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A new approach and insightful financial diagnoses for the IT industry based on a hybrid MADM model

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ABSTRACT

Financial performance is vital for information technology (IT) companies to survive intense global competition. Because of the complexity in the business environment and the rapidly advancing technologies, companies lack specific guidance to understand the implicit relationship among crucial financial indicators for improving prospects in a contextual approach. To resolve the aforementioned concern, this study proposed a new approach by combining the variable consistency dominance-based rough set approach (VC-DRSA) with the decision-making trial and evaluation laboratory (DEMATEL) technique to explore the complex relationship among financial variables and improve future performances. In addition, a fuzzy inference system was devised on the basis of the findings of the VC-DRSA and DEMATEL technique to examine granulized knowledge and implications. A group of real IT companies listed on the Taiwan stock market were used as an empirical case to present the benefits of the new approach. The results generated a set of decision rules that can be used for forecasting future performance prospects and diagnosing the directional influences of crucial variables to gain insights; certain strong decision rules were further examined using fuzzy inference to verify the obtained implications. The findings contribute to the financial applications of decision-making science and computational intelligence in practice.

1. Introduction

Financial ratios are widely used for evaluating the competitiveness and worthiness of a company. This evaluation is often conducted by inspecting financial ratios of a specific industry or by comparing the current state of a company with its historical performance [35], and is termed as fundamental analysis (FA) [18]. By using FA, potential investors, shareholders, management teams, and external creditors may predict the financial performance (FP) of a company. Because of pressure from the capital market, it is crucial for the management teams of publicly listed companies to devise various plans (e.g., strategy planning, research and development roadmap, and financial planning) for improving FP. However, because of complex and rapidly changing business dynamics, obtaining a practical and understandable guidance for achieving this goal remains a challenge. Thus, considering the rapid advancement in technological innovation and the intense competition in the IT industry, this study focused on the FP analyses of IT companies.

In conventional studies, researchers primarily relied on statistical models to investigate the relationship between financial ratios and the subsequent change in the performance of businesses [1,20,28,33], predominantly the FP (e.g., earnings per share growth rate or stock returns). The main difference in these studies was the included variables and explained performance indicators. Although this approach is widely used in financial studies, the unrealistic assumptions of regression models (e.g., independent relationship among considered variables and normal distribution of errors) might yield unpersuasive results [24]. Furthermore, the regressions primarily represent average results, which are insufficient to guide a decision maker (DM) [44]. Therefore, the complexity of multiple dimensions and criteria enticed researchers from other fields to resolve performance prediction problems, such as multiple attribute decision making (MADM) [7,19] and computational intelligence [8,18,34].

Although the performance prediction problems have gained attention in various research fields, most studies have used a subjective approach to collect the knowledge of domain experts for modeling [19,41] or the data mining approach to explore implicit relationships among large datasets [9,12,34]. An integrated model that can be used to retrieve useful knowledge from the two

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aforementioned approaches requires further exploration. Therefore, this study proposed a new approach for determining the FP by integrating the computational intelligence model and the knowledge of experts to solve the FP prediction problem. This study initially inducted decision rules from a group of real IT companies by using an extended rough set approach (RSA), and then used the retrieved core attributes to collect the knowledge of experts, thus guiding a company to analyze its FP by illustrating the influences of certain criteria or dimensions in a specific context. In addition, to verify the obtained knowledge, a fuzzy inference system (FIS)—based on strong decision rules and the decision-making trial and evaluation laboratory (DEMATEL) analysis—is devised to examine the reasoning logics (i.e., knowledge or implications).

To understand the core attributes that may enable the prediction of subsequent performance change in the IT industry, this study proposed a new approach for attaining an insightful analysis. This study attempted to obtain comprehensible decision rules by considering the relative importance and directional influences of various criteria (i.e., financial attributes or ratios). The proposed model provided a diagnosing tool and a process that might determine the influences shaping future prospects. The insights acquired during the process should be meaningful to support strategy formulation, planning, and decision making, which could not be achieved through statistical analyses. The implications are expected to provide constructive meanings both in academia and practice.

The remainder of this paper is structured as follows: Section 2 briefly introduces FA and certain MADM methods related to this study, Section 3 describes the proposed model, Section 4 presents an empirical study of real IT companies in Taiwan, and Section 5 describes the empirical results. Finally, Section 6 concludes the study and discusses future research directions.

2. Preliminaries

This section briefly reviews the methods and techniques used in this study, including the variable consistency dominance-based rough set approach (VC-DRSA) and the hybrid MADM methods (including the DEMATEL technique and fuzzy inference).

2.1. The rough set approach and extended approaches

The RSA is a mathematical theory that may induct rules from a dataset with multiple attributes and was proposed by Pawlak [30]. The RSA is considered suitable for handling uncertain, imprecise, or vague datasets primarily used for retrieving knowledge by making classifications. Generally, objects are described according to attributes and divided into groups. However, the preference relationships of attributes were disregarded in the conventional RSA, which is inadequate for modeling some real-world problems. To enhance the conventional RSA, previous studies [13,14] have developed a dominance-based rough set approach (DRSA) by considering the dominance (preference) relationship of attributes, which subsequently led to the development of the VC-DRSA [3,14] that allows a controlled degree of inconsistency for inducting rules. The VC-DRSA explores imprecise and uncertain patterns by allowing some minor inconsistency, which might be inevitable in certain social science problems. Most financial decision problems must consider the dominance relationship of financial variables; for example, high profitability is generally preferred in performance comparison. From the aforementioned points (i.e., dominance relationship and minor degree of inconsistency), the VC-DRSA is suitable for tackling the complexity of and uncertainty in the business environment. The VC-DRSA classifies objects into classes and generates a group of decision rules. The obtained decision rules are easy to understand [22,23,39,40] and use for DMs; however, insufficient directional and influential guidance prevents users from acquiring in-depth insights. Thus, the DEMATEL technique [10], discussed in the next section, was used to integrate the knowledge of experts for enriching the implications for improvement planning.

2.2. Multiple attribute decision-making methods in the proposed model

Because of the evolving dynamic and complex business environment, practitioners often encounter difficulties analyzing a problem by using conventional decision tools such as regression and operational research methods. Most problems have distinct characteristics and constraints; thus, a universal model for analyzing all business problems is unlikely to be provided. Developing a suitable method or model by infusing suitable methods or techniques for the addressed problem is more practical [44]. Although various MADM methods are applied in finance, for brevity, only the DEMATEL technique and fuzzy inference adopted in the proposed model are discussed.

The Battelle Memorial Institute of Geneva ([11], a project of United Nation) proposed the DEMATEL technique to analyze and solve complex problems. The technique helps DMs explore the interrelationships among criteria; therefore, we can use the DEMATEL-based concept to facilitate identifying influential directions and the weights of considered variables (or criteria) and analyze the FP. The DEMATEL technique was initially used to explore or evaluate a completely interdependent system (i.e., all the criteria in a system are interrelated, as is common in certain social science problems) and divide interrelated criteria into a cause and an effect group [47]. According to previous studies on MADM [31,53], the results of DEMATEL analysis can be used to form a clear illustration, termed as the influential network relation map (INRM).

Because the DEMATEL technique exhibits flexibility in exploring interrelated and nonlinear relationships, it has been used to analyze various practical problems, such as to evaluate e-learning performance [47], select knowledge management strategies [52], alleviate the portfolio selection problem [15], select suppliers of a green supply chain [16], develop a value-created system for a science park 21, improve information security risk control assessment [29], and select glamor stocks [41]. In this study, we attempted to advance the knowledge of forecasting and determining the FP by incorporating the DEMATEL analysis to guide improvements.

In certain circumstances of most MADM problems, it is essential to incorporate experts' (or DMs') opinions for analyses; therefore, fuzzy set theory, proposed by Zadeh [54,55], has been broadly adopted to transform DMs' knowledge (opinions) into various MADM models [24,56], which are capable of processing natural language-like concepts. Linguistic concepts (variables) could be described in rules and aggregated by fuzzy logics—termed as fuzzy inference [25]—to emulate experts' approximate reasoning. The fuzzy inference proposed by Mamdani was among the earliest systems that retrieved experts' knowledge for controlling a steam engine, which was based on the fuzzy algorithms and operations by Zadeh [54]. Extensive discussions of fuzzy inference could be found in previous works [37,38,17]. Because the present study intended to refine the VC-DRSA decision rules by using DEMATEL analysis (to identify the cause–effect relationship among the core criteria for improvement planning), the FIS was used to analyze and verify the obtained knowledge. The fuzzy inferences from experts should establish a reasonable foundation for combining decision rules and DEMATEL analysis to plan improvement.

Recently, the importance of sophisticated MADM methods has been noticed, and some of the aforementioned methods have been applied in real business operations [24,48].

3. Hybrid MADM model based on VC-DRSA and DEMATEL techniques

This section presents the proposed new hybrid model for forecasting the FP of IT companies. The model comprises three parts, namely the VC-DRSA (to induct decision rules and identify crucial financial variables for analysis), DEMATEL analysis (to acquire the directional influences among core criteria and dimensions), and FIS (to validate the obtained knowledge by experts).

3.1. Variable consistency dominance-based rough set approach

The VC-DRSA originates from the classical RSA, which starts from a 4-tuple information system $IS = (U, Q, V, f)$, and involves the extended consideration of dominance relationships and a controlled level of consistency in the classified patterns. The set U is a finite set of a universe, and the set Q is a finite set of attributes, often comprising a conditional set C and a decision set D. The term V_q is the value domain of attribute q, where $V = \bigcup_{q\in Q} V_q$ and $f: U \times Q \to V$ is a total function, in which $f(x,q) \in V_q$ for each $q \in Q$ and $x \in U$. In this study, the conditional set C is composed of the considered financial attributes, and the decision set D involves three decision classes (DCs) (i.e., Bad, Mediocre, and Good).

The relation operator $\succeq_q$ is defined as a complete outranking relationship on set U with respect to the attribute $q \in Q$, in which $x \succeq_q y$ denotes that "x is at least as good as y with respect to the attribute q." If $\succeq_q$ represents a complete outranking relationship, then x and y are always comparable with respect to the attribute q. Regarding the decision set D, let $Cl = \{Cl_t, t = 1, \ldots, h\}$ be a set of DCs of U. Given the preferred order of DCs, for example, if $k \succ h$, then the decision class Cl_k is preferred to Cl_h. Thus, upward union and downward union of DCs can be defined as follows:

$$Cl_t^{\geqslant} = \bigcup_{s \geqslant t} Cl_s \tag{1}$$

$$Cl_t^{\leqslant} = \bigcup_{s \leqslant t} Cl_s \tag{2}$$

On the basis of Eqs. (1) and (2), the dominance relation D_P for $P \subseteq C$ can be derived (where C is the conditional set). If object x P-dominates y with respect to P, then $x \succeq_q y$ for all $q \in P$, denoted as xD_Py. In this study, the fundamental objective was to explore the rules associated with superior FP in the subsequent period for improvement planning; therefore, we focused on and primarily used the upward union of DCs for illustration. For $P \subseteq C$ and $x, y \in U$, the P-dominating set and P-dominated set can be denoted as follows:

$$D_P^+(x) = \{y \in U : yD_Px\} \tag{3}$$

$$D_P^-(x) = \{y \in U : xD_Py\} \tag{4}$$

In the DRSA, the P-lower and P-upper approximation of $Cl_t^{\geqslant}$ can be denoted as $\underline{P}(Cl_t^{\geqslant})$ and $\overline{P}(Cl_t^{\geqslant})$, respectively, and defined using the following equations (where $t = 2, \ldots, h$):

$$\underline{P}(Cl_t^{\geqslant}) = \{x \in U : D_P^+(x) \subseteq Cl_t^{\geqslant}\} \tag{5}$$

$$\overline{P}(Cl_t^{\geqslant}) = \{x \in U : D_P^-(x) \cap Cl_t^{\geqslant} \neq \emptyset\} \tag{6}$$

