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APPLICATIONS USING HYBRID INTELLIGENT DECISION SUPPORT SYSTEMS FOR SELECTION OF ALTERNATIVES UNDER UNCERTAINTY AND RISK

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Abstract. *Alternative selection of a portfolio has been a challenging research area in finance and investment decision making. Recent advances in single Decision Support Systems (DSS), soft computing and machine learning models are to solve the problems in selection of alternatives under uncertain market and risk environments. These models have not considered concurrently uncertain values including quantitative and qualitative stock-market factors, together with experts' feelings and preferences about market dynamics. This affects the capability of an investment system to deal with various market conditions. The study is to solve the existing problems in the selection of the most appropriate alternatives (companies, company groups and stocks) at the right time for stock trading. In this paper, we propose Hybrid Intelligent DSS models using Kansei Evaluation integrated with other single DSS techniques, aiming to aggregate experts' preferences with the selection of the most suitable stocks to achieve investment returns and risk reduction by dealing with complex situations in market dynamics. The proposed models have been tested and performed well in both simulated trading results and real-world stock trading on the HOSE, HNX (Vietnam), NYSE and NASDAQ (US) stock markets to validate the integrated DSS methods in various stock markets. In order to evaluate the effectiveness of this approach, experimental results show that the proposed approach performs better than other current DSS methods and hybrid models to select the right alternatives at the right trading time under uncertainty and risk.*

Keywords: Intelligent decision support system (DSS), Kansei evaluation, Self-organizing map (SOM), Group decision support system (GDSS), Stock market investment

1. **Introduction.** In real-world problems, alternatives in a selection are dynamically changing in uncertain environments, which are challenging in DSS nowadays. When considering uncertainty in processes of multiple decisions for the selection of alternatives in dynamic environments, models that use a single Decision Support System (DSS) have faced limitations for the selection of alternatives in complex situations under uncertainty and risk. Feasible single DSS models include methodologies for selection of companies or stocks in financial time series, multi-objective optimization of expected investment return and risk reduction. In Decision Support Systems (DSS) and Expert Systems (ES)

applications [12, 38], the approaches are concerned with decision making on stock trading, instead of quantitative and qualitative factors in analysis. These approaches have faced limitations of market conditions when decision makers select companies or stocks for investment.

When trading stocks, stock assessments are significant decision-making problems affected by dynamic market conditions, market trends and market risks. Even using several commercial trading stock software applications and intelligent systems to make trading decisions, investors may face uncertain conditions in dynamic stock market environments such as government policies, bank interest rates, world stock market prices, financial rule changes, and real-time stock trading trends. Risk management mostly involves utilizing a variety of trading activities and financial analysis, one of the most complicated stock trading skills for professional traders [20]. Successful investors employ many risk management skills for stock trading, as they know how important it is to avoid mistakes when investing in the stock market. Fundamental analysis aims to select potential stocks based on study of the fundamental data of a company such as financial weights, macroeconomics, financial proportions, and stock-market news [21]. Contrary to this approach, technical analysis attempts to predict price by analyzing historical data of the correlation between prices and market behavior volumes for trading stocks [5, 21]. Furthermore, the trading behaviors of group/individual investors are commonly affected by the news published by economic news, websites and other publishing news. In real-time trading stocks, uncertain values including market conditions, investor emotion, sensibility and impression in selling/buying stocks on dynamic stock environments may affect uncertain conditions on a stock market.

In related works [11,22,25-32], many studies have shown appropriate approaches of forecasting price based on historical data of a stock market. Hybrid intelligent systems, soft computing models and DSS methods provide cohesive presentations and classifications for problems in stock trading and decision [11,20-26]. Recently, the new approach using Rule-base Evidential Reasoning [39] is concerned with the synthesis of the fuzzy logics and Dempster-Shafer theory and presented in stock trading naturally. Although this approach is recently shown in an expert stock trading system based on evidential reasoning, the limitation of this approach is that it selects superior stocks at the suitable trading time mostly based on historical data, technical analysis indicators, and trading rules. According to the related works mentioned above, most research is only concerned with quantitative factors, such as index values, technical indicators, financial factors and volume behaviors based on historical data. In addition, these models have not been considered concurrently uncertain values including market conditions, quantitative and qualitative stock-market factors, together with experts' feelings and preferences about trading decisions. This affects the capability of an investment system to deal with various market conditions.

This paper presents a framework using Hybrid Intelligent DSS including three proposed models (Hybrid SOM-AHP, Hybrid *Kansei*-SOM, Hybrid *Kansei*-risk SOM) for the selection of multiple alternatives under uncertainty in the domain of stock trading. This framework which uses qualitative and quantitative attributes of alternatives, together with expert sensibilities under uncertain market conditions, aims to find out a short list of appropriate alternatives (companies, company groups, and stocks) for investment. In terms of stock selection in real-world trading, the advantages in this study include addressing these issues as follows: (1) To enhance capability for investment returns of the proposed framework, this uses uncertain values consisting of quantitative and qualitative factors to evaluate companies for investment; (2) To select appropriate companies in trading decisions, the quantification of expert sensibilities and impressions about stock trading in market conditions allows the proposed model to determine the potential companies (superior stocks) at the right time for stock trading; To confirm these models' performance, we have selected Vietnam and US stock markets, representing economically developing and developed countries. The proposed system was tested and performed well in daily stock trading on the HOSE, HNX (Vietnam), NYSE and NASDAQ (US) stock markets through case studies and compared with the new approach using Rule-base Evidential Reasoning [39], using similar data sets under the same conditions.

The remainder of this paper is organized as follows. Research backgrounds and problems are mainly discussed in Section 2. Section 3 presents a framework using Hybrid Intelligent DSS for selection of alternatives under uncertainty and risk. The data collection in experiments for data process are mainly described in Section 4. Experimental results through case studies of the trading system are demonstrated in Section 5. The evaluation shows the experiment results of the models in comparison under the same data sets and conditions of stock markets to validate the proposed methods in this framework, as demonstrated in Section 6. Finally, Section 7 concludes this paper.

2. **Research Backgrounds.** According to Gass [3, 9], the problem of decision is the selection from competing alternative solutions. A Group Decision Support System (GDSS) can be a key strategic combination in group interaction and decision making through expert preferences [7, 38]. Group decision makers may dynamically change their decision preferences during the group decision-making process in terms of alternative selection. Dynamic problems involve risks that may occur with uncertain timing. This applies to application domains such as dynamic markets, stock markets, and financial investment markets. In stock trading, there are many complex situations in various domains by dealing with dynamic decision problems. Furthermore, investors may face uncertain conditions in dynamic stock market environments, such as government policies, bank interest rate changes, world stock market prices, financial rule changes and real-time stock trading trends [5]. To select alternatives in market dynamics, decision makers have faced uncertain market conditions and risky decisions.

In multiple decision making processes, Group Decision Making (GDM) can be applied to coordinate decision making in individuals in order to solve complex business problems [30, 38]. Decision makers can share their ideas and learn how previous decisions have been made. In other words, GDSS can be used in solving problems for decision makers with multiple criteria. In the study, DSS models are integrated with a Self-Organizing Map (SOM), using Decision Making or GDM for optimal alternative selection under uncertainty and risk.

In general, a clustering algorithm is a division of data into groups of similar objects. There are a number of clustering methods for visualizing various data sets, such as K-means, Partitioning Around Medoids (PAM), Support Vector Machine (SVM), evolutionary, hierarchical clustering, and partitioning algorithms [10]. These algorithms have some limitations in complex data sets and integration of expert knowledge during the modeling process. The advantage of SOM is data mapping which is easily interpreted. In addition, a SOM is capable of organizing large and complex data sets [2]. However, the disadvantages of SOM are that it is difficult to determine what input weights to use mapping in divided clusters. Uncertain values, market conditions and expert preferences are difficult to aggregate in a conventional SOM model.

