2" $\succ$ "F_6" (Table 10). This is principally because the original PROMETHEE method uses the max-min values of the attributes in a finite alternative as the positive and negative ideal points (i.e., Eqs (C2) and (C3)), respectively. However, this strategy may be unsuitable because it may not accurately reflect real situations. For example, in the original model there were several attributed with zero gaps in "F_4" (Table 12), but our model (Table 10) showed several places that required improvement. Compared with the original PROMETHEE method (Brans & Vincke, 1985; Brans & Mareschal, 1995), the addition of the concept of the aspiration level should more reasonably reflect real-world situations (Liou et al., 2019). For personnel selection problems, "F_4" is the best candidate among the eight personnel because of having the smallest aspiration gap. This new PROMETHEE-AS method can be applied to improve each attribute and the overall performance of the personnel. The proposed method can also more correctly assess the aspiration gaps for individual attributes and the final ranking of each candidate.

Table 12. Relative gaps and ranking for the eight personnel with the original PROMETHEE method

Aspects /Attributes	Weight	F_1	F_2	F_3	F_4	F_5	F_6	F_7	F_8
Personal (C_1)	0.333	0.344	0.344	0.119	0.119	0.119	0.119	0.119	0.119
Responsibility (C_{11})	0.225	1.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000
Ethics and integrity (C_{12})	0.279	0.000	1.000	0.000	1.000	0.000	1.000	0.000	0.000
Continuous learning (C_{13})	0.239	0.500	1.000	0.500	0.000	0.500	0.500	0.500	0.500
Intelligence (C_{14})	0.257	0.000	0.000	0.000	0.000	1.000	1.000	0.000	0.000
Professional competency (C_2)	0.325	0.741	0.741	0.741	0.545	0.741	0.741	0.741	0.741
Innovative thinking (C_{21})	0.196	1.000	1.000	1.000	0.000	1.000	1.000	1.000	1.000
Service orientation (C_{22})	0.207	1.000	1.000	0.000	0.500	1.000	1.000	1.000	0.500
Professional skills (C_{23})	0.259	0.000	0.000	0.000	0.000	1.000	1.000	0.000	0.000
Teamwork (C_{24})	0.338	1.000	1.000	0.000	1.000	1.000	1.000	1.000	1.000
General competency (C_3)	0.342	0.868	0.868	0.581	0.868	0.868	0.868	0.581	0.581
Independence (C_{31})	0.287	1.000	1.000	0.000	1.000	1.000	1.000	0.000	0.000
Problem prevention and improvement (C_{32})	0.149	1.000	1.000	0.000	0.000	1.000	1.000	1.000	1.000
Work efficiency improvement (C_{33})	0.300	1.000	1.000	0.500	0.000	0.500	1.000	0.500	0.500
Self-development (C_{34})	0.265	0.500	0.500	1.000	0.000	1.000	0.500	0.500	0.500
Total in-flow		1.546	2.289	0.472	0.902	2.131	2.580	0.546	0.445
Total out-flow		0.749	0.430	2.929	2.648	0.622	0.280	1.543	1.711
Total net flow		0.798	1.859	−2.457	−1.746	1.509	2.300	−0.997	−1.266
Rank		5	7	1	2	6	8	4	3

Note:
1. The values of the normalized aspiration gap represent real aspiration gaps for each attribute or aspect.
2. All values of three flows were weighted (based on systemic influential relation).
3. Smaller net flow values were preferable.

Concluding remarks

Selecting suitable personnel and improving personnel performance are critical problems encountered by many companies. This study proposes a novel data-driven MADM model, which can be used to derive analytical strategies from historical data, thereby avoiding the bias associated with reliance upon the limited and subjective opinions of experts. Data obtained from a Chinese food production company were used in a case study to demonstrate the feasibility of the proposed model. With this model the ISNRM and influential signifi-cance-weights were obtained directly from the RST-DANP results alleviating the need for the pairwise comparison required by the original DEMATEL and DANP methods. The data-driven decision-making results obtained by treating each attribute depending upon varying degrees of influence that are more reasonable than those obtained with past methods and are consistent with the ISNRM results. The PROMETHEE-AS method results combined with

