Asemi *et al. Journal of Big Data* (2023) 10:87
https://doi.org/10.1186/s40537-023-00784-7

Journal of Big Data

RESEARCH

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Adaptive neuro-fuzzy inference system for customizing investment type based on the potential investors' demographics and feedback

Asefeh Asemi[1], Adeleh Asemi[2] and Andrea Ko[3*]

*Correspondence:
andrea.ko@uni-corvinus.hu

[1] Doctoral School of Economics, Business, and Informatics, Institute of Data Analytics and Information Systems, Corvinus University of Budapest, Budapest, Hungary
[2] Department of Software Engineering, Faculty of Computer Science and Information Technology, Universiti Malaya, Kuala Lumpur, Malaysia
[3] Corvinus University of Budapest, Budapest, Hungary

Abstract

The proposed model is an adaptive neuro-fuzzy inference recommender system that utilizes customer investment service feedback and fuzzy neural inference solutions to generate personalized investment recommendations. The model is designed to support the investment process for the customers and takes into consideration seven factors to implement the proposed investment system model through the customer or potential investor data set. These include demographic data and investment type. The model is divided into three main phases: data gathering, data analysis, and decision-making. In the data gathering phase, initial data is collected through a web-based platform, and in the data analysis phase, the potential investors' demographic criteria are extracted and grouped, and the types of investments are then clustered. The output obtained is transferred to the ANFIS layer, and investment-type recommendations are extracted for each group of potential investors. Investor feedback is received to improve and develop the system. JMP and MATLAB are used to propose the model, which serves as a framework for investment recommender systems. It demonstrates how to use this framework to offer pertinent and precise recommendations for the best sort of investment type to potential and present investors by combining the expertise of the experts and the demographic information of potential investors. Overall, this paper provides a new, novel model for investment recommender systems, which can assist investment companies, individual investors, and fund managers in their investment decisions.

Keywords: "Adaptive Neuro-Fuzzy Inference System", "ANFIS", "Recommender System", "Demographic Data", "Investment Type", "Investment Product", "Potential Investors", "Investor Feedback", "Investment Service"

Introduction

One of the most important sources for understanding a company's past, present, and future is customer demographic data and statistics. These facts and figures are crucial in recommender systems as they help the user receive personalized and relevant recommendations. This is particularly important as Kanaujia and his colleagues have highlighted that recommender systems should be tailored to meet the specific needs of clients [17]. In order to address this issue, this study proposes a novel business model for an investment recommender system that utilizes adaptive neural fuzzy inference (ANFIS) to suggest the appropriate type of investment based on the demographic data collected from potential investors. This data is categorized and analyzed using machine learning techniques, serving as the system input, and the system output is the recommended type of investment for the individual investor.

Theoretical framework

This research includes several concepts. These ideas encompass investor and potential investor, demographics of potential investors, investment, recommender systems for investments, and machine learning. The customer and the investor in this study are the same. The following list summarizes the theoretical underpinnings:

Investor and potential investors

An investor is typically someone who invests money to gain a profit or an edge in something (Cambridge Dictionary). Anyone who purchases services or investment goods from an investment company qualifies as an investor on their behalf. The investor could be a legitimate source or a real individual. From the perspective of a business, a potential investor is someone or something that is in talks with the business about funding. Potential investors in this study are different people who respond to "Investment Questionnaire" questions. These persons may not all be active investors. A community or organization's members can generally be thought of as potential investors. In this case, a person rather than an organization is the potential investor, and the current study is based on data from respondents to the "Investment Questionnaire" regarding their demographics. Typically, when making an investment decision, an investor seeks advice. Professional investors attempt to speak with subject-matter specialists in addition to gathering the information they need before making an investment. It goes without saying that a person's demographic and behavioral traits will influence how they learn about investments and consult with others. People who influence an investor's decisions frequently have a variety of professional interests. Potential investors have various investment requirements depending on their demographics. As a result, they select various forms of investments. For instance, the most crucial criteria in selecting the sort of investment may be income, savings, and employment.

Potential investors' demographic

Demography, as defined by Merriam-Webster [21], is "the statistical study of human populations, particularly with regard to size and density, distribution, and vital statistics" in sociology. In the context of customer demographics, this refers to certain statistical information about individuals, such as their identity information, gender, age, marital status, and education level. This data can also include spatial information, such as mailing addresses. According to Onsgard [22], other relevant consumer demographic information includes buyer types, purchase objectives, and information about the buyer's lifestyle. When making decisions to improve the service or product offered by an investment company, it is crucial to consider the demographic profile of potential investors.

Factors such as age, gender, occupation, educational attainment, field of study, domicile, place of employment, and other pertinent personal data can provide valuable insight into how investors and potential investors use and evaluate the company's services and products. This understanding can also help predict the behavior of current and potential customers. Intelligent recommender systems can be an effective tool in this prediction and direction. These systems can establish membership functions for investment-type memberships and membership functions related to customer demographics. Additionally, the expertise of experts can be utilized to add additional rules based on their knowledge, resulting in more personalized recommendations tailored to the needs of the user. Overall, considering customer demographics is an important aspect of decision-making for investment companies, as it can provide valuable insights into how customers use and evaluate the company's services and products.

Investment

To invest is to set aside money with the hope of gaining something later. According to finance 2020, the advantage of investment is referred to as a return on investment ("Investment"). All stocks, bonds, options, derivatives, and other financial instruments that investors invest money in with the aim of making a profit are collectively referred to as "investment products" [9]. The process of modifying assets over the short, medium, or long term might be included in an investment. For example, the effectiveness of this procedure may be determined by sales, revenue from dividends, income from apartments, etc., or a mix of other approaches. The return could potentially include gains from foreign investments or losses because of changes in foreign exchange rates. Typically, investors want higher returns on riskier bets. A low-risk investment often yields a low return as well. Like excessive risk, excessive returns are also present. Any financial counseling, investment management, or other related activities are referred to as "investment services." The FCA Handbook states that any service relating to a financial instrument may be provided, such as receiving and transmitting orders about one or more financial instruments, carrying out orders for clients, engaging in trading for one's own account, managing a portfolio, issuing personal recommendations, underwriting financial instruments and/or placing them on a firm commitment basis, placing financial instruments without a firm commitment basis, etc. The investment products included in this study's investment types were listed stock mutual funds, voluntary pension funds, government securities, and bonds, as well as other financial products.