In addition, the P-boundary of $Cl_t^{\geqslant}$ can be denoted as $Bn_p(Cl_t^{\geqslant})$, which can be defined as

$$Bn_P(Cl_t^{\geqslant}) = \overline{P}(Cl_t^{\geqslant}) - \underline{P}(Cl_t^{\geqslant}), \quad t = 2, \ldots, h \tag{7}$$

However, the P-lower approximation of $Cl_t^{\geqslant}$ in the DRSA consists of only consistent objects. To relax the condition, the VC-DRSA includes objects that are adequately consistent in the P-lower approximation. Consistency measures are divided into two types, namely the gain type (a higher value indicates a higher consistency) and cost type (a lower value indicates a higher consistency). The gain type takes into account all subsets of the set of considered attributes [5], which may induct more plausible decision rules for evaluation. Therefore, to consider more contexts (i.e., decision rules) for analyses, the gain-type consistency measure is illustrated and applied in this study. For $Cl_t^{\geqslant} \subseteq U, z \in U$, the gain-type consistency measure and fixed gain threshold can be denoted as Θ_X and θ_X, respectively, and the P-lower approximation of $Cl_t^{\geqslant}$ (according to a probabilistic measure) with gain threshold θ_X can then be defined as

$$\underline{P}^{\theta_X}(Cl_t^{\geqslant}) = \{z \in Cl_t^{\geqslant} : \Theta_X(z) \geqslant \theta_X\} \tag{8}$$

The definition of the P-upper approximation and P-boundary of $Cl_t^{\geqslant}$ in the VC-DRSA involves using the complementarity of rough approximation. We used notations similar to a previous study [5]. For $P \subseteq C, X$ is used to represent $Cl_t^{\geqslant}, \neg X \subseteq U$, in which $\neg X = U - X$; Eqs. (9) and (10) represent the P-upper approximation of set X (i.e., $Cl_t^{\geqslant}$) and the P-boundary of set $X(Cl_t^{\geqslant})$, respectively, as follows:

$$\overline{P}^{\theta_X}(Cl_t^{\geqslant}) = \overline{P}^{\theta_X}(X) = U - \underline{P}^{\theta_X}(\neg X) \tag{9}$$

$$Bn_P^{\theta_X} = \overline{P}^{\theta_X}(X) - \underline{P}^{\theta_X}(X) \tag{10}$$

The detailed gain-type consistency measure (μ-consistency) was based on that of the previous research [6]. The accuracy of the approximation for set X (i.e., $Cl_t^{\geqslant}$) can be defined as $\alpha_P^{\theta_X}(X)$,

$$\alpha_P^{\theta_X}(X) = |\underline{P}^{\theta_X}(X)| \Big/ |\overline{P}^{\theta_X}(X)| \tag{11}$$

The term $\gamma_P^{\theta_X}(X)$ denotes the ratio of all correctly classified objects for $P \subseteq C$ with consistency threshold θ_X. Each minimal subset $P \subseteq C$ that can satisfy $\gamma_P^{\theta_X}(X) = \gamma_C^{\theta_X}(X)$ is termed as REDUCT, denoted as $RED_X(P)$. In addition, the intersection of all REDUCTs is called a CORE ($CORE_X$) of the IS. The dominance-based relationship can thus provide the capability for DCs of set X to form a set of decision rules in the form of "**if** *antecedent* (premise), **then** *consequence* (conclusion)." According to a previous study [6], a decision rule in the VC-DRSA suggests that the categorization into set X be denoted as r_X. The condition and decision parts of r_X are denoted as $\Phi(r_X)$ and $\Psi(r_X)$, respectively. Furthermore, $\|\Phi(r_X)\|$ denotes the set of objects that satisfy the condition part of r_X. The gain-type consistency measure (μ-consistency) of decision rule r_X in the VC-DRSA can then be defined as

$$\mu_X(r_X) = |\|\Phi(r_X)\| \cap \underline{X}| / \|\Phi(r_X)\| \tag{12}$$

The rule induction algorithm used in the VC-DRSA is based on sequential covering and called VC-DomLEM [2,4].

To demonstrate the use of the VC-DRSA, the following are the steps for the retrieval of the CORE attributes and decision rules:

Step 1: Discretize the raw financial figures. The proposed model is based on the comparison of the relative performance of a company with its peer group on each indicator to predict its FP in the subsequent year. For consistency, a three-level discretization (i.e., high, middle, and low) is proposed using the general reasoning practice of FA; the transformation processes used in this study are explained in Section 4.1.

Step 2: Apply the VC-DRSA to the target dataset (in the form of financial attributes and DCs). Because the VC-DRSA allows for minor inconsistency in the classified alternatives, various consistency thresholds θ_X can be tested; thus, the θ_X value that may lead to an acceptable classification rate can be determined.

Step 3: Examine the obtained VC-DRSA model by analyzing the classification results. This step can be enhanced by performing n-fold cross-validation as discussed in Section 4.3.

Step 4: The VC-DRSA model could generate a CORE and a set of μ-consistency decision rules. The CORE comprises critical attributes for discerning the DCs, which can be used for the DEMATEL analyses in the next step.

3.2. Decision-making trial and evaluation laboratory technique

The DEMATEL technique is used for determining the total and net influential weights of the dimensions and attributes (criteria). The procedures involved in the DEMATEL technique can be divided into the following steps:

Step 5: Calculate the initial average influence relation matrix $\boldsymbol{A}$ by collecting the opinions of domain experts. Domain experts are provided with questionnaires to answer the direct influence that they feel attribute i has on another attribute j, expressed as a_{ij}. The criteria used in this step are the attributes obtained in Step 4 (the CORE attributes from the VC-DRSA). The expected scale ranges from 0 (*no influence*) to 4 (*extremely high influence*).

$$\boldsymbol{A} = \begin{bmatrix} a_{11} & \cdots & a_{1j} & \cdots & a_{1n} \\ \vdots & & \vdots & & \vdots \\ a_{i1} & \cdots & a_{ij} & \cdots & a_{in} \\ \vdots & & \vdots & & \vdots \\ a_{n1} & \cdots & a_{nj} & \cdots & a_{nn} \end{bmatrix} \tag{13}$$

In this study, n equals the number of attributes included in the CORE.

Step 6: Obtain the direct influence relation matrix $\boldsymbol{D}$ by normalizing the initial average influence relation matrix.
The matrix $\boldsymbol{D} = [d_{ij}]_{n\times n}$ can be derived using Eqs. (14) and (15) and is obtained by determining a constant k to normalize $\boldsymbol{A}$.

$$\boldsymbol{D} = k\boldsymbol{A} \tag{14}$$

$$k = \min\left\{\frac{1}{\max_i \sum_{j=1}^{n} a_{ij}}, \frac{1}{\max_j \sum_{i=1}^{n} a_{ij}}\right\} \tag{15}$$

where $i,j \in \{1,\ldots,n\}$.

Step 7: Calculate the total influence relation matrix $\boldsymbol{T}$.
The total influence relation matrix $\boldsymbol{T}$ can be obtained by normalizing the direct influence relation matrix $\boldsymbol{D}$. Because the indirect effects of the problem diminish as the power of $\boldsymbol{D}$ increases, the total influence relation matrix $\boldsymbol{T}$ can be expressed as follows:

$$\begin{aligned} \boldsymbol{T} &= \boldsymbol{D} + \boldsymbol{D}^2 + \cdots + \boldsymbol{D}^w = \boldsymbol{D}(\boldsymbol{I} - \boldsymbol{D}^w)(\boldsymbol{I} - \boldsymbol{D})^{-1}, \\ &= \boldsymbol{D}(\boldsymbol{I} - \boldsymbol{D})^{-1}, \quad \text{when } \lim_{w\to\infty} \boldsymbol{D}^w = [0]_{n\times n} \end{aligned} \tag{16}$$

Step 8: Decompose the matrix $\boldsymbol{T}$ to analyze the influential weights of the attributes.
The sum of rows and the sum of columns of the total influence matrix $\boldsymbol{T}$ are expressed as vector $\boldsymbol{r} = \left(\sum_{j=1}^{n} t_{ij}\right) = (r_1,\ldots,r_i,\ldots,r_n)'$ and vector $\boldsymbol{s} = \left(\sum_{i=1}^{n} t_{ij}\right)' = (s_1,\ldots,s_j,\ldots,s_n)'$, respectively. The superscript $'$ denotes a transpose operation of a matrix. Because vectors $\boldsymbol{r}$ and $\boldsymbol{s}$ contain the same number of elements, the operations $\boldsymbol{r}+\boldsymbol{s}$ and $\boldsymbol{r}-\boldsymbol{s}$ form two column vectors for $i,j \in \{1,\ldots,n\}$, where $i = j$. The th element $r_i + s_i$ of the column vector $\boldsymbol{r}+\boldsymbol{s}$ indicates the importance of the ith attribute. In addition, the column vector $\boldsymbol{r}-\boldsymbol{s}$ separates the attributes into a cause group and an effect group. Generally, when the element $r_i - s_i$ is positive, the ith attribute belongs to the cause group; otherwise, the attribute belongs to the effect group. Then, based on these results, the influential network relation map (INRM) can be plotted (as Fig. 3 in Section 4.3).

Step 9: Form a directional flow graph (DFG) to analyze the influence of core attributes on the performance change.
The decision rules obtained in Step 4 can be integrated with the influential weights of the criteria to determine the directional influences for each decision rule. This step is further explained in the following empirical case.

3.3. Fuzzy inference system for examining granulized knowledge

The FIS is based on a set of rules (or logics) and fuzzy reasoning to map a group of crisp (or fuzzy) inputs to an aggregated output. There are two prevailing types of FIS: the Mamdani type [25] and Sugeno type [45]. The main difference between the two is the format of the output membership functions. The output membership functions of the Mamdani type are assumed to be fuzzy set; whereas those of the Sugeno type are either linear or constant (the Sugeno type is widely incorporated with the neural network technique to form neuro-fuzzy inference systems [37]). Because no specific assumption (e.g., as linear or constant type) was made on the output membership functions in the empirical case, the Mamdani-type FIS was adopted in this study.

The FIS comprises three key components: (1) a set of inputs with predefined fuzzy intervals for the corresponding fuzzy membership functions (fuzzify linguistic inputs into granulized fuzzy concepts), (2) a logical reasoning pool, and (3) an aggregated output (defuzzify the aggregated fuzzy values into a crisp output). A typical FIS is illustrated as follows (see Fig. 1):

The Mamdani-type FIS mainly uses *min* and *max* as T-norm and T-conorm operators for fuzzy inference, respectively (the T-norm and T-conorm [37] were adopted for fuzzy reasoning in this study).

4. Empirical case of the Information Technology Industry in Taiwan

A group of IT companies in Taiwan were analyzed for exploring the key indicators used for forecasting the FP. The opinions of domain experts were collected using questionnaires. The proposed model comprises three parts; a diagram of the involved steps is shown in Fig. 2.

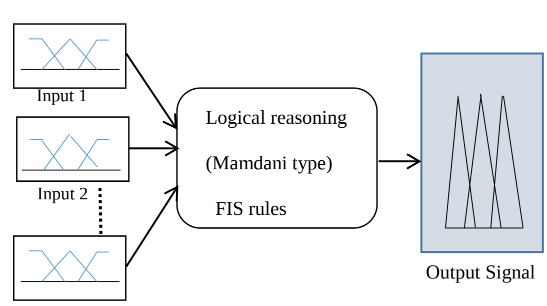

Fig. 1. Illustration of a fuzzy inference system.