the weights obtained from the RST-DANP produces the influential significance-relation patterns among attributes based upon real performance data. The results showed that "teamwork (C_{24})" had the highest influential significance weight in the entire competency system, with "responsibility (C_{11})" being the system's root factor. Efficiency is one of the key factors for success for any business in today's competitive global marketplace, and the individual's sense of responsibility and teamwork will naturally affect the results. Managers can provide training courses to emphasize and improve teamwork and thus improve the success of a company. The results show "F_4" to be the best candidate. The new method also provides suggestions for reducing the aspiration gap, rather than merely ranking candidates. To sum up, the academic innovations of the proposed model include the (1) use of rough set theory to generate the input data for DANP analysis, thereby avoiding the time-consuming pairwise comparisons required in the original methods; (2) derivation of a more objective and consistent ISNRM for examining the cause and effect relationships between attributes; (3) the addition of the aspiration concept to the PROMETHEE analysis to more accurately reflect the real-world situation. For practical applications, this model can help human resource managers select the most suitable person for a position. Our findings indicate that teamwork and ethics are two important factors affecting the employees' work efficiency. Teamwork can maximize individual strengths by sharing the strengths of others to increase the success rate of reaching common goals. Good business ethics can help companies keep valuable employees, attract new customers and investors, and improve their corporate image. Also, the findings can help the HR department to decide upon appropriate training programs for employees to improve their capabilities and skills. The data-driven MADM modelling concept and procedure proposed in this study makes innovative contributions to academia and practical applications.

Although this study provides new insights into how to take advantage of information in the era of big data, further work is still required. The directions for future research are multifaceted. First, the influential significance-relation degree should be considered under additional uncertain situations as shown in real data. Second, non-additive methods (e.g., fuzzy integral) may be considered in aggregation methods. Finally, the data-driven concept of the proposed MADM model can be applied to solve decision-making problems in different areas and the model could be applied for other companies or in other industries. The conclusions drawn from this study are based on the requirements of the case company; this study is merely a demonstration of the model. Every company should establish competency attributes on the basis of their own specific environment and position characteristics; therefore, conclusions drawn from studies on other companies may be different.

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Author contributions

Yen-Ching Chuang wrote the article, data-driven decision modeling, and calculation. Shu-Kung Hu provided new ideas for PROMETHEE-AS method. James J. H. Liou confirmed the content of the entire research design. Finally, James J. H. Liou and Gwo-Hshiung Tzeng revised the content of the entire paper.

Disclosure statement

The authors declare no conflict of interest.

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APPENDIX A
Rough set theory

Definition 1. Information system.

An information system can be represented as $S = (U, A, V, f)$, where U is a finite non-empty set of objects called the universal set and A is a nonempty finite set of properties or attributes; that is, $A=\{a_1, a_2, a_3,\ldots,a_n\}$ such that $a:U \to V_a$, where V_a is the value set of attribute a_i (i.e., $V = \bigcup_{a \in A} V_a$) and $f:U \times A \to V$ is an information description function defined from $U \times A$ toward V (e.g., $\forall x \in U$ if $a \in A$ then $f(x,a) \in V_a$). For any information system such as a decision system, the form $S = (U, A, V, f)$ can be rewritten as $S = (U, A = C \cup D, V, f)$, where C represents the condition attribute, D represents the decision attribute, and the union of C and D represents the elements of set A.

Definition 2. Indiscernibility relation.

The concept of indiscernibility relation involves defining a relationship between more than two objects. The indiscernibility relation of any condition attribute subset $B \subset C$ is defined as shown in Eq. (A1):

$$IND(B) = \left\{ (x,y) \in U \,\middle|\, \forall a \in B, f_a(x) = f_a(y) \right\}, \tag{A1}$$

where $IND(B)$ is the subset B-indiscernibility relation, meaning that pairs of $(x,y) \in U$ are indiscernible by the subset of condition attributes B. Hence, $IND(B)$ can generate a partition over U; that is, $U / IND(B) = \left\{ I_B \middle| x \in U \right\}$, where I_B is the equivalence class of an object that comprises all objects $y \in U$ such that x is indiscernible with y by the condition attribute subset B. The definition can help us to identify the relationships between the condition and the decision attributes in the subsequent process.

Definition 3. Sets of lower and upper approximations.