Investment recommender systems

According to Burke [7], recommender systems are software tools that employ various methods to offer advice to users based on their interests. As stated by Resnick et al. [28] and Resnick & Varian [29], these recommendations are highly relevant to a specific user's interests. Liang [20] also notes that recommender systems play the role of decision support, making recommendations based on the outcomes of examining user behavior. Asemi and Ko [4] note that customers may receive specific offers from recommender systems based on their needs. This is why it is important to not treat users as a separate class when integrating recommender systems into information systems. In investment recommender systems, both the investor and the investment service or product must be considered. By identifying advanced communication patterns between the two parties and enhancing the system, the degree to which the system's recommendations match the customer's needs is successfully increased. According to the proposals made, these kinds of technologies ought to be able to boost the company's profitability. It is even possible to build a comparison capability for the system to compare the feedback given in the context of the system's ideas regarding the types of suggested investments based on customer input to predict. This may be determined by investor or client needs.

Machine learning

One of the subfields of artificial intelligence is machine learning, where the performance and capability of the system are improved depending on previous results [12]. Machine learning aims to provide computers with the ability to learn on their own by utilizing available data and generating precise predictions [1]. The primary benefit of machine learning is its capacity for learning from data, which is absent from many traditional databases [37]. Artificial intelligence, natural language processing, data mining, mathematics, statistics, computer science, and deep learning are the primary fields associated with machine learning (Sarkar, Bali & Sharma, [30]). There are various machine learning tasks, such as feature engineering for dimensionality reduction, association rule learning, data clustering, regression analysis, classification analysis, and deep learning techniques [31]. Supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning are the four categories of machine learning based on their intended use [6, 31]. In this study, unsupervised learning was employed. The challenge in unsupervised learning is to uncover a hidden structure in a collection of unlabeled data (Agrawal et al., 2005). In this type of learning, the only information present is the data itself, which is used to group similar concepts together. Unlabeled data is used in the system's learning process, and each category's notions are distinct from those of other categories. One unsupervised machine learning technique is clustering, where categories are not predetermined and it is also unclear which category is categorized in accordance with which feature. Numerous clustering techniques exist, such as the k-means clustering method and hierarchical clustering (Han, Kamber & Pei, [13]). A set of data is clustered into groups that share the greatest characteristics. Clustering is a frequent descriptive technique for locating homogeneous groupings of objects based on their characteristics. Groups may overlap or be isolated. Data without tags are analyzed via clustering, which divides them into groups based on the maximization of similarity within groups and the minimization of similarity between groups (Agrawal et al., 2005).

Literature review

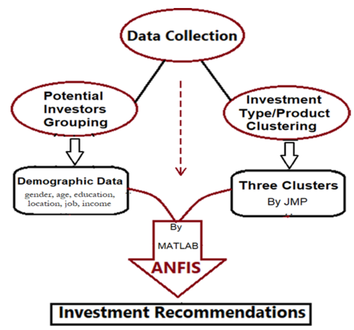
The research of this study builds upon the foundation of previous studies that have explored the use of recommender systems in the field of investment. Several studies have been conducted in this area. Paranjape-Voditel and Umesh [23] proposed a stock market portfolio recommender system based on association rules that analyzes inventory records and makes stock portfolio recommendations. Kanaujia et al. [17] proposed using Apache Hadoop and Apache Mahout as a common filtering-based recommendation device for financial analysis based on savings, costs, and investments. Hernández et al. [14] evaluated the state of financial technology and proposed a social computing platform built on virtual organizations that enable users to gain more experience in movements related to the financing of recommendations. Tejeda-Lorente et al. [35] proposed a recommender system that considers various factors, such as current yields, historical performance, and industry-wide diversity while being aware of the risks connected with hedge funds. Faridniya and Faridniya (2019) used data envelopment analysis to present a model for resource allocation and investment type selection, focusing on the Social Security Organization (SSO) in Iran as a case study. Tarnowska et al. [34] created a recommender system to increase customer loyalty, which considers various issues such as assisting managers in recognizing strategic moves in their choices. Sulistiyo and Mahpudin [33] looked at how demographics affected the type of investments people made, using amateur golfers in Karawang City as a sample. Casuat et al. [8] developed an expert-based system for improving students' employability using fuzzy logic techniques. The proposed system uses the concept of fuzzy membership degree, and it considers both qualitative and quantitative data while making recommendations. Patro et al. [25] presented a knowledge-based preference learning model for a recommender system using an adaptive neuro-fuzzy inference system. The paper presents a new approach to recommending products to customers by utilizing their preferences and past purchases. Kovacs, Ko, and Asemi [4] explored the investment patterns of potential retail banking customers using a two-stage cluster analysis to determine the best method for identifying the customer groups that are most likely to use a bank. Asemi and Ko [4] presented a novel combined business recommender system model using customer investment service feedback. The main objective of this type of system is to provide information about the products or services that are like those purchased by customers so they can make an informed decision. Sharma et al. [32] aimed to build a recommender system for the cold start in social media, which means when the user has not made any previous purchase yet. They focused on building a demographic profile-building tool to identify potential customers. Yassine et al. [36] focused on the intelligent recommender system using unsupervised machine learning techniques and demographic attributes of users as input data. Paryudi et al. [24] discussed the performance of a personality-based recommender system for fashion with demographic data-based personality prediction. The study evaluated the effectiveness of this technique in predicting fashion preferences based on personality traits. Fuzzy logic, a new and advanced method of reasoning, is used in this study to solve the problem of incompleteness in classical logic. It has been applied to many fields such as engineering, management, economics, etc. There has been a significant amount of research conducted in the field of recommender systems for investments. However, many of these studies focus on specific areas such as stock market portfolios, hedge funds, or resource allocation. It is clear from the aforementioned studies that there is a significant amount of research that has been conducted on the topic of recommender systems and expert-based systems. However, none of these studies have specifically focused on developing a recommender system for the type or product of investment based on the demographics of potential investors using ANFIS. The new model introduced in this study aims to address this gap in the literature. This ANFIS-based investment recommender system evaluates the potential investor's demographic information and, using a combination of professional judgments, suggests which investment type is best for each customer demographic. This study generates rules using an intelligent fuzzy framework, and based on the advice of experts, membership functions can also be improved during the rule-generation process. Therefore, it fills the gap in the literature that few studies have used the ANFIS technique and demographic information to recommend the investment types. Overall, this study makes a valuable contribution to the field by providing a new and innovative approach to the problem of investment recommendations.

