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Integrated news mining technique and AI-based mechanism for corporate performance forecasting

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ABSTRACT

The deterioration in a corporation's profitability not only threatens its interests and sustainable development but also causes tremendous losses to other investors. Hence, constructing an effective pre-warning model for performance forecasting is an urgent requirement. Most previous studies only analyzed monetary-based ratios, but merely considering such ratios does not depict the full perspective of a corporation's business conditions. This study thus extends monetary-based ratios to non-monetary-based ratios and aggregates them through the analytic network process (ANP) with a risk-adjusted strategy to establish performance ranks of corporations. Analyzing a corporation's business relationships can help it to react to changes in the market and improve profit margins, as it draws upon such relationship networks for the transfer of scarce resources and knowledge. We believe that no current study adopts such a method to construct a forecasting model. To fill this gap in the literature, this study implements the social network (SN) technique to examine a corporation's competitive edge from seemingly noisy big media data, which are subsequently fed into an artificial intelligence (AI)-based technique to construct the model. The introduced model, examined through real-life cases under numerous conditions, offers a promising alternative for performance forecasting.

1. Introduction

The subprime mortgage crisis of 2007 began in the U.S., promptly took the form of a full-blown systemic crisis there, and quickly rolled over into a near all-out global financial crisis [45]. Because this macroeconomic shock had wide-ranging and non-paralleled consequences, constructing a financial warning model has turned into an attractive research issue for numerous academics working in the field of economics and finance [11]. In contrast with well-examined research topics, such as financial crisis prediction and credit risk prediction, studies on corporate operating performance assessment are notably rare. Kamei [28] stated that 99% of financial crises encountered by corporations resulted from poor operating performance. In other words, insolvency problems and credit defaults do not just occur suddenly. Instead, there are distinct root causes that precede a financial crisis, and it is the inability to cope with such causes appropriately at an early stage that can trigger the destruction of corporate development [43]. In short, the pre-stage, before any financial crisis erupts, is when corporations begin to suffer from chronic bad operating performance. Therefore, constructing a model for corporate

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operating performance forecasting is an urgent requirement for decision makers who make reliable portfolio investments, as well seeking to maximize their personal wealth.

Return on assets (ROA) and return on equity (ROE) are the most widely known proxies for corporate operating performance assessment, but both are monetary-based measures that do not thoroughly describe the full operating situation faced by firms. When envisioning a corporation's future development, most researchers no longer focus chiefly on monetary-based measures in the financial domain, but instead now also devote considerable attention to non-monetary-based measures. The balanced scorecard (BSC) is one of the most recommended and well-established performance assessment methods because it promotes equilibrium between short- and long-term objectives, between monetary and non-monetary ratios, between the criteria of tendencies and occurrences, and between internal and external aspects of performance [27]. When utilizing BSC, one must fundamentally consider the relationship between cause and effect, as BSC is not a set of disconnected, conflicting, or isolated objectives but rather a coordinated architecture. However, one critical challenge of BSC is that it does not incorporate risk exposure, which certainly affects profit and more increasingly, risk management. To provide a more comprehensive analysis for decision makers, this study adds the risk-adjusted concept into BSC to form a risk-adjusted BSC (RABSC) for operating performance measurement.

Supply chain partnerships and alliance relationships have turned out to be much more essential than ever before in the current highly fluctuating economic atmosphere [13]. Building upon Porter's linear value chain architecture, for instance, a supply chain is viewed as a system consisting of production facilities, material suppliers, distribution services, and customers linked together via a feed forward flow of materials and feedback flow of information [25]. Today, traditional linear supply chains are being substituted by global, non-linear, complicated supply network structures that contain a diverse set of vertical and horizontal interactions among manufacturers, suppliers, retailers, and a large number of customers [29]. With growing interdependencies among corporations in these complicated network structures, risks of all types - consisting of financial troubles, operational failures, depressed economic climates, labor cost issues, cultural dissimilarities, and political instability - can promptly cascade throughout the whole supply chain and deteriorate firms' operating performance [9]. Without an appropriate foundation of supply chain organizational relationships, any effort to manage the flow of information across a supply chain is likely to be useless and unsuccessful [12]. Thus, relationship issues that surround supply chains have become an attractive field in the discipline of sociology, economics, and business.

Although coming up with some generally accepted conclusions is quite complicated, it is widely recognized that corporate networking relationships (i.e., supply chain relationships) are among the prescribed means of addressing the challenges of globalization and upgrade industrial development (OECD). The rationale is that involvement in a corporate association network can help a firm react to changes in the market, create customer value and loyalty, shorten product lead-time, and improve profit margins, by drawing on the network for the transfer of scarce resources, information, knowledge, and opportunities [8,26]. Spekman and Davis [44] found that supply chain networks that exhibit collaborative behaviors tend to be more responsive and that supply chain-wide costs are hence reduced [13]. This finding is also in accordance with Dyer and Nobeoka [15], who demonstrated empirically that a higher level of involvement in network relationships lowers transaction costs (costs associated with monitoring, negotiating, and enforcing contracts). Gnyawali and Madhavan [22] also stated that a corporation's network position shapes its competitive priorities and translates into informational and reputational advantages.

There are few articles in the literature describing real-life supply chain networks due to the opaque nature of a corporation's business relationships and the difficulties in obtaining such data [25]. One of the more precise ways to identify these types of relationships is through interview surveys, but the weaknesses are that it is very time-consuming and is costly in terms of human resources and money. To overcome these obstacles, this study extracts a corporation's business relationships from mass media by a text mining technique and later uses a social network (SN) technique to determine a firm's competitive edge embedded within this specific business network. Corporations with superior network relationships may promote their informal interactions and collaborative exchanges, permitting them to know extra information about their contacts (such as special skills and patents). Deepening such mutual exchanges can eliminate uncertainty about other corporations' business strategies and tactical actions. The more a corporation knows about others, the more it may trust or distrust them.

This research sequentially feeds business relationship information and financial information into an artificial intelligence (AI)-based technique to construct a forecasting model. Support vector machine (SVM), grounded on statistical learning theory, has demonstrated its powerful computational capability, and it has been widely applied in several domains with satisfactory performance [32,45]. However, a lack of computational efficiency (it spends considerable resources on dealing with the large quadratic programming problem) is one of the critical challenges for SVM, and this weakness tremendously restricts any real-life large-scale applications. To solve this problem, an amended version of SVM - called the extreme support vector machine (ESVM), which replaces the SVM kernel with the extreme learning machine (ELM) kernel - was introduced [31]. Apart from the original SVM, the training dataset in ESVM is accurately mapped into a feature space by the ELM kernel with its input weights randomly decided. Thus, this approach avoids dealing with the QPP task faced by SVM and preserves SVM's superior generalization ability.