Based on the equivalence class function $I_B \left[x \right]$, the object $X \subset C$ can be used to obtain lower $\underline{B}X$ and upper $\overline{B}X$ approximation sets, which are defined in Eqs (A2) and (A3), respectively:

$$\underline{B}X = \{x \in U \mid I_B[x] \subseteq X\}; \tag{A2}$$

$$\overline{B}X = \{x \in U \mid I_B[x] \cap X \neq \varnothing\}, \tag{A3}$$

where is also called the positive region of X and is represented by $POS_B(X)$.

Definition 4. Dependency degrees of condition attributes.

The universal U can be divided by D, representing the indiscernibility relationship between the decision attributes, as described in Eq. (A4):

$$U / IND(D) = \left\{ D_1, D_2, \ldots, D_k \right\}, \tag{A4}$$

where $U = \bigcup_{i \in \{1,\ldots,k\}} D_i$, $\underline{B}D_i$ represents the lower approximation of each partition D_i by the subset of condition attributes B. The positive region of the decision attribute D, which is represented by a subset of condition attributes B, can be represented by $POS_B(D)$, as presented in Eqs (A5) and (A6):

$$POS_B(D) = \cup_i^k POS_B(D_i);$$ (A5)

$$POS_B(D_i) = \underline{B}D_i = \{x \in U \,|\, I_B[x] \in D_i\}.$$ (A6)

The degree of dependence between the subset of condition attributes B and the subset of decision attributes D is represented by Eq. (A7):

$$\gamma_B(D) = \frac{|POS_B(D)|}{|U|},$$ (A7)

where $\gamma_B(D)$ denotes the relationship between the subset of decision attributes D and condition attributes B. These results can be divided into three relations: (1) the subset of decision attributes D is independent of the subset of condition attributes B ($\gamma_B(D) = 0$); (2) the set of decision attributes D is completely dependent on the subset of condition attributes B ($\gamma_B(D) = 1$); and (3) the subset of decision attributes D is partially dependent on the set of condition attributes B ($0 < \gamma_B(D) < 1$).

Definition 5. Significance degree of condition attributes.

The value of $\gamma(C,D)$ represents the degree of dependence between the condition attribute C and the decision attribute D. Therefore, we can observe the change in the coefficient $\gamma(C,D)$ when the condition attribute is deleted. The condition attribute C_1 as an example of the difference between $\gamma(C,D)$ and $\gamma(C - \{C_1\}, D)$ can be normalized, and the significance of the condition attribute C_1 is defined in Eq. (A8):

$$\sigma_{(C,D)}(C_1) = \frac{\left(\gamma(C,D) - \gamma(C - \{C_1\}, D)\right)}{\gamma(C,D)} = 1 - \frac{\gamma(C - \{C_1\}, D)}{\gamma(C,D)},$$ (A8)

where $\sigma(C_1)$ is between 0 and 1 (i.e., $0 \leq \sigma(a) \leq 1$), with higher value signifying that condition attribute C_1 has a higher level of importance.

APPENDIX B
DANP method

Step 1: Establishing an initial influential significance-relation matrix.

The k value of direct influential strength-relation matrix $\boldsymbol{E} = [e_{io}]_{n \times n}$, $i, o \in \{1, 2, \ldots, n\}$ can be obtained from practical performance data through RST, where eio represents the influential significance degree of conditional attribute i on another indicator decision attribute o; all principal diagonal elements are equal to zero. The initial influential strength-matrix $\boldsymbol{Q}$ ($\boldsymbol{Q} = [q_{io}]_{n \times n} = [(\sum_{\varphi=1}^{k} e_{io}^{\varphi}) / k]_{n \times n}$) is obtained using the average value at the conclusion of this step.

Step 2: Obtaining a normalized influential significance-relation matrix.

The initial influential significance-influence matrix $\boldsymbol{Q}$ uses Eqs (B1) and (B2) to obtain a normalized influential significance-relation matrix $\boldsymbol{D}$ in which the maximum sum of row or column elements is 1.

$$Z = Q / \Delta; \tag{B1}$$

$$\Delta = \max_{i,o}\left\{\max_i \sum_{o=1}^{n} q_{io}, \max_o \sum_{i=1}^{n} q_{io}\right\}, i,o \in \{1,2,\ldots,n\}. \tag{B2}$$

Step 3: Generating a total influential significance-relation matrix.