Methods

In this study, both quantitative and qualitative methods were employed to present a new model for an investment recommender system. The model fuses previously learned information with fresh concepts and utilizes fuzzy inference logic and machine learning techniques to implement its methods. One specific technique used is clustering, where a portion of the data was clustered using the JMP clustering toolbox to categorize prospective investors' preferred investment types and products. The simplest machine learning algorithm without supervision, K-Means clustering, was used in this study. The number k represents the clusters in this type of clustering and each data point's cluster is determined based on its distance from a cluster. Centroids were kept as small as possible in this study, leading to the identification of three clusters for different investment types. Furthermore, the Adaptive Neuro-Fuzzy Inference System (ANFIS) was employed in this study. Jung first presented this system in 1993 (Jung, 1993), and its primary benefit is how it simplifies the establishment of logical judgment [3]. ANFIS is based on the Sugeno fuzzy inference system, which operates using "IF–THEN" logic. The input membership functions serve as the foundation for the rules generated by the system, and the architecture of a FIS consists of three components: fuzzy rules, membership functions, and an output generation reasoning process. During the machine learning stage, the data is trained using the ANFIS network and the output of the system's previous operation serves as the system's input. To determine the input and output of the ANFIS system, the study includes processing and preparation of the data. Based on ratings for various investment types, the recommender system suggests a final output, suggesting a specific type of investment to a group of potential investors. During the generation stage of fuzzy rules in the ANFIS system, two categories of rules are taken into consideration. The system generates a set of rules that are used to predict the type of investment based on customer demographic groups. The rules that system experts develop for investment systems are based on input from experts in investment science and feedback from investors. To gather this feedback, a feedback form can be set up with two general questions: a closed-ended question and an open-ended question. For example, the closed-ended question could ask investors whether the system's suggestions align with their requirements and offer options for a response such as "it somewhat corresponds," "it's not entirely unrelated," or "it has no connection at all." The open-ended question could request additional feedback on the effectiveness of the system, allowing for the identification of weak recommendations and mistakes through responses. System-generated rules are then supplemented by manually created rules and rules based on professional knowledge to make the system more efficient. The conceptual phases of the research, including the use of a portion of the Portfolio Investment Questionnaire to define variables, are outlined in Table 1. The questionnaire is available in the Hungarian language

Table 1 Conceptual stages of research

	Conceptual stages of research
Data Collection Tool	Online Questionnaire Data Collection
Input	Investment Type Data
Machine learning	Investment Type Clustering(JMP)
Output	Investment Types Clusters
Input	Investment Types Clusters Demographic Data Groups
Intelligent Neuro-Fuzzy technique	ANFIS (Hybrid learning algorithm) Expert knowledge intervention
Output	Investment Type's Recommendations Investors Feedback



on the website https://www.portfolio.hu/befektetesi-kerdoiv/?page=1. The research is conducted using a completed dataset, which has been exported based on the answers to the Portfolio Investment Questionnaire. According to the Worldbank.org (2020), portfolio investment refers to a variety of securities, including stocks, bonds, and other investment vehicles. A diversified portfolio reduces the risk of potential loss if one or more investments perform worse than anticipated ("Portfolio Investment," 2019).

1542 responses from an online survey conducted in 2019 were included in the analysis for the study entitled "Project 2018–1.3.1-VKE-2018–00007." The survey was conducted in Hungarian and the researchers were given permission to use the data for additional research and publications as per the Consortia agreement point 6.2 of the project (refer to Attachment 1 for details). The data used in this study were selected based on the study's objectives and included information on the respondents' demographics and the type of investment they had previously made. The data was first translated into English and underwent thorough cleaning before being imported into JMP for investment type clustering and MATLAB version R2022b for ANFIS analysis. The data here don't need to be analyzed frequently. The data is only analyzed (training fetching rules from data) once. Then the created rules will be applied to any new set of inputs. Therefore, the computational time is considered one time.

The proposed investment recommender system model

The model of the investment recommender system is based on ANFIS, as was already mentioned, and it is used to present recommendations regarding the type of investment. The investment type cluster advises using demographic information on customer groups. Several stages are considered in the outlined model.

- Data Gathering and Processing: The first stage of the model involves gathering, storing, and preliminary processing of data. This includes acquiring demographic information on customer groups and investment types, as well as any other relevant data that may be used in the model.

- Machine Learning Technique Stage: In the second stage, the model uses machine learning techniques to classify and cluster the data. This includes establishing two categories of information about customer groups and investment-type clusters using demographic data.
- ANFIS System Implementation: The third stage involves implementing the ANFIS system to analyze the data and make recommendations. This step uses the classification and clustering of data from the previous stage to generate investment-related advice.
- Decision Phase: The final stage of the model is the decision phase, where the customer receives the system's recommendations through applications. The customer is also given a survey form to provide feedback on the system's performance.
- Iterative Improvements: The model's cycle is repeated by using customer feedback to improve recommendations and fix any system flaws that may have been identified. The proposed model's structure is shown in Fig. 1 and is broken down into these detailed steps to assist in the investment recommendations process.

The proposed model's structure is broken down into the following details to help with investment recommendations.

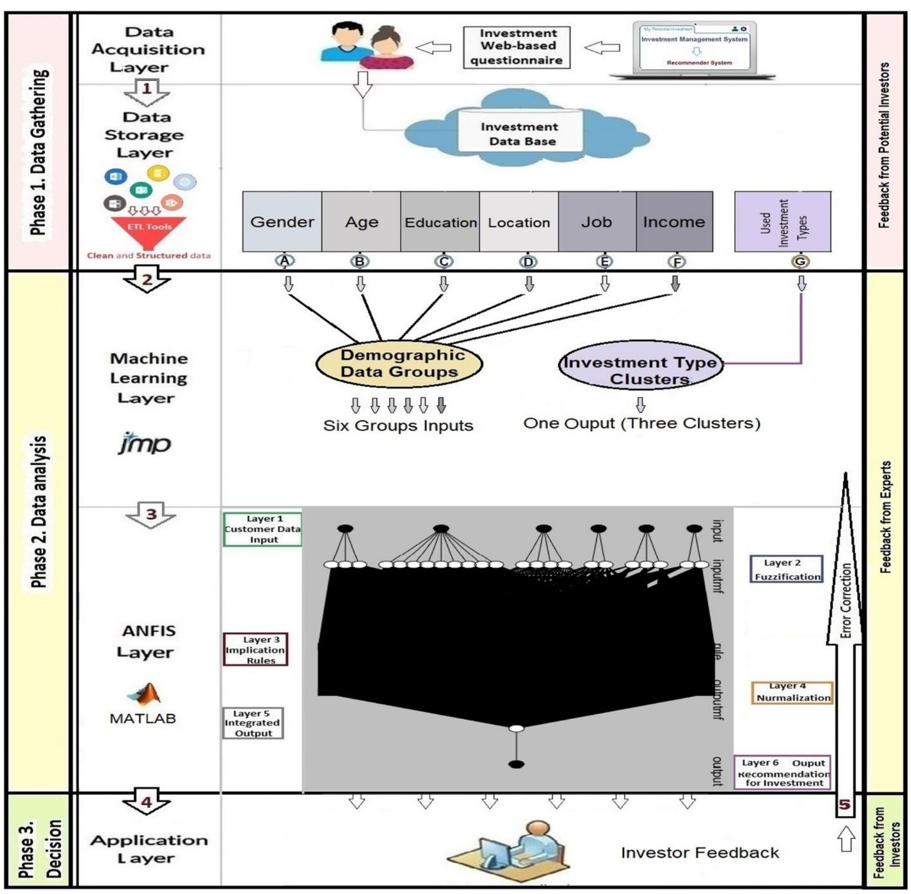


Fig. 1 A Recommender System Model for Investment Type based on the Potential Investors' Demographic

Data acquisition and processing layer

Data from prospective investors is gathered by this layer. Potential investors' demographic information includes their gender, age, level of education, place of residence, job title, and income. Certain investment products, such as mutual funds, voluntary pension funds, securities, government bonds, and other financial products, are associated with investment type data. A web-based questionnaire is used to gather demographic information as well as investment-related data. After initial processing and cleaning, the collected data is moved to the following layer.

