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# Combined soft computing model for value stock selection based on fundamental analysis

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ABSTRACT

The stock selection problem is one of the major issues in the investment industry, which is mainly solved by analyzing financial ratios. However, considering the complexity and imprecise patterns of the stock market, obvious and easy-to-understand investment rules, based on fundamental analysis, are difficult to obtain. Therefore, in this paper, we propose a combined soft computing model for tackling the value stock selection problem, which includes dominance-based rough set approach, formal concept analysis, and decision-making trial and evaluation laboratory technique. The objectives of the proposed approach are to (1) obtain easy-to-understand decision rules, (2) identify the core attributes that may distinguish value stocks, (3) explore the cause–effect relationships among the attributes or criteria in the strong decision rules to gain more insights. To examine and illustrate the proposed model, this study used a group of IT stocks in Taiwan as an empirical case. The findings contribute to the in-depth understanding of the value stock selection problem in practice.



## 1. Introduction

In this paper, we propose a combined soft computing model for value stock selection that is based on financial ratio analysis, also termed "fundamental analysis" (FA). The stock selection problem can be traced back to the efficient market hypothesis (EMH) [1], which assumes that investors cannot use available information to form an investing strategy for consistently outperforming the stock market. In the hope of finding a useful strategy, researchers have used various investment plans to examine the EMH [2–4]. Among those investing strategies, value investing is widely examined in academia and in practice [5]; it originated from the classical work of Graham and Dodd [6]. Value investing strategy is based on the idea that out-of-favor stocks are sometimes underpriced because of the inefficiency of the stock market. Smart investors may earn extra premium by investing in these underpriced stocks. In finance, researchers often classify stocks that have high book-to-market equity (B/M) or earnings-to-price (E/P) ratios as value stocks [7]; the value premium has been discovered in many markets [2,3,7–9]. Though the essential idea of value investing is generally accepted, further selection among a group of generic high B/M or E/P ratio stocks is a challenging task. In practice, the evaluation of the worthiness and prospect of a value stock mainly relies on FA [10,11]. Although the use of relevant financial variables to assess the prospect of a stock is widely adopted, opinions on the inclusion of information and analyzing methods are divided.

The stock selection problem is solved using two main approaches. In the conventional approach, financial studies tend to use regression models for determining the relationship among historical financial ratios and future earnings (or stock performance). To examine the usefulness of a value investing strategy, Piotroski [9] included nine financial variables from three aspects to discriminate winners and losers by forming a logit-regression model (F-Score model). Similarly, Mohanram [12] developed a G-Score model for selecting glamor stocks. Both the F- and G-Score models obtained positive results in their proposed experimental periods. The aforementioned studies mainly used regression models, which might be suitable for explaining some phenomenon; nevertheless, the complexity and nonlinear relationships among financial ratios and the subsequent stock returns often impede practitioners in determining useful investing rules in a specific context [13].

In addition, in the nonconventional approach, researchers from other fields, such as artificial intelligence (AI) and multiple criteria decision making (MCDM) have attempted to leverage the computational strength of computer programming to solve the complex

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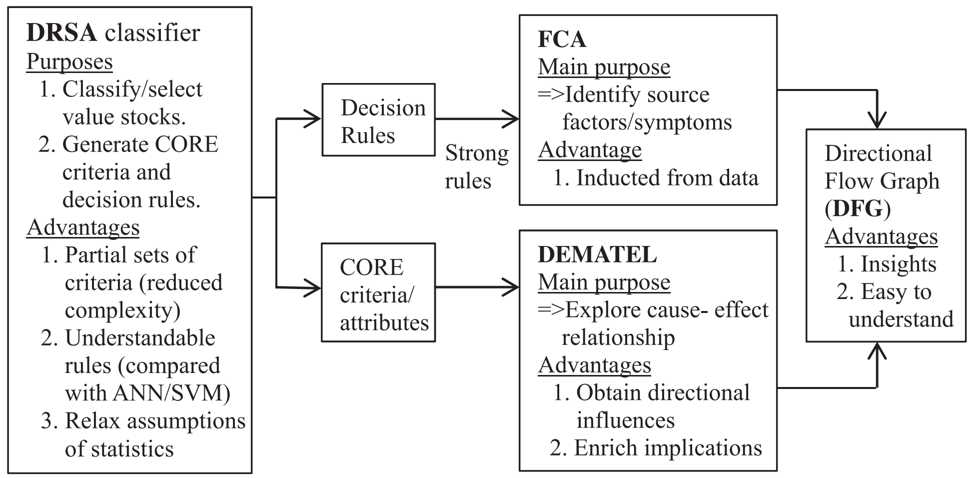



**Fig. 1.** Conceptual framework of the proposed approach.

stock selection problem. Among various AI techniques, artificial neural networks (ANNs) are widely used to predict stock performance because of their superior capability to model a nonlinear relationship. For instance, Lam [10] combined the fundamental and technical variables in the ANN model to predict financial performance. Recent studies have proposed an integration approach for enhancing the learning capability of the ANN model. For example, Hadavandi et al. [14] integrated the genetic fuzzy system with ANN to forecast stock prices. Hsu [15] used a hybrid approach to combine ANN with genetic programming. Although the aforementioned studies generated positive outcomes from their models, drawing useful conclusions for future investment from the learning results of ANNs is often difficult. The black-box processing characteristic of ANN and support vector machine (SVM) [16] impedes investors in understanding the complex relationship among the considered variables of each model. In another nonconventional approach, MCDM considers multiple criteria for tackling the complex stock rankings and selection problem. The group decision methods—analytic network process (ANP) and decision-making trial and evaluation laboratory (DEMATEL)—were used for retrieving experts' domain knowledge regarding investment practice [13,17]. The obtained results hinged on the experts' subjective judgments. Each experts provided his opinions (by questionnaire) to incorporate his knowledge into the model. Another main method in the MCDM is the data envelope analysis (DEA) that uses mathematical programming to gauge the efficiency of the considered stocks [18,19]. Although the DEA method is useful for portfolio selection, it cannot explore the relationships among financial variables.

As discussed, existing studies (i.e., statistics and certain AI techniques) have limitations in exploring the complex relationships among financial variables to induct applicable knowledge of value stocks. Therefore, the major motivation of this study was to devise a model that may relax the unrealistic assumptions of statistics and tackle the vague and imprecise financial data to obtain understandable knowledge or implications for value stock selection. As a result, this paper proposes a combined soft computing model by using the dominance-based rough set approach (DRSA), formal concept analysis (FCA), and DEMATEL techniques, to obtain applicable knowledge for this problem. The conceptual framework of this study is illustrated in Fig. 1; in addition, the purpose and advantages of the proposed approach (compared with previous techniques, such as statistics, ANNs, and SVM) are highlighted.

The key parts of the proposed approach are discussed as below. First, the DRSA classifier reduces the considered criteria (i.e., obtained CORE criteria) and generates a set of decision rules to select value stocks with strong prospects. Compared with the AI techniques (e.g., ANNs and SVM), DRSA may generate a set of decision rules for investors to comprehend (instead of a black-box). In addition, DRSA may consider partial sets of criteria in each context (i.e., decision rule), which is closer to how domain experts make judgments (ANNs, DEA, or SVM must process all input variables simultaneously to adjust their parameters during the learning phase); it is difficult for a human brain to make decisions based on all criteria in each time [20]. In addition, DRSA does not have to assume the distribution of data or the independence of variables. Second, the FCA is incorporated to induct the plausible symptoms that may satisfy the premises in the DRSA decision rules. This deepens the understanding of decision rules obtained from objectively inducted implications, which may enhance the findings from DRSA. Furthermore, the CORE criteria from the DRSA model could be analyzed using the DEMATEL technique, which may leverage domain experts' knowledge to identify cause–effect relationships (directional influences) among the CORE dimensions (criteria). Last, the obtained symptoms and source criteria of decision rules from FCA and DEMATEL analyses may complement each other to support the result. These findings along with the strong DRSA decision rules, could be illustrated as a directional flow graph (DFG) for enhancing the understanding of value stock investment in practice. The proposed approach not only supports the identification of value stocks with superior prospects, but also aims at retrieving understandable implications for investors, which have been underexplored in previous studies.

To illustrate the proposed approach, Taiwan's stock market was examined as an empirical case. The stock market was regarded as a "big data set," composed of more than 1400 stocks and numerous financial attributes. Inducting effective and critical patterns from the big data set is a challenging yet valuable task. The proposed soft computing model intends to explore or retrieve the effective patterns from the stock market with easy-to-understand decision rules for supporting the value stock selection problem.

The remainder of this paper is divided into five sections. Section 2 gives a short review of FA and discusses the proposed DRSA, FCA, and DEMATEL techniques. Section 3 introduces the DRSA methodology and the FCA. In Section 4 the proposed method is used to explore Taiwan's stock market as an empirical case with an experimental result. Section 5 discusses the result, and Section 6 concludes this paper.

## 2. Preliminary

This section reviews studies related to value investing strategy and FA. In addition, the proposed DRSA, FCA, and DEMATEL techniques are briefly discussed. Furthermore, the reason for using the DRSA method for solving the value stock selection problem is explained.

### 2.1. Value investing and FA

Empirical studies have used various investing strategies to examine the efficiency of the market. The value investing strategy is widespread in both practice and academia. Value investing is widely used in practice because of the accomplishments of the world class investor Warren Buffett [21] (by Schroeder). In the financial literature, researchers have often classified stocks with high B/M or E/P ratios as value stocks. The value premium suggests that a portfolio composed of high B/M stocks often outperforms a group of low B/M stocks or market indices [22,23]. This has been examined in many markets with confirmed results [3,7,23,24]. Nevertheless, to conduct value investing for making decisions, selecting among a group of generic high B/M stocks is required. The selection and evaluation of a stock mainly relies on analyzing the financial information from financial statements. The use of FA can help in several domains, such as providing information to creditors or suppliers, evaluating competitive positions of rivals, and projecting the future stock performance for existing or potential investors [25]. Although the use of FA by analyzing financial ratios is a common practice, the decisions of including which variables and modeling methods are still divided. Delen et al. [26] used 31 ratios in their model. To examine the value investing strategy, Piotroski [9] presented the F-Score model, and included nine variables from three aspects to differentiate expected winners and losers. The research mainly relied on regression models to capture the relationship among financial ratios and the subsequent stock returns; therefore, in practice, the financial variables were presumed to be independent, not realistic [27]. A model with a less strict assumption is required for exploring the relationship of the considered financial criteria to guide the value stock selection problem.