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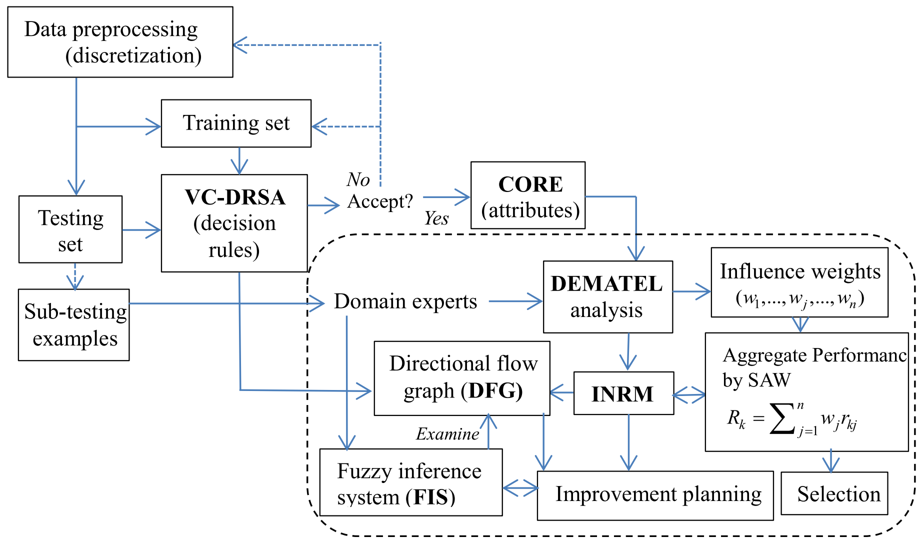

Fig. 2. Illustration of the research flows.

4.1. Data

All the included IT companies are publicly listed, and their financial data were collected from the Taiwan Economic Journal database. Because the model is used to predict the FP, the financial ratios of the companies (condition attributes) in 2011 were matched with their corresponding FP changes in 2012. In this study, we adopted the changed earnings per share (EPS) performance, which is widely used for measuring the FP [32], in the subsequent period as the proxy for FP improvement. Almost all of the major information (17 financial attributes) available on Taiwan's Market Observation Post System [27] was used, and Table 1 shows the definitions of those attributes. To cover the IT industry, 396 companies from various sub-industries were initially identified, and 234 (approximately 60% of 396) were randomly included by using the stratified sampling method. The sampling was conducted by ranking the total assets of the 396 companies in 2012 into three groups (i.e., large, middle, and small); 78 companies were then randomly selected from each group ($78 \times 3 = 234$) as the training set. In addition, to validate the trained model, an untouched testing set composed of 100 companies (i.e., condition attributes in 2012 and decision attributes in 2013) was formed in the next time frame by using the similar sampling approach. As suggested in a previous study [43], the RSA generates superior outcomes when the attributes' domains for continuous variables (e.g., financial ratios in this study) are finite sets of low cardinality (e.g., low, middle, and high). Therefore, a three-level discretization was conducted in the empirical case.

The coding for the condition attributes was conducted by ranking each attribute, a process called discretization. For each condition attribute, one-third of the top, middle, and bottom alternatives were assigned the values "*H*," "*M*," and "*L*," respectively. In addition, the decision attribute was ranked from high to low as three DCs (i.e., "Good," "Mediocre," and "Bad"). Two discretization methods were adopted for the decision attribute, namely the one-third and normal-based discretization methods. The one-third discretization method ranked the alternatives' values on the decision attribute, and the top, middle, and bottom third alternatives were classified as "Good," "Mediocre," and "Bad" DCs, respectively. The normal-based discretization method also ranked the alternatives' values on the decision attribute; and the alternatives above $\bar{x} + 0.25SD$, between $\bar{x} \pm 0.25SD$, and below $\bar{x} - 0.25SD$ were classified as "Good," "Mediocre," and "Bad" DCs, respectively. Thus, the values of the 234 alternatives in condition and decision

Table 1
Financial ratios used in the VC-DRSA model for finding CORE attributes.

Dimensions	Financial attributes	Symbols	Definition and brief explanation
Profitability	Return on asset	*ROA*	Net profit before tax/average total asset
	Gross profit	*GrossProfit*	Gross profit/total revenue
	Operational profit	*OpeProfit*	Operational profit/total revenue
	Net profit after tax	*NetProfitAT*	Net profit after tax/total revenue
Growth	Net profit after tax growth rate	*ΔNetProfitAT*	(Net profit after tax-previous net profit after tax)/(previous net profit after tax)
	ROA growth rate	*ΔROA*	(ROA-previous ROA)/previous ROA
	Total assets growth rate	*ΔTotalAsset*	(Total asset-previous total asset)/previous total asset
	Revenue growth rate	*ΔREV*	(Total revenue-previous total revenue)/previous total revenue
	Gross profit growth rate	*ΔGrossProfit*	(Gross profit-previous gross profit)/previous gross profit
Liquidity	Quick ratio	*QUICK*	(Current asset-inventory)/current liability
	Liquidity ratio	*LIQUID*	Current asset/current liability
	Cash ratio	*CASH*	(Operational cash flow-cash dividend for preferred stocks)/weighted average equity
Solvency	Debt ratio	*DEBT*	Total debt/total asset
	Interest coverage ratio	*INTEREST*	(Net profit before tax + interest expense)/interest expense
Asset utilization and operational efficiency	Asset turnover rate	*AssetTurnover*	Total revenue/total asset
	Inventory turnover rate	*InvTurnover*	Total operational cost/average inventory
	Average days for sales	*DAYs*	(Average ending inventory/operational cost) $*$ 365 days

attribute were assigned. Most of the financial attributes, such as the return on asset (*ROA*), correspond with the "gain" property (i.e., the higher the more satisfactory). Nevertheless, two attributes, namely the debt ratio (*DEBT*) and average sales days (*DAYs*), correspond with the "cost" property (i.e., the higher the less satisfactory). This concern was addressed in a specific setting during the induction.

4.2. Variable consistency dominance-based rough set approach model

The VC-DRSA model was divided into two parts. The first part explored the training set by comparing the average classification accuracy of various classifiers (a 5-fold cross validation was conducted five times for each classifier) and examining the two types of discretization on the decision attribute. The second part employed the untouched testing set (100 companies) to validate the VC-DRSA model by using certain statistical tests. The VC-DRSA was conducted using the jMAF [2], developed by the Laboratory of Intelligent Decision Support Systems, Institute of Computing Science, Poznan University of Technology. In addition, support vector machine (SVM) and decision tree (DT) models were constructed by using DTREG [42] for comparison. As shown in Table 2, VC-DRSA models (based on the one-third discretization method) yielded superior classification results compared with the SVM and DT models. Furthermore, the VC-DRSA model (when the consistency level (CL) = 0.95) seemed to outperform the other classifiers; thus, we assumed that the training set was suitable for being modeled through the VC-DRSA to provide the recent financial patterns of IT companies.

The second part involved developing VC-DRSA models by using the entire training set for induction, and the untouched testing set (100 companies in the subsequent time frame) was used to validate it. The classification accuracy (CA), mean absolute error (MAE), and root mean square error (RMSE) were all measured for each VC-DRSA model, as shown in Table 3. The corresponding confusion matrices for the testing set at different CLs are shown in Table 4.

The trained VC-DRSA model (CL = 0.95) was validated using the testing set, and the output of the model (forecasted DCs for 100 companies) was compared with the original DCs of the testing set. The rank correlation between the two datasets was analyzed by setting Good = 3, Mediocre = 2, and Bad = 1 (Spearman's rho = 81.6%, which was significant at the 0.05 level). In addition, the Mann–Whitney U test (asymptotic significance = 98.8%) and the Kolmogorov–Smirnov test (asymptotic significance = 99.4%) could not reject the hypothesis that the distributions of these two datasets are not different (two-tailed significance level = 5%). The result from the testing set thus validated the VC-DRSA model (CL = 95%).

In the training set, the CORE of the VC-DRSA model (CL = 0.95) consisted of only one set of REDUCT and indispensable financial attributes used for discerning DCs, which were adopted to construct the INRM through the DEMATEL technique. The involved attributes of the CORE are listed in Table 5, and the major

Table 2
Classification accuracy of the training set (234 companies).

	Classification accuracy (hit rate) for each model					
	VC-DRSA (%)				SVM (RBF kernel) (%)	Decision tree (%)
	(CL = 1.00)	(CL = 0.95)	(CL = 0.90)	(CL = 0.85)		
Average (one-third)[a]	77.78	78.98	76.58	76.07	70.86	65.72
SD (one-third)[a]	2.01	1.34	1.02	1.00	3.20	0.95
Average (normal-based)[b]	69.92	71.80	71.63	68.63	67.70	65.91
SD (normal-based)[b]	1.62	0.80	1.78	1.27	2.80	0.81

[a] The 5-fold cross validation was repeated five times (by the "one-third" discretization on the decision attribute).
[b] The 5-fold cross validation was repeated five times (by the "normal-based" discretization method on the decision attribute).

Table 3
VC-DRSA model classification accuracies (in three measures) by using the one-third discretization method on the decision attribute.

		VC-DRSA (%)			
		CL = 1.00	CL = 0.95	CL = 0.90	CL = 0.85
Training set	CA[a]	83.76	87.40	86.53	84.51
Training set	RMSE[a]	43.11	38.73	40.54	40.64
Training set	MAE[a]	18.58	15.27	16.44	16.51
Testing set	CA[b]	64.00	86.00	84.00	67.00

[a] The result was calculated by a 5-fold cross validation conducted once on the training set (234 companies).
[b] The testing set (100 companies) was classified by the trained VC-DRSA classifiers at different consistency levels.

Table 4
Confusion matrices for VC-DRSA models (testing set).

	(CL = 1.00)				(CL = 0.95)				(CL = 0.90)				(CL = 0.85)		
	B	M	G		B	M	G		B	M	G		B	M	G
B	10	19	0	B	24	3	1	B	23	3	1	B	23	2	1
M	0	54	0	M	0	52	0	M	0	51	0	M	2	35	0
G	0	17	0	G	0	6	10	G	0	6	10	G	0	6	9

Note: Some of the alternatives were unclassified; therefore, the sum of each matrix was not always 100.

Table 5
CORE and the included financial attributes.

Set	Number	Included attributes
CORE	14	*ROA, GrossProfit, OpeProfit, NetProfitAT, ΔREV, ΔGrossProfit, ΔTotalAsset, ΔROA, CASH, LIQUID, QUICK, DEBT, InvTurnover, DAYs*

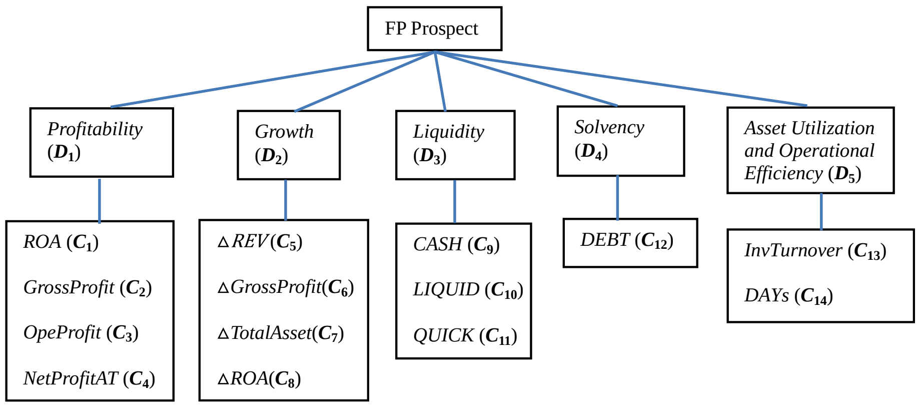

Fig. 3. Hierarchical structure of the evaluation model for the DEMATEL technique.

dimensions and pertinent criteria (14 financial attributes) are illustrated in Fig. 3.

4.3. Decision-making trial and evaluation laboratory analysis

Although the CORE attributes might not be comprehensive, those criteria denote the minimal and indispensable attributes for discerning the future FP changes in the VC-DRSA model; fewer variables are also helpful for reducing the complexity of the subsequent analyses and are easier for DMs to comprehend. Therefore, the CORE attributes were adopted for the DEMATEL analysis; Appendix B shows detailed calculations of the analysis. The DEMATEL analysis involved the use of a questionnaire (Appendix A) for collecting the implicit knowledge of domain experts. This study collected the opinions of eight domain experts who each have more than 10 years of working experience in the IT or financial industry. In addition, their job titles included chief financial officer, financial manager, investment manager, senior consultant, associate manager, and manager. According to the opinions of the experts, the directional influences of the 14 financial attributes were obtained for analysis (confidence of significance level is 96.91%, refer Appendix B, note in Table B.1).