Data storage and protection layer

This layer is responsible for storing and protecting the data processed in the previous step. In this layer, the data can be updated in real-time or in batches. Cloud or database storage is an option. Data reconfiguration and data backup are done in this layer Additionally, data archiving, data auditing, and versioning are done in this layer as well.

Machine learning layer

This layer oversees grouping information about the type of investment. This layer creates three clusters from the data related to the type of investment using data mining and machine learning algorithms. The data is prepared in this layer and then sent to the ANFIS layer after being received from the previous layer. Three categories of clusters are established for the type of investment regarding it. Unsupervised machine learning methods are used for this. For customer groups, six categories of demographic data that fall under those six categories have been examined.

ANFIS deployment layer

The ANFIS deployment layer, based on the Sugeno fuzzy model, uses six categories of demographic information about potential investors as inputs and suggests investment types using three clusters of investment types as outputs. The input of investment experts and their specialized knowledge is used to enhance the system and add rules. The ANFIS system consists of several layers, including fuzzification, implication rules, normalization, defuzzification, integration, and output presentation. The first layer directs input signals to the subsequent layers, with the fuzzy rule layer being the second layer and the normalization layer being the third. The fourth layer, the propagation layer, receives the first input signals, while the fifth layer, the output layer, transforms the fuzzy output into numerical output and aggregates the results. The final layer, the sixth layer, presents the recommended investment type to the client through appropriate applications.

Application layer

In this layer, the application offers suggestions to the client from the layer before. These recommendations are related to the type of investment, and for a particular group of clients, a cluster of the type of investment is considered. Using the application that is installed on the suitable device, the investor can receive system recommendations in his or her profile. The investor provides his system with feedback in this layer. Potential flaws in earlier layers are fixed and the system is improved based on investor feedback.

Experiments and results

There are three parts to this section. On the basis of the responses from prospective investors, the first section deals with the data clustering of various investment types. The second section discusses the ANFIS's description of its demographic data. The third section discusses the ANFIS's inputs and outputs.

Clustering data related to investment types

The data was grouped according to the investment types or products that potential investors used, in order to implement the proposed investment recommender system first. The following steps involve clustering data using JMP software for this purpose:

Figure 2 illustrates how data is imported into JMP to cluster the various investment types that potential investors use. Investment type is a topic covered by questions P24–P27. Listed stock mutual funds, voluntary pension funds, government securities/bonds, and other financial products were included in the data on investment type.

The questionnaire's questions about the different types of investments are listed in Table 2. The potential investors' responses were coded and transformed into numerical data based on their responses, allowing MATLAB and JMP to analyze them. Figure 3 displays the JMP preparation data for K-Means clustering.

The K-Means technique in JMP is used in Fig. 4 to cluster the investment type into three clusters. It is 2038 in each row. Iterative clustering using the K-Means method is displayed in JMP in Fig. 5. The first cluster has a count of 592, the second has a count of 406, and the third has a count of 340, according to the cluster summary. Each K is now the nucleus of its respective cluster. JMP assigns data points to the closest cluster

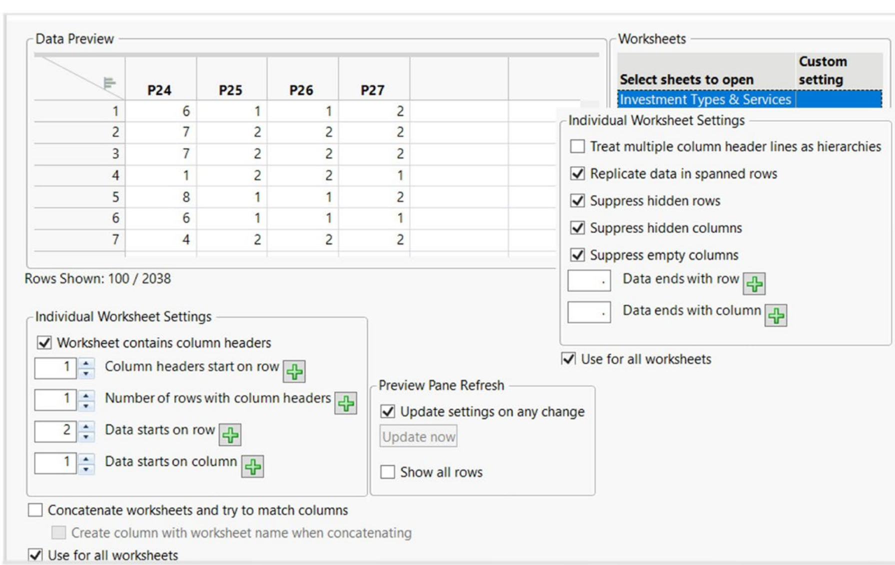


Fig. 2 Import data to JMP to cluster used investment types by potential investors

Table 2 Questions and answers for investment type

	Question	Answers	Answer code
P24	Which of the following investment products do you think is right for you? (Multiple answers marked)	Listed stock/equity, Mutual fund, Voluntary pension fund, Government securities, and Other financial products	Based on the answers given to the question, there were 31 different combinations of answers. which was coded from 1 to 31
P25	Have you had a stock market investment in the last 3 years?	Yes No	1 2
P26	If so, do you regularly monitor/follow the performance of the stock?	Yes No	1 2
P27	Do you have a government bond investment?	Yes No	1 2