The normalized influential significance-relation matrix D uses the computing process of Markov chain matrices to obtain a total influential significance-relation matrix T. The corresponding calculation is presented in Eq. (B3), where I is the identity matrix.

$$T = Z + Z^2 + \ldots + Z^h = Z(I - Z)^{-1}, \text{ when } \lim_{h\to\infty} Z^h = [0]_{n\times n}. \tag{B3}$$

When the structure of an evaluation system is hierarchical, matrix $T = [t_{io}]$ can be divided into $T_C = [t_C^{io}]_{n\times n|m<n, \sum_{o=1}^{m} m_o = n}$ (for attribute level with n attributes) and $T_D = \left[t_{io}^{D_{io}}\right]_{m\times m}$ (for aspect level with m aspects), as shown in Eqs (B4) and (B5) derived from Eq. (B3):

$$T_C = \begin{array}{c} \\ D_1 \\ \vdots \\ D_i \\ \vdots \\ D_m \end{array} \begin{array}{c} c_{11} \\ \vdots \\ c_{1m_1} \\ c_{i1} \\ \vdots \\ c_{im_i} \\ c_{m1} \\ \vdots \\ c_{mm_m} \end{array} \begin{bmatrix} t_C^{11} & \cdots & t_C^{1o} & \cdots & t_C^{1m} \\ \vdots & & \vdots & & \vdots \\ t_C^{i1} & \cdots & t_C^{io} & \cdots & t_C^{im} \\ \vdots & & \vdots & & \vdots \\ t_C^{m1} & \cdots & t_C^{mo} & \cdots & t_C^{mm} \end{bmatrix}_{n\times n|m<n, \sum_{o=1}^{m} m_o = n,} \tag{B4}$$

where D_m is the mth aspect, c_{mm} is the mth attribute in the *m-th* aspect, and t_C^{io} is an element of the influential significance-relation matrix for the attributes from a comparison of the ith aspect with the oth aspect.

$$T_D = \begin{array}{c} D_1 \\ \vdots \\ D_i \\ \vdots \\ D_m \end{array} \begin{bmatrix} t_{11}^{D_{11}} & \cdots & t_{1o}^{D_{1o}} & \cdots & t_{1m}^{D_{1m}} \\ \vdots & & \vdots & & \vdots \\ t_{i1}^{D_{i1}} & \cdots & t_{io}^{D_{io}} & \cdots & t_{im}^{D_{im}} \\ \vdots & & \vdots & & \vdots \\ t_{m1}^{D_{m1}} & \cdots & t_{mo}^{D_{mo}} & \cdots & t_{mm}^{D_{mm}} \end{bmatrix}_{m\times m}. \tag{B5}$$

Step 4: Producing an ISNRM.

Matrix T can be evaluated to obtain influence vector sets given and received for each attribute or aspect, as presented in Eqs (B6) and (B7):

$$g_i = \left(g_i\right)_{n\times 1} = (g_1,\ldots,g_i,\ldots,g_n) = \left[\sum_{o=1}^{n} t_{io}\right]_{n\times 1}; \tag{B6}$$

$$r_i = \left(r_i\right)_{n\times 1} = \left(r_o\right)'_{1\times n} = (r_1,\ldots,r_o,\ldots,r_n)' = \left[\sum_{i=1}^{n} t_{io}\right]'_{1\times n}, \tag{B7}$$

where the superscript' indicates transpose and g_i indicates the sum of direct and indirect effects of elements i on the other elements. Similarly, r_i indicates the sum of the direct and indirect effects that element o has received from the other elements. Furthermore, "prominence $(g_i + r_i)$" provides a strong degree of influential significance relation given and received for each element. This means that element i plays a central role in this problem. Another "relation $(g_i - r_i)$" provides the cause-effect degree of total influence strength on each element, whose values may be classified into positive and negative. A positive value implies that element i affects other elements, whereas a negative value implies that element i is influenced by other elements.

Step 5: Constructing an unweighted super-matrix.