The contributions of this study can be summarized as follows: (1) it uses the structural features of a business network derived from seemingly noisy data by the SN technique to discover essential knowledge (i.e., a firm's competitive edge); (2) it incorporates the risk exposure concept into BSC to give a more comprehensive analysis for decision makers; (3) it provides a promising alternative for corporate operating performance forecasting; and (4) it can be utilized by the public sector to identify which corporations can be prioritized due to their outstanding competitiveness. The government can thus consider potential implications and initiate suitable policies (such as financing incentives) to promote highly potential corporations and to upgrade the country's industrial competitiveness.

The remainder of this study is organized as follows. Section 2 briefly reviews the literature on supply chain management (SCM), social network (SN) analysis, and balanced scorecards (BSC). Section 3 discusses the SN methodologies and artificial intelligence (AI)-based forecasting techniques. Section 4 reports the data and main results of the empirical test. Section 5 presents the study's conclusions.

2. Literature review

2.1. Supply chains as a complicated networked structure

Supply chains have become a strategic topic for any enterprise seeking to achieve specific goals in terms of economic competitiveness, as well as timeliness and quality of service, especially in a business environment characterized by trade globalization and the acceleration of industrial circulation [43]. Supply chains are composed of a diverse set of vertical and horizontal interactions between inter-connected enterprises that engage in procurement, utilization, and transformation of raw materials in order to provide products and services [23]. Due to the complicated interactions among system (i.e., SCM) members, the term 'network' has been introduced into the supply chain management (SCM) research domain and represents a pressing need to view supply chains as a network for enterprises to obtain superior operating performance, operational efficiencies, and eventually sustainable competitiveness [25]. Thus, it is increasingly essential to analyze the network architecture of supply chain relationships.

The resource-based view (RBV) theory in the enterprise literature highlights the essence of obtaining scarce resources that are not directly accessible to an enterprise but rather are accessible through the network in which the corporation is embedded [19]. Each corporation's specific network structure is an important factor in the obtainment of resources, thus posing a great influence on corporations' performance and competitive edge [34]. Burt [7] stated that a corporation's network structure has a positive correlation to its rate of return and that the network structure can be viewed as a multidimensional construct consisting of centrality and a structural hole. The most comprehensive notion of point centrality in communication is grounded on the structural property of betweenness. On the basis of this view, a point embedded into a communication network is central to the extent that it falls upon the shortest path between pairs of other points [20]. Bavelas [4] first introduced the concept of point centrality and suggested that when a person in a group is placed on the shortest communication distance/path connecting pairs of others, then that person is located in a central position [20]. The other members embedded into a communication network are presumed to be 'responsive' to persons in such a central position who pose as the authority that influences the group by means of "withholding the circulation of message/information flow, coloring or twisting it in transmission." Another network structure is a structural hole [7], in which the merits of social capital result from the various kinds of information and brokerage chances generated by the lack of connection between separate clusters in a social network. Corporations located in brokerage positions between those clusters find it more convenient to access the useful information and relish comparative advantages in communication prestige, allowing them to know about more opportunities and to secure better essential terms in the opportunities they decide to chase [21].

Jarillo and Stevension [24] and Nishiguchi [38] conducted case studies that illustrate how such enterprises as Benetton and Nissan have reached their competitive advantage through their specific supply networks. Uzzi [47] examined how network relationships and network structure affect a corporation's acquisition and cost of capital. Harland et al. [23] demonstrated that an existing inter-organizational network structure has a considerable impact on a firm forming new alliances, which ultimately adjusts the existing network. Some studies placed emphasis on developing taxonomies of supply networks. Carter et al. [10] gave a case of the utilization of network theory in a logistics context and Autry and Griffis [2] applied network theory in a supply chain context. However, still lacking in such works is a theoretical framework that relates network theory to supply chain management as well as a comprehensive utilization of network theory to study supply networks.

2.2. Supply network risk management and balanced scorecards

The management of risk exposure in supply networks/chains has appeared as one of the core research issues in recent supply chain management literature [8]. This interest is cultivated by the rising uncertainty in highly unstable economic situations, business trends, such as increased multinational strategic alliances, and outsourcing. Additionally, great progress in information technology has triggered the development of complicated supply networks/chains [25]. Aside from their major advantages, extended supply networks/chains are more vulnerable and the corporations embedded into them face a higher level of risk exposure. How to mitigate the consequences of potential business risks has turned into a real problem for firms. It is widely recognized that a corporation's operating performance can be viewed as a good reflection of its risk-absorbing ability and competitiveness. Thus, it is important for enterprises to establish proper performance assessing criteria and measurement techniques.

Determining a corporation's operating performance is a sophisticated and multidimensional phenomenon. Venkatraman and Ramanujam [48] stated that traditional monetary measures are not sufficient enough to assess firm performance or to yield a direction for strategic action. Traditional monetary measures usually implemented by corporations - for example, various measures of return (return on investment: ROI; return on assets: ROA) or operating margins (gross margin; net

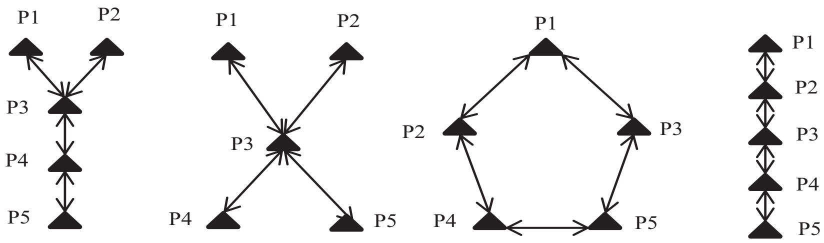

Fig. 1. The architectures of communication.

margin) - represent merely past outcomes and say little regarding expectations of future development. To mitigate this challenge, Kaplan and Norton [27] constructed an emerging performance measurement architecture - called balanced scorecard (BSC) - that seeks to include new assessing criteria, especially non-monetary ones, that encompass the internal and external perspectives of an enterprise, which may be more aligned with its goal and mission. BSC stresses that a corporation should pursue equilibrium between the long term and short-term, leading and lagging indices, monetary and non-monetary indices, as well as between internal and external performances, converting its vision and strategy focus into concrete action targets and implementing these targets as a basis for constructing proper assessing criteria. The assessing criteria can be divided into four main perspectives: (1) financial, (2) customer, (3) internal processes, and (4) learning and growth; they are aimed at providing decision-makers with a thorough view of their corporation's operating situation. Moreover, BSC has been applied successfully and has yielded promising results in numerous research settings, such as local governments and municipalities, manufacturing corporations, banks and insurance companies, as well as hospitals and healthcare centers [27].

Although BSC has caught the attention of academics and practitioners, there are various critical challenges of it as stated in prior research. One example is that BSC does not take risk exposure into consideration, which will affect profit variation and increasingly risk management [14]. To alleviate this challenge, this study expands the fundamental concept of BSC by integrating the idea of risk management and aggregating the measures in risk-adjusted BSC (RA-BSC) for users to comprehensively depict the multifaceted nature of an enterprise's operating situation.