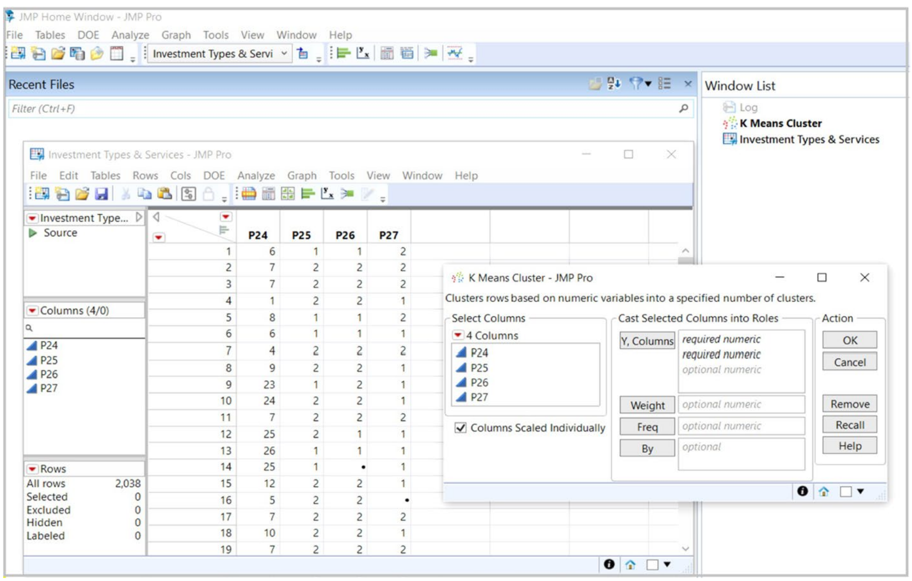


Fig. 3 Preparing data to cluster by K-Means technique in JMP

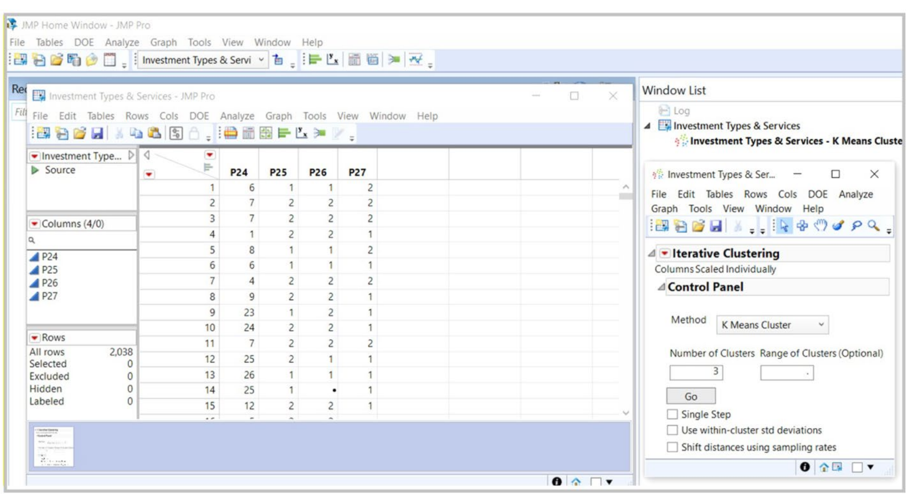
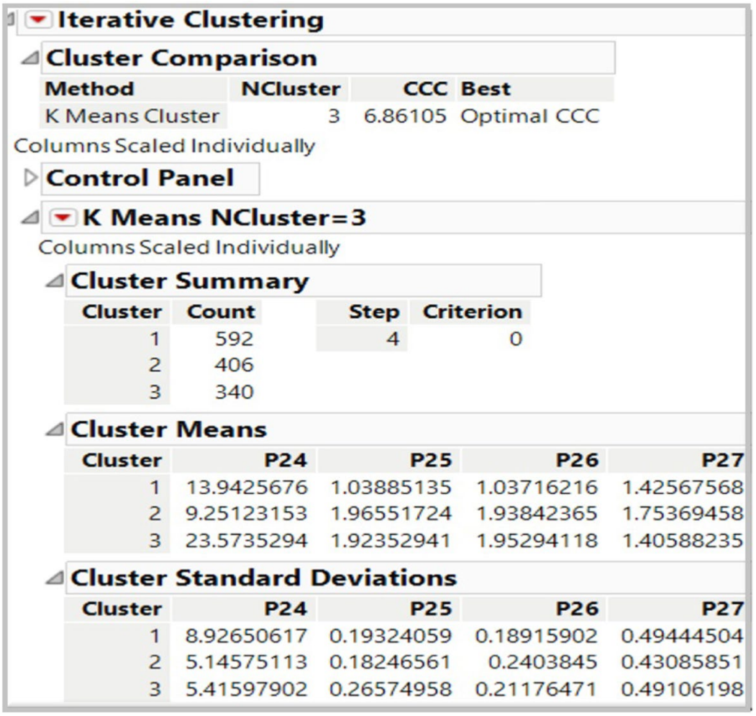


Fig. 4 Clustering data in three clusters by K-Means technique in JMP


Iterative Clustering

Cluster Comparison

Method	NCluster	CCC	Best
K Means Cluster	3	6.86105	Optimal CCC

Columns Scaled Individually

Control Panel

K Means NCluster=3

Columns Scaled Individually

Cluster Summary

Cluster	Count
1	592
2	406
3	340

Step	Criterion
4	0

Cluster Means

Cluster	P24	P25	P26	P27
1	13.9425676	1.03885135	1.03716216	1.42567568
2	9.25123153	1.96551724	1.93842365	1.75369458
3	23.5735294	1.92352941	1.95294118	1.40588235

Cluster Standard Deviations

Cluster	P24	P25	P26	P27
1	8.92650617	0.19324059	0.18915902	0.49444504
2	5.14575113	0.18246561	0.2403845	0.43085851
3	5.41597902	0.26574958	0.21176471	0.49106198

Fig. 5 Iterative Clustering by K Means technique in JMP

center. Until the data points stay in their cluster, the nearest center is assigned to each data point 4 times. K-Means are updated when new data is added to the dataset in real-time, and the clusters are updated as a result.

The optimal number of clusters can be determined using elbow curves and silhouette plots. The elbow curve method is useful in identifying the point where increasing the number of clusters no longer significantly reduces the within-cluster sum of squares. On the other hand, silhouette plots provide additional information by calculating the average silhouette width for each cluster and indicating the degree of separation between clusters. After clustering, potential investors are grouped into different categories. The results obtained from these groups are then used as metrics for the ANFIS model to make investment recommendations.