In DSS techniques, Professor Thomas Saaty set out to develop a mathematically-based technique for analyzing complex situations which was sophisticated in its simplicity [9, 11]. Analytic Hierarchical Process (AHP) was developed in the 1970s and a technique for organizing the information and judgments was used in making decisions. This technique became known as the AHP and has become very successful in helping decision makers to structure and analyze a wide range of problems.

2.1. ***Kansei* evaluation.** *Kansei* Engineering (KE) [17, 18] has been developed as a methodology to deal with human feelings, demands, and impressions of business applications. *Kansei* is a Japanese term meaning sensibility, impression, and emotion [8, 22]. In trading stocks, *Kansei* Evaluation makes it possible to quantify investor perception, sensation, cognition, and sentiment about trading actions such as buying-selling decisions and investment risk events. In *Kansei* Evaluation, we have determined adjective pairs called *Kansei* words: Synonym – Antonym, Synonym – Not Synonym. For instance, the pairs of adjectives *good – bad* and *successful – unsuccessful* are *Kansei* words. These *Kansei* words are influenced by the hierarchical factor structure [26, 27]. To evaluate companies in terms of stock trading evaluation and investment risk, *Kansei* evaluation is used to quantify expert sensibilities under uncertain market conditions.

Let $X^S = \{X_1^S, X_2^S, \ldots, X_m^S\}$ be a set of *Kansei* words which are used to evaluate companies, where m is the number of *Kansei* words. In order to quantify investor's sensibilities in stock trading, we have refined the most important *Kansei* words in X^S to evaluate a company with respect to criteria and stock market factors in stock market S.

Let $W_m^S = \{W_m^-, W_m^+\}$ be opposite pairs of *Kansei* words with respect to X_m^S. Suppose that P senior investors collect their preferences by surveys. To evaluate company C_j^S, its *Kansei* weight w_{ij}^t represents the i-th *Kansei* word of the j-th company evaluated by the t-th investor.

2.2. **Fuzzy logic and fuzzy reasoning.** Fuzzy logic is defined as fuzzy set-based methods for approximate reasoning under uncertainty, a subtopic of Artificial Intelligence (AI). In particular, Fuzzy logic is to represent expert knowledge in a rule-based style that reflects this knowledge [14, 15]. Fuzzy reasoning [13] enables approximate human reasoning capabilities to be applied to knowledge-based systems. After the first introduction of the fuzzy sets and fuzzy logic [14, 15], the idea of the reasoning was introduced by L. A. Zadeh [16].

In this study, linguistic expressions can be used to represent rules for expert decision situations and uncertain market conditions are represented in fuzzy rules. Common Sense Human Reasoning [8, 28] can be presented as an integration of fuzzy reasoning and rules, quantitative knowledge and reasoning evidence.

2.3. **Data sets for matrices construction.** The purpose of *Kansei* stock matrix construction is to quantify *Kansei*, stock-market data sets, together with expert preferences for evaluation of companies, representing in fuzzy weight values $[0, 1]$. There are three matrices which have been constructed for the framework.

To evaluate a company based on quantitative stock-market factors, quantitative factors consist of financial weights obtained from a stock market to normalize these weights in fuzzy weight values $[0, 1]$. For getting quantitative factor weights of each company from a real-time stock market, we apply a Sigmoid function [28] to normalizing quantitative factors, supported for experts to evaluate a company.

Let $B^S = \{B_1^S, B_2^S, \ldots, B_h^S\}$ be a set of group companies in stock market S, where h is the number of group companies. Let $C^S = \{C_1^S, C_2^S, \ldots, C_n^S\}$ be a set of companies in stock market S, where n is the number of companies in stock market S. $C_i^S \in B_j^S$ and C_i^S represents the i-th company belonging to the j-th company group in the same industry.

Let $f^S = \{f_1^S, f_2^S, \ldots, f_l^S\}$ be a set of qualitative factors in stock market S, where l is the number of qualitative factors. Factor f_j^S is evaluated by expert preference so that each factor has a different significant factor degree.

Let $B^R = \{B^R_1, B^R_2, \ldots, B^R_p\}$ be a set of potential group companies for investment, where p is the numbers of potential group companies in system result R. Let $G^R = \{G^R_1, G^R_2, \ldots, G^R_k\}$ be a set of risk group companies for risky investment, where k is the numbers of risky group companies in system result R.

$\{K^S_{n\times m} | (i = 1, \ldots, n, j = 1, \ldots, m)\}$ is a *Kansei* matrix construction, where n and m is the number of companies and *Kansei* words respectively.

$\{Q^S_{n\times g} | (i = 1, \ldots, n, j = 1, \ldots, g)\}$ is a Quantitative-qualitative matrix of stock market S, where n is the number of companies and g is the number of quantitative and qualitative factors. A Quantitative-qualitative stock matrix $Q^S_{n\times p}$ is constructed, representing in membership weight values $[0, 1]$ for the results of qualitative and quantitative factor quantification of company assessments.

$\{M^S_{n\times p} | (i = 1, \ldots, n, j = 1, \ldots, p)\}$ is a *Kansei* stock matrix of stock market S, where n is the number of companies and p is the number of *Kansei* words, qualitative factors, and quantitative factors. A *Kansei* stock matrix $M^S_{n\times p}$ is constructed, representing in fuzzy weight values $[0, 1]$ for the results of *Kansei* evaluation and company assessments.

$\{p^S_t (t = 1, \ldots, c)\}$ is a set of stock trading strategies and Decision matrix $\{A^S_{q\times k} | (i = 1, \ldots, q, j = 1, \ldots, k)\}$ represents expert decisions about stock trading in stock market S.

An expert provides his/her preference β^S_i. Further more, an expert may evaluate stocks in terms of investment risks based on his/her preference γ^S_i. Both β^S_i and γ^S_i can be defined in a five-point scale (0: *oppose*, 0.25: *almost oppose*, 0.5: *have no preference*, 0.75: *almost agree*, 1: *agree*). An expert decision matrix $A^S_{q\times k}$ is constructed and risk decision matrix $R^S_{q\times v}$ is the similar decision matrix manner.

A *Kansei* stock matrix $M^S_{n\times p}$ is constructed by joining *Kansei* matrix $K^S_{n\times m}$ and Quantitative-qualitative matrix $Q^S_{n\times g}$ with the Decision matrix $A^S_{q\times k}$, where n is the number of companies, $k = m+g$ is the total number of dimensions (*Kansei* words, quantitative and qualitative factors) and $p = t + n$ is the total number of dimensions (companies and experts). The constructed matrices are shown in Figure 1.

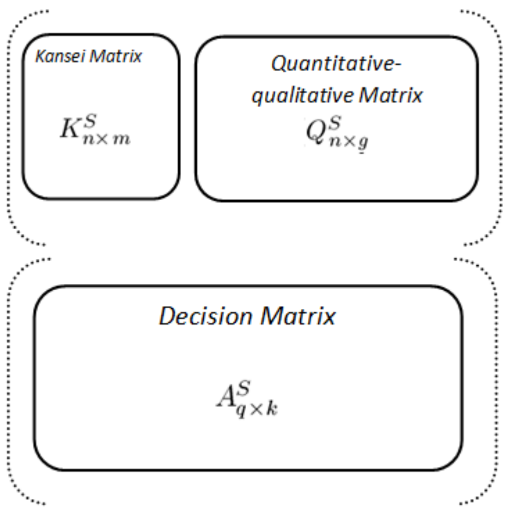


FIGURE 1. Construction of *Kansei* stock matrix

3. Hybrid Intelligent DSS for Selection of Alternatives under Uncertainty and Risk.

3.1. Framework for selection of alternatives under uncertainty and risk. We propose a framework for the selection of multiple alternatives (companies, stocks, and company groups) under uncertain market conditions and risky decisions. This framework aims to optimize trading decisions in the selection of multiple alternatives and reduce risky decisions for investment. Figure 2 shows the proposed framework consisting of three integrated intelligent DSS, for selection of alternatives from a large number of alternatives by aggregating either individual or multiple expert decisions, aiming for optimizing trading decisions and reducing risky decisions.