3. Applied methods

3.1. Social network analysis

Researchers have developed the fundamental concept of social network analysis, illustrated the relational justifications of financial behaviors, and tested the potential influence of social ties [47]. Network analysis is effective as a technique to determine the advantages of a structural position in a number of ways [26]. The main purpose of network theory is to explain how patterns of social ties reach superior financial results and why inter-enterprise networks are formed, collapse, succeed, or fail [16]. In other words, the merits of analyzing network theory can help decision makers understand how to share expertise and professional knowledge in an efficient way and to assess the performance of individuals, groups, or the whole network structure [1].

The "Bavelas–Leavitt Experiment" is one of the earliest works in network structure analysis that relates human communication patterns to performance [4,30]. The experiment is composed of numerous groups; each group consists of five members, and each member has to communicate with each other through enclosed cubicles to address the puzzle. Fig. 1 depicts the four dissimilar architectures for communication channels between members of the groups. The empirical results state that the groups utilizing the "Star" and "Y" architectures exhibit better performance in communication. Leavitt [30] inferred that centralization is the most influential element on performance - that is, centrality has an essential structural impact on leadership, efficiency, and satisfaction, which represents the importance of a node in the network [21].

Betweenness centrality is one type of centrality measure that assesses the number of times a particular node lies 'between' the various other nodes in the network. The intermediary will have a dissimilar impact on the enterprises it links with, whether directionally or non-directionally [25]. Assessing betweenness centrality starts with an assumption that a connection between two nodes, n_e and n_f, follows their geodesics. Eq. (1) represents the mathematical formation of betweenness centrality.

$$C_B(n_d) = \sum_{e<f} \frac{h_{ef}(n_d)}{h_{ef}}, \tag{1}$$

where h_{ef} depicts the total number of geodesics linking the two nodes, and $h_{ef}(n_d)$ represents the number of those geodesics that contain n_d. Here, n_d's betweenness is then simply the aggregation of the probabilities that the node lies between other nodes. When n_d falls on all geodesics, the betweenness reaches the maximum, and when n_d falls on no geodesics, the betweenness reaches the minimum of zero. Eq. (2) represents the betweenness that has undergone the normalization process to a value between 0 and 100.

$$C'_B(n_d) = \frac{C_B(n_d)}{[(h-1)(h-2)/2]} * 100. \tag{2}$$

Freeman [20] and Borgatti and Everett [6] stated that betweenness can be used to identify how much 'gatekeeping' n_d does for the other nodes. Gatekeeping occurs when a node falls on a geodesic that can most frequently control the flows of information, materials, or communications in the network. When applied to a materials flow network, enterprises with a higher value of betweenness centrality play the role of a hub or pivot that transmits materials along the supply network, and the value relates to the extent to which they potentially influence downstream enterprises' daily operations and eventually the performance of the whole supply network [25]. In contrast, if an enterprise with a higher value of betweenness centrality transmits materials to an improper place, then it can easily result in supply disruptions. In brief, an enterprise with a dissimilar value of betweenness centrality reveals its specific ability to access external information, knowledge, and desired scarce resources and subsequently transforms this into specific competitive edge.

3.2. Extreme support vector machine: ESVM

Consider the binary classification task of discriminate m points in n-dimensional real space R^n, expressed as a $m \times n$ matrix B. A $m \times m$ diagonal matrix G with $\{\pm 1\}$ along its diagonal specifies the membership of class $\{\pm B\}$ of each point B_i. Fung and Mangasarian [18] pointed out that for this task, the formulation of linear ESVM and linear proximal SVM is the same and is given by the following quadratic problem with parameter $v > 0$ and linear equality constraint.

$$\begin{aligned} &\min_{(w,r,y)\in R^{n+1+m}} \quad \frac{v}{2}\|y\|^2 + \frac{1}{2}\left\|\begin{bmatrix} w \\ r \end{bmatrix}\right\|^2 \\ &sbject \quad to \\ &G(Bw - er) + y = e \end{aligned} \tag{3}$$

This problem tries to determine the proximal discriminating planes, $x'w - r = \pm 1$, where w denotes the orientation to the origin, r depicts the relative location to the origin, and y expresses the slack variable. These two discriminating planes are proximal to the points in class $B+$ and class $B-$, respectively; and the middle discriminating plane between the two aforementioned proximal planes is depicted as $x'w - r = 0$, which is set up to do a classification task.

$$x'w - r \begin{cases} > 0, & then \quad x \in B+ \\ < 0, & then \quad x \in B- \\ = 0, & then \quad x \in B+ \quad or \quad x \in B- \end{cases} \tag{4}$$

The linear ESVM can be extended to a non-linear version by performing a special devised non-linear mapping function $\phi(\cdot) : R^n \to R^{\tilde{n}}$, and the formulation is depicted as:

$$\phi(x) = D(Wx^1) = \left(d\left(\sum_{j=1}^{n} W_{1j}x_j + W_{1(n+1)}\right)\right), \ldots, d\left(\sum_{j=1}^{n} W_{\tilde{n}j}x_j + W_{\tilde{n}(n+1)}\right)\Bigg)', \tag{5}$$

where $x \in R^n$ denotes the input vector, $x^1 = [x'1]'$, $W = R^{\tilde{n}\times(n+1)}$ depicts the matrix whose elements are generated arbitrarily, $\phi(x)$ expresses the vector x mapped onto the feature space, and the notation $D(\cdot)$ represents a map that takes a matrix Z with element z_{ij} and implements another matrix of the same size with element $d(z_{ij})$, where d is an activation function.

For a $m \times n$ matrix B, $\phi(B)$ is defined as $\phi(B) = [\phi(B'_1), \ldots, \phi(B'_m)]'$. Sequentially, the non-linear version ESVM with a parameter $v > 0$ can be represented as follows.

$$\begin{aligned} &\min_{(w,r,y)\in R^{\tilde{n}+1+m}} \quad \frac{v}{2}\|y\|^2 + \frac{1}{2}\left\|\begin{bmatrix} w \\ r \end{bmatrix}\right\|^2 \\ &s.t. \qquad G(\phi(B)w - er) + y = e \end{aligned} \tag{6}$$

According to the linear constraint of Eq. (6), we can acquire an explicit expression of y. The following unconstrained minimization can be derived by replacing y with the explicit regression shown in Eq. (6).

$$\min_{(w,r)\in R^{\tilde{n}+1}} \quad \frac{v}{2}\|G(\phi(B)w - er) - e\|^2 + \frac{1}{2}\left\|\begin{bmatrix} w \\ r \end{bmatrix}\right\|^2 \tag{7}$$

We set the parameters w and r to zero and note that $G^2 = I$ gives the following sufficient and necessary optimality conditions for Eq. (7).

$$\begin{aligned} &v\phi(B)'(\phi(B)w - er - Ge) + w = 0 \\ &ve'(-\phi(B)w + er + Ge) + r = 0 \end{aligned} \tag{8}$$