The matrix of indicator level T_C (i.e., Eq. (B4)) is normalized to the total influence significance-relation matrix T_C^Φ by using its aspects and transposing it into the unweighted super-matrix W^∇, as shown in Eq. (B8):

$$W^\nabla = (T_C^\Phi)^{transposed} = \begin{array}{c} \\ D_1 \\ \\ \\ D_i \\ \\ \\ D_m \\ \end{array} \begin{array}{c} c_{11} \\ \vdots \\ c_{1m_1} \\ \vdots \\ c_{i1} \\ \vdots \\ c_{im_i} \\ \vdots \\ c_{m1} \\ \vdots \\ c_{mm_m} \end{array} \begin{bmatrix} T_{\Phi C}^{11} & \cdots & T_{\Phi C}^{1o} & \cdots & T_{\Phi C}^{1m} \\ \vdots & & \vdots & & \vdots \\ T_{\Phi C}^{i1} & \cdots & T_{\Phi C}^{io} & \cdots & T_{\Phi C}^{im} \\ \vdots & & \vdots & & \vdots \\ T_{\Phi C}^{m1} & \cdots & T_{\Phi C}^{mo} & \cdots & T_{\Phi C}^{mm} \end{bmatrix}_{n \times n | m < n, \sum_{o=1}^m m_o = n}, \tag{B8}$$

where T_C^Φ denotes the normalized total influence significance-relation matrix of indicators T_C by aspects T_D, in which $t_{\Phi C}^{11}$ is an example derived by dividing the total influence significance-relation matrix T_C by $c_i^{11} = \sum_{o=1}^{m_1} t_{Cio}^{11}, i = 1,2,...,m_1$, as shown in Eq. (B9). Finally, $T_{\Phi C}^{mm}$ can be obtained through a similar process.

$$T_{\Phi C}^{11} = \begin{array}{c} c_{11} \\ \vdots \\ c_{1i} \\ \vdots \\ c_{1m_1} \end{array} \begin{bmatrix} t_{C11}^{11}/c_1^{11} & \cdots & t_{C1o}^{11}/c_1^{11} & \cdots & t_{C1m_1}^{11}/c_1^{11} \\ \vdots & & \vdots & & \vdots \\ t_{Ci1}^{11}/c_i^{11} & \cdots & t_{Cio}^{11}/c_i^{11} & \cdots & t_{Cim_1}^{11}/c_i^{11} \\ \vdots & & \vdots & & \vdots \\ t_{Cm_11}^{11}/c_{m_1}^{11} & \cdots & t_{Cm_1j}^{11}/c_{m_1}^{11} & \cdots & t_{Cm_1m_1}^{11}/c_{m_1}^{11} \end{bmatrix} =$$

$$\begin{array}{c} c_{11} \\ \vdots \\ c_{1i} \\ \vdots \\ c_{1m_1} \end{array} \begin{bmatrix} t_{\Phi C11}^{11} & \cdots & t_{\Phi C1o}^{11} & \cdots & t_{\Phi C1m_1}^{11} \\ \vdots & & \vdots & & \vdots \\ t_{\Phi Ci1}^{11} & \cdots & t_{\Phi Cio}^{11} & \cdots & t_{\Phi Cim_1}^{11} \\ \vdots & & \vdots & & \vdots \\ t_{\Phi Cm_11}^{11} & \cdots & t_{\Phi Cm_1o}^{11} & \cdots & t_{\Phi Cm_1m_1}^{11} \end{bmatrix}_{m_1 \times m_1}. \tag{B9}$$

Step 6: Obtaining a weighted supermatrix.

The normalized total influence significance-relation matrix of aspect level T_D^∇ can be obtained by dividing the matrix of aspect level T_D by $d_i = \sum_{o=1}^{m} t_{io}^{Dio}, i = 1,2,...,m$ and transposing the matrix. The corresponding result is shown in Eq. (B10):

$$T_D^\nabla = (T_D^\Phi)^{transposed} = \begin{bmatrix} t_{11}^{D_{11}}/d_1 & \cdots & t_{1o}^{D_{1o}}/d_1 & \cdots & t_{1m}^{D_{1m}}/d_1 \\ & \vdots & & \vdots & \\ t_{i1}^{D_{i1}}/d_i & \cdots & t_{io}^{D_{io}}/d_i & \cdots & t_{im}^{D_{im}}/d_i \\ & \vdots & & \vdots & \\ t_{m1}^{D_{m1}}/d_m & \cdots & t_{mj}^{D_{mo}}/d_m & \cdots & t_{mm}^{D_{mm}}/d_m \end{bmatrix} =$$