This framework consisting of its components is described as follows:

- **Data Model**: The data model includes quantitative and qualitative stock-market factors, uncertain market conditions and expert preferences and sensibilities. The data model of stock market investments is used to apply various market conditions on stock markets such as HOSE, HNX, NYSE and NASDAQ.
- **DSS Database**: The database consists of *Kansei* data sets which respond from investors and experts based on their preferences. In a stock market environment, quantitative and qualitative factors obtained from a stock market are evaluated by decision makers. Most processes of training data sets and fuzzy rules are executed in the DSS database.

3.2. Framework for selection of alternatives by steps. The proposed framework is shown in Figure 2 for the selection of stock in trading decisions. This framework uses uncertain values of quantitative and qualitative factors, together with the quantification of expert sensibilities and preferences in uncertain environments. These weights can be

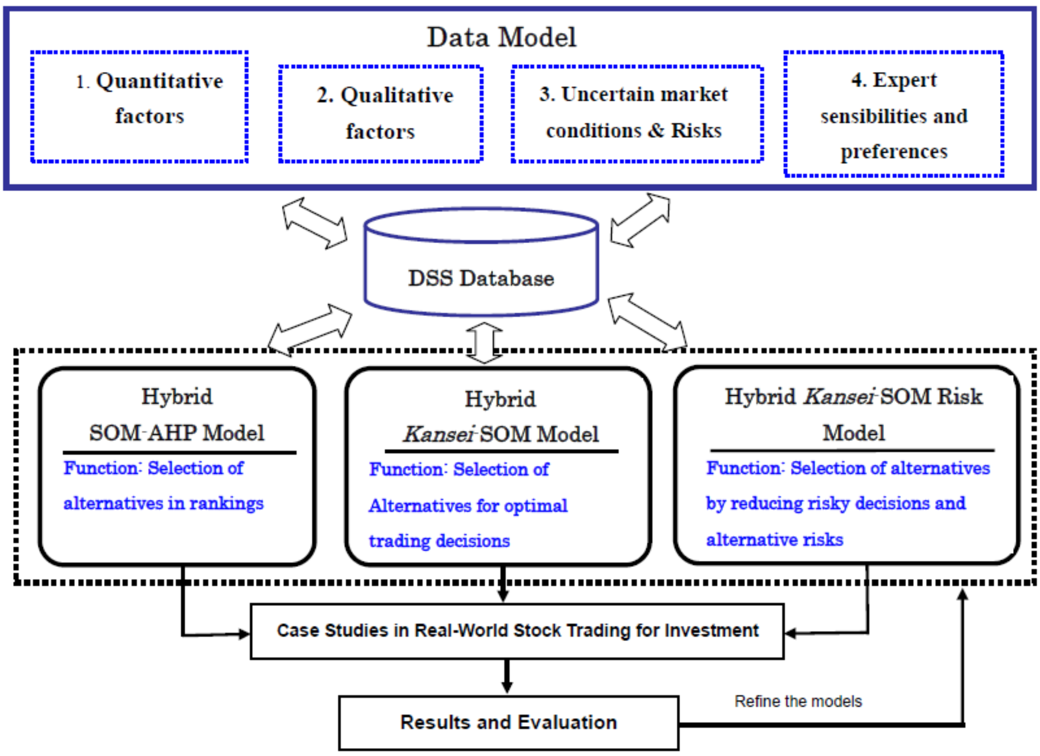


FIGURE 2. Framework for selection of alternatives in stock market investments

transformed through for the framework, represented in interval values $[0,1]$. These data sets, including *Kansei* and stock-market data sets, are updated in the DSS database.

Step 1. Hybrid SOM-AHP Model is to rank a short list of companies for investment

The first model, called the Hybrid SOM-AHP model, is a Self-Organizing Map (SOM) integrated with Analytic Hierarchy Process (AHP). This model using an individual expert aims to select short-list investment alternatives in rankings for stock trading. Stock market factors including qualitative and quantitative factors are structured in the hierarchical model. Additionally, these factors are also placed in Quantitative-qualitative matrix $Q^S_{n\times g}$.

Step 1.1. Alternative attribute distance definition. To calculate differences among *Kansei* stock attributes of companies, the *Kansei* stock distance $d^S_{C_i\to C_j}$ between two vectors $D^S_{C_i}$ and $D^S_{C_j}$ represents attributes of companies C^S_i and C^S_j respectively, as defined by Euclidean distance given by Equation (1).

$$d^S_{C_i\to C_j} = \| D^S_{C_i} - D^S_{C_j} \| \tag{1}$$

Step 1.2. Finding appropriate companies for investment by SOM training. A stock matrix $Q^S_{n\times g}$ is visualised by SOM to find similar features of stocks in terms of hight financial weights, considered by an expert. These group results in a SOM map are shown in a short list of companies for investment.

Step 1.3. Evaluating short-list companies for investment using Analytic Hierarchy Process (AHP). To rank the alternatives in the short-list companies, these alternatives are used in AHP model to evaluate the companies for investment by checking consistency ratios (CR), where RI is the random index and CI is the consistency index. Decision makers input data sets in the judgment matrix if CR is less than 0.1. The AHP results are appropriate companies in short-list rankings for investment.

Step 2. Hybrid Kansei-SOM model for selection of companies matching with trading strategies

Step 2.1. Expert preference distance definition. Expert preference distance $d^S_{e_i\to e_j}$ between two vectors $D^S_{e_i}$ and $D^S_{e_j}$ represents expert preferences, as defined by Euclidean distance given by Equation (2).

$$d^S_{e_i\to e_j} = \| D^S_{e_i} - D^S_{e_j} \| \tag{2}$$

Step 2.2. Visualizing *Kansei* stock matrix by SOM. The *Kansei* stock matrix $M^S_{n\times p}$ is visualized by SOM in order to find the similar attributes of companies by aggregating expert preferences, matching with appropriate trading strategies.

Step 2.3. Calculating *Kansei* stock weights by identifying distances between expert and the average of expert group. The distance between expert and the average of expert group x^t_{ij} at iteration t of each group is expressed by Equation (3).

$$x^t_{ij} = \frac{1}{K}\sum_{\xi=1}^{K} w^t_{\xi j} - v^t_{ij} \tag{3}$$

where

x^t_{ij} represents a member of expert decision matrix.

$w^t_{\xi j}$ represents the *Kansei* stock weight of the ξ-th expert preference for the j-th *Kansei* word, or quantitative and qualitative factor, in order to calculate the distances between expert preference and other member preference within his/her group.

v^t_{ij} represents the *Kansei* stock weight of the i-th expert preference for the j-th *Kansei* word, or quantitative and qualitative factor, which is a member of both the *Kansei* stock matrix and expert decision matrix.

K is the number of experts in the group; $(j = 1, \dots, p)$ and p is the number of *Kansei* words, or quantitative and qualitative factors.

Step 2.4. Updating *Kansei* stock weights of an expert decision matrix. An expert decision matrix $A^S_{q\times k}$ is updated by its weights given by Equation (4). After that, the expert decision matrix $A^S_{q\times k}$ is joined with *Kansei* stock matrix $M^S_{n\times p}$ and its weights are updated to $M^S_{n\times p}$.

$$v^{t+1}_{ij} = v^t_{ij} + v^t_{ij}x^t_{ij} \tag{4}$$

where K is the number of experts in each group. To select trading strategies $(p^S_1, p^S_2, \dots, p^S_c)$, $K \in [1, \dots, c]$ is the number of experts in each group, representing in its trading strategy.

To aggregate multiple expert trading decisions, the similar steps are repeated between Step 2.2 and Step 2.4 until c expert groups are updating weights to the expert decision matrix completely in training process.