### 2.2. The concept of rough set approach and dominance-based rough set approach methods

Various methods are available that may retrieve knowledge from a large-scale data set, such as the fuzzy information system (FIS), ANN, SVM, and rough set approach (RSA). The classical RSA was proposed by Pawlak [28], in an attempt to tackle the indiscernibility and ambiguity of complex data sets. Although the classical RSA achieved major success in discovering useful knowledge in various applications—such as personal investment portfolio analysis [29], prediction of financial distress and credit assessment decision—the RSA was constrained in dealing with the non-ordered data of the classification problems [30]. However, in practice, many problems require handling of data by using preference-ordered attributes. For example, for the credit risk detection problem, a company with lower debt ratio is usually preferred. Therefore, certain extended RSA models were proposed to examine the ordering relation between attribute values, such as Tolerance Rough Sets (TRS) [31,32] and DRSA. The TRS model proposed an uncertainty function to define the level of tolerance for attributes and recognize two objects as indiscernible if the difference in their attributes was below a predefined tolerance level. This approach has the advantage of searching for the optimized approximation of concepts (attributes/criteria); however, determining an ideal tolerance level for attributes (also the subsets of combination of attributes) for a model would require intensive experiments, and the complexity would increase rapidly if the number of attributes in a model was large. By contrast, to focus on the preference relation, DRSA mainly preserves the dominance relation of attribute values and attempts to discover implicit knowledge of multiple attributes. Developed by Greco et al. [33], DRSA has been widely used for resolving various decision problems, such as finding the customers' preference in the airline industry [34], obtaining marketing guidance for customer relationship management [35], and diagnosing the financial performance of commercial banks [36]. The DRSA method is regarded as a knowledge discovering system. The assumption of independence among variables (attributes) is not required, and the probability distribution of data set is not to be assumed. Compared with the classical RSA, the main advantage of the DRSA is the capability of deriving "**if** *antecedent*, **then** *consequent*" decision rules. The stock selection problem based on FA has multiple dimensions and pertaining financial indicators. In practice, financial variables often have relations, and traditional regression models are insufficient to model the complex relations of financial attributes without the assumption of independencies among the considered criteria [27]. The DRSA method may overcome this obstacle with the capability to obtain decision rules. To find practical and useful decision rules for investment, we used the DRSA method for initially solving the value stock selection problem. In this section, the general concept of the DRSA was introduced; in addition, the reason for its use in this study was discussed. For more in-depth theoretical foundations of the DRSA, refer to [33,37–40].

### 2.3. Formal concept analysis

The FCA is regarded as a mathematical theory [41] that clarifies the formalization of concepts and conceptual thinking. According to the survey by Poelmans et al. [42], the major applications of the FCA include software engineering, knowledge discovery, and information retrieval. The financial application of FCA has gained relatively little attention. Previous studies that combined RSA with FCA have emphasized the selection among a group of decision rules generated from the RSA analysis [43]. However, FCA was used in this study to explore the relationship among the involved main criteria by analyzing the value stocks (objects) included in the strong decision rules. The constructed lattice diagram from FCA can generate hierarchical classification and obtain subconcept–superconcept relations among the involved financial attributes. The results may enrich the implications obtained using the DRSA method.

### 2.4. DEMATEL technique

The DEMATEL technique [44], which belongs to the MCDM approach was proposed for tackling complex decision problems. This technique has been applied to explore various business problems, such as vendor [45] and portfolio selection problems [46]. The strength of the DEMATEL technique is to discover the directional influence relationships among the considered dimensions and criteria. The technique's strength was leveraged to enhance the findings in this study. The involved steps for calculation are illustrated in Appendix A, range from how to collect opinions from experts (Step 1) to forming directional influences among the dimensions and criteria (Step 4).

## 3. Methodology

The aim of the proposed methodology is to discover useful knowledge for selecting value stocks. As the evaluation of a stock comprises multiple dimensions and pertaining criteria, it is reasonable to adopt the MCDM approach for the analyses. In this study, we proposed the DRSA methodology as a knowledge discovery system at the initial stage to explore applicable rules for the value investing strategy. The conceptual framework of the proposed model is illustrated in Fig. 1, and the combining of these three parts (i.e., DRSA, FCA, and DEMATEL) is explained and examined using a real example in Section 4. This section mainly discusses the background and essential knowledge of these three techniques.

DRSA, which originated from the classical RSA [28], is an extended data mining technique for ordinal classification problems in a data set. The strength of DRSA is in replacing classical RSA's indiscernibility relation with a dominance relation for analyzing preference-ordered data. The derived dominance relation offers the possibility for modeling the preferences of a decision maker with understandable rules. The use of DRSA relies on the background knowledge about the ordinal evaluation of objects (i.e., value stocks in this study) from a universe (a group of generic high B/M ratio stocks). In addition, the ordinal characteristic of attributes could be defined from the essential financial knowledge, for example, the higher ratio of profitability in Return on Equity (ROE) is preferred in stock selection. Additional details about the DRSA may be found in [33,37–40].

### 3.1. Information system of the DRSA

The system of DRSA begins with an ordered information table. Objects are often placed in rows and attributes are placed in columns. If an attribute represents a criterion, it is accompanied by a preference-ordered characteristic. The data table is in the form of a 4-tuple information system $IS = (U, Q, V, f)$, where $U$ is a universe, comprises of finite objects; $Q = \left\{q_1, q_2, \ldots, q_k\right\}$ is a finite set of $k$ attributes, $V_q$ is the value domain of attribute $q$, $V = \bigcup_{q \in Q} V_q$, and $f : U \times Q \to V$ is a total function where $f(x, q) \in V_q$ for each $q \in Q$ and $x \in U$. The set $Q$ is often divided into condition set $C$ and decision set $D$, and set $C$ often comprises more than one attribute in practice, which is suitable for solving the MCDM problem.

### 3.2. Rough approximation of ordered classes

Define $\geq_q$ as a complete outranking relation on $U$ with respect to a criterion $q \in Q$, in which $x \geq_q y$ implies "$x$ is at least as good as $y$ with respect to the criterion $q$". If $\geq_q$ represents a complete outranking relation, $x$ and $y$ are always comparable with respect to the criterion $q$. Let $Cl = \{Cl_t, t = 1, \ldots, n\}$ be a set of decision classes of $U$, in which $t \in T$, and for each $x \in U$ belonging to only one class $Cl_t \in Cl$. Assume that the classes are preference ordered, that is, for all $r, s = 1, \ldots, n$, if $r > s$, the decision class $Cl_r$ is preferred to $Cl_s$. Given a set of decision classes $Cl$ (for $Cl = \{Cl_t, t = 1, \ldots, n\}$), we then define upward and downward unions of classes (where $Cl_m \in Cl$), that is,

$$Cl_t^{\geq} = \bigcup_{m \geq t} Cl_m \tag{1}$$

$$Cl_t^{\leq} = \bigcup_{m \leq t} Cl_m \tag{2}$$

With the upward and downward unions of classes, we further defined the dominance relation $D_P$ for $P \subseteq C$, where $C$ belongs to the criteria subset (conditional set) of $Q$. If object $x$ $P$-dominates $y$ with respect to $P$, this implies $x \geq_q y$ for all $q \in P$, and is denoted by $xD_Py$. For $P \subseteq C$ and $x, y \in U$, the $P$-dominating set and $P$-dominated set may be denoted as

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

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

The $P$-dominating set and $P$-dominated set can be used to represent a collection of upward and download unions of decision classes. The $P$-lower and $P$-upper approximations of an upward union $Cl_t^{\geq}$ with respect to $P \subseteq C$ may then be defined by $\underline{P}\left(Cl_t^{\geq}\right)$ and $\overline{P}\left(Cl_t^{\geq}\right)$, respectively.

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

$$\overline{P}\left(Cl_t^{\geq}\right) = \bigcup_{x \in Cl^{\geq}} D_P^+(x) = \left\{x \in U : D_P^-(x) \cap Cl_t^{\geq} \neq \varnothing\right\} \tag{6}$$

The $P$-lower approximation $\underline{P}\left(Cl_t^{\geq}\right)$ comprises all objects $x$ of $U$, whereas all objects $y$ have at least the same evaluation regarding all criteria $P$ belonging to class $Cl_t^{\geq}$ or a more satisfactory evaluation, according to Eq. (5). The $P$-upper approximation of an upward union $Cl_t^{\geq}$ with respect to $P \subseteq C$, can be interpreted as the set of all the objects belonging to $Cl_t^{\geq}$. Similarly, the $P$-lower and $P$-upper approximations of $Cl_t^{\leq}$ with respect to $P$ can be defined as follows.

$$\underline{P}\left(Cl_t^{\leq}\right) = \left\{x \in U : D_P^-(x) \subseteq Cl_t^{\leq}\right\} \tag{7}$$

$$\overline{P}\left(Cl_t^{\leq}\right) = \bigcup_{x \in Cl^{\leq}} D_P^-(x) = \left\{x \in U : D_P^+(x) \cap Cl_t^{\leq} \neq \varnothing\right\} \tag{8}$$

The $P$-lower and $P$-upper approximations can be interpreted as the sets belonging to the superior/inferior class ($Cl_t^{\geq}/Cl_t^{\leq}$) with certainty and the sets that might belong to the superior/inferior class ($Cl_t^{\geq}/Cl_t^{\leq}$), respectively. The logical relationship can be shown by the following equations:

$$\underline{P}\left(Cl_t^{\leq}\right) \subseteq Cl_t^{\leq} \subseteq \overline{P}\left(Cl_t^{\leq}\right) \tag{9}$$

$$\underline{P}\left(Cl_t^{\geq}\right) \subseteq Cl_t^{\geq} \subseteq \overline{P}\left(Cl_t^{\geq}\right) \tag{10}$$

Thus, the $P$-boundaries ($P$-doubtable regions) of $Cl_t^{\geq}$ and $Cl_t^{\leq}$ are defined as follows:

$$Bn_P\left(Cl_t^{\leq}\right) = \overline{P}\left(Cl_t^{\leq}\right) - \underline{P}\left(Cl_t^{\leq}\right) \tag{11}$$

$$Bn_P\left(Cl_t^{\geq}\right) = \overline{P}\left(Cl_t^{\geq}\right) - \underline{P}\left(Cl_t^{\geq}\right) \tag{12}$$

The accuracy of approximation of $Cl_t^{\geq}$ and $Cl_t^{\leq}$ can be defined by the following equations:

$$\alpha_P(Cl^{\leq}) = \left|\underline{P}\left(Cl_t^{\leq}\right)\right| / \left|\overline{P}\left(Cl_t^{\leq}\right)\right| \tag{13}$$

$$\alpha_P(Cl^{\geq}) = \left|\underline{P}\left(Cl_t^{\geq}\right)\right| / \left|\overline{P}\left(Cl_t^{\geq}\right)\right| \tag{14}$$

In addition, the classification rate can be further defined by the ratio $\gamma_P(Cl)$ for the criteria $P \subseteq C$.

$$\gamma_P(Cl) = \frac{\left|U - \left(\bigcup_{t \in \{2,\ldots,n\}} Bn_P\left(Cl_t^{\leq}\right)\right)\right|}{|U|} = \frac{\left|U - \left(\bigcup_{t \in \{1,\ldots,n-1\}} Bn_P\left(Cl_t^{\geq}\right)\right)\right|}{|U|} \tag{15}$$

In Eq. (15), $|\cdot|$ is the cardinality of a set. The $\gamma_P(Cl)$ represents the ratio of all correctly classified objects for criteria $P \subseteq C$. Each minimal subset $P \subseteq C$ that gives $\gamma_P(Cl) = \gamma_C(Cl)$ is called a REDUCT of $P \subseteq C$ with respect to $Cl$, and is denoted as $RED_{Cl}(P)$. The intersection of all the REDUCTs is the core of the information system, called $CORE_{Cl}$. With the dominance-based rough approximation of upward and downward unions of decision classes, a generalized description of decision rules can be obtained in terms of "**if** *antecedent*, **then** *consequent*."