$$\begin{bmatrix} t_{11}^{\Phi_{11}} & \cdots & t_{1j}^{\Phi_{1o}} & \cdots & t_{1m}^{\Phi_{1m}} \\ \vdots & & \vdots & & \vdots \\ t_{i1}^{\Phi_{i1}} & \cdots & t_{io}^{\Phi_{io}} & \cdots & t_{im}^{\Phi_{im}} \\ \vdots & & \vdots & & \vdots \\ t_{m1}^{\Phi_{m1}} & \cdots & t_{mj}^{\Phi_{mo}} & \cdots & t_{mm}^{\Phi_{mm}} \end{bmatrix}_{m \times m}. \tag{B10}$$

The weighted supermatrix W^Θ can then be easily obtained through Eq. (B11), where $t_{11}^{\Phi_{11}}$ is a scalar and $\sum_{j=1}^{m} m_j = n$.

$$W^\Theta = T_D^\nabla \times W^\nabla = \begin{bmatrix} t_{11}^{\Phi_{11}} \times W^{11} & \cdots & t_{i1}^{\Phi_{i1}} \times W^{i1} & \cdots & t_{m1}^{\Phi_{m1}} \times W^{m1} \\ \vdots & & \vdots & & \vdots \\ t_{1o}^{\Phi_{i1}} \times W^{1o} & \cdots & t_{io}^{\Phi_{io}} \times W^{io} & \cdots & t_{mo}^{\Phi_{mo}} \times W^{mo} \\ \vdots & & \vdots & & \vdots \\ t_{1m}^{\Phi_{m1}} \times W^{1n} & \cdots & t_{im}^{\Phi_{im}} \times W^{in} & \cdots & t_{mm}^{\Phi_{mm}} \times W^{mm} \end{bmatrix}_{n \times n | m < n, \sum_{o=1}^{m} m_o = n}. \tag{B11}$$

Step 7: Limiting weighted super-matrix and getting influential strength weights.

When the weighted supermatrix W^Θ is multiplied by itself several times, a limited weighted supermatrix W can be obtained, which becomes a steady-state supermatrix. The values of the limited weighted supermatrix are the global weights of the influential strength relation for each indicator. In this step, the limiting process of the supermatrix is executed by raising it to limited powers until the weighted supermatrix converges. This is similar to the concepts of the Markov chain and ANP.

$$W = \lim_{\Omega \to \infty} (W^\Theta)^\Omega. \tag{B12}$$

APPENDIX C

PROMETHEE-AS method

Step 1: Creating a performance matrix.

Alternatives with multiple attributes are listed in the column and row of a performance matrix. The matrix shows the performance of different personnel concerning the attributes. In this study, the data for the performance matrix were obtained from real auditing data of personnel performance in a case company (Eq. (C1)):

$$\boldsymbol{F} = \begin{bmatrix} f_{11} & \cdots & f_{1j} & \cdots & f_{1n} \\ \vdots & & \vdots & & \vdots \\ f_{p1} & \cdots & f_{pj} & \cdots & f_{pn} \\ \vdots & & \vdots & & \vdots \\ f_{l1} & \cdots & f_{lj} & \cdots & f_{ln} \end{bmatrix}_{l \times n.} \tag{C1}$$

Step 2: Setting aspiration level and worst level for attributes.

Conventionally, positive and negative ideal points are defined by max-min values of attributes from a finite alternative (i.e., Eqs (C2) and (C3)). Although this approach can be easily used to rank alternatives, it cannot reflect the gaps of attributes in each alternative. This means that the conventional approach can help decision-makers to solve the selection problem but cannot solve the improvement problem. When an MCDM problem belongs to an MADM problem, the measurement scale of each indicator is generally within a known range. In this situation, the absolute range can replace the relative range. Therefore, we apply the aspiration level concept for setting positive and negative ideal points, as shown in Eqs. (C4) and (C5):

$$\text{Positive ideal: } f_j^* = \max_p f_{pj} \big| j = 1,2,...,n \text{ (attributes); } p = 1,2,...,l \text{ (candidates);} \tag{C2}$$

$$\text{Negative ideal: } f_j^- = \min_p f_{pj} \big| j = 1,2,...,n \text{ (attributes); } p = 1,2,...,l \text{ (candidates).} \tag{C3}$$