To determine the optimal number of clusters for the investment type cluster, the K-Means algorithm is employed, clustering the data for each value of k and calculating the Sum of Squared Errors (SSE) for each k. These SSE values are plotted against k to generate the Elbow curve and identify the point where the SSE starts to level off, which can indicate the optimal number of clusters. Additionally, the Silhouette score is calculated for each k, measuring how well each data point fits into its assigned cluster compared to other clusters. The Silhouette scores are plotted against k to identify the value of k that maximizes the Silhouette score, which can also provide insight into the optimal number of clusters. Prior to clustering, it is essential to preprocess

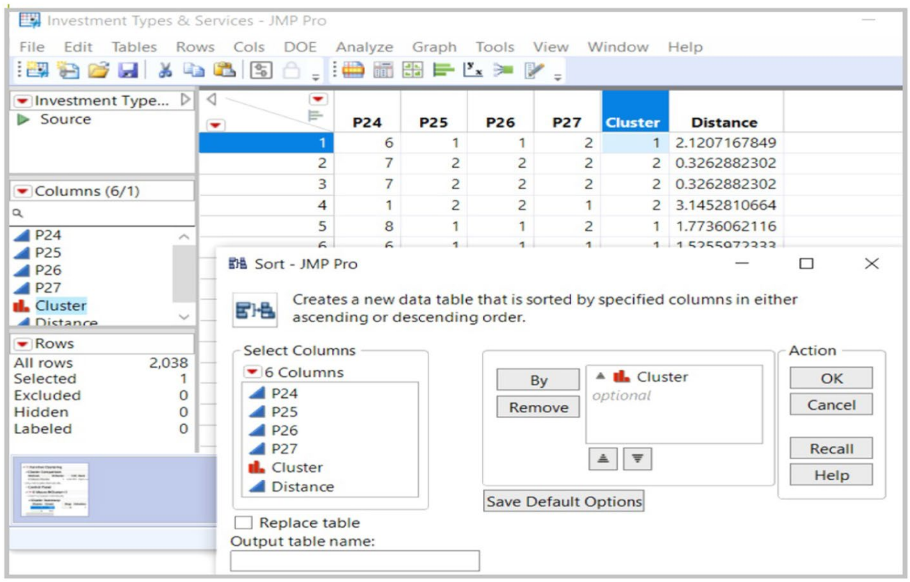


Fig. 6 Sorting by clusters in JMP

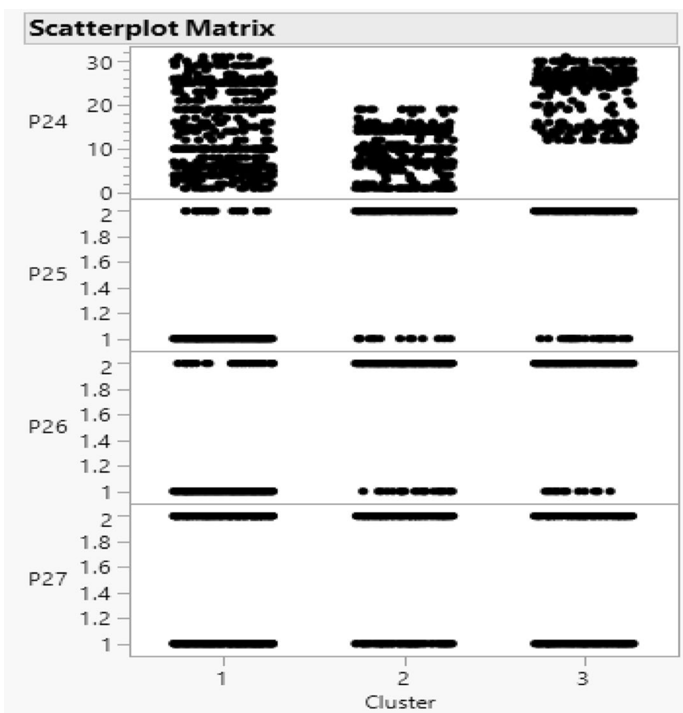


Fig. 7 Scatterplot for the investment type's clusters in JMP

the data and remove any missing values. The script used for this analysis is written in Python and designed to run in JMP.

JMP's cluster sorting is shown in Fig. 6. Based on the cluster, each row's distance is indicated. The scatterplot for the investment-type clusters in JMP is displayed in Fig. 7.

Demographic ANFIS

The questionnaire contained some questions that measured data related to the demographic. The respondents were questioned about the demographic data in six ways (inputs 1–6). This data sought to identify the respondents' demographics and their choice of investment strategy. Their responses help us better understand how demographics and financial attitudes are related, and ultimately how these factors influence the choice of investment type/product.

Demographic ANFIS inputs & output

The gender of the potential investors is related to input 1 (gender) with 2 MFs. Option 1 is considered for MF1, and Option 2 is considered for MF2. The age of the respondents is indicated by the three MFs in input 2 (age). For MF1, option 1 "15–34 years old," option 2 "35–54 years old," and option 3 "55–79 years old" are all taken into consideration. The location of the potential investors' homes is indicated by input 3 (location) with 2 MFs. Budapest, option 1, is considered for MF1, and "other location," option 2, is considered for MF2. The level of education of potential investors is reflected in input 4 (education) with 4 MFs. Option 1 "College or university economics" is taken into consideration for MF1, Option 2 "College or university non-economics" is taken into consideration for MF2, Option 3 "Postgraduate" is taken into consideration for MF3, and Option 4 "Other" is taken into consideration for MF4. Input 5 (job) with 9 MFs is related to the job of the potential investor. Employee middle management, option 1, is considered for MF1. Option 2, "Small-medium business," is considered for MF2. Option 3, "Graduate freelance," is considered for MF3. Option 4 for MF4, "Employed lower manager," is taken into consideration. Option 5 for MF5, "Subordinate intellectual worker," Option 6 for MF6, "Skilled Worker," Option 7 for MF7, "Employed Senior Management," Option 8 for MF8, "Micro or Self-Employed," and Option 9 for MF9 are also taken into consideration. The monthly income of the potential investors is represented by input 6 (income), which has three MF. For MF1, option 1 of "Under 200,000 HUF," option 2 of "200,000–349,999 HUF," and option 3 of "Above 350,000 HUF," are taken into consideration (Table 3).

Three clusters were included in one output that was defined for the investment type/product (investment type). Listed stock mutual funds, voluntary pension funds, government securities/bonds, and other financial products were included in the data on investment type.