In this study, we aimed to classify generic high B/M ratio stocks into two classes: "at least Good" and "at most Bad." Furthermore, the "at least Good" decision class should comprise value stocks with satisfactory financial prospects in the subsequent period. To further explore the relative importance and influential hierarchies of the critical criteria of the stocks included in the "at least Good" decision class, FCA was conducted at the next stage.

### 3.3. Formal concept analysis

In FCA, the data are described by formal context ($U$, $A$, $R$), in which $U$ is a universe set, $A$ is the set of attributes, and $R$ denotes the relationship of $U$ and $A$ (i.e., $R \in U \times A$). When performing FCA for data processing, two major concerns are essential: the formal concept and concept lattice. The formal concept includes the objects and sets of attributes, which may be regarded as a unit in the formal context. For a predefined formal context ($U$, $A$, $R$), the objects defined in the formal concept are called its "extensions," and the attributes included are termed as its "intensions." Furthermore, the formal concepts of a formal context can be formed as a lattice structure, and are termed as the lattice diagram. In a lattice diagram, the relationship of all formal concepts can be defined in an orderly conceptual relation, that is, a subconcept–superconcept relation [41]. All edges in a lattice diagram denote a subconcept–superconcept relation. The superconcept in the higher position represents a more general concept; and the subconcept in the lower position represents a relatively specific concept.

In this study, the stocks included in the strong decision rules associated with the "at least Good" decision class are the candidates for "extensions," and the relations among the involved attributes (i.e., intensions) are the targets to be explored. The supports for the strong decision rules (defined by the decision maker) are the objects involved, and the attributes included in the strong decision rules are classified as "L," "M," and "H," representing the degree of "low," "middle," and "high" for each attribute, respectively. The detailed application of FCA is further explained in the empirical case, and the details of mathematical foundation are demonstrated by Wille [41].

## 4. Empirical case and research results

A group of publicly listed stocks was examined for illustrating the proposed model. Because Taiwan plays a major role in the global IT industry, the IT sector is not only crucial to the economic growth of Taiwan but also supports global advancements in technology; therefore, we selected the publicly listed stocks from the IT industry in Taiwan as an empirical case. The experiment processes and their purposes are illustrated in Fig. 2.

### 4.1. Data and sample

We analyzed the publicly listed companies' financial information and their subsequent stock returns from 2010 to 2012. The authority in Taiwan requests all listed companies to release their annual financial statements before the end of April in the following year; therefore, we selected all of the listed IT stocks at the end of April 2011 on the basis of their financial outcomes in 2010. All of the data were retrieved from the Taiwan Economics Journal (TEJ) database. The original sample group was composed of 395 stocks from the IT sector. After excluding stocks with incomplete financial information or stock returns, the number of stocks was 337; the top one-third high B/M ratio stocks (112 stocks) from the pool were categorized as value stocks. To induct the "**if** *antecedent*, **then** *consequent*" decision rules from the outperformed and underperformed stocks in the subsequent period, we ranked the selected 112 stocks (value stocks) based on their holding-period-return (HPR) from April to December 2011. The top and bottom 33% stocks (37 + 37 = 74 stocks) were selected and categorized as "Good" and "Bad" decision classes, respectively. The sample selection process is illustrated in Fig. 3.

### 4.2. Financial criteria (ratios)

The Taiwan Stock Exchange categorizes 17 financial ratios from five dimensions for the listed companies to report their financial summary in the open Market Observation Post System (MOPS) [47]. We followed the MOPS to adopt the 17 financial ratios as the input variables for the proposed DRSA method, with minor modifications. We added five new ratios (the growth rates of revenue, gross profit, net profit after tax, total asset, and return on asset (ROA)) to replace some of the original ratios with those of a similar characteristic for capturing the growth tendency of profitability and operational performance. The definitions and brief explanations of each financial attribute are shown in Table 1. The selected 112 value stocks were used for assigning ranking scores for each stock on each criterion. The original financial ratios (attributes) were changed to "1", "2", and "3" for each criterion, by mapping to the lowest (37 stocks), the middle (38 stocks) and highest (37 stocks) one-third stocks, respectively. For example, if stock $A$'s ROA belongs to the highest one-third stocks, its transformed score on the ROA criterion is "3". Similarly, we assigned rankings for each criterion for discretization in the DRSA model.

### 4.3. CORE and decision rules of the DRSA method

The jMAF software developed by the laboratory of intelligent decision support systems (IDSS), Poznan University of Technology, was used for generating the DRSA results in this study. The

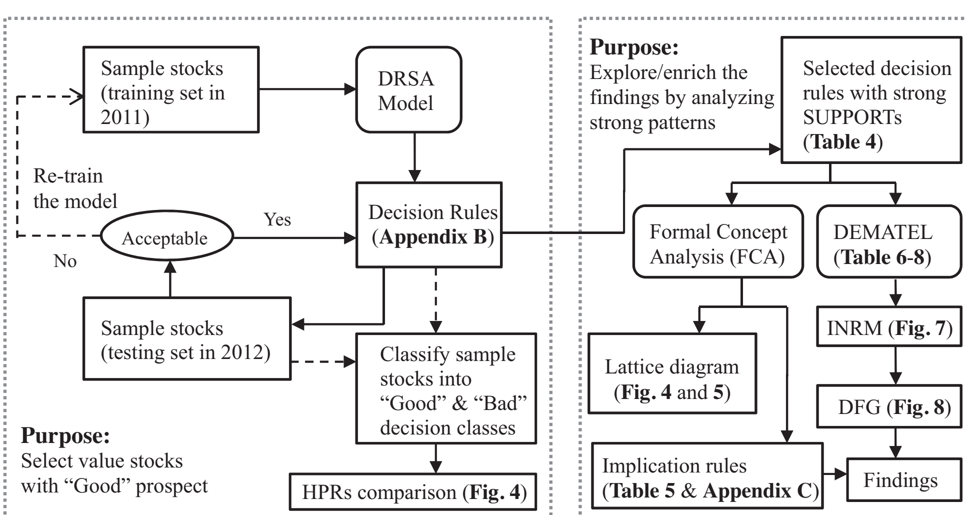



**Fig. 2.** The steps involved in the experiment.

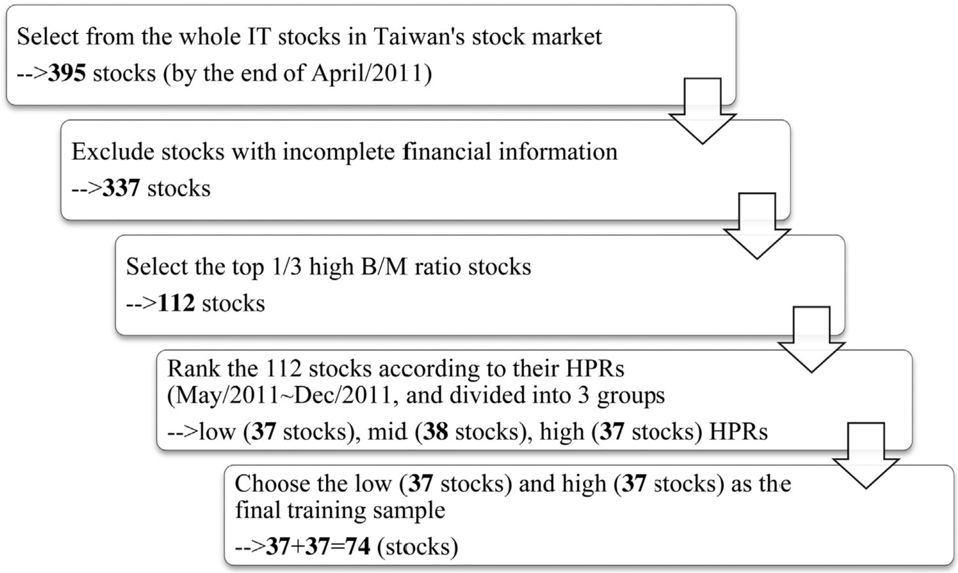



**Fig. 3.** The sampling process for the development of the DRSA model.

**Table 1**
Financial indicators used in the DRSA model.

| Dimensions | Financial indicators | Symbols | Definitions and brief explanations |
|---|---|---|---|
| Profitability dimension (***P***) | Return on asset | *ROA* | Net profit before tax/average total asset |
| | Operational gross profit | *OGrossProfit* | Operational gross profit/total revenue |
| | Operational profit | *OProfit* | Operational profit/total revenue |
| | Net profit after tax | *NPAT* | Net profit after tax/total revenue |
| Growth dimension (***G***) | Net profit after tax growth rate | *ΔNPAT* | (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 dimension (***L***) | 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 dimension (***S***) | Debt ratio | *DEBT* | Total debt/total asset |
| | Interest coverage ratio | *INTEREST* | (Net profit before tax + interest expense)/interest expense |
| Operational efficiency dimension (***E***) | 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 |

induction processes from the jMAF used the VC-DOMLEM algorithm (consistency level = 1), developed by Błaszczyński et al. [48]. The DRSA modeling was divided into two stages. At the first stage, the training set (74 stocks, as shown in Fig. 3) was analyzed five times by DRSA through a five-fold cross validation. Furthermore, SVM, decision tree (DT), and discriminant analysis (DISCRI) classifiers were implemented on the training set through the five-fold cross validation by using DTREG software [49]. In Table 2, the DRSA classifier reveals the highest classification accuracy (CA) on average (i.e., 75.95%); in addition, the nonparametric Mann–Whitney *U* test indicated that the classification result obtained using DRSA outperformed the other three classifiers (significant level = 0.01, two-tailed). Therefore, a group of randomly selected 50 high B/M stocks were tested by the end of April 2012, to examine the effectiveness of the DRSA model at the second stage. The entire training set was inducted to generate the decision rules, and the 42 correctly classified stocks gained 84% accuracy in approximation.

To examine the relevance of the included financial ratios in discriminating value stocks, we obtained 11 REDUCTs. The CORE that was retrieved from the 11 REDUCTs was composed of six attributes (financial ratios). The original 17 attributes and the six attributes of the CORE are shown in Table 3.

In addition, the jMAF generated a set of "**if** *antecedent*, **then** *consequent*" decision rules, in which we explored the rules that may help to identify "Good" stocks with superior stock returns in

**Table 2**
Classification accuracy of various classifiers (unit: %).

| | DRSA | SVM[a] | DT | DISCRI |
|---|---|---|---|---|
| 1 | 75.68 | 64.86 | 62.16 | 54.05 |
| 2 | 78.38 | 62.16 | 60.81 | 52.70 |
| 3 | 74.32 | 62.16 | 59.46 | 51.35 |
| 4 | 74.32 | 60.81 | 56.76 | 52.70 |
| 5 | 77.03 | 63.51 | 60.81 | 56.76 |
| Average | 75.90 | 62.70 | 60.00 | 53.51 |
| SD[b] | 1.76 | 1.54 | 2.05 | 2.05 |

[a] The SVM classifier used the RBF kernel function.
[b] SD denotes standard deviation.