By employing Eq. (8), we acquire the following intuitive expression of w and r in terms of the problem data.

$$\begin{bmatrix} w \\ r \end{bmatrix} = \left(\frac{1}{v} + A'_{\phi}A_{\phi}\right)^{-1} A'_{\phi}Ga, \tag{9}$$

where $A_{\phi} = [\phi(B) - a] \in R^{m\times(\tilde{n}+1)}$. For an unknown point x, the discriminating hyperplane of a non-linear ESVM can be used to perform a classification decision.

$$\phi(x)'w - r \begin{cases} > 0, & then \quad x \in B+ \\ < 0, & then \quad x \in B- \\ = 0, & then \quad x \in B+ \quad or \quad x \in B- \end{cases} \tag{10}$$

Comparing both linear and non-linear ESVM, we see that their mathematical formations have a lot in common. The only difference between the two is that the non-linear ESVM is modeled in a feature space by an explicit mapping function. ESVM has demonstrated its superior forecasting quality, and to our knowledge, no current research has implemented ESVM to forecast corporate operating performance. To fill this gap in the literature, this study utilizes ESVM.

4. Experimental results

4.1. Sample data

Among all capital-intensive industries in Taiwan, its electronics industry plays the most important role in the global supply chain and is part of a large capital market to global investors, as well. Over the years, Taiwan's authorities or central and local governments have announced numerous financial incentives or policies, such as tax credits, capital, land, and training courses, for this specific industry, turning it into the backbone of the local stock market. Hence, we take this specific industry as our research sample, with the data gathered from public websites, such as Taiwan Economic Journal Data Bank (TEJ), Taiwan Stock Exchange (TWSE), and Taipei Exchange (TE), for the period 2013–2015.

4.2. Dependent variable

Performance measurements contain many avenues for employees to refine their work, to make final judgments, and to initiate communication procedures for improvement plans. Kaplan and Norton [27] noted that performance measurements can be viewed as one way to review a corporation's goals, both financially and non-financially. Most previous research studies on performance ranking merely rely on simple and consistent monetary indicators, such as ROI and ROA, but these performance rankings only consider the monetary parts and are unsuitable for depicting the full aspects of a corporation's operating performance. Moreover, they are unable to highlight strategies that can lead to top performances in this highly fluctuating economic world. Non-monetary indicators such as customer satisfaction, inventory turnover, staff productivity, communities, and employees are also vital and integral to a corporation's winning strategy. Thus, BSC consists of four main perspectives - financial, customer, internal processes, and learning and innovation - to handle the task of performance rankings.

First, in accordance with prior related studies, this study does consider some essential financial criteria such as ROA, ROI, and gross margin rate, but these measures do not take risk exposure into consideration, which has been widely recognized as being the core element to explain profit variation. Mitchell [36] presented that the variance of returns scaled by their mean is a valuable risk metric, following directly from the theoretical consideration of Markowitz [37] and Roy [41]. Thus, this study incorporates the concept of risk management with the traditional BSC and yields a risk-adjusted BSC for measuring a corporation's operating condition. Second, the criteria from the customer perspective include market share and sales return (taken as a percentage of total sales). Due to their opaque nature and difficulty in analysis, customer satisfaction and loyalty are not a part of the measuring criteria. Third, the criteria for internal processes include inventory turnover, research and development (R&D) expenditure (taken as a percentage of total sales), and the number of patents. Fourth and finally, the criteria for learning and innovation include employee predisposition (seniority and education degree) and staff productivity (see Table 1).

Although BSC has proven its effectiveness and usefulness, there are still some weaknesses, such as it often appears too general. Hence users may have trouble using it, or it cannot give a precise direction for users to follow. How to aggregate BSC's four perspectives and to systematically give prioritization is of interest to researchers. This task is a classic multiple criteria decision making (MCDM) problem, and MCDM techniques can be executed to solve it. Among all MCDM techniques, the analytic network process (ANP) permits the representation of the identified relationships in BSC as a network with inner and outer dependences and not as a hierarchy. Due to this advantage, ANP is widely proven to be a useful tool to weigh indicators and give an aggregated outcome (see Table 2). The performance rank calculated from RABSC by ANP in the highest quintile (top 20%) denotes corporations with superior operating performances, while those in the lowest quintile (bottom 20%) denote corporations with inferior operating performances.

Table 1
The weight of each assessment measure.

Perspective	Measure	Illustration
F: Financial	F1: Risk-adjusted ROA (RAROA)	ROA/σROA
	F2: Risk-adjusted ROE (RAROE)	ROE/σROE
	F3: Risk-adjusted GPR (RAGPR)	GPR/σGPR
C: Customer	C1: Market share (MS)	Total sales/whole market sales
	C2: Sales return rate (SRR)	Sales return/total sales
I: Internal processes	I1: Inventory turnover (IT)	Annual cost of goods sold/inventory
	I2: R&D expenditure rate (R&D)	R&D/total sales
	I3: Patents (P)	Number of patents
L: Learning and innovation	L1: Employee work seniority (EWS)	Average service seniority
	L2: Employee education degree (EED)	Highly educated employees/employees
	L3: Staff productivity (SP)	Total sales/employees

Table 2
Weight of each assessment measure.

Perspective (Weight)	Measure	Weight of each measure
F: Financial (0.64)	F1: RAROA	0.33
	F2: RAROE	0.53
	F3: RAGPR	0.14
C: Customer (0.22)	C1: MS	0.67
	C2: SRR	0.33
I: Internal processes (0.05)	I1: IT	0.16
	I2: R&D	0.54
	I3: P	0.30
L: Learning and innovation (0.09)	L1: EWS	0.25
	L2: EED	0.13
	L3: SP	0.62

*The weight is determined by ANP.

4.3. Independent variables

Corporate operating performance forecasting is highly related to the topic of financial crisis forecasting, whereby the selected variables are taken as the surrogate for participating in model construction. The selected independent variables are X1: WC/TA (Working capital to total assets), X2: TL/TA (Total liability to total assets), X3: I/S (Inventory to sales), X4: OI/TA (Operating income to total assets), X5: FA/TA (Fixed assets to total assets), X6: NI/TA (Net income to total assets), X7: LTL/TA (Long-term liabilities to total assets), X8: TL/TE (Total liabilities to total equity), X9: CL/CA (Current liabilities to current assets), X10: RE/TA (Retained earnings to total assets), and X11: S/TA (Sales to total assets).

A corporation's supply chain relationships are its competitive edge in this highly competitive world economy, but no current works examine their influence on corporate operating performance forecasting. To fill this research gap, this study constructs corporate business networks and examines their impact on forecasting quality. The information used to construct corporate business relationship networks was gathered from two main sources: mass media news and annual reports. The news was collected from Yahoo!Finance in Taiwan (https://tw.stock.yahoo.com/), because news information there is not restricted to only news available from yahoo.com but also includes other news sources, such as Bloomberg, Forbes, and Fortune. There are many different categories on this website, such as portfolios, investment suggestions, futures and options, and stock information. We only focus on stock-related information that contains numerous useful messages about a corporation's future performance, its suppliers' and manufacturers' information, and its competitive advantages. Yahoo!Finance organizes news stories by corporation and by date and presents a corporation's specific stock ticker.