The top two supported decision rules (i.e., with higher supports) associated with each type of DC are listed in Table 6. Two useful decision rules emerged: the decision rules associated with "$\succeq$Good" (at least Good) and "$\preceq$Bad" (at most Bad). By observing the "at least Good" decision rules, management teams may discover effective paths to improve their future performance. By using the "at most Bad" decision rules, indications of deteriorating FP could be identified and used as warning signals.

In the next stage of the DEMATEL analysis, the domain experts answered questions regarding the influence of one criterion on another (for financial attributes included in the CORE). As shown in Fig. 3, the FP evaluation of a company comprises five dimensions: *Profitability* (D_1), *Growth* (D_2), *Liquidity* (D_3), *Solvency* (D_4), and *Utilization* (D_5) (i.e., asset utilization and operational efficiency). The CORE consists of 14 attributes (criteria) from the five dimensions. The relative importance of the dimensions (Table 7) and attributes (Table 8) were obtained.

As shown in Table 7, the influences of dimensions can be divided into a cause group (i.e., $r_i^D - s_i^D \geqslant 0$) and an effect group (i.e., $r_i^D - s_i^D \leqslant 0$) with relative degree of influences. The relationship between the cause and effect groups exhibits a directional effect (i.e., from the cause group to the effect group). In the center of Fig. 4 (the cluster of dimensions), the position of each circle denotes the relative degree of directional influence for each dimension (a high directional influence dimension is positioned high according to $r_i^D - s_i^D$), and the directional influences between dimensions are indicated by arrow lines. For example, the dimension *Profit* (D_1), which belonged to the cause group, yielded the highest relative directional influence of 0.307. The dimension *Solvency* (D_4) belonged to the effect group and yielded the lowest relative directional influence of −0.217. The arrow line from D_1 to D_4 represents the directional influence from *Profit* to *Solvency*. The subplots adjacent to each dimension indicate the extended attributes in each dimension. In each dimension, the directional

Table 6
The high-support decision rules in each decision class.

Rules conditions	DCs	Supports
R1: (*ROA* ⩾ H) & (Δ*NetProfit* ⩾ H) & (Δ*TotalAsset* ⩾ M) & (*AssetTurnover* ⩾ H)	$\succeq$Good	27
R2: (*ROA* ⩾ M) & (Δ*REV* ⩾ H) & (Δ*GrossProfit* ⩾ M) & (*QUICK* ⩾ M) & (*AssetTurnover* ⩾ H)	$\succeq$Good	22
R3: (*OpeProfit* ⩾ M) & (*CASH* ⩾ M) & (Δ*NetProfit* ⩾ M) & (*INTEREST* ⩾ M)	$\succeq$Mediocre	94
R4: (*CASH* ⩾ M) & (Δ*GrossProfit* ⩾ M) & (*INTEREST* ⩾ M)	$\succeq$Mediocre	94
R5: (*OpeProfit* ⩽ L) & (Δ*TotalAsset* ⩽ L) & (Δ*ROA* ⩽ M) & (*LIQUID* ⩽ L)	$\preceq$Bad	28
R6: (*ROA* ⩽ L) & (Δ*ROA* ⩽ M) & (*LIQUID* ⩽ M) & (*DEBT* ⩾ M) & (*AssetTurnover* ⩽ L)	$\preceq$Bad	26

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Table 7
Relative importance of influential dimensions.

Dimensions		r_i^D	s_i^D	$r_i^D + s_i^D$	$r_i^D - s_i^D$
Profit	D_1	2.166	1.859	4.025	0.307
Growth	D_2	1.805	1.892	3.697	−0.087
Liquid	D_3	1.839	1.970	3.809	−0.131
Solvency	D_4	1.311	1.528	2.839	−0.217
Utilization	D_5	1.801	1.672	3.473	0.129

Table 8
Relative importance of influential attributes.

Criteria		r_i^C	s_i^C	$r_i^C + s_i^C$	$r_i^C - s_i^C$
ROA	C_1	5.562	5.575	11.137	−0.013
GrossProfit	C_2	6.804	4.785	11.589	2.019
OpeProfit	C_3	6.595	5.937	12.532	0.658
NetProfitAT	C_4	6.035	5.711	11.746	0.324
ΔREV	C_5	6.417	5.666	12.083	0.751
ΔGrossProfit	C_6	6.102	5.286	11.388	0.817
ΔTotalAsset	C_7	4.282	5.731	10.013	−1.450
ΔROA	C_8	3.993	5.422	9.415	−1.429
CASH	C_9	5.442	5.635	11.077	−0.193
LIQUID	C_{10}	5.959	6.112	12.072	−0.153
QUICK	C_{11}	4.441	5.539	9.981	−1.098
DEBT	C_{12}	3.884	4.576	8.460	−0.692
InvTurnover	C_{13}	6.111	5.926	12.037	0.185
DAYs	C_{14}	4.242	3.969	8.211	0.272

influence originated from a high $r_i^C - s_i^C$ and ended at a low $r_i^C - s_i^C$. Corresponding to the cluster of dimensions, the position of each attribute in each subplot was indicated using the same approach. For example, the relative directional influences $(r_i^C - s_i^C)$ of the attribute *GrossProfit* C_2 and that of *ROA* C_1 (in the dimension *Profitability* D_1) were 2.019 and −0.013, respectively. Thus, the arrow line from C_2 to C_1 indicates the directional influence from *GrossProfit* to *ROA*.

The INRM can be combined with strong decision rules to indicate directional influences in a rule; the obtained contextual guidance is termed as DFG in this study. During the comparison of the two attributes from different dimensions, the directional influence between the dimensions should be used to indicate the influential direction. Take the strongest decision rule (i.e., R1, support = 27)—associated with the "at least Good" DC—for example, the combined DFG is illustrated in Fig. 5a; in addition, the strongest decision rule associated with the "at most Bad" DC is illustrated in Fig. 5b.

4.4. Fuzzy inference system for supporting the findings from a directional flow graph

Although the DEMATEL analysis provides directional guidance among the core criteria (dimensions), the directional influences

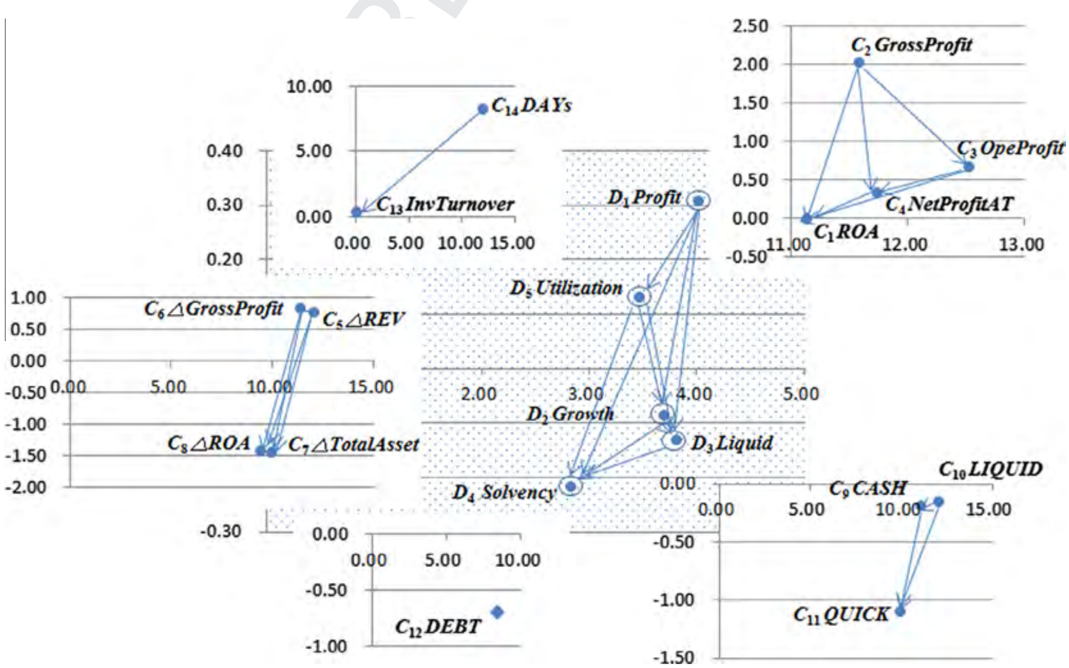

Fig. 4. Influential network relation map for guiding influence directions.

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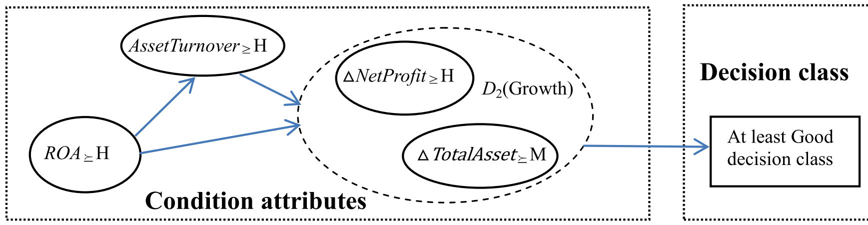

Fig. 5a. Directional flow graph of the strongest "at least Good" decision rule.

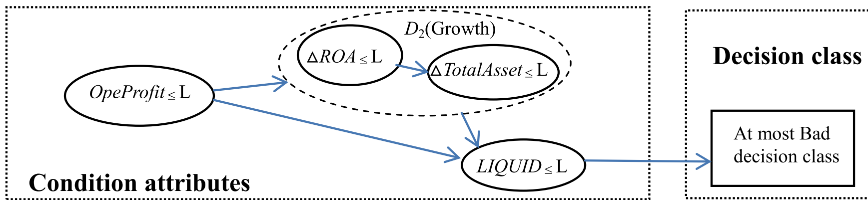

Fig. 5b. Directional flow graph of the strongest "at most Bad" decision rule.

are not granulized (e.g., high, middle, and low denote granulized concepts) knowledge, which could be further transformed into an FIS to examine the implications (e.g., low *OpeProfit* would cause at most low *LIQUID*, as shown in Fig. 5b). The DFGs in Fig. 5a (the strongest rules associated with the "at least Good" DC) and Fig. 5b (the strongest rule associated with the "at most Bad" DC) were used as an example to illustrate how to form the corresponding FIS.

To transform the granulized concepts and reasoning logics (Figs. 5a and 5b) into an FIS, three steps are required. (1) From the experts, collect the fuzzy numbers that may denote the concepts of high, middle, and low for each criterion and the fuzzy numbers for the output DC "Good," "Mediocre," or "Bad". (2) Transform the VC-DRSA decision rules in Figs. 5a and 5b into a set of rules for fuzzy inference. (3) Collect the opinions of experts on the performance of the sample companies for the included criteria. In this empirical case, the prevailing triangular membership function was used, and the range was from 0 (i.e., the lowest) to 10 (i.e., the highest). Experts were requested to provide their concepts on "Low," "Middle," and "High," respectively, and the assumed shapes of the corresponding triangular membership functions are shown in Fig. 6; the corresponding interval for each triangular membership function was thus denoted by a set of triangular fuzzy numbers (TFNs).

The TFNs for the three concepts (i.e., Low, Middle, and High) were assumed to be the same for all the attributes. In addition, the TFNs that denote the DCs "Good," "Mediocre," and "Bad" were also collected in a similar approach. The average parameters for the input attributes and the output DCs are consolidated in Table 9 (the original opinions from the experts are shown in Appendix C, Tables C.1 and C.2). The dominance characteristic of the VC-DRSA decision rule might cause an attribute to address more than one concept (e.g., $\geqslant M$ addresses two concepts: Middle and High); therefore, the associated decision rules in Figs. 5a and 5b were

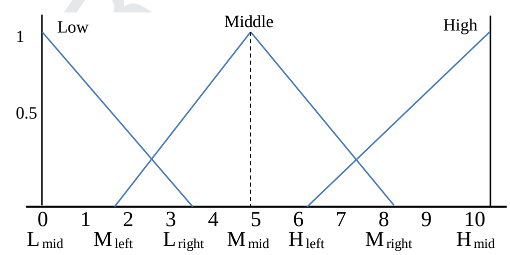

Fig. 6. Assumed shape of fuzzy intervals for the triangular fuzzy membership functions.

transformed into four rules (Table 10) in the FIS to cover all the plausible combinations.

