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A Novel Combined Business Recommender System model Using Customer Investment Service Feedback

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Abstract The aim of the study was to present a new business model of an investment recommender system using customer investment service feedback based on fuzzy neural inference solutions and customized investment services. The model designed to support the system's process in investment companies. The type of research was qualitative and used of exploratory study and extensive library research. The model divided into two main parts using customer investment service feedback: data analysis and decision making. In this model, seven group factors proposed to implement the model of the proposed system of investment jobs through the potential investors. Machine learning use in this process and next ANFIS, which is an implementation of the neural art community uses the establishment of fuzzy logic judgment directly forward. The system act like a system consultant, studies the investor's past behavior and recommends relevant and accurate recommendations to the user for most appropriate investment.

Keywords: recommender system, business model innovation, investment, customer feedback, ANFIS

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1 Introduction

The study of customer behavior in the management of affairs is in many respects almost a new issue, in this regard, there are very few resources to study and learn about the experiences of others in the world. The importance and dimensions of paying attention to the behavior of online customers have not yet received enough attention. Recommendation systems are the tools used to supply pointers to customers based on their requirements (Kanaujia et al., 2017). This research will provide a new method for investment service customization using a recommender system based on ANFIS. We designed a novel combined recommender system framework based on a neuro-fuzzy inference system. In this way, the effective factors from customer experiences will categorize by machine learning techniques and factor analysis. Since a recommender system framework will design to provide suitable and novel customer investment service. These systems act usefully if they implement based on customer experience. The main issue in this research is what business model can be designed for a recommender system ANFIS-based, to present investment recommendations based on investor types and investment indicators?

2 Theoretical Framework

In this research, the customer is the investor. The investor, as a customer, buys services or investment products from the investment company or investment consulting companies. Investor is "a person who puts money into something in order to make a profit or get an advantage" (Cambridge Dictionary, n.d.). The theoretical foundations of this research are summarized in key concepts as the following.

2.1 Investor Behavior

Understanding the investor's behavior as a customer is complex in the decision-making process when buying a product or service. Investor behavior is the result of various cognitive processes, social interactions and social institutions, and the ability of investment firms to predict investor behavior is very important. A deep understanding of investors behavior creates more opportunities to predict and guide their behavior. The use of intelligent recommender systems is also an effective tool in predicting investor behavior. Various factors influence the analysis of investor behavior. One of these factors refers to the experience that the customer or investor gains in using the services or product of an investment company. This experience has a significant impact on both his loyalty and attracting new investors. One of the important dimensions of customer behavior is its social nature. Although we collect data from investors about their behavior, but the influence of other investors, social institutions and social regulations governing society are also very important in these behaviors. Therefore, the investors can only be understood and examined based on their relationships with other investors and in the framework of a larger social environment. "Customer engagement behavior can serve as a useful framework for classifying and segmenting customers, based on their propensity to engage and the types of engagement behaviors they display" (van Doorn et al., 2010). Of course, investors can be either individuals or organizations. Due to the differences between these two types of investors, there is a lot in common between them.

2.2 Investor Behavior in Investment Decision Making

Most investors do not act individually in decision making and consider the opinions of different people in the investment process. In families, different people may be involved in different stages of the investment decision process. The lower the investment, the smaller the number of people involved in the decision-making process. Of course, depending on the cognitive aspects of individuals and their individual characteristics, how they consult with different people in decision making is different. People who are involved in decision-making may even come from a variety of backgrounds. In a family decision, the number of people present in a decision and the type of people are usually constant. Investor behavior varies in different investment situations and in the decision-making process. This behavior includes how to decide on the type of investment, how to invest, places to invest, review of different portfolios, evaluation of services and products offered by investment companies. The decision-making method varies depending on whether the investor is involved in a new investment or needs an extension of a previous investment. In a simple investment situation, the investor needs to take a series of simple steps, but in a non-simple investment situation, he needs more information and time to ensure the investment decision. Of course, it is necessary to point out that in some investments, such as investing in cryptocurrency, it is a kind of game with money. In this regard, a large amount of information and technical and fundamental analysis is required. Slovic (1972) says the basic tenet of those in charge of helping the investor to make market decisions seems to be "the more information, the better." Various key factors play a role in investor behavior when making investment decisions. For example, the opinion of specialists, the opinion of people who have experience in the field of investment and are experts in the field of investment. Even the opinion of people who have invested in a field for the first time can be effective in the decision-making process of other investors. Direct or indirect marketing of media and social networks in the field of investment news can have a great impact on investor behavior when making investment decisions. Executors or agents of investment in various fields and their performance are also effective in this process. Finally, it can be said that the most important and effective factor is the opinion of investors who directly use the products and services of an investment company. Awareness of the needs of investors and knowledge of the investment decision process is the basis of the success of an investment company. These companies must be able to pass the investor through various decision-making stages step by step. Including in recognizing the need, gathering information about that investment field of interest to the investor or suitable for the investor, evaluating different options, investing decisions and significant issues in investor behavior after the investment. Adequate knowledge and understanding of investment companies helps them to design effective and successful portfolios for investment. Christensen and Bower (1996) stated that "technological advances can exceed the required performance in a market, technologies that can initially only be used later in emerging markets can attack major markets and move incoming companies to victory over established companies". It can be said that the design of investment proposing systems is one of these technical and effective advances in the investment market.