**Table 3**
Comparison of the original financial attributes and the CORE.

| Set | Number | Variable name |
|---|---|---|
| Original attributes | 17 | *ROA, OGrossProfit, OProfit, NPAT, ΔNPAT, ΔROA, ΔTotalAsset, ΔREV, ΔGrossProfit, QUICK, LIQUID, CASH, DEBT, INTEREST, AssetTurnover, InvTurnover, DAYs* |
| CORE | 6 | *ΔREV, ΔGrossProfit, ΔROA, DEBT, AssetTurnover, DAYs* |

the following period. In total, 20 decision rules (Appendix B) were obtained after conducting the DRSA analysis, and nine decision rules formed the "Good" decision class. Furthermore, the accuracy of approximation (for the testing set) for the unions of classes "at least Good" and "at most Bad" were 100% and 84.06%, respectively.

### 4.4. Examination of the selection result

To explore the effectiveness of the obtained DRSA model in selecting value stocks, we used the obtained decision rules to classify the 50 sample stocks in 2012. Only eight stocks were categorized as "at least Good," four stocks were unclassified, and 38 stocks were classified as "at most Bad." We examined the differences between the average monthly HPRs of the eight ("at least Good") and the 38 ("at most Bad") stocks; in addition, the differences between the eight stocks and the market index (the market's weighted average index) from May 2012 to December 2013 were examined. The descriptive statistics of the monthly HPRs of the three groups are summarized in Table 4, and the average monthly HPRs—Good, Bad, and market weighted average index (Weighted AVG)—are shown in Fig. 4.

To test the significance of the ranking result, the paired $t$ tests were conducted. The differences among these three groups (20 observations for each group) were all significant (significance

**Table 4**
The HPR summary of the three groups.

| | Mean (%) | Standard deviation (%) | Minimum (%) | Maximum (%) |
|---|---|---|---|---|
| Good | 11.52 | 6.34 | 4.68 | 22.05 |
| Bad | −5.91 | 5.14 | −14.50 | 1.61 |
| Weighted average index | 5.04 | 2.96 | 1.33 | 9.09 |

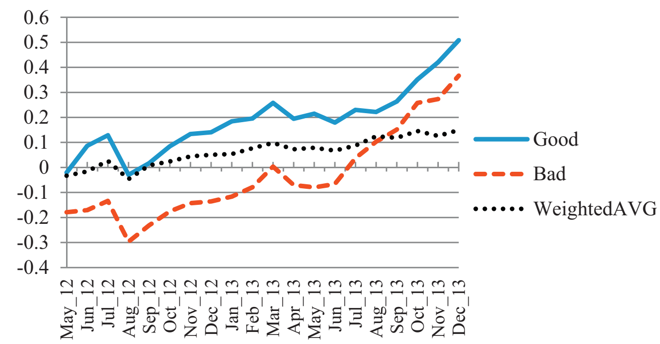



**Fig. 4.** The monthly HPR comparison of the three portfolios.

level = 0.01, two tailed), and the eight selected stocks (categorized as "at least Good") outperformed the 38 stocks (categorized as "at most Bad") and the market weighted average index in the observed months. The average HPRs of the "Good" stocks reached 11.52% (SD = 0.063) while the weighted average index was 5.04% (SD = 0.051)—which indicated the effectiveness of the proposed model.

To derive more implications from the decision rules, two strong decision rules (Table 5) associated with the "Good" decision class with more than eight SUPPORTs were further analyzed using the FCA method. The lattice diagram is shown in Fig. 5, and the node (attribute) in the higher position indicates a more important/generalized concept.

The FCA was conducted using ConExp software, and two lattice diagrams (Figs. 5 and 6) with hierarchical relations of the critical concepts were obtained. For example, in the higher position of Fig. 5, "AssetTurn_H" denotes the concept of high asset turnover rate.

The attributes in the higher position, which are the superconcepts of the formal context, are more crucial (commonly shared by objects). Fig. 6 shows the adjusted lattice diagram with object counts, where the top four superconcepts are AssetTurn_H (i.e., high *AssetTurnover*), InvSaleD_L (i.e., low *DAYs*), Debt_L (i.e., low *DEBT*), and RevG_H (i.e., high *ΔREV*).

To conduct the DEMATEL analysis, seven criteria were retrieved from the CORE and the two strong decision rules. These seven criteria and their dimensions are shown in Table 6. The criteria were used to design a questionnaire, and eight domain experts were

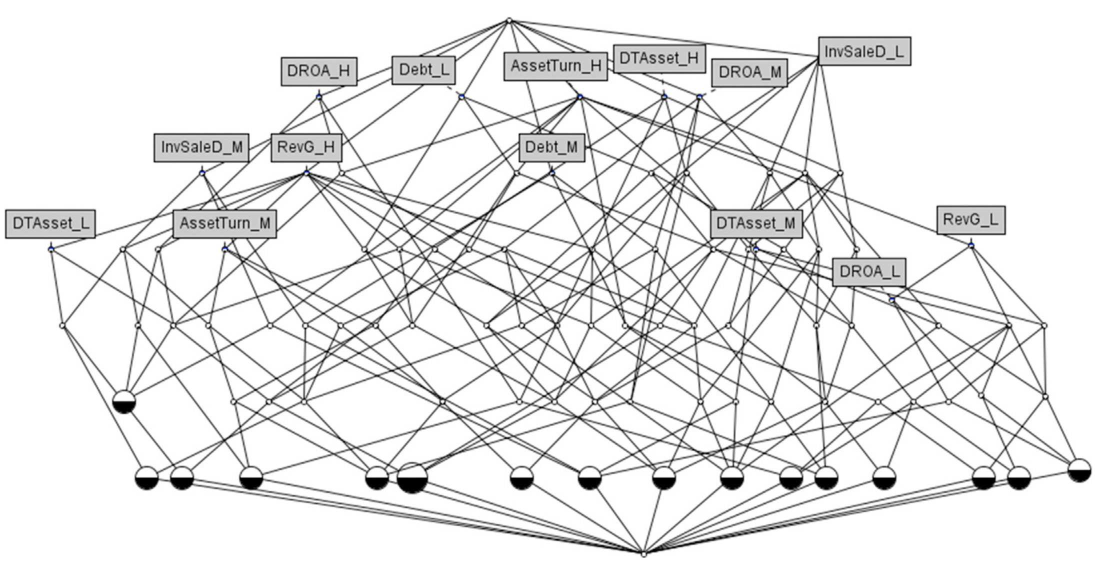



**Fig. 5.** Lattice diagram obtained from the two strong decision rules.

**Table 5**
Two strong decision rules associated with the "Good" decision class.

| Conditional attributes (**If** conditions hold) | Decision class (**then**) | SUPPORTs |
|---|---|---|
| $\Delta TotalAsset \geq 2$ & $DEBT \leq 2$ & $AssetTurnover \geq 3$ & $DAYs \leq 2$ | $HPR \geq$ G (at least Good) | 9 |
| $\Delta REV \geq 3$ & $\Delta ROA \geq 2$ & $AssetTurnover \geq 2$ & $DAYs \leq 2$ | $HPR \geq$ G (at least Good) | 10 |

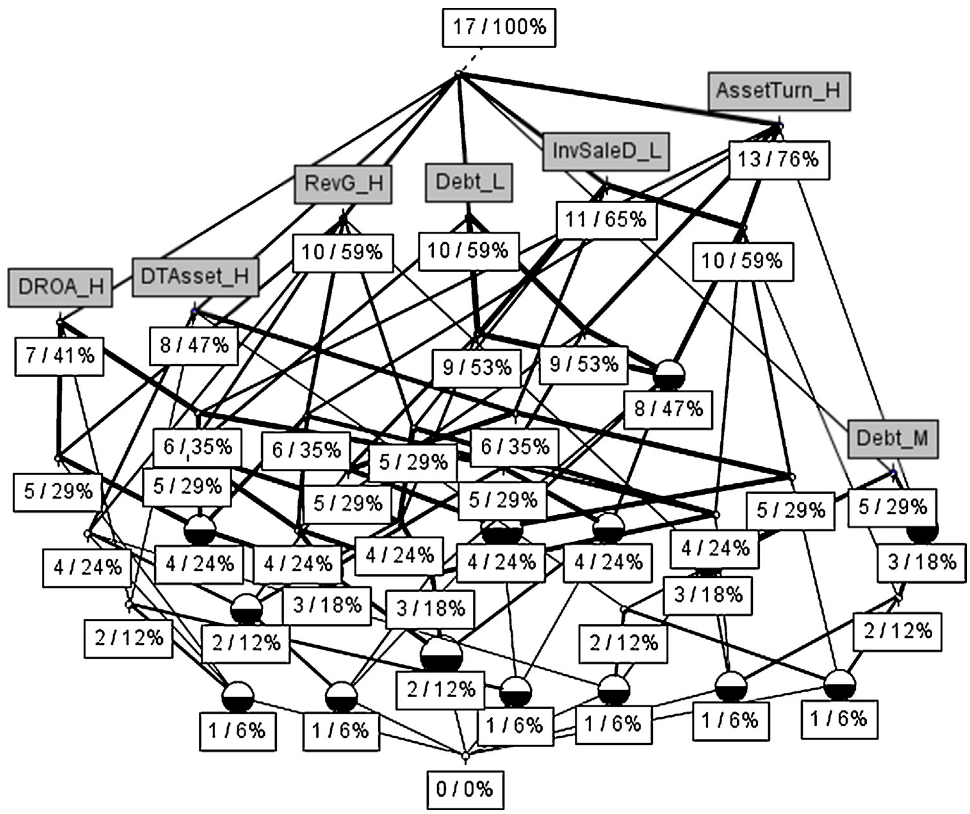



**Fig. 6.** Adjusted lattice diagram with object counts.

requested to rate the influence degree of one criterion on another. The ratings ranged from 4 (*very high influence*) to 0 (*no influence*), and all eight experts had more than 10 years of work experience in the financial industry. The occupations of the experts are as follow: Analyst (two analysts from an investment company), Manager (two managers from asset management companies), Chief Financial Officer (information technology company), Vice President (financial consulting company), Partner (venture capital), and Associate Professor (retired government official who worked in the Ministry of Finance) (Table 7).