Step 3. Hybrid *Kansei* SOM risk model for selection of companies under risk

Step 3.1. Alternative risk attribute distance definition. To calculate differences among *Kansei* risk attributes of companies, the *Kansei* risk distance $d^R_{C_i\to C_j}$ between two vectors $D^R_{C_i}$ and $D^R_{C_j}$ also represents attributes of companies C^R_i and C^R_j in terms of investment risks respectively as defined by Euclidean distance given by Equation (5).

$$d^R_{C_i\to C_j} = \| D^R_{C_i} - D^R_{C_j} \| \tag{5}$$

Step 3.2. Visualizing *Kansei* risk matrix by SOM. The *Kansei* risk matrix $Q^S_{n\times p}$ is visualized by SOM in order to find the similar attributes of companies by aggregating expert preferences in terms of investment risks.

To eliminate risky stocks, we apply similar steps to calculate *Kansei* risk weight among expert preferences, as given by Equation (3) from Steps 2.3 to 2.4. These alternatives are clustered in groups, occurred by risky decisions.

Step 3.3. Comparison of the results by SOM visualization. After the *Kansei* stock and *Kansei* risk matrices are visualized by SOM, these SOM results are showed on a map. Assume that B^R_i and Γ^R_i are appropriate company groups in SOM results of *Kansei* stock matrix and *Kansei* risk matrix, respectively visualized by SOM. The final result on a map of the proposed system is determined by the following conditions.

IF $C^S_j \subseteq B^R_i$ AND $C^S_j \nsubseteq \Gamma^R_i$ **THEN**
C^S_j is a potential company (superior stock) for investment
ELSE C^S_j is not a candidate.

Based on *Kansei* stock distance among expert preferences with the closest company having similar attributes, the final result on a map is shown in selected superior stocks, matching with appropriate trading strategies and eliminating risky stocks.

4. Experiments.

4. Experiments. The framework including three models (Hybrid SOM-AHP, Hybrid *Kansei*-SOM, Hybrid *Kansei*-SOM Risk) have been implemented by C++ and PHP languages for web applications. We has selected Vietnam and USA stock markets, representing economically developing and developed countries, to apply the models in this framework for stock trading. To validate the performance of this framework, these models have been tested and performed well in simulated trading and real-world stock trading by experiments in case studies on the HOSE, HNX (Vietnam) and NYSE and NASDAQ (USA) stock markets.

In case studies for stock market investments of this framework, experiments in real-world stock trading have been conducted by the experts. In this study, we planned data collection for on-line by Internet and off-line by surveys and interviews in data collection to international financial and securities companies in Hanoi, Vietnam. The experiments collected data sets with 12 experts from 8 international nationalities in the fields of economics and financial at Graduate school of Economics, Ritsumeikan University and 5 experts working at Vietcombank securities, VietinBank Securities, Maritime bank securities and other international financial companies for real-world trading and simulated trading results on the HOSE, HNX (Vietnam) and NYSE, NASDAQ (USA) stock markets from the period of March 2012 to April 2013.

In the experiments, we have conducted experiments through case studies in daily real-world stock trading on the HOSE, HNX, NYSE and NASDAQ stock markets. There was a group of three to five investors and experts participating in each trading period for making the surveys of data connection during the experiments. In the Internet online and off-line data connection, survey forms are used to collect investors/experts and surveys in the experiments using a five-point scale definition (0: *oppose*, 0.25: *almost oppose*, 0.5: *have no preference*, 0.75: *almost agree*, 1: *agree*). Interviews for experts are considered in market conditions that use fuzzy rules present these conditions in the framework. After collecting data sets from experts and investors, we have conducted the experiments of these models (Hybrid SOM-AHP, Hybrid *Kansei*-SOM, Hybrid *Kansei*-SOM Risk) using virtual trading systems. The results of stock selections in experiments have set feedbacks to experts and investors. Feedbacks of expert and investors are good for improvement of these models' performance.

In the preliminary experiment, the surveys were done by 12 investors with 8 companies for the HOSE (Vietnam) stock market. We have collected 36 *Kansei* words and 23 significant stock-market factors [26, 27]. In a stock factor structure, the AHP model as the hierarchy model is constructed by decomposing a problem in the hierarchy of elements in levels: objectives, criteria, sub criteria and alternatives. To study global stock markets in Japan, Vietnam, Australia and the USA, we have constructed the AHP model with the factors' hierarchy structure consisting of 23 significant stock-market factors influencing in a company evaluation. These factors have been used to construct a stock matrix for Hybrid SOM-AHP model. The first level has four criteria (*company assessments, financial ratios, technical indicators, investment risks*). In the second level, company assessment criteria have 5 significant factors (*structure and management system, organization, planning strategy, brand name, period evaluation*) evaluated with 11 *Kansei* words. Most significant factors in financial ratios consist of 7 factors (P/E (*price-to-earnings*) *ratio*, EPS (*earnings per share*), P/B (*price-to-book*) *ratio*, ROE (*return on equity*) *ratio*, ROA (*return on assets*) *ratio*, *market price*, *profit margin*) evaluated with 9 *Kansei* words. In technical analysis, technical indicators include 5 significant factors (*stochastic oscillator, moving average convergence, moving average divergence, relative strength index* (RSI), *a moving average weight*) that are strongly related to market price, trading volume and historical statistic data. There are 10 *Kansei* words, based on investors' feelings, to evaluate the technical indicators. For instance, investment risks consists of 6 factors (*input price risk, economic risk, equity risk, interest rate risk, political risk, financial risk*) that use 6 *Kansei* words in an evaluation such as Popular-Unpopular, Confirmed-Unconfirmed, Determined-Undetermined, Failed-Not failed, Certain-Uncertain, and Safe-Risky.

In terms of risk management for an evaluation, *Kansei* words are relevant to investment risks criteria such as company assessments, stock market risks, and environment risks that affect to evaluate companies. We have collected 20 *Kansei* words and 14 significant stock-market factors, influencing 3 criteria for company evaluation on a stock market in terms of risk management [28, 29].

4.1. **Application of hybrid SOM-AHP model in case studies of real-world stock trading.** Mechanisms of Hybrid SOM-AHP model are from Steps 1.1 to 1.3, as described in Section 3.2. Experiments of the proposed model have been done by expert in financial and economy at Ritsumeikan University on the HOSE and HNX stock markets from June to October 2012, and carried out by the the expert with data collection in surveys of experts from Agri-Bank and Vietcombank securities companies within five stages in this system: (1) real-world stock data sets obtained from a stock market are evaluated by expert in order to construct a stock matrix; (2) the quantitative-qualitative matrix is visualized by SOM training and screens out the company groups from among hundreds of companies for investment; (3) the potential companies (superior stocks) are identified based on financial factor weights in decision making results; (4) AHP is applied to select the companies in rankings for investment; (5) appropriate actions (buying, selling and holding) are determined by expert decisions, based on market conditions.

4.2. **Application of hybrid *Kansei*-SOM model in case studies of real-world stock trading.** Mechanisms of Hybrid *Kansei*-SOM model is from Steps 2.1 to 2.3, as described in Section 3.2. Here is one of the experiments on the NYSE and NASDAQ stock markets in the year of 2012, being carried out by investors and experts from Agri-Bank and Hanoi-Saigon securities' companies within four stages in this system: (1) real-world stock data sets obtained from a stock market are evaluated by experts' preferences in order to construct a *Kansei* stock matrix; (2) the *Kansei* stock matrix is visualized by SOM training and screens out the potential companies (superior stocks) from among hundreds of companies for investment; (3) the potential companies (superior stocks) are matched with appropriate trading strategies for investment; (4) appropriate actions (buying, selling and holding) are determined by expert preferences, based on *Kansei* evaluation in market conditions. The experiments through case studies are applied to real-world stock trading using the Group Decision Support System (GDSS) for investment.