2.3 Investor experience & feedback

An investor's experience as a customer is the result of the investor's interaction with the company that assists an individual or organization in investing and uses the company's products and services in the investment. This investment can be made directly by the investor or by an intermediary. The experience gained can be during and after the investment. "This interaction is made up of three parts: the customer journey, the brand touchpoints the customer interacts with, and the environments the customer experiences (including digital environment) during their experience. Good customer experience means that the individual's experience during all points of contact matches the individual's expectations. Gartner asserts the importance of managing the customer's experience" (Verhoef, et al, 2009). Customer experience implies customer involvement at different levels – such as rational, emotional, sensorial, physical, and spiritual (Janakiraman, Meyer, & Morales, 2006). The experience of investors may be gained directly or indirectly. In direct experience, the process of interaction starts from the investor, while in indirect experience, the investor gains the experience from news media in different contexts. Even this experience can be achieved through verbal interaction with other investors. "Customer experience is created by the contribution of not only the customers' values but also by the contribution of the company providing the experience" (Gentile et al, 2007). All of the events experienced by customers before and after a purchase are part of the customer experience. What customer experience is personal and may involve sensory, emotional, rational, and physical aspects to create a memorable experience. In the retail industry, both companies and customers play a big role in creating customer experience (Andajani, 2015). The investor's experiences can be in the form of "investor feedback". Customer feedback exposes their degree of satisfaction and assists product, customer success, and advertising groups to recognize the place there is room for improvement. Companies can gather customer feedback proactively via polling and surveying customers, interviewing them, or asking for reviews (Customer Feedback Definition | Pendo.io Glossary). Gartner believes that "the company's customer outstanding experience greatly influences their long-term exchange behavior and reflects the true drivers of loyalty" (www.gartner.com). The investor feedback helps to measure the satisfaction of the investment company's products and services. Without investor feedback, no company can be assured of the value of the product or service it offers. The more importance is given to investor feedback, the easier it is to retain the investor and the higher the investor loyalty. It is possible to receive feedback in different ways. Depending on the different investor groups, types of services, and products, the appropriate application can be used. The method of receiving investor feedback should be commensurate with their needs and conditions and it should be at any time and in the simplest possible way with proper access. Another important issue is the proper and timely use of investor feedback in the use of products and services. The use of intelligent systems is very effective in skillful and timely analysis of investor feedback.

2.4 Investment Recommender System

The information system here is any kind of system where a lot of information is stored, and the information system can be equipped with Recommender Systems. "Recommender Systems (RSs) are software tools and techniques that provide suggestions for items that are most likely of interest to a particular user" (Burke, 2007), (Resnick et al., 1994), (Resnick &Varian, 1997). Liang (2008) believes that RSs are a type of DSSs that analyzes user behavior and proposes based on its results. Recommender systems are a digital solution supporting financial investments. This digital support is usually implemented by recommender systems, which gives customized offer for customers according to their needs. Figure 1 shows the relation between the basic sections of the ontology with Recommender System. As mentioned before, the information system here is any kind of system with a large amount of stored information. This information system can be equipped with recommender systems. In the recommender investment systems, this program uses the techniques and methods of the recommender system to meet the information needs of the customer in investing. In fact, a recommender system is designed for the user. Customer or investor behavior plays a key role in evaluating the recommender system. We cannot evaluate the recommender system without considering the user as a separate class. For this reason, we consider the behavior of the user (investor) of this system as the main feature of the investor in using the recommender system.