As shown in Table 8, the *Solvency* ($D_2$) and *Operational Efficiency* ($D_3$) dimensions belong to the cause group, and the *Growth* ($D_1$) dimension belongs to the effect group. Furthermore, within the $D_1$ dimension, the criteria $\Delta REV$ and $\Delta GrossProfit$ influence the criteria $\Delta ROA$ and $\Delta TotalAsset$. The directional influence relationship among the dimensions and criteria is illustrated in Fig. 7. By integrating the strong decision rules and the influential network relation map (INRM) (Fig. 7), the directional influences are indicated by the DFG (Fig. 8). Transformed using the DEMATEL analysis, the INRM (Fig. 7) denotes the directional influences among the CORE dimensions (criteria). In Fig. 7, the arrow lines

**Table 6**
Critical criteria for DEMATEL analysis.

| Dimension | Criterion | Symbol |
|---|---|---|
| Growth ($D_1$) | $\Delta REV$ | $G_1$ |
| | $\Delta GrossProfit$ | $G_2$ |
| | $\Delta ROA$ | $G_3$ |
| | $\Delta TotalAsset$ | $G_4$ |
| Solvency ($D_2$) | $DEBT$ | $S_1$ |
| Operational Efficiency ($D_3$) | $AssetTurnover$ | $E_1$ |
| | $DAYs$ | $E_2$ |

**Table 7**
Initial average matrix $A$.

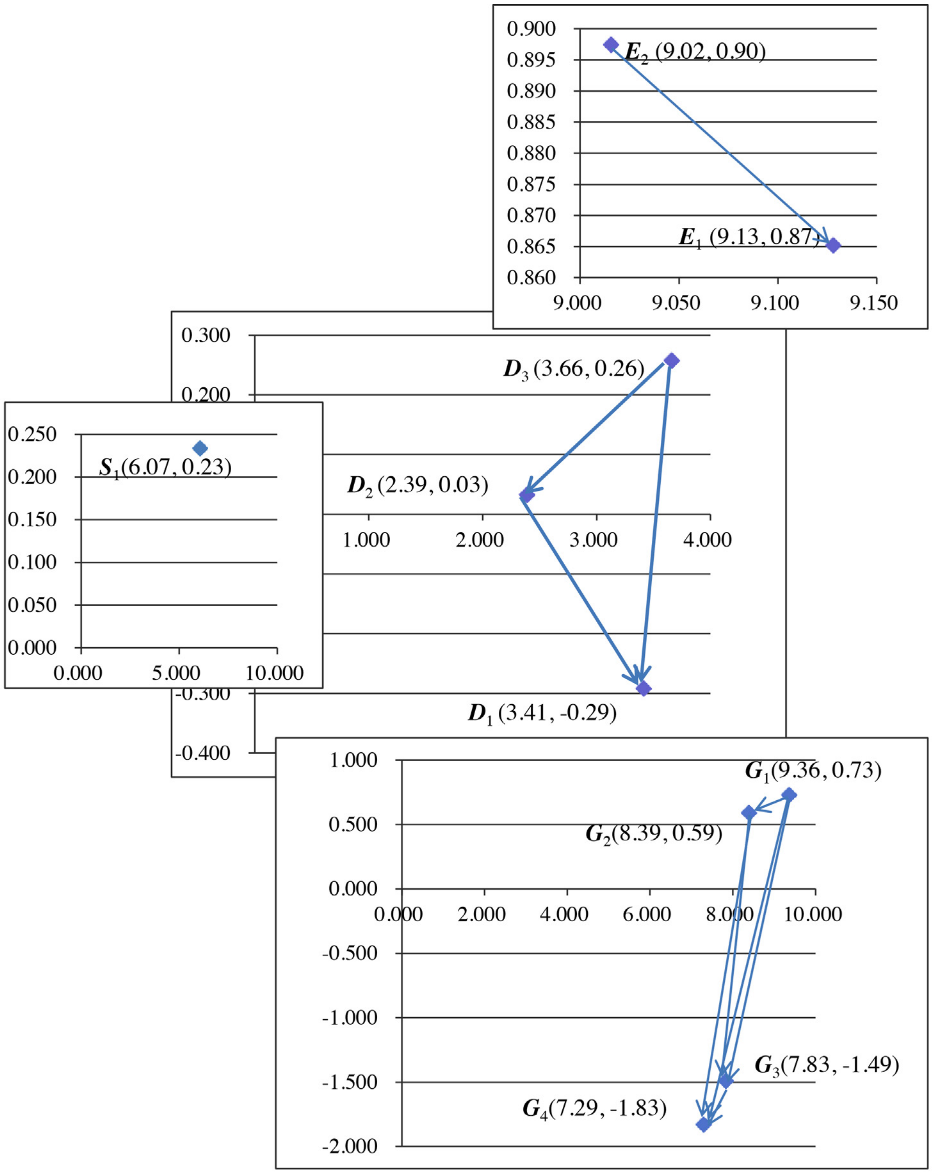
| | $G_1$ | $G_2$ | $G_3$ | $G_4$ | $S_1$ | $E_1$ | $E_2$ |
|---|---|---|---|---|---|---|---|
| $G_1$ | 0.000 | 3.500 | 3.500 | 2.750 | 1.250 | 3.125 | 3.500 |
| $G_2$ | 3.125 | 0.000 | 3.143 | 2.125 | 2.250 | 2.250 | 2.750 |
| $G_3$ | 1.500 | 1.125 | 0.000 | 3.429 | 2.000 | 2.125 | 1.125 |
| $G_4$ | 1.250 | 1.375 | 2.000 | 0.000 | 1.286 | 1.750 | 1.500 |
| $S_1$ | 2.125 | 1.250 | 2.625 | 2.000 | 0.000 | 1.286 | 1.625 |
| $E_1$ | 3.625 | 3.125 | 2.125 | 3.375 | 1.500 | 0.000 | 3.571 |
| $E_2$ | 3.625 | 3.000 | 3.125 | 2.125 | 1.500 | 3.625 | 0.000 |

Note: Refer Table A.1 in Appendix A.

**Table 8**
Dimensional influences.

| | $r_i^D$ | $c_i^D$ | $r_i^D + c_i^D$ | $r_i^D - c_i^D$ |
|---|---|---|---|---|
| $D_1$ | 1.560 | 1.852 | 3.412 | −0.291 |
| $D_2$ | 1.211 | 1.177 | 2.388 | 0.033 |
| $D_3$ | 1.959 | 1.701 | 3.660 | 0.258 |

Note: Refer Table A.7 in Appendix A.




$D_1$: *Growth*; $D_2$: *Solvency*; $D_3$: *Operational Efficiency*;
$G_1$: $\Delta$*REV*; $G_2$: $\Delta$*GrossProfit*; $G_3$: $\Delta$*ROA*; $G_4$: $\Delta$*TotalAsset*; $S_1$: *DEBT*; $E_1$: *AssetTurnover*; $E_2$: *DAYs*.

**Fig. 7.** Influential network relation map.

from $D_3$ to $D_2$ and $D_1$ indicate that the *Operational Efficiency* ($D_3$) dimension influences the *Solvency* ($D_2$) and *Growth* ($D_1$) dimensions; similarly, the *Solvency* ($D_2$) dimension influences the *Growth* ($D_1$) dimension. The left coordinate of each dimension indicates that dimension's influential weight. For example, $D_3$ (3.66, 0.26) implies that the influential weight of $D_3$ is 3.66 (Table 8 and Fig. 7). The subplots adjacent to each dimension indicate the directional influences among the criteria within a dimension, in which arrows denote the directional influences. For example, the arrow from $E_2$ to $E_1$ (dimension $D_3$) indicates that $E_2$ (9.02, 0.90) influences $E_1$ (9.13, 0.87), where 9.02 and 9.13 denote the influential weights of $E_2$ and $E_1$, respectively.

Fig. 8 illustrates the two strong decision rules (Table 5) of the DRSA model with directional influences among the dimensions and criteria. The directional influences are indicated by arrows, as shown in Fig. 7. Criteria *DAYs* ($E_2$) and *AssetTurnover* ($E_1$) are grouped in the *Operational Efficiency* ($D_3$) dimension; criteria *ΔREV* ($G_1$), *ΔROA* ($G_3$), and *ΔTotalAsset* ($G_4$) are grouped in the *Growth* ($D_1$) dimension. As suggested by DEMATEL analysis (Tables 8 and 9) and INRM (Fig. 7), the dimensions and criteria

**Table 9**
Criteria influences.

| | $r_i$ | $c_i$ | $r_i+c_i$ | $r_i-c_i$ |
|---|---|---|---|---|
| $G_1$ | 5.046 | 4.316 | 9.362 | 0.730 |
| $G_2$ | 4.492 | 3.900 | 8.392 | 0.592 |
| $G_3$ | 3.169 | 4.658 | 7.827 | −1.489 |
| $G_4$ | 2.732 | 4.560 | 7.292 | −1.829 |
| $S_1$ | 3.150 | 2.916 | 6.066 | 0.234 |
| $E_1$ | 4.997 | 4.131 | 9.128 | 0.865 |
| $E_2$ | 4.957 | 4.059 | 9.016 | 0.897 |

Note: Refer Table A.6 in Appendix A.

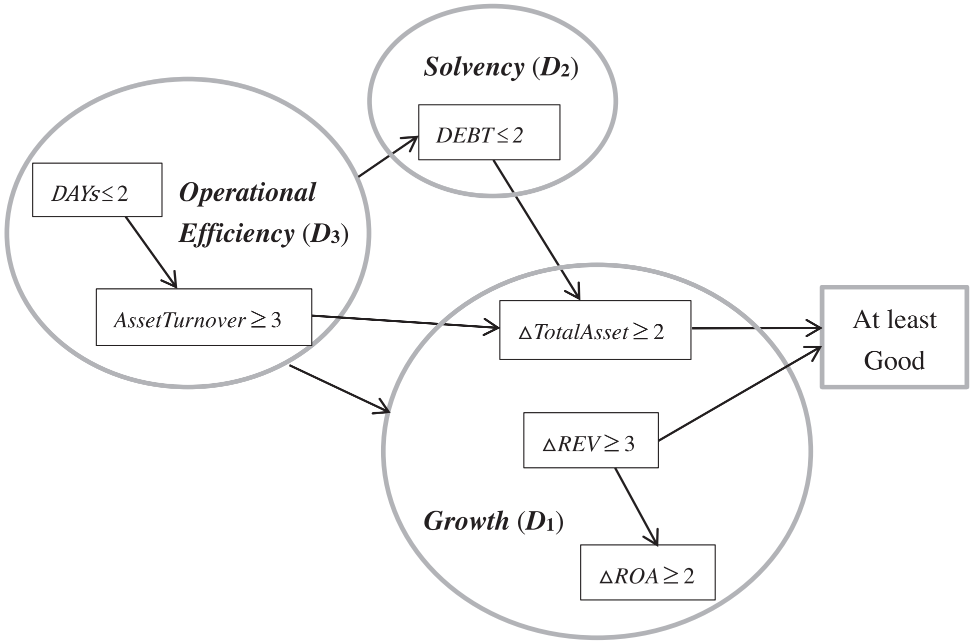



**Fig. 8.** Directional flow graph.

that form the “at least Good” decision class are illustrated with directional influences. Decision makers (investors) may thus comprehend the cause–effect relationships among dimensions and criteria of the strong decision rules obtained using DFG to gain more insights.

## 5. Discussion

The experimental results suggest that the proposed DRSA model could distinguish value stocks with satisfactory financial returns in the subsequent period, which included multiple financial attributes and 20 decision rules (i.e., 20 = 9 + 11; nine decision rules associated with the “Good” decision class and 11 associated with the “Bad” decision class). A group of generic high B/M ratio stocks (74 stocks) from the IT sector in 2011 were used to obtain the DRSA model, which was examined by a group of high B/M ratio stocks (50 stocks), in 2012. The distinguished “Good” portfolio considerably outperformed the “Bad” portfolio and the market index from May 2012 to the end of 2013.

The second strong decision rule associated with the “at least Good” decision class (Table 5) demonstrated that the growth dimension plays a major role. The growth of revenue and profit indicates the degree of improvement in business, which implies a tendency toward a more satisfactory state. This finding is in line with previous research [50], and was obtained by analyzing investment experts’ subjective judgments. The next major implication is in the *Operational Efficiency* ($D_3$) dimension (Table 5): *AssetTurnover* (asset turnover rate) and *DAYs* (average days for sales). Value stocks might show growth in total asset, revenue, or profit; nevertheless, if it lacks support from high operational efficiency, it might not show superior financial return in the subsequent period; this point has not been emphasized in previous studies.