4.3. **Application of hybrid *Kansei* SOM risk model by aggregating expert decisions and reducing risky decisions.** Mechanisms of Hybrid SOM-AHP model are from Steps 3.1 to 3.3, as described in Section 3.2. A Hybrid *Kansei* SOM risk model is an extendable model of risk management, based on the Hybrid *Kansei* SOM model. Risk management is applied in the Hybrid *Kansei* SOM model, aiming to reduce risky decisions and stock risks. The proposed system was tested by expert working at financial and economics over 600 companies on the NYSE stock markets and 5 experts for stock trading in the period from May to October 2012. The experiment was carried out by experts from Ritsumeikan University, VietcomBank and international securities companies. To begin this experiment, experts loaded data sets and determined appropriate companies for investment. Factors of a stock market and pairs of *Kansei* words are used in the *Kansei* stock matrix that represents 37 dimensions (*Kansei* words, quantitative and qualitative factors) for evaluation of 160 companies. To evaluate companies in terms of investment risks, investment risk factors and pairs of *Kansei* words are used in the *Kansei* risk matrix that represents 28 dimensions (*Kansei* words and stock-market risk factors) for evaluation of 160 companies. *Kansei* data sets and company attributes of the companies were input to this system. After SOM training, the map showed a group of companies, as shown in Figure 3.

The final result showed the *Kansei* stock distances among the appropriate companies in a group on the map. The expert selected the closest companies by reducing the maximum *Kansei* stock distance of the companies and eliminating those that have a distance greater than the selected threshold. The expert selected the map results based on the map of

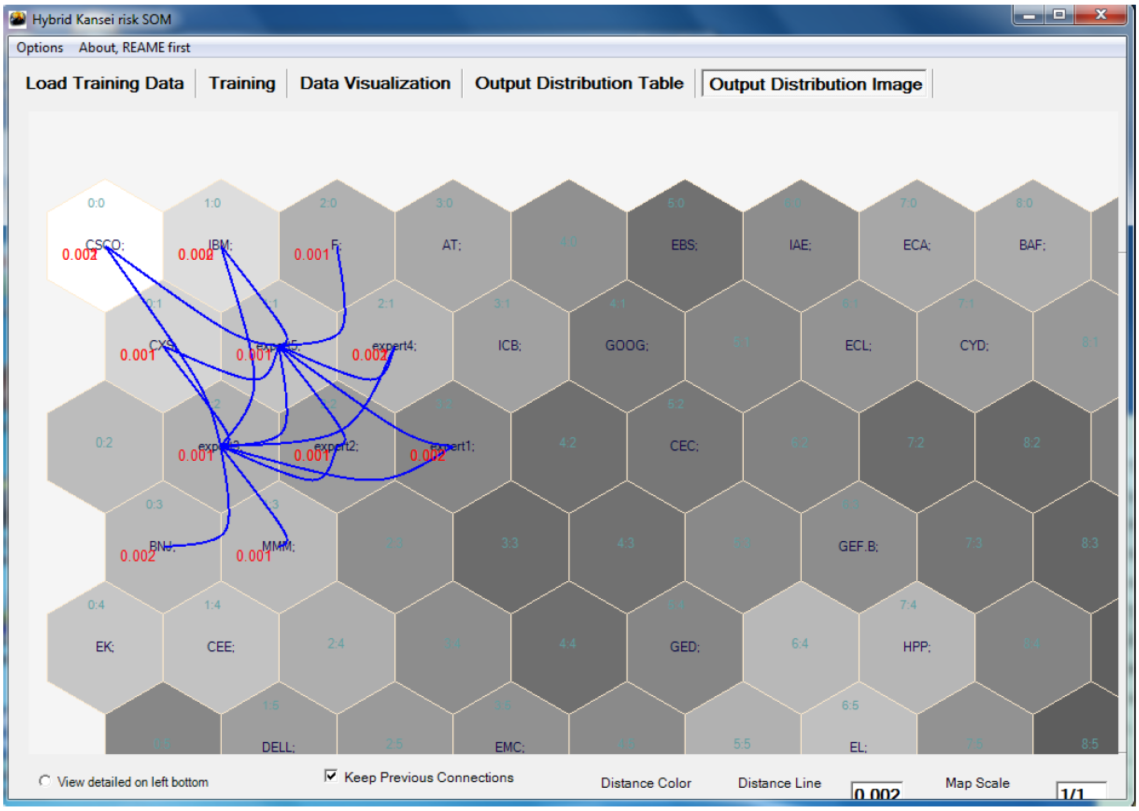
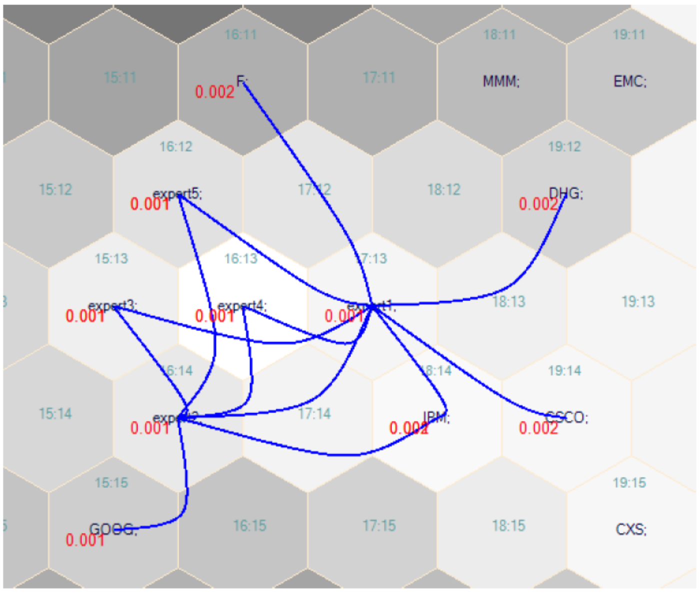


FIGURE 3. The results of companies for investment evaluated by experts

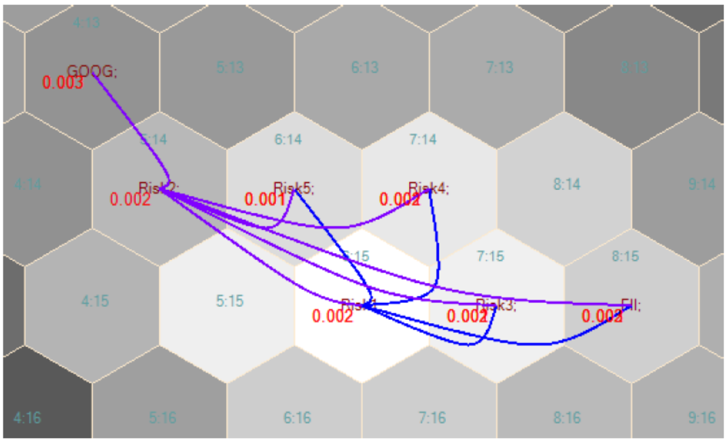
Figure 3. For the next step, the expert decided to select companies (CSCO, GOOG, DHG, F and IBM) for investment, as shown in Figure 4(a).

In the proposed system, the *Kansei* risk matrix was also visualized by SOM as shown in the map of Figure 4(b); the final result showed the closest risky stocks based on *Kansei* risk distances, selected by expert preferences. The system recommends the companies (GOOG and FII) eliminated from a list of investment companies. Compared with the list for investment, the superior stocks (CSCO, DHG, F and IBM) were selected for stock trading. These stocks were invested from the period of June to October 2012 using a virtual stock trading system. To determine trading actions (selling or holding), expert sensibilities considered using *Kansei* evaluation in stock trading, together with specific market conditions during the period. The profits of these stocks were estimated at 10%, 9%, 11% and 9%, for CSCO, DHG, F and IBM respectively when calculated for investment returns.