Bao et al. [3] stated that corporations co-appearing in the same piece of news imply that there is probably some type of business relationship among them. Taking advantage of Yahoo!Finance's specific organizing style, the stock ticker information was used to construct corporate business relationship networks. In total we collected approximately 12,000 news items from Yahoo!Finance for the period 2013–2015. To strengthen the business relationship networks, a corporation's annual report was also taken into consideration. There are approximately 400 publicly listed electronics firms in Taiwan. We collect all of their annual reports from 2013 to 2015, construct the business relationship lexicon (i.e., supply, purchase, procure, lend, cooperate, ally, collaborate, joint, together, partner), and then match them with a corporation's annual report to identify business relationships with other corporations. Thus, we construct a much more concrete business relationship network (see Fig. 2) for decision makers to identify each corporation's competitive priority and edge.

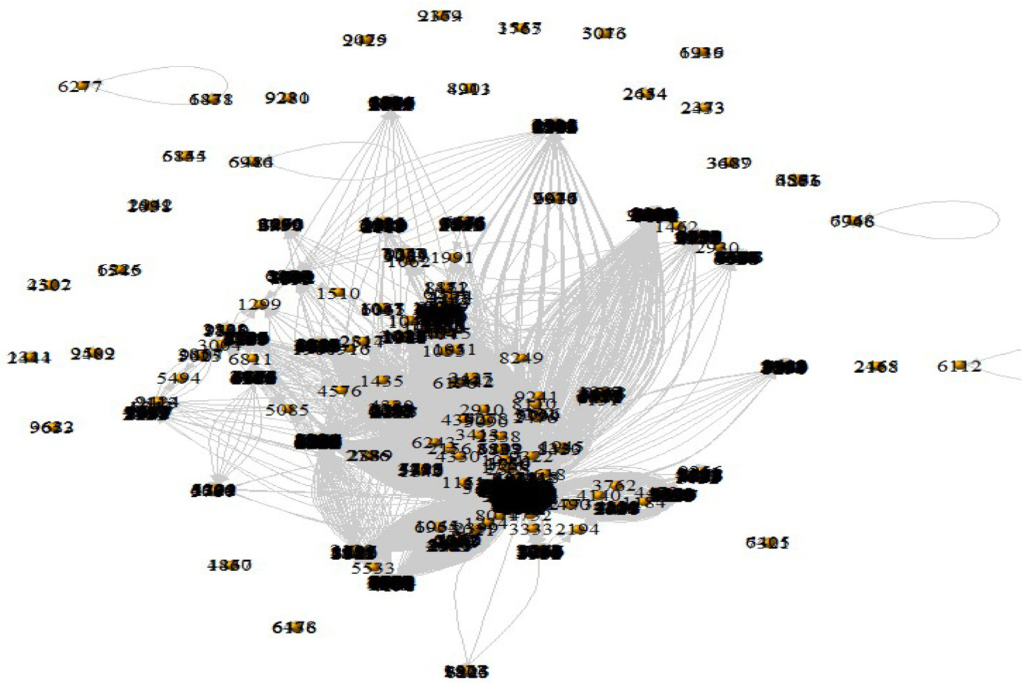

Fig. 2. Partial mapping of a business relationship network.

4.4. Results

With the tremendous development of information technology and the Internet, users can easily gather a huge amount of information about firms. However, it takes considerable time and human resources to analyze the collected information deeply. In addition, the information is full of useless, irrelevant messages that deteriorate interpretability, as well as misleading the research outcome. Hence, how to filter and condense the information is a necessary pre-process for the setup of a forecasting model. The *t*-test can be used to answer the underlying question: Is there a significant difference between two groups' mean that can be widely implemented to address the feature selection task.

Table 3 presents the selected features. We can see that a corporation with superior operating performance usually exhibits satisfactory profitability, asset utilization efficiency, suitable capital structure, and good business relationships. To examine the influence of business relationships on performance forecasting, the research design is set up in a "with" versus "without" scenario. The preciseness of the forecasting outcome is the most commonly adopted measure. Judging a model's forecasting performance only by one measure is neither reliable nor trustworthy. Thus, this study further considers three other measures: precision, recall, and F-score.

To test the usefulness of the introduced t-ESVM-GA model, this study takes the introduced model as a baseline and compares it with the other forecasting techniques. The forecasting techniques in business, finance, and accounting domains can be roughly divided into two different categories: statistical-based techniques and artificial intelligence (AI)-based techniques. Logistic regression (LR) and discriminant analysis (DA) are the most popular statistical-based techniques and perform a satisfactory job in binary outcome forecasting; thus, this study employs LR and DA. Neural network (NN) can appropriately handle data with a non-linear structure that is difficult to solve by using classical parametric techniques. Decision tree (DT), with the merits of being easy-to-use, comprehensive, and robust, automatically sifts through complicated databases to search for and isolate the most essential patterns and relationships [50]. Rough set theory (RST) is a powerful mathematical algorithm to handle insufficient, uncertain, and incomplete knowledge and has been widely and successfully implemented to solve numerous research problems, such as feature selection, classification, and knowledge extraction [33,35,49]; therefore, NN, DT and RST are also utilized in this study. Five-fold cross-validation (CV) is adopted to eliminate the impact of over-fitting. To ensure the outcome does not occur by chance, this study conducts a Wilcoxon signed-rank test. It is a non-parametric approach that is much stronger and safer than a parametric approach without the assumption of normal distribution.

Table 4 lists the results. We can see that the model with the competitive edge variable performs better than the model without the competitive edge variable. Among all forecasting models, the introduced t-ESVM-GA model achieves the best forecasting quality under four dissimilar measures. This result is in accordance with Tsai [46], who stated that different network positions represent different opportunities for enterprises to access new knowledge and useful information that are integral to developing new ideas or products. Such a network of inter-enterprise links enables organizational units to

Table 3
Descriptive statistics of the predictors.