Proposition of demographicanfis

Based on input membership functions, the "IF–THEN" rules govern how the ANFIS functions (MFs). A FIS's architecture is divided into three sections. Fuzzy rules make up the first part, MFs make up the second, and the reasoning process that produces the output makes up the third. Four inputs and one output, each with three membership functions, make up the financial ANFIS. The maximum and minimum membership functions for each input were one and zero, respectively. Data processing in MATLAB was done using a fuzzy logic toolbox. A fuzzy toolbox of MATLAB is used for this purpose in six

Table 3 MFs of the Demographic ANFIS inputs

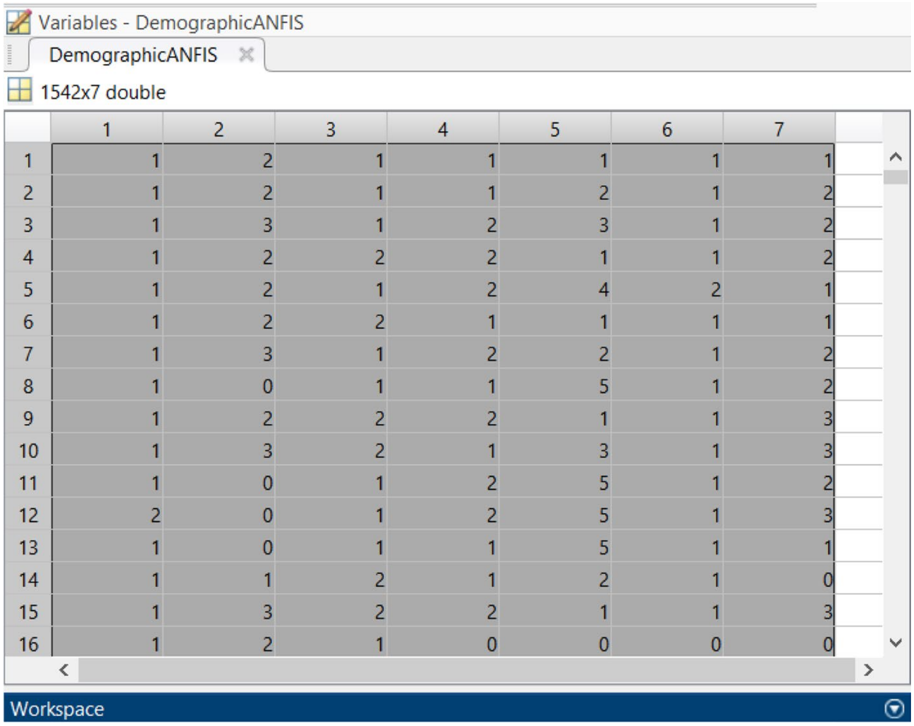
	MFs	Gender	Frequency
Input1	MF1	Male	1307
	MF2	Female	191
Input2	MFs	Age/year	Frequency
	MF1	15–34	359
	MF2	35–54	387
	MF3	55–79	100
Input3	MFs	Location	Frequency
	MF1	Budapest	784
	MF2	Other	704
Input4	MFs	Education	Frequency
	MF1	College or university economics	564
	MF2	College or university non-economics	596
	MF3	Postgraduate	73
	MF4	Other	278
Input5	MFs	Job	Frequency
	MF1	Employee middle management	231
	MF2	Small medium business	115
	MF3	Graduate freelance	69
	MF4	Employed lower manager	138
	MF5	Subordinate intellectual worker	659
	MF6	Skilled worker	51
	MF7	Employed senior management	67
	MF8	Micro or self-employed	88
	MF9	Other	80
Input6	MFs	Income/HUF	Frequency
	MF1	Under 200,000	1385
	MF2	200,000–349999	104
	MF3	Above 350,000	7

fundamental fuzzy function steps to implement Demographic ANFIS: Data import, FIS design, data loading, FIS creation, FIS training, and FIS testing.

Figure 8 displays the imported data in MATLAB, which consists of 7 columns, 6 of which are related to the potential investors' demographics. The final column relates to clusters of the investing kind. The inputs and output for the Demographic ANFIS are indicated in the fuzzy function. A new FIS with demographics and a Sugeno-type design. Figure 9 depicts the DemographicANFIS system's layout and characteristics.

A sample of the MFs in DemographicANFIS is shown in Fig. 10. This graph displays the total number of MFs. The MFs can be edited and are of the gaussmfs kind. Output MF kind is regarded as constant. Additionally, 1542 train data pairs are taken into consideration. In this case, aggregation is max while the implication is considered min. Aggregation is the process of combining all fuzzy sets that represent each rule's outputs into a single set. For each output variable, this aggregation takes place just once before the final defuzzification stage.

The loaded data for the subsequent data training and testing steps is shown in Fig. 11. A grid partition is taken into consideration for the new FIS's training data. Additionally, the method's optimization is regarded as a hybrid with epochs 3 and error tolerance 0.



	1	2	3	4	5	6	7
1	1	2	1	1	1	1	1
2	1	2	1	1	2	1	2
3	1	3	1	2	3	1	2
4	1	2	2	2	1	1	2
5	1	2	1	2	4	2	1
6	1	2	2	1	1	1	1
7	1	3	1	2	2	1	2
8	1	0	1	1	5	1	2
9	1	2	2	2	1	1	3
10	1	3	2	1	3	1	3
11	1	0	1	2	5	1	2
12	2	0	1	2	5	1	3
13	1	0	1	1	5	1	1
14	1	1	2	1	2	1	0
15	1	3	2	2	1	1	3
16	1	2	1	0	0	0	0

Fig. 8 Imported data to MATLAB to implement Demographic ANFIS

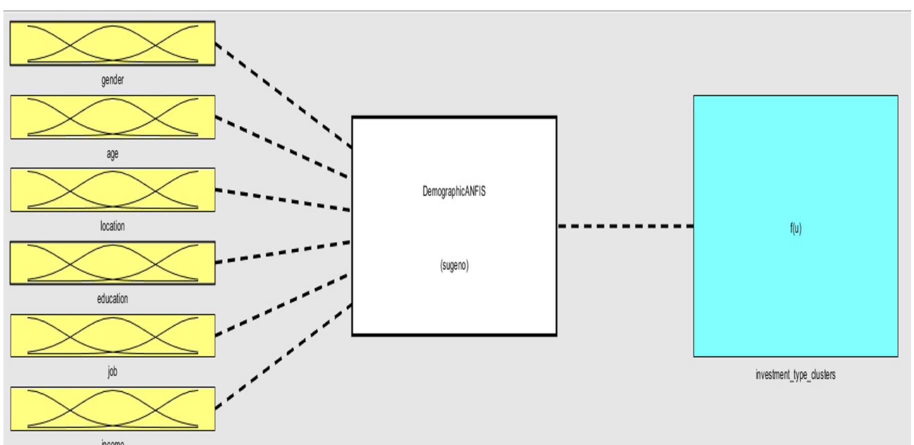


Fig. 9 Designing DemographicANFIS

Then a new FIS called the DemographicANFIS was created (Fig. 12).

Figure 13 shows that the DemographicANFIS network is trained. The Gaussian functions are used for each input during the training procedure. The number of inputs is considered six for demographic groups, and the number of outputs is considered one for investment types. The FIS training method is a hybrid with three epochs. Epoch 3: error = 0.8668.