To gain more implications from the obtained decision rules, FCA was conducted to explore the conceptual relations among the critical attributes. The combination of rough set, flow graph, and FCA for analysis is not new [51]; however, this study proposed the integration of DEMATEL technique to clarify the directional influences in a flow graph. The upper side of Fig. 6 shows two major conditional attributes: AssetTurn_H (i.e., high *AssetTurnover*) and InvSaleD_L (i.e., low *DAYs*), which is also in line with the finding from the aforementioned DRSA decision rules. Association rules that may lead to the two superconcepts are shown in Table 6, and all the association rules are listed in Appendix C. For example, the subconcepts—InvSaleD_L (low *DAYs*), Debt_L (low *DEBT*), and DROA_H (high $\Delta ROA$)—are associated with the most crucial superconcept AssetTurn_H (Fig. 6, 13/17 = 76%) with more than 85% matching percentage (Table 10).

Compared with the findings from the DRSA model, the subconcept Debt_L is further highlighted. The capital structure (*DEBT*) is often more stable compared with the operational indicators (such as the *AssetTurnover* and *DAYs*). According to the DFG (Fig. 8), the operational efficiency (including low *DAYs* and high *AssetTurnover*) influences the capital structure (*DEBT*) and the *Growth* ($D_1$) dimension (including high $\Delta REV$, $\Delta ROA$, and $\Delta TotalAsset$). Both the lattice diagram (Fig. 5) and the DFG (Fig. 8) indicate that the high *Operational Efficiency* dimension ($D_3$) influences the *Solvency* ($D_2$) and *Growth* ($D_1$) dimensions (such as $\Delta REV$, $\Delta ROA$, and $\Delta TotalAsset$). The obtained results from the two methods—the FCA and DEMATEL—further support the consistency of these findings (influential relationships).

**Table 10**
Association rules that imply the two critical conditional attributes.

| Sub-concepts (conditional attributes) | Object number | Matching percentage (%) | Object number | Super-concept |
|---|---|---|---|---|
| InvSaleD_L | 11 | 91 | 10 | AssetTurn_H |
| Debt_L | 10 | 90 | 9 | AssetTurn_H |
| Debt_L and InvSaleD_L | 9 | 89 | 8 | AssetTurn_H |
| DROA_H | 7 | 86 | 6 | AssetTurn_H |
| RevG_L and Debt_L and AssetTurn_H | 10 | 90 | 9 | InvSaleD_L |
| Debt_L | 5 | 100 | 5 | InvSaleD_L |

The findings in this study may help investors make decisions before and after their investments. The DRSA model may discriminate value stocks with strong financial prospects before the investment. After value stock investment, a decision maker can further observe the changes in the operational indicators in the short- and mid-term and in the yearly debt level to decide if the value stock is still worth holding. If the operational efficiency indicators show inferior outcomes, investors are suggested to sell their holdings. On the basis of the findings from the DRSA, FCA, and DEMATEL techniques, the patterns and decision rules for the value stock selection problem are found with rich insights.

## 6. Conclusions

This study used the combined soft computing model to explore the usefulness of FA in selecting satisfactory value stocks. The three major contributions of this study are summarized as follows: (1) Identify the contexts (decision rules) and core criteria to discern value stocks with satisfactory prospects; (2) Explore the cause–effect relationships among the CORE attributes (by using the DEMATEL technique), which enables investors to observe the source factors (from FCA) that might improve or deteriorate the future prospects of value stocks; (3) Illustrate the proposed approach with clearly defined steps and operational procedures, which may help practitioners understand how to leverage advanced soft computing and MCDM techniques to solve real world problems in finance.

Taiwan's stock market comprises more than 1400 stocks and numerous financial attributes. The complex relationship among the financial attributes and future stock returns is unlikely to be solved using linear models, such as the regressions. However, the proposed DRSA model can explore the vague and imprecise patterns without the unrealistic assumptions of conventional regressions (i.e., the independence of the considered variables, and the linear relationship among the dependent and the independent variables). By adopting the proposed approach, the value stocks with satisfactory prospects could be identified, which is valuable for supporting investments in practice. Furthermore, the findings from FCA (inducted from historical data) and DEMATEL (retrieved from experts) techniques suggest that *Operational Efficiency* ($D_3$) is the source dimension that would influence the prospects of value stocks. Investors may observe the changes in related criteria (i.e., *DAYs* and *AssetTurnover*) before or after the investment of value stocks, and make corresponding adjustments in their portfolio. Aside from investors, the management teams of high B/M stocks may learn the plausible influences among the CORE criteria, regarding how the capital market evaluates value stocks, and improve their underperformed criteria on the basis of the implications obtained from DRSA (Table 5), FCA (Table 10), INRM (Fig. 7), and DFG (Fig. 8). The obtained findings thus contribute to the understanding of value stock selection and stock performance improvement in finance.

Despite the advantages of the DRSA method, the proposed model has limitations. First, the developed model used previous financial information for obtaining a decision result in the following period. Only one-period-ahead financial ratios and growth rate ratios were used to induct decision rules and classify decision classes. The model only reflected recent two years' fundamentals to capture future stock performance. Second, the result was influenced by the discretization method. We divided each criterion into three states (low, mid, and high; or 1, 2, and 3), which limited the size of the granule of knowledge. The extent to which a criterion can be discretized to gain higher accuracy was not determined in this study. Future research may incorporate other soft computing techniques or statistical methods for enhancing the model. Another interesting and underexplored research direction is the performance improvement of value stocks. As companies are constrained by limited resources (e.g., monetary and human capital), allocating resources and budgets to yield an optimal effect (i.e., improve performance of value stocks) could be considered in the context of multiple objective decision making (MODM) in the future.

## Appendix A.

Developed by the Battelle Memorial Institute of Geneva [48], DEMATEL was proposed to explore complex social problems, in which dimensions/criteria were assumed to be fully interrelated. As the variables/criteria of social problems are often interrelated, the DEMATEL technique is suitable to identity the influential relationships among criteria, which has been adopted in various applications, such as financial performance diagnoses [36], smartphone improvement [52], and select suppliers in a green supply chain [53]. In this study, DEMATEL technique is adopted to explore the cause–effect relationships among the CORE criteria; the obtained findings may support investors to observe the changes of source criterion/criteria to foresee the prospect of value stocks. The required steps are explained as below, and the details can be found in the previous works [44–46,52,53].

Step 1: *Using questionnaire to collect the initial average relation matrix* $\boldsymbol{A}$. Experts are asked to judge the influence degree that they feel attribute/criterion $i$ will have on attribute/criterion $j$, indicated as $a_{ij}$. The rating scale ranges from 4 (very high influence) to 0 (no influence). The initial average matrix takes the arithmetic mean of the respondents' feedbacks for forming the initial average matrix $\boldsymbol{A}$, and the matrix $\boldsymbol{A}$ is shown in Eq. (A.1). The opinions collected from the eight experts are organized in Table A.1.

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

(In the following tables, $\{C_1, C_2, C_3, C_4\}$ denote $\{G_1, G_2, G_3, G_4\}$; $C_5$ denotes $S_1$; $\{C_6, C_7\}$ denote $\{E_1, E_2\}$ for the empirical case)

Step 2: Normalize the initial average relation matrix **A** for obtaining the direct-influence matrix **D**. The matrix $\boldsymbol{D} = [d_{ij}]_{n\times n}$ can be derived by Eqs. (A.2) and (A.3) as below. The initial average relation matrix **A** and the direct-influence matrix **D** of the empirical case are shown in Tables A.2 and A.3 respectively.

$$\boldsymbol{D} = p\boldsymbol{A} \tag{A.2}$$

$$p = \min\left\{\frac{1}{\max_i \sum_{j=1}^{n} a_{ij}}, \frac{1}{\max_j \sum_{i=1}^{n} a_{ij}}\right\}, \quad i, j \in \{1, 2, \ldots, n\} \tag{A.3}$$

Step 3: *Transform the normalized direct-influence matrix* $\boldsymbol{D}$ *into the total-influence relation matrix* $\boldsymbol{T}$. The total-influence relation matrix $\boldsymbol{T}$ for forming influential network relationship map (INRM) can be obtained by multiplying the inverse of $(\boldsymbol{I}-\boldsymbol{D})$ with $\boldsymbol{D}$, as the Eq. (A.4). In the equation, $\boldsymbol{I}$ denotes the identity matrix. $(\boldsymbol{I}-\boldsymbol{D})$ and the inverse of $(\boldsymbol{I}-\boldsymbol{D})$ are shown in