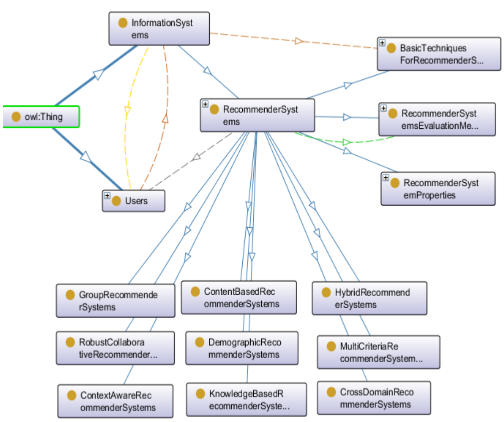

Figure 1: Relation between the basic sections of the ontology with recommender system

Usually, the client or investor is looking for an answer to their information needs in investing. Seek means search, and search is what the user says when the search is done. Of course, instead of a human user, we can also consider a machine user or, in a more advanced form, an investor robot. To implement the core function of the investment recommender system, identifying useful items for the client or investor must anticipate that an item is worth the investment recommendation. To do this, the system must be able to predict the profitability of some items for investment. Even the system can compare the usefulness of some items for investment with others. Based on this comparison, the system then decides which items to recommend for investing based on the customers' group. Various recommendation techniques are used to predict items based on the needs or preferences of the investor.

2.5 Business Model Innovation

Business model innovation is the development of new, unique concepts supporting an organization's financial viability, including its mission, and the processes for bringing those concepts to fruition (Cole, 2015). In this research, we presented a novel model of investment recommender system that supports the processes of achieving the goals of investment companies in the business model. Various technologies in the application of recommender systems are important applications in presenting current business models applied in investment portfolio to investors.

3 Literature Review

Paranjape-Voditel and Umesh (2013) proposed a stock market portfolio recommender machine based totally on association rule mining that analyses inventory records and suggests a ranked basket of stocks. In 2017 proposed a collaborative filtering-based recommender device for monetary analysis based on Saving, Expenditure, and Investment the usage of Apache Hadoop and Apache Mahout (Kanaujia et al.,2017). Hernández et al. (2019) evaluated the state of the art on Financial Technology for the layout of a novel recommender system. They presented a social computing platform that is proposed, based on Virtual Organizations, that allows enhancing person experience in moves that are related to the method of funding recommendation. Tejeda-Lorente et al (2019) proposed a novel recommender system, which is conscious of the risks related to unique hedge funds, considering multiple factors, such as modern-day yields, historic performance, diversification by way of industry, etc. Tarnowska et al., (2020) presented a Recommender System for Improving Customer Loyalty. This recommender system addressed various important problems. (1) it presents a favored framework to assist managers to decide which moves are possible to have the largest **influence** the internet promoter rating. (2) the consequences are based totally completely definitely on multiple clients. (3) its dietary supplements ordinary textual content mining alternatives. The recommender gadget allows users to view specific, anonymous feedback related to the right clients. (4) ultimately, the computer offers a sensitivity assessment feature.

4 Research Methodology

The study is exploratory research. The qualitative data collection methods applied to collect data from previous research and library studies. In this research, a novel business model for an investment recommender system proposed based on ANFIS that analyses customer data and suggested several recommendations based on customer needs. This model is different compared to existing systems because it found the correlation between potential customers' demographic/personality traits, potential customer's investment indicators, and investment's products and services and on this base, recommends a portfolio based on the customers' needs. An intelligent fuzzy framework uses for generating association rules. The novel methods implement using machine learning and fuzzy logic. Thorough experimentation performs on the Portfolio dataset based on a web-based investment questionnaire. Our approach demonstrates the application of soft computing techniques like data mining, machine learning, factor analysis, and fuzzy classification in the design of recommender systems.

5 A Novel Combined Recommender System Business Model

Based on the extensive study on the previous research, we propose four main steps in our investment recommender system business model. In the first step, the customer's types clustered by an unsupervised machine learning technique based on multiple variables that are extracted from gathered data by the questionnaire. In the second step, the same variables analyze by the factor analysis method to identify customer's investment indicators. This nomination can be based on strong features in each category. Also, the expert viewpoints can use to finalize the indicators. In the third step, an ANFIS solution develops based on the output of the first step for predicting the customer investment type. An artificial neural community implementation, ANFIS is based totally on Takagi–Sugeno FIS at first presented by Jang (1993). It makes fuzzy logic judgment deployment extra straightforward in contrast to the normal neural network simulations as defined in (Asemi & Asemi, 2014). The input of ANFIS is a summarization of factors in the previous step and the output is scoring categories for the customer. For example, if a category gets the highest score means that the considered customer's investment belongs to this category. In ANFIS two types of rules are contributed for prediction, i) rules which are designed based on data training and ii) rules which we design based on our analysis from customer categorization and expert viewpoints. In this model, we designed membership functions on ANFIS based on the nature of input factors and measurement scales. In the fourth step, a recommender system provides proper recommendations for the customer with a predicted type. The customers can invest based on these recommendations. Figure 2 shows the research framework. It shows how we answered the research question of the study. According to different functions, the research design divided into three phases:

First Phase (Data gathering): The data-gathering phase includes the data acquisition layer and the data storage layer. Second Phase (Data analysis): The second phase includes two functions: (a) machine learning techniques (clustering and factor analysis) and (b) ANFIS. Third Phase (Decision): This phase includes the recommendation layer, and it presents information to the customer and receives their feedback. This feedback shows the probability errors, then the errors refer to the data analysis phase for correction. According to different functions, the business recommender system model structure includes these layers: 1. data acquisition layer, 2. data storage layer, 3. machine learning layer, 4. ANFIS layers (fuzzification, implication rules, normalization, defuzzification, integration, or aggregated output membership function), 5. investment recommendation and feedback layer, or application layer. All the parts of the research framework are specified as follows:

5.1 Data Acquisition Layer

The purpose of this layer is to collect data from the users and find out how conscious their readers are about their finances. In the web-based investment questionnaire, they asked about the savings, spending habits, use of digital financial solutions, communication ways, satisfaction form different financial companies, banks, & organizations, or their view of the state of the economy in the years to come, and demographic data. The data transfer to the next layer cloud data storage from this layer. This type of system recommends items based on user demographics. The basic premise of these recommender systems is to provide different recommendations for different groups of users. Many websites today offer simple and effective recommendations based on user demographic and personalized information. For example, users are referred to specific websites based on their language or country. The offers may also be customized according to the age of the user. While these approaches have been quite common in the marketing, relatively little recommender systems research has been done on demographic based recommender systems.

5.2 Data Storage Layer

The data storage layer stores all the data of users in the company's private server. The data storage layer adopts a set of different data processing formats so that it can focus on data storage. The investment data reformat in this layer and transfer to the machine learning layer. The customer/user's data analyse based on the attributes. The data classified based on the demographic and personality traits in this section.

5.3 Machine Learning Layer

Clustering and Factor Analysis is the most important part of this layer, which performs data analysis through data mining and machine learning algorithms. This layer takes data from the data storage layer and transfers classified factors to the ANFIS layer. The data entered the machine learning layer after data collection and integration into the storage space for data analysis. In the proposed layer, the attributes classification used to automatically classify the customer types and to identify customer investment indicators.

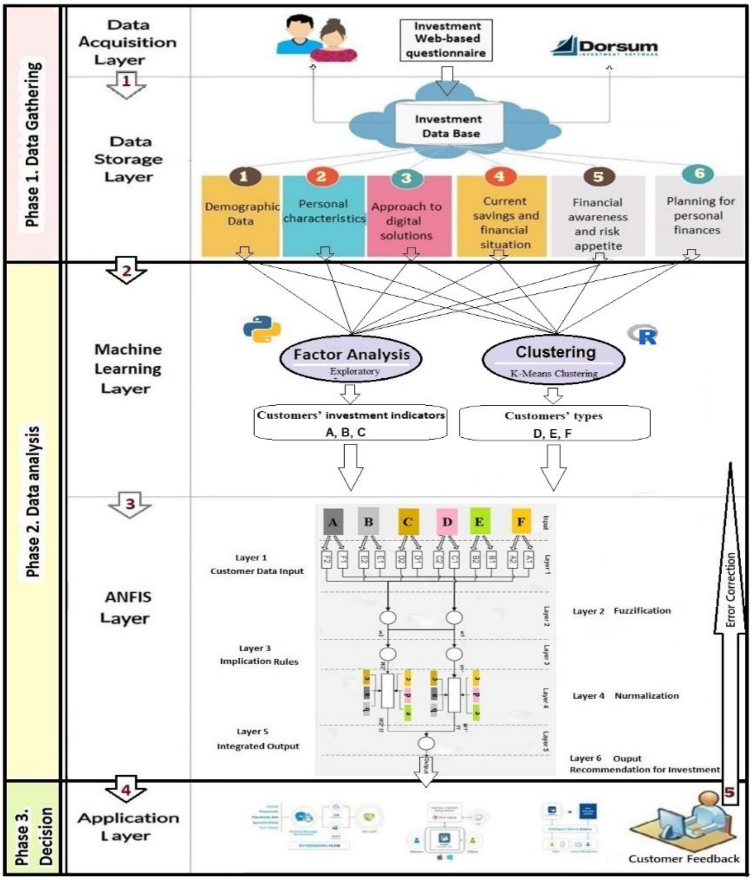

Figure 2: A Novel Business Recommender System Model Using Customer Investment Service Feedback