To examine the FIS, three companies from the testing set (with condition attributes in 2012) were adopted as examples: Lite-On Technology (*A*), United Microelectronics (*B*), and Rectron Semiconductor (*C*), and they were classified as "Good," "Mediocre," and "Bad" by using the VC-DRSA model. The raw financial data (i.e., condition attributes) of the three sample companies in 2012 were provided to the experts with the industry averages of the seven financial ratios, and the experts were requested to provide their opinions for the three companies. The average opinions (from 0 to 10) of the experts on the seven attributes and the corresponding FIS outputs of the three companies are shown in Table C.3 (Appendix C). The FIS calculations were performed using the fuzzy module of MATLAB. The three companies' FIS outputs suggested that the companies *A*, *B*, and *C* should be categorized as "Good," "Mediocre," and "Bad," respectively; in other words, the results from the FIS are consistent with the classifications of the VC-DRSA, supporting the implications of the two DFGs (i.e., Figs. 5a and 5b).

Table 9
Average parameters of the fuzzy triangular membership functions.

Granulized concepts	Low			Middle			High		
	L_{left}	L_{middle}	L_{right}	M_{left}	M_{middle}	M_{right}	H_{left}	H_{middle}	H_{right}
For input variables	(0.00,	0.00,	3.94)	(2.81,	5.00,	7.31)	(6.56,	10.00,	10.00)
	Bad			Mediocre			Good		
	B_{left}	B_{middle}	B_{right}	M_{left}	M_{middle}	M_{right}	G_{left}	G_{middle}	G_{right}
For output DCs	(0.00,	0.00,	2.81)	(1.94,	4.88,	7.63)	(6.44,	10.00,	10.00)

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Table 10
Transformed rules for the FIS (from Figs. 5a and 5b).

FIS rules	Conditions	DCs
FIS R1	IF (*ROA*=H) & (Δ*NetProfit*=H) & (Δ*TotalAsset*=H) & (*AssetTurnover*=H)	At least Good
FIS R2	IF (*ROA*=H) & (Δ*NetProfit*=H) & (Δ*TotalAsset*=M) & (*AssetTurnover*=H)	At least Good
FIS R3	IF (*OpeProfit*=L) & (Δ*TotalAsset*=L) & (Δ*ROA*=M) & (*LIQUID*=L)	At most Bad
FIS R4	IF (*OpeProfit*=L) & (Δ*TotalAsset*=L) & (Δ*ROA*=L) & (*LIQUID*=L)	At most Bad

5. Discussions and implications

The VC-DRSA model (CL = 0.95) generated 42 decision rules to classify the subsequent FP of the IT companies, and achieved more than 85% accuracy of approximation for both the training set and testing set (Table 3). In addition, the attributes obtained were analyzed using the DEMATEL technique to collect the directional influences among the CORE. The combination of decision rules and directional influences among the criteria may thus provide an insightful guidance for IT companies to improve. After a company identifies its underperformed attribute/attributes, it may further select the corresponding decision rules to form an FIS to examine the granulized knowledge in a specific context.

For example, company *B* underperformed on the criteria *AssetTurnover* and Δ*NetProfit*, as shown in the DFG (Fig. 5a) (the original values on both these attributes were "Low" according to the one-third discretization method), and the VC-DRSA output was "Mediocre". In the context of Fig. 5a, company *B* may learn that it should improve its attribute *AssetTurnover* to influence its *Growth* dimension. This kind of insightful analysis is the novelty and contribution of the proposed model, which combines the machine learning technique with the MADM method for financial applications.

Although ranking or selection by using the proposed approach were not emphasized, DMs may also synthesize the final performance score for target alternatives by using the influential weights (i.e., $r_i^c + s_i^c$ in Table B.9) from the DEMATEL analysis. The CORE attributes represent the minimum indispensable attributes to discriminate the FP prospect of IT companies (in the VC-DRSA model). The DMs may give their opinions on the CORE attributes for target alternatives and use the simple additive weight (SAW) method to synthesize the final performance score for each company; it is also one of the functions of the proposed approach.

Except for improvement planning and alternatives ranking, the obtained VC-DRSA decision rules or DFGs (e.g., Fig. 5b) associated

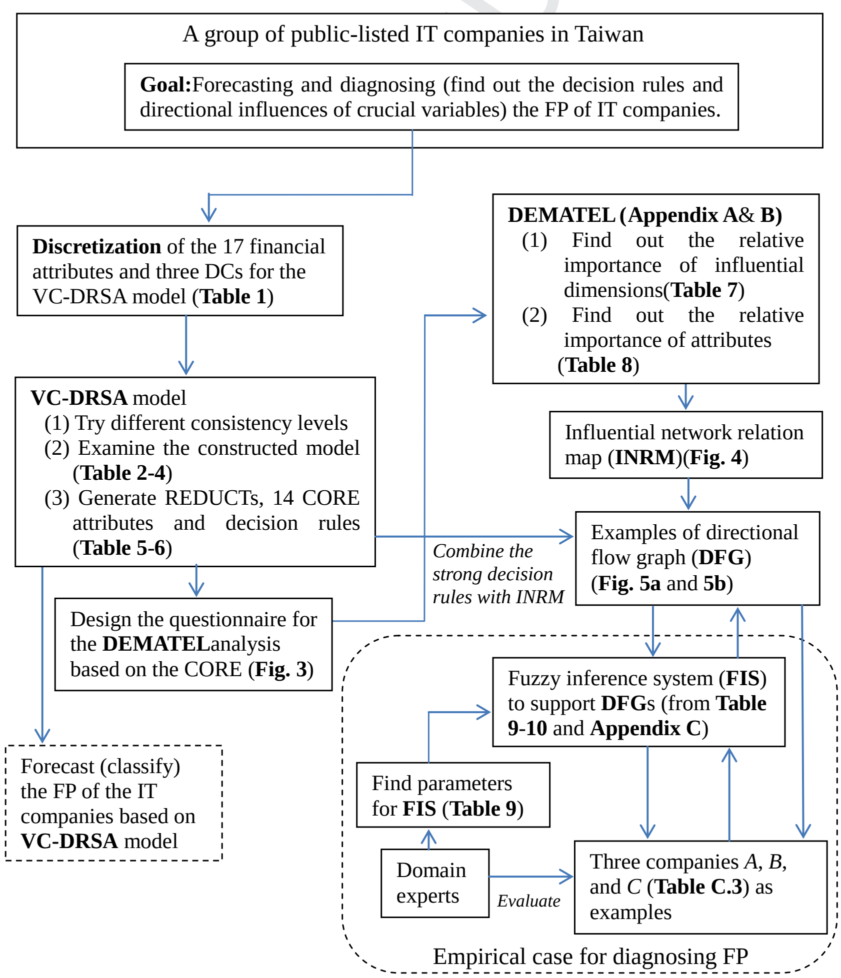

Fig. 7. Research flow of the empirical case.

with the "at most Bad" DC could be used as warning signals to comprehend the deterioration of the FP. For example, the DFG (Fig. 5b) suggests that the inferior operational profitability of a company might yield an inferior (or negative) growth rate in *ROA* and total assets, and therefore require the company to increase its current liability (short debts) to support its business (i.e., lower liquidity ratio). If the aforementioned symptoms occurred as a negative loop, it would be a warning signal for a company's future FP. Occasionally, avoiding failure might be more crucial than becoming successful; this study provided a basis for handling these two critical concerns. The aforementioned improvement guidance and managerial implications are the major novelty and contributions of the proposed approach.

6. Conclusion and remarks

This study proposed an integrated approach that utilizes the advantages of two approaches for improving the FP of the IT industry: the VC-DRSA and DEMATEL technique; in addition, the integrated DFG (infusing decision rules and the INRM) provided DMs additional insights on improvement planning. Furthermore, this study examined the implications in the DFGs (Figs. 5a and 5b) by adopting fuzzy inference, which processed the granulized concepts and supported the findings. Fig. 7 depicts a diagram of the empirical case with the involved steps.

The addressed questions were answered in the study. First, the CORE consisted of 14 attributes, which were identified for forecasting FP. Second, decision rules with strong patterns for FP changes were obtained (Table 6). Third, the required directional influences of dimensions and attributes were incorporated with the decision rules to obtain managerial insights (see DFGs) for guiding improvements. Fourth, the incorporated FIS supported the implications in the empirical case. The obtained outcomes cannot be provided by using conventional statistical models; for example, in regression models, all of the observed instances must be considered to represent the average results [44]. However, for identifying strong patterns, the proposed hybrid model provided meaningful guidance with a partial set of instances in each context, thus providing insightful implications for IT companies.

Although the benefits of the proposed approach have been shown, it still has certain limitations. First, the constructed VC-DRSA model is based on the assumption that the recent FP patterns will reoccur in the near future. However, if a strong impact (such as a financial crisis) changes the FP patterns after the training period, the decision rules obtained might be invalid for capturing future changes. Second, the proposed model only adopted financial attributes to obtain the decision rules. Other dimensions (e.g., technology and marketing) are not included. Third, the prevailing proxy EPS was chosen to categorize DCs in the VC-DRSA; some other FP change measurements (e.g., change in ROE) might yield a different result. DMs or researchers should base on their focus to choose the proxy for FP changes. Fourth, considering the plausible complexity of the FIS, only the strongest decision rules associated with the "at least Good" and "at most Bad" DC were examined and illustrated; too many rules might not be feasible in constructing an effective FIS. Despite the aforementioned limitations, the proposed model showed its capability in helping IT companies diagnose the FP in a systematic and contextual approach; this has constructive meanings both in academia and practice.

7. Uncited references

[26,36,46,49–51].

Appendix A

A.1. Questionnaire used for the DEMATEL analysis

Your kindly support is appreciated! This is an academic study on "**A new approach and insightful financial diagnoses for the IT industry based on a hybrid MADM model**". The purpose is to explore the relative weights of dimensions and attributes in making company's financial performance prediction. All the information provided will be used for academic analysis only, and will not be separately announced to the outside or transferred for other usage. Therefore, please feel at ease in filling out answers. Your support will be very helpful to the completion of this research. We sincerely hope that you may spend some time to express your opinions to be taken as reference for this research. Your kindly help is highly appreciated. Thank you again and wish you all the best!

1. Instructions for filling out the questionnaire

This questionnaire is divided into six parts: (1) instructions for filling out; (2) dimensions and criteria description; (3) method for filling out; (4) comparison of the impact of the five dimensions; (5) comparison of the impact of the 14 attributes; and (6) personal data.

2. Descriptions of dimensions and attributes

All decision dimensions and criteria are shown in Table 1 and Fig. 3.

(Fig. 3 shows the dimension 1–5 and attributes 1–14; the explanations of the dimensions and attributes are in Table 1.)

3. Method for filling out

Filling factors influence level: Scales from 0 to 4; No influence (0), Minor influence (1), Middle influence (2), High influence (3), Extreme influence (4).

For example: The influence degree of A to B is extreme influence, then filling 4 under column B.

Criteria	A	B	C	D	E
A		4			
B					

Examples

(1) The influence degree of "*ROA*" to "*GrossProfit*" is Extreme influence then filing **4** into the cross blank of C_1 and C_2.
(2) The influence degree of "*GrossProfit*" to "*ROA*" is Minor influence then filing **1** into the cross blank of C_2 and C_1.