On the basis of the aspiration level concept, we can rewrite Eqs. (C2) and (C3) as Eqs. (C4) and (C5), respectively:

$$\text{The aspiration levels: } f_j^{aspired} = (f_1^{aspired},...,f_j^{aspired},...,f_n^{aspired}); \tag{C4}$$

$$\text{The worst levels: } f_j^{worst} = (f_1^{worst},...,f_j^{worst},...,f_n^{worst}). \tag{C5}$$

The auditing data of the case company were scored on a scale from 0 to 6 ("worst" ← 0, 1, 2, 3, 4, 5, 6 → "best") to evaluate the performance of each employee. Therefore, for each attribute, the aspiration level can be set to 6 ($f_j^{aspirted} = 6$) and the worst value to 0 ($f_j^{worst} = 0$).

Step 3: Obtaining a normalized aspirated performance matrix.

The original performance matrix can use Eq. (C6) to obtain a normalized aspirated performance matrix $\boldsymbol{F}^{\Phi} = [f_{pj}^{\Phi}]_{l \times n}$.

$$f_{pj}^{\Phi} = \left(\left| f_j^{aspired} - f_{pj} \right| \right) \bigg/ \left(\left| f_j^{aspired} - f_j^{worst} \right| \right). \tag{C6}$$

Step 4: Using domain linear preference function for attributes in all alternatives.

Brans and Vincke (1985) proposed six basic types of preference functions. This method employs the preference function of "Type V: Criterion with Linear Preference and Indifference Area" to calculate the function for the degree of preference for attributes in all alternatives. The performance matrix can be obtained by using a measurement scale from 0 to 6 ("worst" $\leftarrow$ 0, 1, 2, 3, 4, 5, 6 $\rightarrow$ "best"); hence, a domain relationship exists between performance attributes in all alternatives. Therefore, we can redefine a preference function in which alternative u outranks alternative v for the jth attribute, as shown in Eq. (C7):

$$S_j(u,v) = \begin{cases} 0 & , \quad f_{uj}^{\Phi} - f_{vj}^{\Phi} \leq f_j^{\Phi aspirted} \\ f_{uj}^{\Phi} - f_{vj}^{\Phi}, & f_j^{\Phi aspirted} < f_{uj}^{\Phi} - f_{vj}^{\Phi} \leq f_j^{\Phi worst} \\ 1 & , \quad \text{otherwise} \end{cases}, \tag{C7}$$

where $S_j(u, v)$ is the superiority of alternative u over alternative v on the jth attribute, $f_{pj}^{\Phi aspirted} = 0$, $f_{pj}^{\Phi worst} = 1$, f_{uj} is the performance score of the jth attribute in the uth alternative, and f_{vj} is the performance score of the jth attribute in the vth alternative.

Step 5: Deriving a multi-attribute preference index for each alternative.

For each attribute, the preference scores can be combined with the attribute weights (the proposed model uses the influential weight of the DANP) to obtain the preference index (named multi-attribute preference index), where the $\pi(u, v)$ index indicates the advantage of alternative u over alternative v, as shown in Eq. (C8):

$$\pi(u,v) = \sum_{j=1}^{n} w_j S_j(u,v), \tag{C8}$$

where w_j is the influential weight on the jth attribute.

Step 6: Obtaining various flow information for alternatives.

Based on the multi-attribute preference index concept and framework, we can compute three flows for each alternative: (1) leaving flow, (2) entering flow, and (3) net flow. The leaving flow represents the degree to which alternative u outranks other alternatives, the entering flow represents the degree to which other alternatives outrank alternative u, and the net flow represents the final score of alternative u, as shown in Eqs. (C9), (C10), and (C11), respectively:

$$\text{The leaving flow: } \phi^+(u) = \sum_{v=1}^{z} \pi(u,v); \tag{C9}$$

$$\text{The entering flow: } \phi^-(u) = \sum_{v=1}^{z} \pi(v,u); \tag{C10}$$

$$\text{The net flow: } \phi(u) = \phi^+(u) - \phi^-(u), \tag{C11}$$

where $\phi(u)$ represents the alternative that is closest to the aspiration level; a lower $\phi(u)$ value is preferred.