5. **Result and Discussions in Three Models.** In order to evaluate the effectiveness of the proposed models for stock trading, a proposed model investment performance in winning stocks is calculated from the average of ratings between profits and losses for the successful investment companies based on trading signals on the stock markets. To evaluate the capability of the proposed system by making profits on the HOSE, HNX, NYSE and NASDAQ, we have calculated the average profits that would be applied by trading stocks from the period of March 2012 to April 2013. Experimental results were calculated by experts in real-world stock trading. These proposed models have been tested in real-world stock trading with multiple expert preferences objectively who are currently working at Vietinbank and Maritime-bank securities, and Graduate School of Economics, Ritsumeikan university from various nationalities. In three trading models, experimental



(a) The map result of appropriate companies (superior stocks)



(b) The map result of risky stocks

FIGURE 4. The final results on SOM maps

results also demonstrate that the proposed models are able to provide accurate stock selection at the right time for trading to yield higher profits.

In the experiments, we have also conducted tests and experiments in comparisons with separated DSS methods and the latest stock trading system. In experiments, decision makers use SPICE SOM [41] which is SOM model for testing data sets when compared with the other models. In result discussions, these models using Hybrid Intelligent DSS are used to select appropriate alternatives at the right trading time for investment. The first model, called the Hybrid SOM-AHP model, is a Self-Organizing Map (SOM) integrated with Analytic Hierarchy Process (AHP). This model aims to select short-list investment alternatives in rankings for stock trading. In experimental results, quantitative and qualitative stock-market factors are visualized by SOM, in order to find grouping companies for investment. Based on the high financial weight results of decision making in appropriate grouping companies, AHP is used to select the best alternatives in rankings for investment. The investment system is estimated only at 68-70% in an overall evaluation. The profit average percent was estimated from 7-8% with high risks (30-32% unsuccessful investment companies). In comparison of Hybrid SOM-AHP model and SOM model [41] for simulated results, the results of real-world stock trading and simulated stock trading show proportion of successful investment companies of the Hybrid SOM-AHP model and SOM model are from 68% to 70%, and from 53% to 58%, respectively on the NYSE and NASDAQ, from the period of May to March 2013. Experimental results show that the model has limited functions when dealing with market dynamics, affected directly to stock prices of companies on the stock markets.

In various market dynamics, trading results were calculated from experts, performed in real-world stock trading on the HOSE, HNX, NYSE and NASDAQ. The second model, called the Hybrid *Kansei*-SOM model, is integrated by SOM with *Kansei* evaluation for optimized trading decisions and selected alternatives with trading strategies. This model is used to quantify qualitative and quantitative attributes of alternatives, together with expert preferences and sensibilities under uncertain market dynamics for selection of alternatives at the right time in stock trading. In terms of winning stocks (successful investment companies), average investment performance of the proposed model has been calculated at about 88% with 10% profits, using a Mixed investment strategy on the NYSE and NASDAQ. Furthermore, it reached 91% with 12% profits and 92% with 11% profits using Short-term investment and Long-term investment strategies, respectively. The experimental results consistently show that the proposed approach using GDSS yielded successful investment companies, from 10% to 12% in terms of profits. In addition, average profits in expert trading results on the HOSE and HNX are estimated higher than 5% trading profits on the NYSE and NASDAQ. Regarding the experimental results of expert feedbacks, short-term investment was an appropriate trading strategy on the HOSE and HNX.

In the third model, Hybrid *Kansei*-SOM Risk model aims to reduce risky decisions and alternative risks under uncertain conditions. Risk management, including investment risk factors and *Kansei*-risk words is used to identify stock risks and reduce risky trading decisions. The results show proportion of winning stocks in the model are the highest (94%) with 15% profits on the the HOSE, HNX and (96%) with 11% profits on the NYSE, and NASDAQ. Compared with Hybrid *Kansei*-SOM model performance, the Hybrid *Kansei*-SOM Risk model performance reduced risky stocks from 3% to 5% better than Hybrid *Kansei*-SOM model performance. It is evident that winning trades and losses of the proposed model are better than those of Hybrid *Kansei*-SOM model.

6. **Evaluation of proposed models.** In case studies of selection for stock trading, we have investigated how these models perform with respect to various market conditions. In this study, the processes of data collection for experiments is shown in Figure 5.

Recently, the new method using Rule-based Evidential Reasoning approach (RER) [39] is concerned with the synthesis of the fuzzy logics and Dempster-Shafer theory and presented in stock trading naturally based on evident reasoning and tested on an actual stock market. Although this approach has been recently shown in an expert stock trading system based on evidential reasoning, the limitation of this approach is that it selects superior stocks at the suitable trading time mostly based on historical data, technical analysis indicators, and trading rules. In particular, we have employed and tested this approach using Wealth-lab Developer 5 software in daily stock trading with various stock market conditions. The experimental results show that the success of a trading system performance relies on overall up-trending signals of stock indices and technical indicators. The Hybrid *Kansei*-SOM model (HKS), Hybrid *Kansei* risk-SOM model (HKRS), and Rule-based Evidential Reasoning model (RER) have been tested in real-world stock trading under the same market conditions and data sets. To evaluate capability for investment returns of the proposed system, there are 7 experts from May to October 2012 and 3 experts from October 2012 to April 2013, running in experiments for these trading results objectively under the same market conditions and data sets, as calculated in the average profits that would be made by these trading stocks. Stock market investment outcomes must be accounted for when calculating investment returns in various stock market conditions. The proposed system has been performed well in daily real-world stock trading for investment on the HOSE and HNX (Vietnam), NYSE, and NASDAQ (US) stock markets, as shown in the experimental results in Table 1.

As observed from Table 1, the percentages of profits in the HKS, HKRS and RER are 10-12%, 11-13% and 6.5-7.5% respectively, as calculated by seven experts performed objectively on the NYSE and NASDAQ. On the HOSE, HNX, NYSE and NASDAQ, the average profit percents of the HKS, HKRS are higher than RER about 3-4%. Compared with HKS and RER, the HKRS model has the highest investment performance (11-13%) with winning stocks (successful investment companies 91%). It indicates that the HKRS provides a better profit percentage than those of the HKS and RER.

In further experiments, there are 12 experts from Ritsumeikan University, Maritime bank, Vietinbank, Vietcombank, and other financial-securities companies conducted in the experiments and interviews for identifying market conditions. Average winning stocks in real-world trading result done by these experts objectively on the NYSE and NASDAQ from May to October 2012 are shown in Figure 6.

The experimental results show that percentages of winning stocks in the proposed approach are mostly evaluated by four expert groups for real-world stock trading on US stock markets. The results consistently show that the HKS and HKRS models using yielded successful profits with winning stocks (85-91%), which was higher than that of RER on the NYSE and NASDAQ.

In further experiments, the experimental data consists of 6 months for simulated trading stocks based on real-time data sets obtained from Yahoo Inc Stock Prices and Market Watch Online on the NYSE and NASDAQ from the period of January to June 2012. When