There are two basic functions in this layer included clustering and the factor analysis for the variables from the previous layer. We clustered due7 to its wide range of features and the ability to compare output in different ways, good guide, efficient graphical interface, compatibility with Windows, and having a comprehensive reference. For the factor analysis the system uses Python. The next function of this layer uses the exploratory factor analysis to indicate customer investment indicators. In this method, the researcher tries to discover the infrastructural structure of a relatively large set of variables. At this stage, there is no initial theory. The researcher must identify and discover the factors involved in the customer's investment that may be hidden. This method is used to summarize a set of variables and new factors identify and introduce based on the correlation between the variables. These factors are prepared to be transferred to the next layer ANFIS for the next function. This exploratory analysis can be structuring, modelling, or hypothesizing.

5.4 ANFIS Layer

In this layer, the Sugeno fuzzy model will use for the ANFIS system. This system includes five layers as the following (Asemi, et al. 2019).

Layer 1: Neurons in this layer only direct the external input signals to the next layer. This layer is the first hidden layer and the fuzzy layer of the ANFIS model. Fuzzy neurons receive an input signal. Then they decide on the degree of dependence of this signal on the neural fuzzy set.

Layer 2: This layer is the fuzzy rule layer and the second hidden layer. Each neuron in this layer is associated with only one fuzzy Sugeno law.

Layer 3: This layer is the normalization layer and the third hidden layer. Each neuron in this layer receives and calculates signals from all neurons in the third layer. This is called normalized Firing Strength. This value determines to what extent the relevant law is valid for the inputs in the result.

Layer 4: This layer is the fourth hidden layer and the diffusion layer. Each neuron in this layer is related to the corresponding normalized neuron in the fourth layer. It also receives the first input signals (x1, x2...). The defuzzied neuron in this layer calculates the weight of the result of a rule.

Layer 5: This layer is called the output layer. In this output layer, the neurons of the previous stage are added together. Finally, by defuzzification, fuzzy outputs are converted to numeric outputs. There is only one neuron in this layer. The defuzzification method is the same as the Centre of Gravity.

5.5 Application Layer

In this layer, the application mainly customized to customers' needs and displays recommendations based on investment company's products and services. The application layer connected to the data analysis phase, so the end-user (customer) can access the source of investment recommendations in their investment platform using companies' applications. Applications required by the customer to use recommendations in the investment platform are in this part of the model. The system can receive the customer's feedback in this layer and the probability errors refer to the data analysis section for detection.

6 Conclusion

The research objective was to provide a new, novel business model for investment recommender systems using customer investment service feedback based on neuro-fuzzy inference solutions and customized for investment service. The research question was what business model can be designed for a recommender system ANFIS-based, to present investment recommendations based on investor types and investment indicators? To answer the question, a business model of an investment recommender system designed to support the investment process for the customers. Tarnowska et al., (2020) presented a Recommender System for Improving Customer Loyalty. The recommender system designed by Tejeda-Lorente et al (2019) relates to unique hedge funds that consider multiple factors, such as modern-day yields, historic performance, diversification by way of industry, etc. In the proposal of Hernandez et al. (2019), they present the functions of agents and an algorithm that improves the accuracy of the Recommender agent which oversees the Case-based reasoning system. The data corresponds to the user's characteristics, asset classes, profitability, interest rate, history stock market information, and financial news published in the media. Paranjape-Voditel and Umesh (2013) proposal was a recommender machine-based totally on association rule mining. The model presented in this research is based on the ANFIS system. This model is divided into three main parts: data collection from the investor, analysis of investor data and decision making. In the designed model, seven group factors are identified to implement the proposed investment system model through the customer or potential investor data set. These seven groups include: demographic data, personality traits, investor attitudes toward digital solutions, investor current financial status and savings, investor awareness of potential risks, and investor financial plan information. In the proposed model, the initial data is collected through a web-based platform and transferred to the machine learning section, which is the first part of the data analysis section. In this section, customer investment criteria and types of customers are extracted. Then the types of investors are clustered and investment indicators are factor analyzed. The output obtained from this layer is transferred to the second part of the data analysis section. In the ANFIS layer, data is analyzed in six steps and investment proposals are extracted for each investor cluster. These suggestions are presented to the customer in the application layer using designed applications. Investor feedback is also received to improve and develop the system at this layer. The objective of this business recommender system model is to support the investment companies, individual investors, and fund managers in their decisions by suggesting the investment products and services based on the customers' needs, experiences, and traits.

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