Attributes	ROA (C_1)	GrossProfit (C_2)	OpeProfit (C_3)	NetProfitAT (C_4)	ΔREV (C_5)	ΔGrossProfit (C_6)	ΔTotalAsset (C_7)	ΔROA (C_8)	CASH (C_9)	LIQUID (C_{10})	QUICK (C_{11})	DEBT (C_{12})	InvTurnover (C_{13})	DAYs (C_{14})
ROA (C_1)		**4**												
GrossProfit (C_2)	**1**													

4. The evaluation of influence relationship for the 5 dimensions

(for reference only, this part could be skipped).

Dimensions	Profitability (D_1)	Growth (D_2)	Liquidity (D_3)	Solvency (D_4)	Asset Utilization & Operational Efficiency (D_5)
Profitability (D_1)					
Growth (D_2)					
Liquidity (D_3)					
Solvency (D_4)					
Asset Utilization and Operational Efficiency (D_5)					

Note: 0 = No influence; 1 = Minor influence; 2 = Middle influence; 3 = High influence; 4 = Extreme influence.

5. The evaluation of influence relationship for the 14 attributes

Attributes	ROA (C_1)	GrossProfit (C_2)	OpeProfit (C_3)	NetProfitAT (C_4)	ΔREV (C_5)	ΔGrossProfit (C_6)	ΔTotalAsset (C_7)	ΔROA (C_8)	CASH (C_9)	LIQUID (C_{10})	QUICK (C_{11})	DEBT (C_{12})	InvTurnover (C_{13})	DAYs (C_{14})
ROA (C_1)														
GrossProfit (C_2)														
OpeProfit (C_3)														
NetProfitAT (C_4)														
ΔREV (C_5)														
ΔGrossProfit (C_6)														
ΔTotalAsset (C_7)														
ΔROA (C_8)														
CASH (C_9)														
LIQUID (C_{10})														
QUICK (C_{11})														
DEBT (C_{12})														
InvTurnover (C_{13})														
DAYs (C_{14})														

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Note: 0 = No influence; 1 = Minor influence; 2 = Middle influence; 3 = High influence; 4 = Extreme influence.

6. Basic personal data

(1) Gender: □ Male □ Female
(2) Education Level: □ College □ University □ Master □ PhD
(3) Service Department: ______
(4) Job Title: ______
(5) Working Experience in Finance and Investment Domain □ Under 5 years (including) □ 5–10 years (including) □ 10–15 years old (including) □ over 15 years
(6) Age: □ Under 30 years old (including) □ 30–35 years old (including) □ 35–40 years old (including) □ 40–50 years old (including) □ Over 50 years old.

Appendix B. Detail calculations of the DEMATEL analysis

B.1. The raw data collected from the eight domain experts

See Table B.1.

*B.2. Form the initial average matrix **A***

The initial average matrix was obtained from Table B.1 by placing the average of the opinions of the eight experts on C_{ij} to indicate the average influence attribute i on attribute j (see Table B.2).

B.3. Obtain the direct influence relation matrix $\boldsymbol{D}, \boldsymbol{I}-\boldsymbol{D}$, and $(\boldsymbol{I}-\boldsymbol{D})^{-1}$

The matrix $\boldsymbol{D} = [d_{ij}]_{n\times n}$ can be derived by using Eqs. (B.1) and (B.2), which is obtained by determining a constant number k to normalize $\boldsymbol{A}$.

$$\boldsymbol{D} = k\boldsymbol{A} \tag{B.1}$$

$$k = \min\left\{\frac{1}{\max_i \sum_{j=1}^{n} a_{ij}}, \frac{1}{\max_j \sum_{i=1}^{n} a_{ij}}\right\} \tag{B.2}$$

where $i, j \in \{1, \ldots, 14\}$ (see Table B.3).

Use an identity matrix I to obtain $\boldsymbol{I}-\boldsymbol{D}$ (Table B.4), and the inverse of $\boldsymbol{I}-\boldsymbol{D}$ could be indicated as $(\boldsymbol{I}-\boldsymbol{D})^{-1}-\boldsymbol{I}$, shown in Table B.5.

Table B.1
Raw data from experts.

Ci-j	Respondents (domain experts)								Average by 8	Average by 7
(Attribute i to j)	1	2	3	4	5	6	7	8		
C1-2	1	1	2	1	2	1	0	2	1.25	1.143
C1-3	3	2	3	3	4	2	3	3	2.875	2.857
C1-4	3	3	2	1	3	3	4	2	2.625	2.714
C1-5	1	1	1	1	2	0	0	1	0.875	0.857
C1-6	3	2	3	3	4	2	3	3	2.875	2.857
C1-7	4	3	3	4	3	4	3	4	3.5	3.429
C1-8	4	3	4	3	3	3	4	4	3.5	3.429
C1-9	1	1	1	1	1	2	1	1	1.125	1.143
C1-10	1	1	1	0	2	1	0	1	0.875	0.857
C1-11	1	1	1	1	1	2	1	1	1.125	1.143
C1-12	2	2	2	1	2	2	1	2	1.75	1.714
C1-13	2	2	2	2	2	1	2	1	1.75	1.857
C1-14	1	1	1	0	3	1	1	2	1.25	1.143
C2-1	3	2	3	3	2	3	4	3	2.875	2.857
C2-3	4	4	4	3	3	4	2	4	3.5	3.429
C2-4	3	3	2	2	1	3	4	3	2.625	2.571
C2-5	3	3	4	2	4	3	3	4	3.25	3.143
C2-6	4	3	3	4	4	3	4	4	3.625	3.571
C2-7	1	1	1	1	1	2	1	1	1.125	1.143
C2-8	2	2	2	2	2	1	2	1	1.75	1.857
C2-9	2	2	2	2	4	3	3	2	2.5	2.571
C2-10	2	1	2	2	3	2	2	1	1.875	2.000
C2-11	3	3	3	2	4	2	3	3	2.875	2.857
C2-12	1	1	1	2	1	1	1	1	1.125	1.143
C2-13	2	2	3	3	2	2	3	2	2.375	2.429
C2-14	1	1	1	0	2	1	2	1	1.125	1.143
C3-1	3	3	3	4	2	3	4	3	3.125	3.143
C3-2	4	2	3	3	2	4	4	3	3.125	3.143
C3-4	3	3	4	3	3	3	4	3	3.25	3.286
C3-5	3	3	2	4	3	4	3	3	3.125	3.143
C3-6	2	2	3	3	2	3	2	3	2.5	2.429
C3-7	1	1	1	2	1	1	1	1	1.125	1.143
C3-8	2	1	2	1	0	3	1	2	1.5	1.429
C3-9	3	2	3	2	2	3	2	3	2.5	2.429
C3-10	2	1	3	1	2	2	1	2	1.75	1.714
C3-11	2	2	2	3	2	1	2	2	2	2.000
C3-12	1	1	2	2	1	0	1	1	1.125	1.143
C3-13	3	2	3	3	2	4	2	3	2.75	2.714
C3-14	1	1	2	2	1	1	2	1	1.375	1.429
C4-1	4	3	4	4	3	4	3	3	3.5	3.571
C4-2	3	3	2	1	3	3	2	3	2.5	2.429
C4-3	3	3	3	4	2	3	4	3	3.125	3.143
C4-5	1	1	2	2	1	0	1	1	1.125	1.143
C4-6	3	2	3	3	2	4	2	3	2.75	2.714

(continued on next page)

Table B.1 (*continued*)

Ci-j	Respondents (domain experts)								Average by 8	Average by 7
(Attribute *i* to *j*)	1	2	3	4	5	6	7	8		
C4-7	1	1	1	2	1	1	1	1	1.125	1.143
C4-8	3	2	3	3	2	4	2	3	2.75	2.714
C4-9	2	2	2	2	2	1	2	1	1.75	1.857
C4-10	2	3	2	3	2	2	3	2	2.375	2.429
C4-11	1	1	2	1	1	2	1	0	1.125	1.286
C4-12	1	1	1	1	2	1	2	1	1.25	1.286
C4-13	2	2	2	2	1	2	3	2	2	2.000
C4-14	1	1	0	1	2	0	2	2	1.125	1.000
C5-1	3	3	2	3	2	3	3	3	2.75	2.714
C5-2	3	2	3	3	2	4	2	3	2.75	2.714
C5-3	3	2	3	3	2	4	3	3	2.875	2.857
C5-4	3	3	3	1	2	3	2	2	2.375	2.429
C5-6	3	2	4	3	2	4	2	3	2.875	2.857
C5-7	1	1	1	2	1	1	2	1	1.25	1.286
C5-8	1	2	1	2	0	0	2	1	1.125	1.143
C5-9	2	2	1	2	3	1	2	1	1.75	1.857
C5-10	3	3	2	3	2	3	3	3	2.75	2.714
C5-11	3	2	3	3	2	4	2	3	2.75	2.714
C5-12	1	2	1	1	2	1	2	1	1.375	1.429
C5-13	3	3	2	3	2	3	3	3	2.75	2.714
C5-14	2	1	2	1	1	0	2	1	1.25	1.286
C6-1	2	2	1	2	3	1	2	1	1.75	1.857
C6-2	4	3	4	4	3	4	3	4	3.625	3.571
C6-3	3	3	2	2	3	2	3	4	2.75	2.571
C6-4	4	4	4	3	3	4	3	3	3.5	3.571
C6-5	2	2	3	1	2	3	2	2	2.125	2.143
C6-7	3	2	2	3	2	3	4	2	2.625	2.714
C6-8	1	1	2	1	0	2	1	1	1.125	1.143
C6-9	2	2	1	2	3	3	2	3	2.25	2.143
C6-10	2	2	1	2	3	1	2	1	1.75	1.857
C6-11	2	2	3	3	2	1	3	2	2.25	2.286
C6-12	1	1	1	2	1	1	3	1	1.375	1.429
C6-13	2	2	2	1	3	2	1	2	1.875	1.857
C6-14	0	0	0	0	0	0	1	1	0.25	0.143
C7-1	1	2	2	1	0	2	1	2	1.375	1.286
C7-2	0	2	0	0	0	0	1	1	0.5	0.429
C7-3	1	1	2	1	0	2	1	1	1.125	1.143
C7-4	1	1	2	1	0	2	1	1	1.125	1.143
C7-5	2	2	3	3	2	1	3	2	2.25	2.286
C7-6	2	2	3	3	2	3	2	2	2.375	2.429
C7-8	3	2	3	2	3	2	3	4	2.75	2.571
C7-9	0	0	0	0	0	0	1	1	0.25	0.143
C7-10	1	1	2	1	0	2	1	1	1.125	1.143
C7-11	1	2	2	1	0	2	1	2	1.375	1.286
C7-12	1	1	1	2	1	1	2	1	1.25	1.286
C7-13	1	1	1	1	2	1	1	1	1.125	1.143
C7-14	0	0	0	0	0	0	1	1	0.25	0.143
C8-1	3	2	3	3	4	2	3	1	2.625	2.857
C8-2	1	1	1	2	1	1	2	1	1.25	1.286
C8-3	0	0	1	1	1	2	0	1	0.75	0.714
C8-4	1	1	1	2	1	3	1	0	1.25	1.429
C8-5	0	1	1	1	1	2	1	1	1	1.000
C8-6	0	1	1	1	0	0	0	1	0.5	0.429
C8-7	2	2	1	3	2	2	3	2	2.125	2.143
C8-9	2	2	1	1	3	2	1	2	1.75	1.714
C8-10	1	1	1	2	1	1	2	1	1.25	1.286
C8-11	2	2	1	1	3	2	1	2	1.75	1.714
C8-12	0	0	0	0	1	1	0	1	0.375	0.286
C8-13	2	2	1	1	3	2	1	2	1.75	1.714
C8-14	0	1	1	0	0	0	1	1	0.5	0.429
C9-1	3	2	3	3	4	2	3	1	2.625	2.857
C9-2	2	2	2	3	2	2	3	1	2.125	2.286
C9-3	2	1	1	3	2	1	1	2	1.625	1.571
C9-4	2	3	1	1	2	1	1	1	1.5	1.571
C9-5	2	3	1	2	2	1	1	1	1.625	1.714
C9-6	1	1	1	1	0	2	1	2	1.125	1.000
C9-7	2	2	2	3	2	2	3	1	2.125	2.286
C9-8	1	1	1	1	0	2	0	1	0.875	0.857
C9-10	4	3	3	4	3	4	3	3	3.375	3.429
C9-11	4	4	3	4	3	4	4	3	3.625	3.714
C9-12	1	1	1	1	0	2	1	2	1.125	1.000
C9-13	0	0	0	1	1	0	1	0	0.375	0.429
C9-14	0	1	1	0	0	1	1	1	0.625	0.571
C10-1	0	1	1	1	0	0	0	1	0.5	0.429