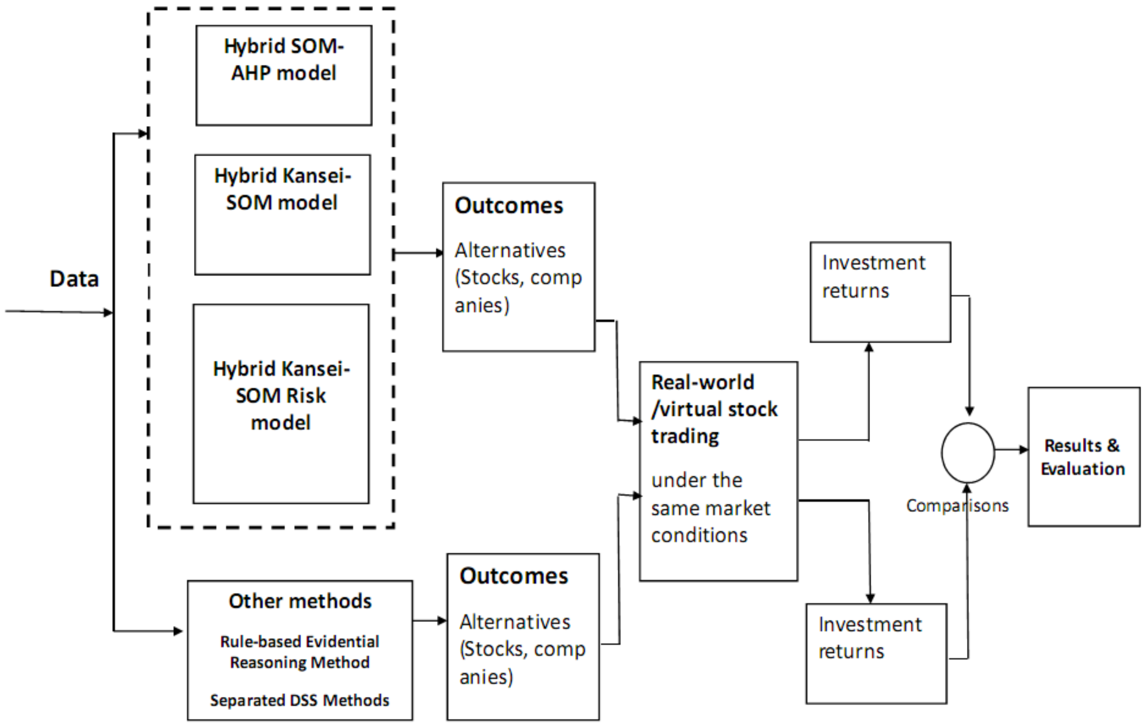


FIGURE 5. Models in evaluation

TABLE 1. Experimental results on the HOSE, HNX, NYSE and NASDAQ

Models	**The HOSE and HNX**		**The NYSE and NASDAQ**	
	Avg.% Profits	Avg.% winning stocks	Avg.% Profits	Avg.% winning stocks
Hybrid *Kansei* SOM (HKS)	10-12%	From May to October 2012: 80%	10-11%	From May to October 2012: 85%
	11-12%	From October 2012 to April 2013: 81%	10.5-11%	From October 2012 to April 2013: 84.5%
Hybrid *Kansei* -Risk SOM (HKRS)	11-13%	From May to October 2012: 90%	10.5-12%	From May to October 2012: 91%
	12-13%	From October 2012 to April 2013: 91%	10-12%	From October 2012 to April 2013: 92%
Rule-based Evidential Reasoning approach (RER)	7-8%	From May to October 2012: 70%	6.5-7.5%	From May to October 2012: 75%
	7-9%	From October 2012 to April 2013: 70%	6-7.5%	From October 2012 to April 2013: 75%

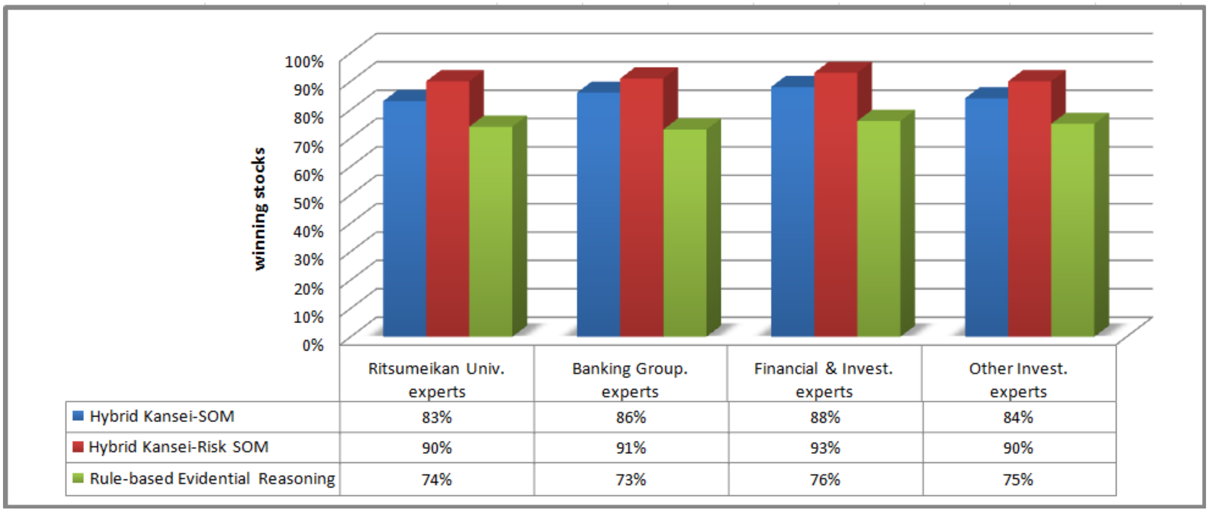


FIGURE 6. Winning stocks in trading results by multiple experts

investing in similar stocks, experts carried out simulated stock trading objectively and showed average winning stocks of these models through experimental simulated trading results as summarized in Table 2.

In terms of winning stocks (successful investment companies), average successful investment companies of the HKRS have been calculated at 92.5% with the highest selected stocks in making profits, done by seven experts in simulated trading results with the same market conditions and data sets. Additionally, it reached 81.4% and 72% winning stocks applied by HKS and RER, respectively. The experimental results consistently show that the HKRS and HKS yielded successful investment companies, was higher than that of RER. In further testing experiments of the proposed models (HKRS and HKS), the estimation results are also achieved through expert feedbacks and experiments show that the

TABLE 2. Evaluation of simulated stock trading results

Models	**Hybrid *Kansei*-SOM (HKS)**		**Hybrid *Kansei* Risk-SOM (HKRS)**		**Rule-based Evidential Reasoning approach (RER)**	
	Expert name	Avg.% winning stocks	Expert name	Avg.% winning stocks	Expert name	Avg.% winning stocks
	BAYU	7/9 (77%)	BAYU	8/9 (85%)		
	DANNIAR	8/10 (80%)	DANNIAR	9/10 (90%)		
	LINH	5/6 (83%)	LINH	6/6 (100%)		
	MAFUT	8/10 (80%)	MAFUT	9/10 (90%)		
	MURAT	6/7 (86%)	MURAT	7/7 (100%)		
	TUYEN	8/10 (80%)	TUYEN	9/10 (90%)		
	CUONG	6/7 (86%)	CUONG	7/7 (100%)	CUONG	5/7 (71%)
	DIEP	8/10 (80%)	DIEP	9/10 (90%)	DIEP	7/10 (70%)
	NG. HA	9/11 (81%)	NG. HA	10/11 (91%)	NG. HA	8/11 (73%)
	NGOC	10/12 (83%)	NGOC	10/12 (92%)	NGOC	9/12 (75%)
	THANG	8/10 (80%)	THANG	9/10 (90%)	THANG	7/10 (70%)
Avg.% Winning stocks in total	**81.4%**		**92.5%**		**72%**	
Avg.% Failed stocks for investment	**18.6%**		**7.5%**		**28%**	

proposed models perform well in real-world stock trading to deal with complex situations of dynamic stock market environments.

7. **Conclusions.** The framework including three models (HS, HKS, HKRS) is a new method for stock trading in order to enhance investment capability and the effectiveness of the stock trading investment system. This framework using *Kansei* evaluation is to quantify experts' sensibilities and preferences about stock trading with uncertain values in market dynamics, selecting companies that match appropriate stock market investment strategies for investment and reducing risky decisions. Experiments using real-world stock trading from Vietnam and United States stock markets indicate that the proposed approach obtains good investment results in term of profitability, successful investment companies, and investment performance. Regarding the overall investment outcome and performance of these models, it is consistently demonstrated that these models have performed better than its individual DSS methods and these results validated the effectiveness of these models in various stock market conditions. When applying risk management, the Hybrid-*Kansei* SOM model performance has enhanced for the the improvement of the performance and reduce risky trading decisions.

Further improvement of an individual company stock price prediction can be considered in future studies. In dynamic investments, the individual company stock price prediction is to deal with complex situations on dynamic stock market environments. To solve the problem, a new model will be integrated by *Kansei* Evaluation and SOM using updated *Kansei* stock distance weights with clustering and negotiating expert preferences that improve the effectiveness of stock trading investment systems.