Predictor	Condition	No	Mean	S.D.	P-value	Selected
X1: WC/TA	Inefficiency	300	0.216	0.243	P = .064(*)	Yes
	Efficiency	300	0.312	0.128		
X2: TL/TA	Inefficiency	300	0.401	0.182	P = .000 (***)	Yes
	Efficiency	300	0.218	0.131		
X3: I/S	Inefficiency	300	0.324	0.183	P = .201	No
	Efficiency	300	0.237	0.165		
X4:OI/TA	Inefficiency	300	0.163	0.103	P = .000 (***)	Yes
	Efficiency	300	0.212	0.042		
X5:FA/TA	Inefficiency	300	0.434	0.138	P = .157	No
	Efficiency	300	0.417	0.135		
X6: NI/TA	Inefficiency	300	−0.018	0.158	P = .002(**)	Yes
	Efficiency	300	0.017	0.086		
X7:LTL/TA	Inefficiency	300	0.315	0.102	P = .108	No
	Efficiency	300	0.306	0.094		
X8:TL/TE	Inefficiency	300	0.513	0.201	P = .121	No
	Efficiency	300	0.431	0.195		
X9: CL/CA	Inefficiency	300	0.511	0.346	P = .005(**)	Yes
	Efficiency	300	0.412	0.308		
X10:RE/TA	Inefficiency	300	0.064	0.261	P = .323	No
	Efficiency	300	0.078	0.143		
X11:S/TA	Inefficiency	300	0.206	1.827	P = .043(**)	Yes
	Efficiency	300	0.401	0.370		
X12: CE	Inefficiency	300	0.132	0.182	P = .000 (***)	Yes
	Efficiency	300	0.537	0.063		

* indicates $p < 0.1$;
** $p < 0.05$;
*** $p < 0.01$; Competitive edge is abbreviated as CE.

Table 4
The forecasting performance of each mechanism.

Evaluation indicator: Accuracy (%)			
Mechanism	With CE	Without CE	Hypothesis: $H_0: med_{diff} = 0$ $H_1: med_{diff} \neq 0$
t-ESVM-GA	87.53	83.03	Z = −2.0226 (p-value = 0.043) (**)
LR	72.40	67.80	Z = −2.0226 (p-value = 0.043) (**)
DA	74.60	70.00	Z = −2.0226 (p-value = 0.043) (**)
DT	79.07	74.62	Z = −2.0226 (p-value = 0.043) (**)
NN	78.84	74.06	Z = −2.0226 (p-value = 0.043) (**)
RST	81.37	75.65	Z = −2.0226 (p-value = 0.043) (**)
Evaluation indicator: Precision (%)			
t-ESVM-GA	87.24	83.58	Z = −2.0226 (p-value = 0.043) (**)
LR	72.8-	70.40	Z = −2.0226 (p-value = 0.043) (**)
DA	74.00	68.80	Z = −2.0226 (p-value = 0.043) (**)
DT	78.43	73.53	Z = −2.0226 (p-value = 0.043) (**)
NN	79.43	74.87	Z = −2.0226 (p-value = 0.043) (**)
RST	81.45	75.73	Z = −2.0226 (p-value = 0.043) (**)
Evaluation indicator: Recall (%)			
t-ESVM-GA	87.72	82.62	Z = −2.0226 (p-value = 0.043) (**)
LR	72.22	66.92	Z = −2.0226 (p-value = 0.043) (**)
DA	74.90	70.49	Z = −2.0226 (p-value = 0.043) (**)
DT	79.45	75.16	Z = −2.0226 (p-value = 0.043) (**)
NN	78.45	73.86	Z = −2.0226 (p-value = 0.043) (**)
RST	82.23	75.75	Z = −2.0226 (p-value = 0.043) (**)
Evaluation indicator: F-score			
t-ESVM-GA	87.48	83.15	Z = −2.0226 (p-value = 0.043) (**)
LR	72.51	68.62	Z = −2.0226 (p-value = 0.043) (**)
DA	74.45	69.64	Z = −2.0226 (p-value = 0.043) (**)
DT	78.93	74.43	Z = −2.0226 (p-value = 0.043) (**)
NN	78.92	74.19	Z = −2.0226 (p-value = 0.043) (**)
RST	81.21	75.62	Z = −2.0226 (p-value = 0.043) (**)

*p-value < 0.1; **p-value < 0.05; ***p-value < 0.01; Competitive edge is abbreviated as CE.

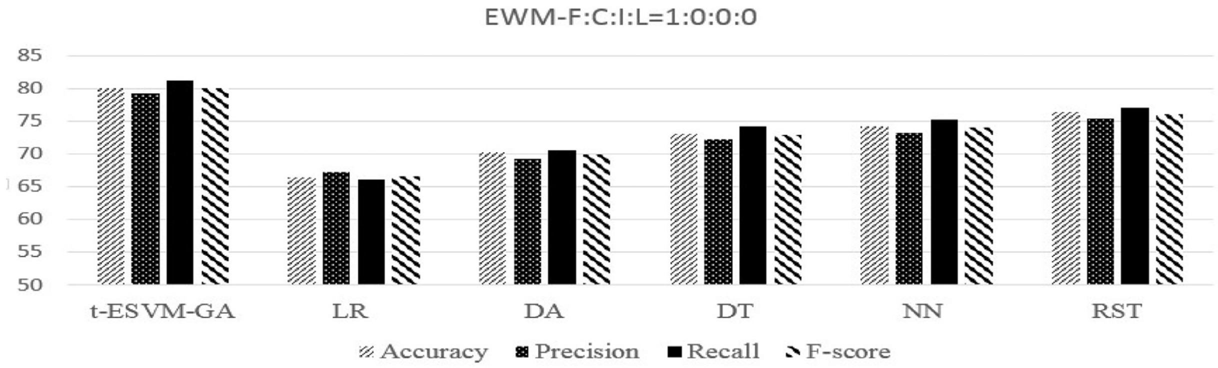

Fig. 3. Result of EWM (Weight F:C:I:L = 1:0:0:0).

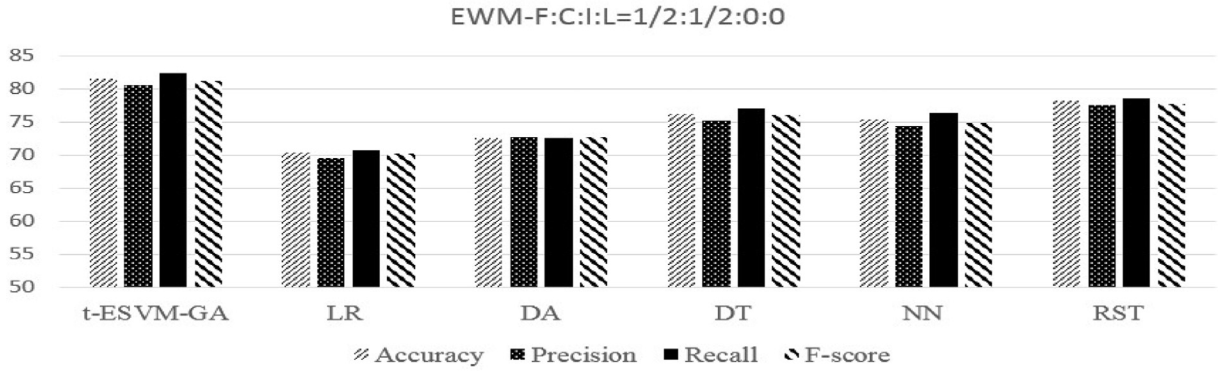

Fig. 4. Result of EWM (Weight F:C:I:L = 1/2:1/2:0:0).