**Table A.1**
Raw data from experts.

| $C_{i\text{–}j}$ (criterion $i$ to $j$) | Respondents (domain experts) | | | | | | | | Average by 8 | Average by 7 |
|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | | |
| $C_{1\text{–}2}$ | 4 | 3 | 4 | 3 | 3 | 4 | 3 | 4 | 3.500 | 3.429 |
| $C_{1\text{–}3}$ | 4 | 3 | 3 | 3 | 4 | 4 | 4 | 3 | 3.500 | 3.429 |
| $C_{1\text{–}4}$ | 3 | 3 | 2 | 4 | 3 | 3 | 2 | 2 | 2.750 | 2.714 |
| $C_{1\text{–}5}$ | 1 | 0 | 0 | 2 | 1 | 2 | 2 | 2 | 1.250 | 1.286 |
| $C_{1\text{–}6}$ | 3 | 3 | 2 | 3 | 4 | 3 | 3 | 4 | 3.125 | 3.143 |
| $C_{1\text{–}7}$ | 3 | 3 | 4 | 3 | 4 | 4 | 3 | 4 | 3.500 | 3.571 |
| $C_{2\text{–}1}$ | 3 | 2 | 3 | 3 | 3 | 4 | 3 | 4 | 3.125 | 3.143 |
| $C_{2\text{–}3}$ | 3 | 4 | 3 | 3 | 4 | 4 | 3 | 1 | 3.143 | 3.143 |
| $C_{2\text{–}4}$ | 2 | 2 | 1 | 2 | 2 | 3 | 3 | 2 | 2.125 | 2.143 |
| $C_{2\text{–}5}$ | 2 | 2 | 1 | 2 | 3 | 2 | 3 | 3 | 2.250 | 2.286 |
| $C_{2\text{–}6}$ | 2 | 3 | 2 | 2 | 2 | 1 | 3 | 3 | 2.250 | 2.286 |
| $C_{2\text{–}7}$ | 2 | 2 | 3 | 3 | 2 | 4 | 2 | 4 | 2.750 | 2.857 |
| $C_{3\text{–}1}$ | 1 | 1 | 2 | 1 | 1 | 2 | 1 | 3 | 1.500 | 1.571 |
| $C_{3\text{–}2}$ | 1 | 1 | 2 | 2 | 1 | 1 | 0 | 1 | 1.125 | 1.143 |
| $C_{3\text{–}4}$ | 4 | 4 | 4 | 4 | 3 | 4 | 1 | 4 | 3.429 | 3.429 |
| $C_{3\text{–}5}$ | 2 | 2 | 2 | 2 | 1 | 2 | 2 | 3 | 2.000 | 2.000 |
| $C_{3\text{–}6}$ | 2 | 2 | 1 | 2 | 3 | 2 | 3 | 2 | 2.125 | 2.143 |
| $C_{3\text{–}7}$ | 1 | 1 | 2 | 1 | 1 | 0 | 1 | 2 | 1.125 | 1.143 |
| $C_{4\text{–}1}$ | 1 | 0 | 2 | 1 | 2 | 1 | 1 | 2 | 1.250 | 1.286 |
| $C_{4\text{–}2}$ | 1 | 2 | 1 | 2 | 1 | 1 | 1 | 2 | 1.375 | 1.429 |
| $C_{4\text{–}3}$ | 2 | 2 | 1 | 3 | 3 | 2 | 2 | 1 | 2.000 | 2.000 |
| $C_{4\text{–}5}$ | 1 | 1 | 2 | 1 | 1 | 0 | 1 | 3 | 1.286 | 1.286 |
| $C_{4\text{–}6}$ | 2 | 2 | 3 | 2 | 1 | 1 | 2 | 1 | 1.750 | 1.714 |
| $C_{4\text{–}7}$ | 1 | 0 | 2 | 2 | 1 | 2 | 1 | 3 | 1.500 | 1.571 |
| $C_{5\text{–}1}$ | 2 | 2 | 1 | 2 | 2 | 3 | 2 | 3 | 2.125 | 2.143 |
| $C_{5\text{–}2}$ | 1 | 1 | 0 | 1 | 2 | 1 | 1 | 3 | 1.250 | 1.286 |
| $C_{5\text{–}3}$ | 3 | 2 | 3 | 3 | 3 | 2 | 3 | 2 | 2.625 | 2.571 |
| $C_{5\text{–}4}$ | 2 | 2 | 1 | 2 | 2 | 3 | 2 | 2 | 2.000 | 2.000 |
| $C_{5\text{–}6}$ | 2 | 1 | 2 | 1 | 2 | 2 | 1 | 0 | 1.286 | 1.286 |
| $C_{5\text{–}7}$ | 1 | 1 | 1 | 2 | 1 | 1 | 2 | 4 | 1.625 | 1.714 |
| $C_{6\text{–}1}$ | 4 | 3 | 4 | 4 | 3 | 4 | 3 | 4 | 3.625 | 3.571 |
| $C_{6\text{–}2}$ | 3 | 3 | 2 | 3 | 3 | 4 | 3 | 4 | 3.125 | 3.143 |
| $C_{6\text{–}3}$ | 2 | 2 | 1 | 2 | 3 | 2 | 3 | 2 | 2.125 | 2.143 |
| $C_{6\text{–}4}$ | 3 | 3 | 3 | 4 | 3 | 4 | 4 | 3 | 3.375 | 3.429 |
| $C_{6\text{–}5}$ | 1 | 2 | 3 | 2 | 1 | 2 | 1 | 0 | 1.500 | 1.571 |
| $C_{6\text{–}7}$ | 4 | 3 | 4 | 4 | 3 | 4 | 4 | 3 | 3.571 | 3.571 |
| $C_{7\text{–}1}$ | 4 | 4 | 4 | 4 | 3 | 3 | 3 | 4 | 3.625 | 3.571 |
| $C_{7\text{–}2}$ | 3 | 2 | 3 | 3 | 3 | 2 | 4 | 4 | 3.000 | 3.000 |
| $C_{7\text{–}3}$ | 3 | 3 | 2 | 2 | 4 | 3 | 4 | 4 | 3.125 | 3.143 |
| $C_{7\text{–}4}$ | 2 | 2 | 1 | 3 | 2 | 2 | 3 | 2 | 2.125 | 2.143 |
| $C_{7\text{–}5}$ | 1 | 1 | 2 | 1 | 1 | 2 | 1 | 3 | 1.500 | 1.571 |
| $C_{7\text{–}6}$ | 4 | 4 | 3 | 4 | 4 | 3 | 4 | 3 | 3.625 | 3.571 |

Note: $(1/n(n-1))\sum_{i=1}^{n}\sum_{j=1}^{n}\left(\left|a_{ij}^{p}-a_{ij}^{p-1}\right|/a_{ij}^{p}\right)\times 100\% = 1.035\% < 5\%$, where $a_{ij}^{p}$ and $a_{ij}^{p-1}$ denote the average influence of criterion $i$ on criterion $j$ by experts $p$ (i.e., $p = 8$ in this case) and $p-1$, respectively; $n$ denotes the number of criteria ($n = 7$ in here). Thus, the results above are consistent at the level of 98.965%, which is higher than 95%.

**Table A.2**
Initial average matrix $\boldsymbol{A}$.

| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ | $C_7$ | $\sum_{j=1}^{7} a_{ij}$ |
|---|---|---|---|---|---|---|---|---|
| $C_1$ | 0.000 | 3.500 | 3.500 | 2.750 | 1.250 | 3.125 | 3.500 | 17.625 |
| $C_2$ | 3.125 | 0.000 | 3.143 | 2.125 | 2.250 | 2.250 | 2.750 | 15.643 |
| $C_3$ | 1.500 | 1.125 | 0.000 | 3.429 | 2.000 | 2.125 | 1.125 | 11.304 |
| $C_4$ | 1.250 | 1.375 | 2.000 | 0.000 | 1.286 | 1.750 | 1.500 | 9.161 |
| $C_5$ | 2.125 | 1.250 | 2.625 | 2.000 | 0.000 | 1.286 | 1.625 | 10.911 |
| $C_6$ | 3.625 | 3.125 | 2.125 | 3.375 | 1.500 | 0.000 | 3.571 | 17.321 |
| $C_7$ | 3.625 | 3.000 | 3.125 | 2.125 | 1.500 | 3.625 | 0.000 | 17.000 |
| $\sum_{i=1}^{7} a_{ij}$ | 15.250 | 13.375 | 16.518 | 15.804 | 9.786 | 14.161 | 14.071 | |

Note: $p = (1/17.625) \times 100\% = 5.674\%$.

Tables A.4 and A.5. In addition, the total-influence relation matrix $\boldsymbol{T}$ and the dimensional influence relation matrix $\boldsymbol{T}^D$ of the empirical case are in Tables A.6 and A.7.

$$\boldsymbol{T} = \boldsymbol{D} + \boldsymbol{D}^2 + \cdots + \boldsymbol{D}^w = \boldsymbol{D}(\boldsymbol{I} - \boldsymbol{D}^w)(\boldsymbol{I} - \boldsymbol{D})^{-1} \tag{A.4}$$

**Table A.3**
Direct-influence matrix $\boldsymbol{D}$.

| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ | $C_7$ | $\sum_{j=1}^{7} d_{ij}$ |
|---|---|---|---|---|---|---|---|---|
| $C_1$ | 0.000 | 0.199 | 0.199 | 0.156 | 0.071 | 0.177 | 0.199 | 1.000 |
| $C_2$ | 0.177 | 0.000 | 0.178 | 0.121 | 0.128 | 0.128 | 0.156 | 0.888 |
| $C_3$ | 0.085 | 0.064 | 0.000 | 0.195 | 0.113 | 0.121 | 0.064 | 0.641 |
| $C_4$ | 0.071 | 0.078 | 0.113 | 0.000 | 0.073 | 0.099 | 0.085 | 0.520 |
| $C_5$ | 0.121 | 0.071 | 0.149 | 0.113 | 0.000 | 0.073 | 0.092 | 0.619 |
| $C_6$ | 0.206 | 0.177 | 0.121 | 0.191 | 0.085 | 0.000 | 0.203 | 0.983 |
| $C_7$ | 0.206 | 0.170 | 0.177 | 0.121 | 0.085 | 0.206 | 0.000 | 0.965 |
| $\sum_{i=1}^{7} d_{ij}$ | 0.865 | 0.759 | 0.937 | 0.897 | 0.555 | 0.803 | 0.798 | |

**Table A.4**
Identify matrix $\boldsymbol{I}$ minus direct influence matrix $\boldsymbol{D}$.

| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ | $C_7$ |
|---|---|---|---|---|---|---|---|
| $C_1$ | 1.000 | −0.199 | −0.199 | −0.156 | −0.071 | −0.177 | −0.199 |
| $C_2$ | −0.177 | 1.000 | −0.178 | −0.121 | −0.128 | −0.128 | −0.156 |
| $C_3$ | −0.085 | −0.064 | 1.000 | −0.195 | −0.113 | −0.121 | −0.064 |
| $C_4$ | −0.071 | −0.078 | −0.113 | 1.000 | −0.073 | −0.099 | −0.085 |
| $C_5$ | −0.121 | −0.071 | −0.149 | −0.113 | 1.000 | −0.073 | −0.092 |
| $C_6$ | −0.206 | −0.177 | −0.121 | −0.191 | −0.085 | 1.000 | −0.203 |
| $C_7$ | −0.206 | −0.170 | −0.177 | −0.121 | −0.085 | −0.206 | 1.000 |

**Table A.5**
Inverse of ($\boldsymbol{I}$–$\boldsymbol{D}$).

| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ | $C_7$ |
|---|---|---|---|---|---|---|---|
| $C_1$ | 1.634 | 0.742 | 0.849 | 0.804 | 0.495 | 0.760 | 0.763 |
| $C_2$ | 0.712 | 1.508 | 0.759 | 0.702 | 0.493 | 0.653 | 0.663 |
| $C_3$ | 0.468 | 0.414 | 1.422 | 0.586 | 0.367 | 0.481 | 0.430 |
| $C_4$ | 0.408 | 0.380 | 0.468 | 1.362 | 0.299 | 0.416 | 0.398 |
| $C_5$ | 0.496 | 0.420 | 0.554 | 0.519 | 1.266 | 0.445 | 0.451 |
| $C_6$ | 0.801 | 0.723 | 0.785 | 0.821 | 0.499 | 1.604 | 0.764 |
| $C_7$ | 0.797 | 0.713 | 0.821 | 0.767 | 0.497 | 0.771 | 1.590 |

**Table A.6**
Total-influence matrix $\boldsymbol{T}$.

| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ | $C_7$ | $r_i$ |
|---|---|---|---|---|---|---|---|---|
| $C_1$ | 0.634 | 0.742 | 0.849 | 0.804 | 0.495 | 0.760 | 0.763 | 5.046 |
| $C_2$ | 0.712 | 0.508 | 0.759 | 0.702 | 0.493 | 0.653 | 0.663 | 4.492 |
| $C_3$ | 0.468 | 0.414 | 0.422 | 0.586 | 0.367 | 0.481 | 0.430 | 3.169 |
| $C_4$ | 0.408 | 0.380 | 0.468 | 0.362 | 0.299 | 0.416 | 0.398 | 2.732 |
| $C_5$ | 0.496 | 0.420 | 0.554 | 0.519 | 0.266 | 0.445 | 0.451 | 3.150 |
| $C_6$ | 0.801 | 0.723 | 0.785 | 0.821 | 0.499 | 0.604 | 0.764 | 4.997 |
| $C_7$ | 0.797 | 0.713 | 0.821 | 0.767 | 0.497 | 0.771 | 0.590 | 4.957 |
| $c_i$ | 4.316 | 3.900 | 4.658 | 4.560 | 2.916 | 4.131 | 4.059 | |

Note: The $r_i$ and $c_i$ in Table A.6 are used to calculate the criteria influences in Table 9.