Table B.1 (*continued*)

Ci-j	Respondents (domain experts)								Average by 8	Average by 7
(Attribute *i* to *j*)	1	2	3	4	5	6	7	8		
C10-2	0	0	0	1	1	0	1	0	0.375	0.429
C10-3	3	2	1	4	4	3	2	3	2.75	2.714
C10-4	1	1	2	1	0	1	2	1	1.125	1.143
C10-5	3	2	4	3	4	3	3	3	3.125	3.143
C10-6	1	1	2	1	0	1	2	2	1.25	1.143
C10-7	3	2	2	3	3	4	2	4	2.875	2.714
C10-8	3	3	3	2	3	2	3	3	2.75	2.714
C10-9	3	2	2	3	3	4	2	4	2.875	2.714
C10-11	3	2	2	3	2	3	2	3	2.5	2.429
C10-12	3	3	4	3	4	3	3	3	3.25	3.286
C10-13	4	3	3	4	3	4	3	3	3.375	3.429
C10-14	4	4	4	3	4	3	4	2	3.5	3.714
C11-1	1	1	2	1	1	2	1	2	1.375	1.286
C11-2	1	1	1	1	2	1	3	1	1.375	1.429
C11-3	1	1	2	1	0	1	2	2	1.25	1.143
C11-4	1	1	2	1	2	1	1	0	1.125	1.286
C11-5	1	1	1	1	2	1	2	1	1.25	1.286
C11-6	1	1	1	2	1	1	2	1	1.25	1.286
C11-7	1	1	1	0	2	1	1	2	1.125	1.000
C11-8	1	1	1	3	1	0	0	2	1.125	1.000
C11-9	3	4	4	3	4	3	3	4	3.5	3.429
C11-10	3	2	1	2	4	3	2	2	2.375	2.429
C11-12	0	1	0	0	0	1	0	2	0.5	0.286
C11-13	0	0	0	0	1	1	0	1	0.375	0.286
C11-14	1	1	2	1	2	1	3	2	1.625	1.571
C12-1	1	1	0	0	0	1	1	2	0.75	0.571
C12-2	0	1	0	0	0	1	0	1	0.375	0.286
C12-3	1	1	2	1	0	1	0	1	0.875	0.857
C12-4	3	1	4	4	4	3	4	3	3.25	3.286
C12-5	1	1	1	2	1	1	2	1	1.25	1.286
C12-6	1	1	1	2	2	1	2	2	1.5	1.429
C12-7	3	2	4	3	3	4	3	3	3.125	3.143
C12-8	1	1	1	2	1	1	2	1	1.25	1.286
C12-9	1	1	2	1	0	0	2	2	1.125	1.000
C12-10	2	2	3	3	2	3	2	1	2.25	2.429
C12-11	1	1	2	2	1	2	1	2	1.5	1.429
C12-13	0	1	1	0	0	0	0	1	0.375	0.286
C12-14	0	1	0	0	0	0	0	1	0.25	0.143
C13-1	2	2	2	1	2	1	2	1	1.625	1.714
C13-2	1	1	2	1	0	0	2	2	1.125	1.000
C13-3	3	2	3	3	2	3	2	2	2.5	2.571
C13-4	2	2	1	2	3	2	1	2	1.875	1.857
C13-5	3	2	2	2	3	2	3	3	2.5	2.429
C13-6	1	1	2	1	0	0	2	2	1.125	1.000
C13-7	3	3	3	2	3	2	4	2	2.75	2.857
C13-8	3	2	3	3	2	4	2	3	2.75	2.714
C13-9	3	3	3	2	3	2	4	2	2.75	2.857
C13-10	4	3	3	4	3	4	4	3	3.5	3.571
C13-11	1	1	1	2	1	2	1	1	1.25	1.286
C13-12	1	1	0	0	0	1	2	1	0.75	0.714
C13-14	4	3	4	4	3	4	3	4	3.625	3.571
C14-1	0	1	1	0	1	0	0	1	0.5	0.429
C14-2	0	0	0	0	0	0	1	2	0.375	0.143
C14-3	1	1	3	1	2	1	1	0	1.25	1.429
C14-4	1	1	2	1	1	0	0	1	0.875	0.857
C14-5	3	2	3	2	4	3	3	2	2.75	2.857
C14-6	0	0	0	0	0	0	2	1	0.375	0.286
C14-7	2	3	1	2	2	1	1	1	1.625	1.714
C14-8	1	1	2	2	1	1	1	2	1.375	1.286
C14-9	0	0	0	0	0	0	1	2	0.375	0.143
C14-10	4	3	4	4	3	3	3	3	3.375	3.429
C14-11	1	1	2	2	1	1	1	2	1.375	1.286
C14-12	0	1	0	0	0	0	1	2	0.5	0.286
C14-13	4	4	4	3	4	3	3	4	3.625	3.571

Note: $\frac{1}{n(n-1)}\sum_{i=1}^{n}\sum_{j=1}^{n}\frac{|a_{ij}^{p}-a_{ij}^{p-1}|}{a_{ij}^{p}}\times 100\% = 3.092\% < 5\%$, where a_{ij}^{p} and a_{ij}^{p-1} denote the average influence of attribute i on attribute j by experts p and $p-1$, respectively; n denotes the number of attributes ($n = 14$ and $p = 8$ in here). Thus, the results above are confidence of significance at the 96.91% level, which is greater than 95% level that is used to test for significance.

Table B.2
Initial average matrix ***A***.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	r_i
C_1		1.25	2.88	2.63	0.88	2.88	3.50	3.50	1.13	0.88	1.13	2.75	1.75	1.25	26.38
C_2	2.88		3.50	2.63	3.25	3.63	1.13	1.75	2.50	1.88	2.88	1.13	2.38	1.13	30.63
C_3	3.13	3.13		3.25	3.13	2.50	1.13	1.50	2.50	1.75	2.00	1.50	2.75	1.38	29.63
C_4	3.50	2.50	3.13		1.13	2.75	1.13	2.75	1.75	2.38	1.13	2.25	2.00	1.13	27.50
C_5	2.75	2.75	2.88	2.38		2.88	1.25	1.13	1.75	2.75	2.75	1.63	2.75	1.25	28.88
C_6	1.75	3.63	2.75	3.50	2.13		2.63	1.13	2.25	1.75	2.25	1.38	1.88	0.25	27.25
C_7	1.38	1.25	1.13	1.13	2.25	2.38		2.75	1.25	1.13	1.38	2.38	1.13	0.25	19.76
C_8	2.63	1.25	0.75	1.25	1.00	0.50	2.13		1.75	1.25	1.75	1.25	1.75	1.25	18.50
C_9	2.63	2.13	1.63	1.50	1.63	1.13	2.13	0.88		3.38	3.63	1.13	2.38	0.63	24.75
C_{10}	0.50	0.38	2.75	1.13	3.13	1.25	2.88	2.75	2.88		2.50	1.25	3.38	3.50	28.25
C_{11}	1.38	1.38	1.25	1.13	1.25	1.25	1.13	1.13	3.50	2.38		1.50	1.38	1.63	20.25
C_{12}	0.75	0.38	0.88	3.25	1.25	1.50	3.13	1.25	1.13	2.25	1.50		0.38	0.25	17.88
C_{13}	1.63	1.13	2.50	1.88	2.50	1.13	2.75	2.75	2.75	3.50	1.25	1.38		3.63	28.76
C_{14}	0.50	0.38	1.25	0.88	2.75	0.38	1.63	1.38	0.38	3.38	1.38	1.25	3.63		19.13
s_i	25.38	21.50	27.26	26.50	26.25	24.13	26.50	24.63	25.50	28.63	25.50	20.77	27.50	17.50	

Table B.3
Direct influence relation matrix ***D***.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	r_i
C_1	0.000	0.042	0.097	0.089	0.030	0.097	0.118	0.118	0.038	0.030	0.038	0.093	0.059	0.042	0.890
C_2	0.097	0.000	0.118	0.089	0.110	0.122	0.038	0.059	0.084	0.063	0.097	0.038	0.080	0.038	1.034
C_3	0.105	0.105	0.000	0.110	0.105	0.084	0.038	0.051	0.084	0.059	0.068	0.051	0.093	0.046	1.000
C_4	0.118	0.084	0.105	0.000	0.038	0.093	0.038	0.093	0.059	0.080	0.038	0.076	0.068	0.038	0.928
C_5	0.093	0.093	0.097	0.080	0.000	0.097	0.042	0.038	0.059	0.093	0.093	0.055	0.093	0.042	0.975
C_6	0.059	0.122	0.093	0.118	0.072	0.000	0.089	0.038	0.076	0.059	0.076	0.046	0.063	0.008	0.920
C_7	0.046	0.042	0.038	0.038	0.076	0.080	0.000	0.093	0.042	0.038	0.046	0.080	0.038	0.008	0.667
C_8	0.089	0.042	0.025	0.042	0.034	0.017	0.072	0.000	0.059	0.042	0.059	0.042	0.059	0.042	0.624
C_9	0.089	0.072	0.055	0.051	0.055	0.038	0.072	0.030	0.000	0.114	0.122	0.038	0.080	0.021	0.835
C_{10}	0.017	0.013	0.093	0.038	0.105	0.042	0.097	0.093	0.097	0.000	0.084	0.042	0.114	0.118	0.954
C_{11}	0.046	0.046	0.042	0.038	0.042	0.042	0.038	0.038	0.118	0.080	0.000	0.051	0.046	0.055	0.684
C_{12}	0.025	0.013	0.030	0.110	0.042	0.051	0.105	0.042	0.038	0.076	0.051	0.000	0.013	0.008	0.603
C_{13}	0.055	0.038	0.084	0.063	0.084	0.038	0.093	0.093	0.093	0.118	0.042	0.047	0.000	0.122	0.971
C_{14}	0.017	0.013	0.042	0.030	0.093	0.013	0.055	0.046	0.013	0.114	0.046	0.042	0.122	0.000	0.646
s_i	0.857	0.726	0.920	0.895	0.886	0.814	0.895	0.831	0.861	0.966	0.861	0.701	0.928	0.591	

Table B.4
Identity matrix ***I*** minus direct influence relation matrix ***D***.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}
C_1	1.000	−0.042	−0.097	−0.089	−0.030	−0.097	−0.118	−0.118	−0.038	−0.030	−0.038	−0.093	−0.059	−0.042
C_2	−0.097	1.000	−0.118	−0.089	−0.110	−0.122	−0.038	−0.059	−0.084	−0.063	−0.097	−0.038	−0.080	−0.038
C_3	−0.105	−0.105	1.000	−0.110	−0.105	−0.084	−0.038	−0.051	−0.084	−0.059	−0.068	−0.051	−0.093	−0.046
C_4	−0.118	−0.084	−0.105	1.000	−0.038	−0.093	−0.038	−0.093	−0.059	−0.080	−0.038	−0.076	−0.068	−0.038
C_5	−0.093	−0.093	−0.097	−0.080	1.000	−0.097	−0.042	−0.038	−0.059	−0.093	−0.093	−0.055	−0.093	−0.042
C_6	−0.059	−0.122	−0.093	−0.118	−0.072	1.000	−0.089	−0.038	−0.076	−0.059	−0.076	−0.046	−0.063	−0.008
C_7	−0.046	−0.042	−0.038	−0.038	−0.076	−0.080	1.000	−0.093	−0.042	−0.038	−0.046	−0.080	−0.038	−0.008
C_8	−0.089	−0.042	−0.025	−0.042	−0.034	−0.017	−0.072	1.000	−0.059	−0.042	−0.059	−0.042	−0.059	−0.042
C_9	−0.089	−0.072	−0.055	−0.051	−0.055	−0.038	−0.072	−0.030	1.000	−0.114	−0.122	−0.038	−0.080	−0.021
C_{10}	−0.017	−0.013	−0.093	−0.038	−0.105	−0.042	−0.097	−0.093	−0.097	1.000	−0.084	−0.042	−0.114	−0.118
C_{11}	−0.046	−0.046	−0.042	−0.038	−0.042	−0.042	−0.038	−0.038	−0.118	−0.080	1.000	−0.051	−0.046	−0.055
C_{12}	−0.025	−0.013	−0.030	−0.110	−0.042	−0.051	−0.105	−0.042	−0.038	−0.076	−0.051	1.000	−0.013	−0.008
C_{13}	−0.055	−0.038	−0.084	−0.063	−0.084	−0.038	−0.093	−0.093	−0.093	−0.118	−0.042	−0.047	1.000	−0.122
C_{14}	−0.017	−0.013	−0.042	−0.030	−0.093	−0.013	−0.055	−0.046	−0.013	−0.114	−0.046	−0.042	−0.122	1.000

*B.4. Calculate the total influence relation matrix **T***

The total influence matrix can be obtained by $(\boldsymbol{I}-\boldsymbol{D})^{-1}-\boldsymbol{I}$, which is shown in Table B.6.