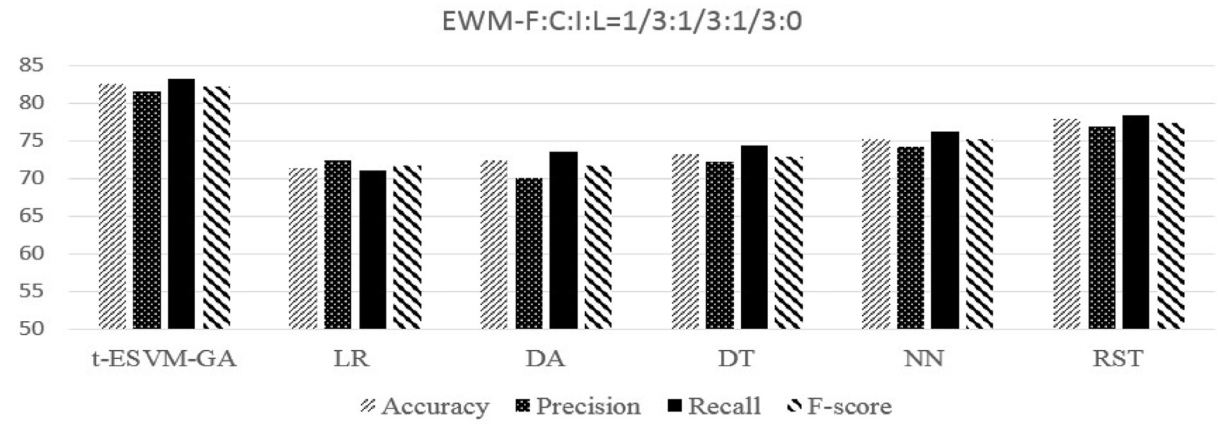

Fig. 5. Result of EWM (Weight F:C:I:L = 1/3:1/3: 1/3:0).

acquire critical competencies that contribute to their competitiveness in the marketplace as well as to increase their market prestige. Popova and Sharpanskykh [39] also noted that a firm's success depends not only on how effectively it manages its internal operating procedures/activities but also on how well its behavior fits with the operational environment (i.e., supply chain network structures) in which it is situated. These rationales support our choice for implementing the social network technique as the theoretical framework behind this study, rather than the focal organization (i.e., isolated business systems).

Because priorities are affected greatly by a user's subjective judgment, the stability of the final ranking under varying pre-decided weights should be tested. This study implements three different methods: extreme weight method (EWM) [40], simple multi-attribute rating technique (SMART) [17], and SMARTER (SMART Exploiting Ranks) [5]. Figs. 3–6 show the results of EWM under four dissimilar conditions (F: C: I: L = 1-0-0-0; 1/2–1/2-0-0; 1/3–1/3–1/3–0; 1/4–1/4–1/4–1/4). The results of

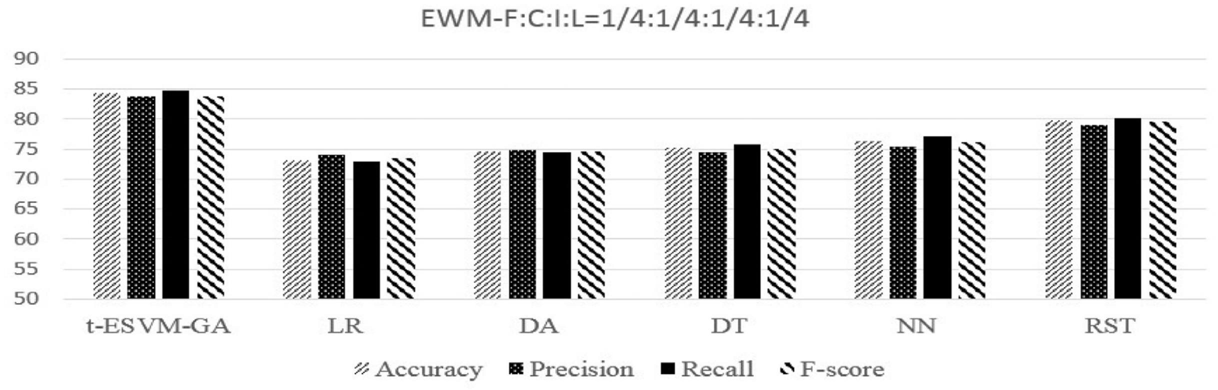

Fig. 6. Result of EWM (Weight F:C:I:L = 1/4:1/4: 1/4: 1/4).

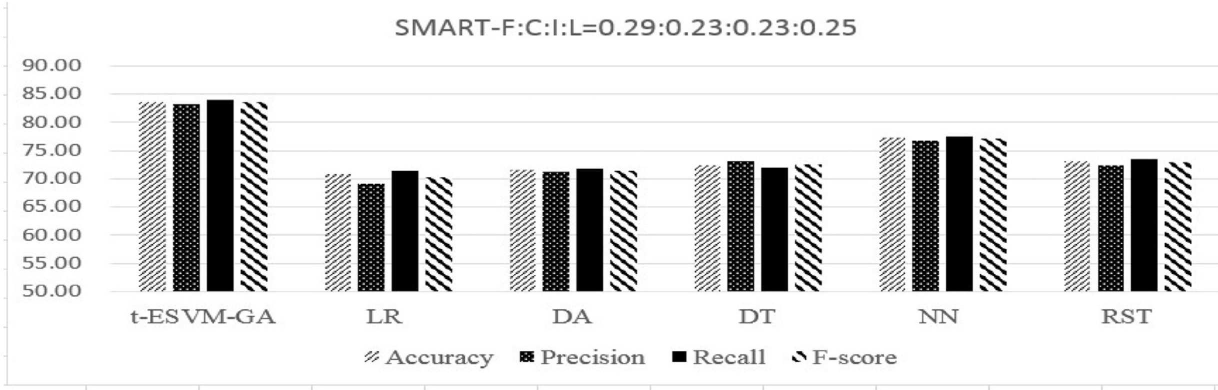

Fig. 7. Result of SMART (Weight F:C:I:L = 0.29:0.23: 0.23: 0.25).

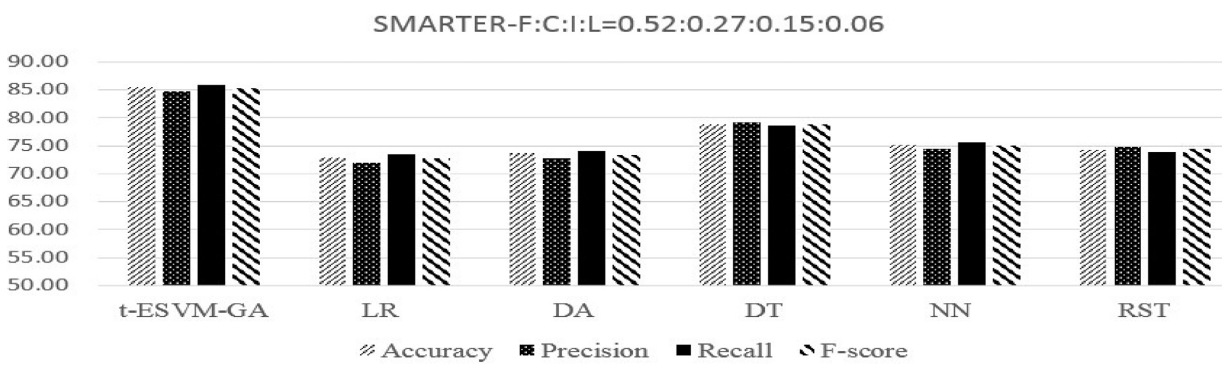

Fig. 8. Result of SMARTER (Weight F:C:I:L = 0.52:0.27: 0.15: 0.06).