**Table A.7**
Dimensional influence matrix $\boldsymbol{T}^D$.

| | $D_1$ | $D_2$ | $D_3$ | $r_i^D$ |
|---|---|---|---|---|
| $D_1$ | 0.576 | 0.413 | 0.571 | 1.560 |
| $D_2$ | 0.497 | 0.266 | 0.448 | 1.211 |
| $D_3$ | 0.778 | 0.498 | 0.682[a] | 1.959 |
| $c_i^D$ | 1.852 | 1.177 | 1.701 | |

[a] Note: The dimensional influences in Table A.7 are obtained from the corresponding cells in Table A.6, by averaging the elements in a cell. For example, 0.682 = (0.604 + 0.771 + 0.764 + 0.590)/4.

thus, when $w \to \infty$, $\boldsymbol{D}^w = [0]_{n \times n}$

$$\boldsymbol{T} = \boldsymbol{D}(\boldsymbol{I} - \boldsymbol{D})^{-1} = [t_{ij}]_{n \times n}, \tag{A.5}$$

Step 4: *Decomposing the total-influence relation matrix for finding the directional influences among the criteria.* The sum of rows and the sum of columns of the total-influence relation matrix $\boldsymbol{T}$ are expressed as the row vector $\boldsymbol{r} = (r_1, \ldots, r_i, \ldots, r_n)$ and the row vector $\boldsymbol{c} =$

$\left(c_1, \ldots, c_j, \ldots, c_n\right)$ (i.e., sum of columns) respectively. The vector $\boldsymbol{r}$ and vector $\boldsymbol{c}$ have the same number of elements; thus, the operations of $\boldsymbol{r}+\boldsymbol{c}$ and $\boldsymbol{r}-\boldsymbol{c}$ will form two row vectors, as Eqs. (A.6) and (A.7).

$$\boldsymbol{r}+\boldsymbol{c}=\left(r_1+c_1, \ldots, r_i+c_i, \ldots, r_n+c_n\right), \quad i \in \left\{1, 2, \ldots, n\right\} \tag{A.6}$$

$$\boldsymbol{r}-\boldsymbol{c}=\left(r_1-c_1, \ldots, r_i-c_i, \ldots, r_n-c_n\right), \quad i \in \left\{1, 2, \ldots, n\right\} \tag{A.7}$$

In Eq. (A.6), the $i$th element of the row vector $\boldsymbol{r}+\boldsymbol{c}$ indicates the importance of the $i$th criterion. Besides, the row vector $\boldsymbol{r}-\boldsymbol{c}$ in Eq. (A.7) separates criteria into the cause group and the effect group. In general, if the element $r_i - c_i$ is positive, the $i$th criterion belongs to the cause group; otherwise, the $i$th criterion belongs to the effect group. In analogy to the decomposition of the criteria, the dimensions can also be divided into the cause group and the effect group. The dimensional influences and criteria influences of the empirical case are in Tables 8 and 9, respectively.

## Appendix B. Decision rules obtained from the DRSA model

The decision rules listed below were obtained by using the whole training set; the antecedents of a decision rule are on the left side, and the corresponding consequence the right side. Take Rule 1 for example, it may be interpreted as "if *DAYs* (i.e., average days for sales) ≤ 1, then HPR (i.e., decision attribute) of a value stock should be classified at least as G (i.e., Good)". The explanation of symbols (criteria) in these decision rules can be found in Table 1.

1. $(DAYs \leq 1)$ => $(HPR \geq \mathrm{G})$
2. $(\Delta TotalAsset \geq 2)$ & $(DEBT \leq 2)$ & $(AssetTurnover \geq 3)$ & $(DAYs \leq 2) \Rightarrow (HPR \geq \mathrm{G})$
3. $(CASH \geq 2)$ & $(\Delta GrossProfit \geq 3)$ & $(\Delta TotalAsset \geq 3)$ & $(AssetTurnover \geq 2) \Rightarrow (HPR \geq \mathrm{G})$
4. $(DEBT \leq 1)$ & $(AssetTurnover \geq 2)$ & $(InvTurnover \geq 3) \Rightarrow (HPR \geq \mathrm{G})$
5. $(\Delta REV \geq 3)$ & $(\Delta ROA \geq 2)$ & $(AssetTurnover \geq 2)$ & $(DAYs \leq 2) \Rightarrow (HPR \geq \mathrm{G})$
6. $(OProfit \geq 3)$ & $(\Delta ROA \geq 3)$ & $(InvTurnover \geq 2)$ & $(DAYs <= 2) \Rightarrow (HPR \geq \mathrm{G})$
7. $(\Delta REV \geq 3)$ & $(\Delta ROA \geq 3)$ & $(DAYs \leq 2) \Rightarrow (HPR \geq \mathrm{G})$
8. $(\Delta TotalAsset \geq 3)$ & $(\Delta ROA \geq 3)$ & $(DEBT \leq 1)$ & $(DAYs \leq 2) \Rightarrow (HPR \geq \mathrm{G})$
9. $(\Delta REV \geq 3)$ & $(\Delta GrossProfit \geq 2)$ & $(\Delta ROA \geq 2)$ & $(LIQUID \geq 3)$ & $(DAYs \leq 2) \Rightarrow (HPR \geq \mathrm{G})$
10. $(DAYs \geq 3) \Rightarrow (HPR \leq \mathrm{B})$
11. $(ROA \leq 1)$ & $(OGrossProfit \leq 2) \Rightarrow (HPR \leq \mathrm{B})$
12. $(\Delta ROA \leq 1)$ & $(AssetTurnover \leq 2) \Rightarrow (HPR \leq \mathrm{B})$
13. $(OProfit \leq 2)$ & $(\Delta REV \leq 1)$ & $(AssetTurnover \leq 1) \Rightarrow (HPR \leq \mathrm{B})$
14. $(OProfit \leq 2)$ & $(\Delta ROA \leq 2)$ & $(AssetTurnover \leq 1)$ & $(InvTurnover \leq 2) \Rightarrow (HPR \leq \mathrm{B})$
15. $(CASH \leq 2)$ & $(\Delta ROA \leq 2)$ & $(AssetTurnover \leq 1) \Rightarrow (HPR \leq \mathrm{B})$
16. $(\Delta GrossProfit \leq 1)$ & $(\Delta ROA \leq 2)$ & $(AssetTurnover \leq 1)$ & $(DAYs \geq 2) \Rightarrow (HPR \leq \mathrm{B})$
17. $(\Delta REV \leq 1)$ & $(InvTurnover \leq 1) \Rightarrow (HPR \leq \mathrm{B})$
18. $(OGrossProfit \leq 2)$ & $(\Delta TotalAsset \leq 1)$ & $(\Delta ROA \leq 2)$ & $(InvTurnover \leq 2)$ & $(DAYs \geq 2) \Rightarrow (HPR \leq \mathrm{B})$
19. $(\Delta REV \leq 2)$ & $(\Delta ROA \leq 2)$ & $(LIQUID \leq 2)$ & $(DEBT \geq 2) \Rightarrow (HPR \leq \mathrm{B})$
20. $(\Delta NPAT \leq 1)$ & $(DEBT >= 3) \Rightarrow (HPR \leq \mathrm{B})$

## Appendix C. Retrieved association rules from FCA

The association rules in below were obtained by FCA analysis, which denote the matching percentage between the subconcept and superconcept. The symbols used in these rules include the status of each criterion; take the third rule for example, Debt_L denotes that the state of criterion DEBT is "Low (categorized as "1" in DRSA model)". On the left side, "<10>" means that there were 10 observations (alternatives) that hold the subconcept "low DEBT"; whereas, on the right side, "<9>" indicates that 9 of the 10 observations also hold the superconcept "high AssetTurnover"; the matching percentage is thus 90% (9/10 = 90%).

1. <11> InvSaleD_L = [91%] ⇒ <10> AssetTurn_H;
2. <10> Debt_L = [90%] ⇒ <9> InvSaleD_L;
3. <10> Debt_L = [90%] ⇒ <9> AssetTurn_H;
4. <11> InvSaleD_L = [82%] ⇒ <9> Debt_L;
5. <9> Debt_L InvSaleD_L = [89%] ⇒ <8> AssetTurn_H;
6. <6> RevG_L = [100%] ⇒ <6> AssetTurn_H;
7. <7> DROA_H = [86%] ⇒ <6> AssetTurn_H;
8. <5> RevG_L Debt_L AssetTurn_H = [100%] ⇒ <5> InvSaleD_L;
9. <5> RevG_L AssetTurn_H InvSaleD_L = [100%] ⇒ <5> Debt_L;
10. <5> DTAsset_L = [100%] ⇒ <5> RevG_H;
11. <5> DTAsset_H Debt_L = [100%] ⇒ <5> InvSaleD_L;
12. <5> DTAsset_H AssetTurn_H = [100%] ⇒ <5> InvSaleD_L;
13. <5> DROA_H Debt_L = [100%] ⇒ <5> AssetTurn_H;
14. <6> InvSaleD_M = [83%] ⇒ <5> RevG_H;
15. <6> DTAsset_H InvSaleD_L = [83%] ⇒ <5> AssetTurn_H;
16. <6> DTAsset_H InvSaleD_L = [83%] ⇒ <5> Debt_L;
17. <6> DROA_H AssetTurn_H = [83%] ⇒ <5> Debt_L;
18. <6> RevG_L AssetTurn_H = [83%] ⇒ <5> Debt_L InvSaleD_L;
19. <4> RevG_H DTAsset_L DROA_H = [100%] ⇒ <4> AssetTurn_H;
20. <4> RevG_H DTAsset_L AssetTurn_H = [100%] ⇒ <4> DROA_H;
21. <4> RevG_H DROA_H AssetTurn_H = [100%] ⇒ <4> DTAsset_L;
22. <4> DTAsset_M = [100%] ⇒ <4> AssetTurn_H;
23. <4> DROA_M AssetTurn_H = [100%] ⇒ <4> InvSaleD_L;
24. <4> DROA_H InvSaleD_L = [100%] ⇒ <4> Debt_L AssetTurn_H;
25. <4> AssetTurn_M = [100%] ⇒ <4> RevG_H;
26. <5> DTAsset_H AssetTurn_H InvSaleD_L = [80%] ⇒ <4> Debt_L;
27. <5> DROA_M InvSaleD_L = [80%] ⇒ <4> AssetTurn_H;
28. <5> DROA_M InvSaleD_L = [80%] ⇒ <4> DTAsset_H;
29. <5> RevG_H InvSaleD_L = [80%] ⇒ <4> AssetTurn_H;
30. <5> RevG_H InvSaleD_L = [80%] ⇒ <4> Debt_L;
31. <5> DROA_H Debt_L AssetTurn_H = [80%] ⇒ <4> InvSaleD_L;
32. <5> Debt_M = [80%] ⇒ <4> DROA_M;
33. <5> RevG_H Debt_L = [80%] ⇒ <4> InvSaleD_L;
34. <5> RevG_H Debt_L = [80%] ⇒ <4> AssetTurn_H;
35. <5> RevG_H DROA_H = [80%] ⇒ <4> DTAsset_L AssetTurn_H;
36. <5> DTAsset_H DROA_M = [80%] ⇒ <4> InvSaleD_L;
37. <5> RevG_H DTAsset_L = [80%] ⇒ <4> DROA_H AssetTurn_H.

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