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REFERENCES

[1] E. Turban, E. A. Jay and T. P. Liang, *Decision Support Systems and Intelligent Systems, Decision Support Systems: An Overview*, Addison-Wesley, 2007.

[2] T. Kohonen, *Self-Organizing and Associate Memory*, Spiringer-Verlag, 1988.

[3] P. G. W. Keen and M. S. Scott-Morton, Decision support systems, *An Organizational Perspective Reading*, 1978.

[4] B. David and K. Bentley, *All About Stock Market Strategies*, McGraw-Hill Professional, 2008.

[5] M. A. Urlich, *Stock Markets, Securities and Investment Issues*, Nova Science, 2008.

[6] H. Wang, Knowledge level analysis of group decision support systems, *Expert Systems with Applications*, vol.13, no.2, pp.155-162, 1997.

[7] E. Turban, E. A. Jay and T. P. Liang, *Decision Support Systems and Intelligent Systems, Decision Support Systems: An Overview*, Addison-Wesley, 2007.

[8] M. Osman, Controlling uncertainty: A review of human behavior in complex dynamic environments, *Psychological Bulletin*, vol.136, no.1, pp.65-86, 2010.

[9] S. L. Gass, *Decision Making Model Algorithms*, John Wiley Son, 1985.

[10] O. A. Abbas, Comparisons between data clustering algorithms, *International Arab Journal of Information Technology*, vol.5, no.3, pp.320-325, 2008.

[11] T. L. Saaty, *The Analytic Hierarchy Process*, Mc. Graw. Hill., New York, 1980.

[12] Y. F. Chung, Y. L. Yu and T. C. Hsiao, A study on fuzzy decision and preferred enterprise strategy, *International Journal of Innovative Computing, Information and Control*, vol.5, no.11(A), pp.3809-3826, 2009.

[13] J. Yen and R. Langari, *Fuzzy Logic: Intelligence, Control, and Information*, Prentice Hall, Upper Saddle River, NJ, 1999.

[14] L. A. Zadeh, Fuzzy sets, *Information and Control*, vol.8, no.3, pp.338-353, 1965.

[15] L. A. Zadeh, Fuzzy algorithms, *Information and Control*, vol.12, no.2, pp.94-102, 1968.

[16] L. A. Zadeh, Outline of a new approach to the analysis of a complex system and decision processes, *IEEE Trans. on Systems, Man, and Cybernetics*, vol.3, no.1, pp.28-44, 1973.

[17] S. Nagasawa, Present state of *Kansei* engineering in Japan, *Proc. of 2004 IEEE International Conference on Systems, Man, and Cybernetics*, The Hague, The Netherlands, pp.333-338, 2004.

[18] T. Jindo and K. Hirasago, Application studies to car interior of Kansei engineering, *International Journal of Industrial Ergonomics*, vol.19, no.2, pp.105-114, 1997.

[19] Md. Z. Hasan, A. A. Kamil, A. Mustafa and Md. A. Baten, Risk-return association of Dhaka stock exchange market: A capital asset pricing model framework, *Procedia Economics and Finance*, vol.2, no.1, pp.1-8, 2012.

[20] G. G. Polak, D. F. Rogers and D. J. Sweeney, Risk management strategies via minimax portfolio optimization, *European Journal of Operational Research*, vol.207, pp.409-419, 2010.

[21] P. Wongbangpo and C. S. Sharma, Stock market and macroeconomic fundamental dynamic interactions: ASEAN-5 countries, *Journal of Asian Economics*, vol.13, no.2, pp.27-51, 2002.

[22] B. Salem, R. Nakatsu and M. Rauterberg, Kansei experience: Aesthetic, emotions and inner balance, *International Journal of Cognitive Informatics and Natural Intelligence*, vol.3, no.2, pp.56-65, 2009.

[23] S. G. Atsalakis and P. K. Valavanis, Surveying stock market forecasting techniques – Part II, *Soft Computing Methods, Expert Systems with Applications*, vol.36, no.3, pp.5932-5941, 2009.

[24] G. Caginalp and V. Ilieva, Hybrid methodology for technical analysis, *Nonlinear Analysis: Hybrid Systems*, vol.2, no.4, pp.1144-1151, 2008.

[25] P. C. Chang, C. Y. Fan and C. H. Liu, Integrating a piecewise linear representation method and a neuron network model for stock trading points prediction, *IEEE Trans. on Systems, Man, and Cybernic*, vol.39, no.1, 2009.

[26] P. V. Hai, C. Thang, I. Nakaoka, J. Kushida, E. W. Cooper and K. Kamei, Web-based DSS using SOM-AHP model for stock market investment, *Proc. of JSAHP2009*, pp.38-39, 2009.
[27] P. V. Hai, C. Thang, I. Nakaoka, E. W. Cooper and K. Kamei, A proposal of hybrid Kansei-SOM model for stock market investment, *Proc. of the 1st International Workshop on Aware Computing*, pp.638-643, 2009.
[28] H. V. Pham, E. W. Cooper, C. Thang, K. D. Tran and K. Kamei, Human reasoning awareness quantified by self-organizing map using collaborative decision making for multiple investment models, *Proc. of the 5th International Conference on Complex, Intelligent, and Software Intensive Systems, IEEE*, pp.101-108, 2011.
[29] H. V. Pham, E. W. Cooper and K. Kamei, Stochastic investment trading model for selection of companies under uncertainty in stock markets, *Proc. of the 43rd ISCIE International Symposium on Stochastic Systems Theory and Its Applications*, pp.118-119, 2011.
[30] I. Nakaoka, M. Matsumura, J. Kushida and K. Kamei, A proposal of group decision support system for Kansei commodity purchase using SOM and its applications, *International Journal of Innovative Computing, Information and Control*, vol.5, no.12(B), pp.4915-4926, 2009.
[31] X. Wang and L. Wang, Study on black-scholes option pricing model based on dynamic investment strategy, *International Journal of Innovative Computing, Information and Control*, vol.3, no.6(B), pp.1755-1780, 2007.
[32] X. Wang and L. Wang, Study on black-scholes option pricing model based on general linear investment strategy (Part I: Put option), *International Journal of Innovative Computing, Information and Control*, vol.5, no.6, pp.1765-1783, 2009.
[33] X. Wang and L. Wang, Study on black-scholes option pricing model based on general linear investment strategy (Part II: Call option), *International Journal of Innovative Computing, Information and Control*, vol.5, no.8, pp.2169-2188, 2009.
[34] Z. Hu and J. Hu, The application of HU theory to stock options, *ICIC Express Letters*, vol.4, no.2, pp.447-454, 2010.
[35] M. Fasanghari and G. A. Montazer, Design and implementation of fuzzy expert system for Tehran stock exchange portfolio recommendation, *Expert Systems with Applications*, vol.37, no.9, pp.6138-6147, 2010.
[36] R. J. Kuo, C. H. Chen and Y. C. Hwang, An intelligent stock trading decision support system through integration of genetic algorithm based fuzzy neural network and artificial neural network, *Fuzzy Sets and Systems*, vol.118, no.1, pp.21-45, 2001.
[37] Q. Wen, Z. Yang, Y. Song and P. Jia, Automatic stock decision support system based on box theory and SVM algorithm, *Expert Systems with Applications*, vol.37, no.2, pp.1015-1022, 2010.
[38] H. Wang, Knowledge level analysis of group decision support systems, *Expert Systems with Applications*, vol.13, no.2, pp.155-162, 1997.
[39] L. Dymova, P. Sevastianov and P. Bartosiewicz, A new approach to the rule-based evidential reasoning: Stock trading expert system application, *Expert Systems with Applications*, vol.37, no.8, pp.5564-5576, 2010.
[40] T. Samatsu, K. Tachikawa and Y. Shi, Visualization for fuzzy retrieval using self-organizing maps, *ICIC Express Letters*, vol.3, no.4(B), pp.1345-1350, 2009.
[41] C. Thang, *SPICE SOM*, Soft Intelligence LAB, Ritsumeikan University, 2008.