SMART and SMARTER are in Figs. 7 and 8, respectively. We can see that the introduced model still outperforms the other five models under all assessment measures in all conditions. The introduced model is a promising alternative for corporate operating performance forecasting.

Lacking interpretability is one of the critical weaknesses of the hybrid AI-based model. If the inherent decision logics embedded in the AI-based model are not easy to realize, then decision makers will probably not have sufficient confidence to form a final judgment and adopt them. Also, the logics decrease the model's practical applications. To eliminate this challenge, this study implements a genetic algorithm (GA) to extract the hidden knowledge and represent it in a human readable format. Table 5 presents the rules, and a detailed description of the rule generation process can be seen in Salleb-Aouissi et al. [42]. In contrast to a corporation with inferior operating performance, we can see that one with superior operating performance normally has better business relationships, higher profitability, and a proper debt structure. The decision rules derived from the t-ESVM-GA model can be taken as a guideline for decision makers to make reliable judgments.

Table 5
The top five decision logics derived from t-ESVM-GA.

Description	Support	Confidence
L1:{X6: [0.21, 0.33], X11: [0.27, 0.36]} ➔{[Efficiency]}	46	82
L2:{X2:[0.21, 0.36], X4: [0.32, 0.41], X12: [0.47, 0.63]}➔{[Efficiency]}	42	76
L3:{X2: [0.46, 0.63], X11: [0.12, 0.22]} ➔{[Inefficiency]}	36	72
L4:{X1: [0.08, 0.16], X12: [0.04, 0.12]} ➔{[Inefficiency]}	32	67
L5:{X6: [0.21, 0.33], X12: [0.47, 0.63]} ➔{[Efficiency]}	27	62

Table 6
Compared results.

Case 1: With ANP	Evaluation indicators			
Mechanism	Accuracy (%)	Precision (%)	Recall (%)	F-score
t-ESVM-GA	87.53	87.24	87.72	87.48
LR	72.40	72.8-	72.22	72.51
DA	74.60	74.00	74.90	74.45
DT	79.07	78.43	79.45	78.93
NN	78.84	79.43	78.45	78.92
RST	81.37	81.45	82.23	81.21
Case 2: Without ANP	Evaluation indicators			
Mechanism	Accuracy (%)	Precision (%)	Recall (%)	F-score
t-ESVM-GA	81.60	81.92	81.40	81.66
LR	63.80	65.12	63.44	64.27
DA	65.32	66.08	65.08	65.57
DT	73.20	73.52	73.06	73.28
NN	76.08	76.56	75.84	76.19
RST	74.16	74.64	73.92	74.26

4.5. Robustness tests

Most previous studies make a final judgment that is merely based on one pre-decided dataset, but it is clear that using dissimilar datasets or assessment measures will easily lead to divergent research outcomes. To make our research outcome more compact and reliable, we establish two dissimilar experimental designs of performance rank determination: (Case_1) BSC's four perspectives are aggregated by ANP (that is, the weight of each measure is not set to be equal to each other, and then we aggregate all measures together to form a final rank); and (Case_2) BSC's four perspectives are not aggregated by ANP (that is, the weight of each measure is set to equal one another, and then we aggregates all measures together to form a final rank).

Table 6 lists the results. We can see that the introduced model still performs a satisfactory job in forecasting performance under these two dissimilar cases. However, the highly complicated financial decision making tasks cannot be clarified only in an equal-weighted framework; hence, the sophisticated and multi-dimensional relationships (i.e., feedback and dependence) among assessment measures need to be captured, as in the case in ANP. In other words, given the tasks encountered in reality, the interdependent relationships among assessment measures are of concern in order to form a reliable and appropriate judgment in today's highly fluctuating business atmosphere.

5. Conclusions

Traditional aspects of an economy, such as a free market, pure competition (enterprises competing as isolated systems against each other), and unconnected/single transactions, are together not considered adequate to explain today's highly competitive economy. Thus, business relationships that occur at the dyad level (i.e., a single supplier-buyer relationship) or at the network level (i.e., a set of relationships among downstream and upstream enterprises in a supply chain) have been introduced in the literature and can be used to describe firms that operate in cooperative industrial networks in order to achieve competitive advantages and synergistic results. The potential implication is that business relationships should not be viewed as developed and created in isolation, but instead as part of a broader or more extensive context - a network structure of interdependent relationships. The literature reveals that an appropriate approach is still missing that can be implemented as a reference for analyzing the influence of an enterprise's interdependence on its operating performance, mainly in the context of complicated cooperative industrial networks [9].

To ameliorate the aforementioned challenges, this study introduces a novel strategy to construct the corporate business relationship network, gathering information from two main sources: (1) mass media news (i.e., a corporation co-appearing with others in the news means that there is some business relationship among them); and (2) annual reports (i.e., the pre-decided business relationship corpus that is matched up with a corporation's annual report can be used to exploit its business relationships with other corporations). A business relationship network is a kind of network structure. Hence, although the SN technique can be implemented to take out the essential knowledge (i.e., competitive edge) from this network structure, no current research studies have examined the effectiveness of a corporation's competitive edge on performance forecasting. To fill this gap in the literature, this study executes SN to determine a corporation's competitive edge and further examines its influence on the model's forecasting quality. The introduced model is tested by real-life cases under numerous experimental designs and achieves a satisfactory outcome. Decision makers can take this model as a decision support system to adjust their personal portfolio investments as well as to help maximize their own wealth. The public sector can also consider the potential implications of this study and set up beneficial policies or financial incentives for corporations that have a superior competitive edge in order to promote or upgrade a country's industrial level and global competitive priority.

For future works, several issues could also be considered. First, the proposed singular model can be extended to a much more sophisticated mechanism, such as ensemble learning (i.e., boosting, bagging, and adaboost). The primary purpose of ensemble learning is to complement any error made by a singular model, which has been widely considered to the most effective way to increase a model's forecasting performance. Second, in addition to implementing the filter method (that is, *t*-test) to determine the essential feature subsets, one can further combine the filter and wrapper methods or hybrid method for a separate comparison.

Disclosure statement

No conflict of interest exists in the submission of this manuscript.

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