*B.5. Decompose **T** for analyzing the influential weights of dimensions and attributes*

B.5.1. Influential weights of dimensions

The total influence matrix of dimensions can be obtained from Table B.6 by taking the average of each cluster to denote the influence of dimension i on dimension j. Take dimension D_1 to D_4 for example.

$$D_{14} = 0.383 = (0.375 + 0.388 + 0.389 + 0.382)/4$$

(see Tables B.7 and B.8).

B.5.2. Influential weights of attributes

The relative influence of each attribute can be calculated by $r_i^C + s_i^C$, and the values of r_i^C and s_i^C can refer to Table B.6 (see Table B.9).

Table B.5
Inverse of $\boldsymbol{I} - \boldsymbol{D}$.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}
C_1	1.352	0.343	0.457	0.443	0.381	0.421	0.468	0.449	0.387	0.406	0.379	0.375	0.420	0.282
C_2	0.523	1.376	0.568	0.524	0.534	0.521	0.474	0.469	0.514	0.527	0.516	0.388	0.529	0.341
C_3	0.516	0.457	1.448	0.528	0.516	0.477	0.462	0.452	0.498	0.510	0.476	0.389	0.526	0.340
C_4	0.490	0.406	0.503	1.393	0.421	0.447	0.430	0.456	0.439	0.485	0.413	0.382	0.465	0.306
C_5	0.490	0.435	0.523	0.490	1.411	0.475	0.455	0.430	0.467	0.526	0.486	0.383	0.515	0.331
C_6	0.447	0.448	0.499	0.504	0.457	1.372	0.471	0.411	0.462	0.473	0.453	0.360	0.465	0.281
C_7	0.315	0.274	0.322	0.315	0.340	0.330	1.278	0.346	0.312	0.328	0.312	0.296	0.318	0.197
C_8	0.331	0.252	0.291	0.294	0.285	0.255	0.327	1.247	0.308	0.314	0.303	0.248	0.320	0.219
C_9	0.421	0.358	0.418	0.395	0.400	0.362	0.419	0.364	1.351	0.478	0.452	0.318	0.437	0.271
C_{10}	0.389	0.333	0.477	0.413	0.479	0.387	0.471	0.446	0.467	1.416	0.450	0.345	0.506	0.380
C_{11}	0.321	0.282	0.337	0.320	0.325	0.302	0.325	0.306	0.391	0.383	1.281	0.275	0.343	0.252
C_{12}	0.270	0.224	0.288	0.349	0.285	0.281	0.347	0.280	0.283	0.334	0.289	1.203	0.270	0.180
C_{13}	0.432	0.362	0.483	0.446	0.471	0.395	0.479	0.459	0.470	0.530	0.422	0.358	1.413	0.390
C_{14}	0.278	0.237	0.323	0.297	0.360	0.261	0.327	0.306	0.286	0.401	0.308	0.257	0.399	1.201

Table B.6
Total influence relation matrix $\boldsymbol{T}$.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	r_i^C
C_1	0.352	0.343	0.457	0.443	0.381	0.421	0.468	0.449	0.387	0.406	0.379	0.375	0.420	0.282	5.562
C_2	0.523	0.376	0.568	0.524	0.534	0.521	0.474	0.469	0.514	0.527	0.516	0.388	0.529	0.341	6.804
C_3	0.516	0.457	0.448	0.528	0.516	0.477	0.462	0.452	0.498	0.510	0.476	0.389	0.526	0.340	6.595
C_4	0.490	0.406	0.503	0.393	0.421	0.447	0.430	0.456	0.439	0.485	0.413	0.382	0.465	0.306	6.035
C_5	0.490	0.435	0.523	0.490	0.411	0.475	0.455	0.430	0.467	0.526	0.486	0.383	0.515	0.331	6.417
C_6	0.447	0.448	0.499	0.504	0.457	0.372	0.471	0.411	0.462	0.473	0.453	0.360	0.465	0.281	6.102
C_7	0.315	0.274	0.322	0.315	0.340	0.330	0.278	0.346	0.312	0.328	0.312	0.296	0.318	0.197	4.282
C_8	0.331	0.252	0.291	0.294	0.285	0.255	0.327	0.247	0.308	0.314	0.303	0.248	0.320	0.219	3.993
C_9	0.421	0.358	0.418	0.395	0.400	0.362	0.419	0.364	0.351	0.478	0.452	0.318	0.437	0.271	5.442
C_{10}	0.389	0.333	0.477	0.413	0.479	0.387	0.471	0.446	0.467	0.416	0.450	0.345	0.506	0.380	5.959
C_{11}	0.321	0.282	0.337	0.320	0.325	0.302	0.325	0.306	0.391	0.383	0.281	0.275	0.343	0.252	4.441
C_{12}	0.270	0.224	0.288	0.349	0.285	0.281	0.347	0.280	0.283	0.334	0.289	0.203	0.270	0.180	3.884
C_{13}	0.432	0.362	0.483	0.446	0.471	0.395	0.479	0.459	0.470	0.530	0.422	0.358	0.413	0.390	6.111
C_{14}	0.278	0.237	0.323	0.297	0.360	0.261	0.327	0.306	0.286	0.401	0.308	0.257	0.399	0.201	4.242
s_i^C	5.575	4.785	5.937	5.711	5.666	5.286	5.731	5.422	5.635	6.112	5.539	4.576	5.926	3.969	

Table B.7
Total influence relation matrix $\boldsymbol{T}^D$.

Dimensions	D_1	D_2	D_3	D_4	D_5	r_i^D
D_1	0.458	0.461	0.462	**0.383**	0.401	2.166
D_2	0.389	0.368	0.395	0.322	0.331	1.805
D_3	0.372	0.382	0.408	0.313	0.365	1.839
D_4	0.283	0.298	0.302	0.203	0.225	1.311
D_5	0.357	0.382	0.403	0.308	0.351	1.801
s_i^D	1.859	1.892	1.970	1.528	1.672	

Table B.8
Relative influences of dimensions.

Dimensions	r_i^D	s_i^D	$r_i^D + s_i^D$	$r_i^D - s_i^D$
D_1	2.166	1.859	4.025	0.307
D_2	1.805	1.892	3.697	−0.087
D_3	1.839	1.970	3.809	−0.131
D_4	1.311	1.528	2.839	−0.217
D_5	1.801	1.672	3.473	0.129

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Table B.9
Relative influences of attributes.

Criteria	r_i^C	s_i^C	$r_i^C + s_i^C$	$r_i^C - s_i^C$
C_1	5.562	5.575	11.137	−0.013
C_2	6.804	4.785	11.589	2.019
C_3	6.595	5.937	12.532	0.658
C_4	6.035	5.711	11.746	0.324
C_5	6.417	5.666	12.083	0.751
C_6	6.102	5.286	11.388	0.817
C_7	4.282	5.731	10.013	−1.450
C_8	3.993	5.422	9.415	−1.429
C_9	5.442	5.635	11.077	−0.193
C_{10}	5.959	6.112	12.072	−0.153
C_{11}	4.441	5.539	9.981	−1.098
C_{12}	3.884	4.576	8.460	−0.692
C_{13}	6.111	5.926	12.037	0.185
C_{14}	4.242	3.969	8.211	0.272

Appendix C. Parameters and results of the fuzzy inference system

See Tables C.1–C.3.

Table C.1
Parameters for the inputs' triangular fuzzy membership functions.

Experts	$(L_{left}, L_{middle}, L_{right})$	$(M_{left}, M_{middle}, M_{right})$	$(H_{left}, H_{middle}, H_{right})$
1	(0.0, 0.0, 3.0)	(2.5, 5.0, 7.0)	(6.0, 10.0, 10.0)
2	(0.0, 0.0, 4.4)	(3.0, 5.5, 8.0)	(7.0, 10.0, 10.0)
3	(0.0, 0.0, 4.0)	(2.5, 5.0, 7.5)	(6.5, 10.0, 10.0)
4	(0.0, 0.0, 3.0)	(3.0, 5.5, 7.5)	(7.0, 10.0, 10.0)
5	(0.0, 0.0, 4.0)	(2.0, 4.5, 7.5)	(6.5, 10.0, 10.0)
6	(0.0, 0.0, 5.0)	(3.5, 5.0, 7.5)	(6.0, 10.0, 10.0)
7	(0.0, 0.0, 4.0)	(3.0, 5.0, 7.0)	(7.0, 10.0, 10.0)
8	(0.0, 0.0, 4.5)	(3.0, 4.5, 6.5)	(6.5, 10.0, 10.0)
Averages	(0.00, 0.00, 3.94)	(2.81, 5.00, 7.31)	(6.56, 10.00, 10.00)

Table C.2
Parameters for the output DC's associated triangular fuzzy membership functions.

Experts	$(B_{left}, B_{middle}, B_{right})$	$(M_{left}, M_{middle}, M_{right})$	$(G_{left}, G_{middle}, G_{right})$
1	(0.0, 0.0, 3.0)	(2.0, 5.0, 7.5)	(6.0, 10.0, 10.0)
2	(0.0, 0.0, 3.5)	(2.0, 5.0.5, 8)	(6.0, 10.0, 10.0)
3	(0.0, 0.0, 3.0)	(1.5, 5.0, 7.5)	(6.5, 10.0, 10.0)
4	(0.0, 0.0, 2.5)	(2.5, 4.5, 8.0)	(7.0, 10.0, 10.0)
5	(0.0, 0.0, 3.0)	(2.0, 4.5, 7.0)	(7.5, 10.0, 10.0)
6	(0.0, 0.0, 3.5)	(1.5, 5.0, 8.0)	(6.0, 10.0, 10.0)
7	(0.0, 0.0, 2.5)	(2.0, 4.5, 7.5)	(6.0, 10.0, 10.0)
8	(0.0, 0.0, 2.2)	(2.0, 5.0, 7.5)	(6.5, 10.0, 10.0)
Averages	(0.00, 0.00, 2.81)	(1.94, 4.88, 7.63)	(6.44, 10.00, 10.00)

Table C.3
Corresponding FIS outputs of the three sample companies.

	ROA	*OpeProfit*	*ΔNetProfit*	*ΔROA*	*ΔTotalAsset*	*AssetTurnover*	*LIQUID*	DCs (FIS outputs)
A	8.44	7.88	8.31	8.13	7.63	7.44	4.63	Good (8.46)
B	7.94	7.81	3.94	4.06	7.81	3.93	3.06	Mediocre (5.00)
C	2.69	2.69	2.63	2.44	2.69	4.06	2.94	Bad (1.21)

Note: The definitions of these attributes could be referred to Table 1, and two attributes (*ΔNetProfit* and *AssetTurnover*) were not included in the CORE.

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