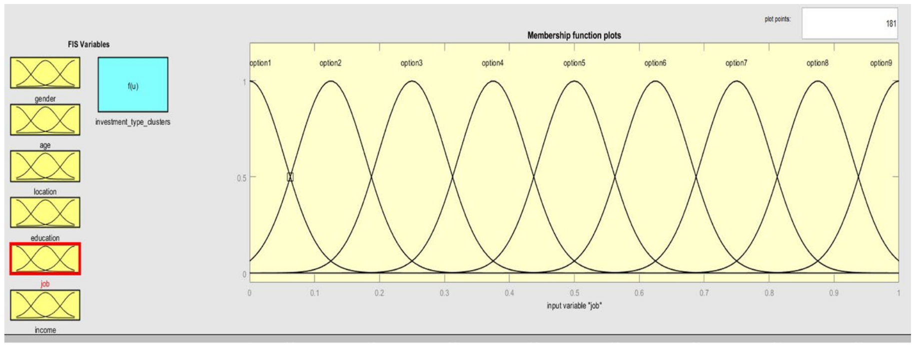


Fig. 10 A sample of membership Functions in DemographicANFIS

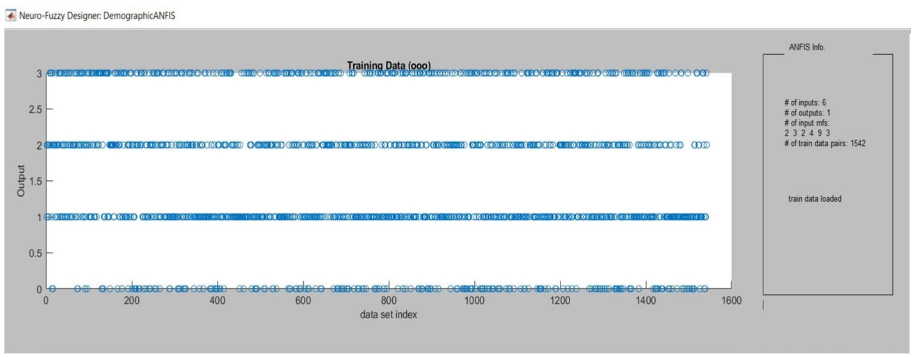


Fig. 11 Loaded Data to Train in DemographicANFIS

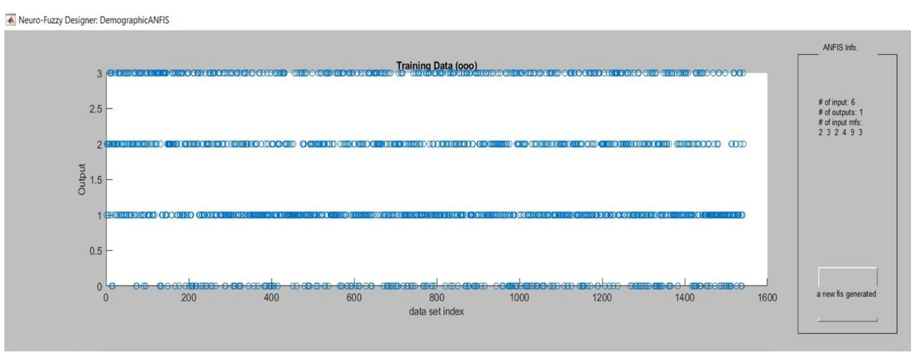


Fig. 12 Generated new FIS (DemographicANFIS)

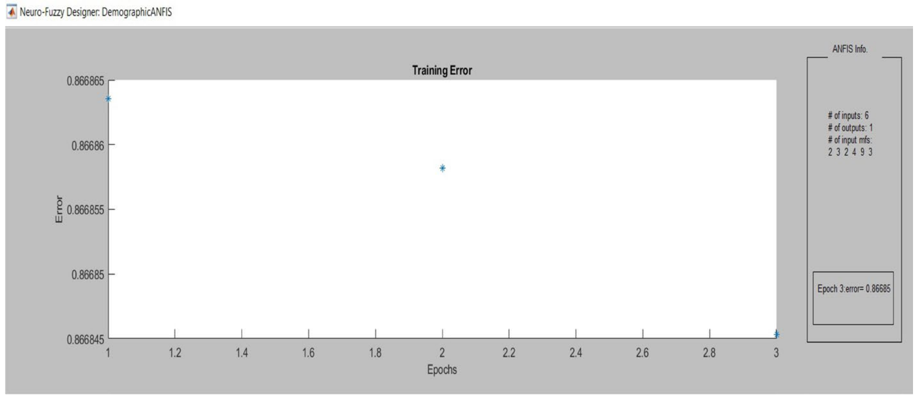


Fig. 13 Training DemographicANFIS

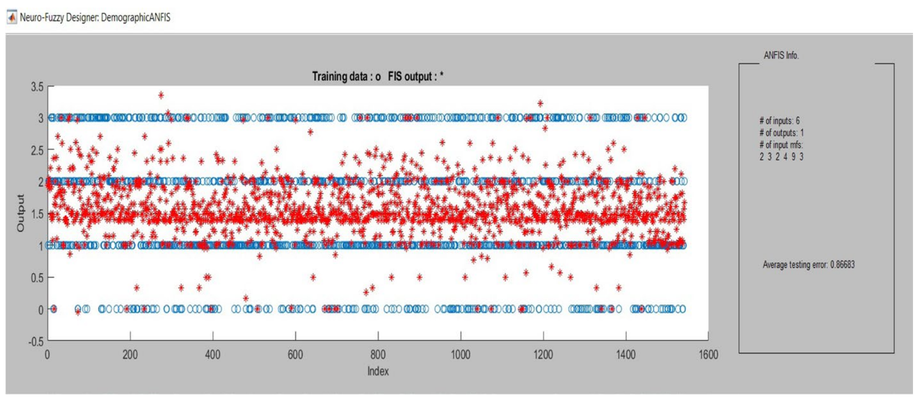


Fig. 14 Testing DemographicANFIS

Start training ANFIS ...
1 0.866845
2 0.86683
Designated epoch number reached. ANFIS training completed at epoch 2.
Minimal training RMSE = 0.86683
>>

Figure 14 displays the DemographicANFIS under test. 0.86683 is the average testing error. In Fig. 15, a portion of the rule viewer is displayed. The open system of the DemographicANFIS is depicted in this figure. There are 101 plot points and 1296 rules.

Figure 16 displays a portion of the system's rules in verbose format. Depending on the opinions of the experts and the feedback from the investors, the rules may be added, modified, or removed. The importance of this possibility for recommender systems.

The relationship between the demographic factors influencing investment type is established by the implemented DemographicANFIS System. The three-dimensional graphs that illustrated how two inputs at once affected the type of investment are shown in Fig. 17a–f. Summary information about the deployed DemographicANFIS system is provided below:

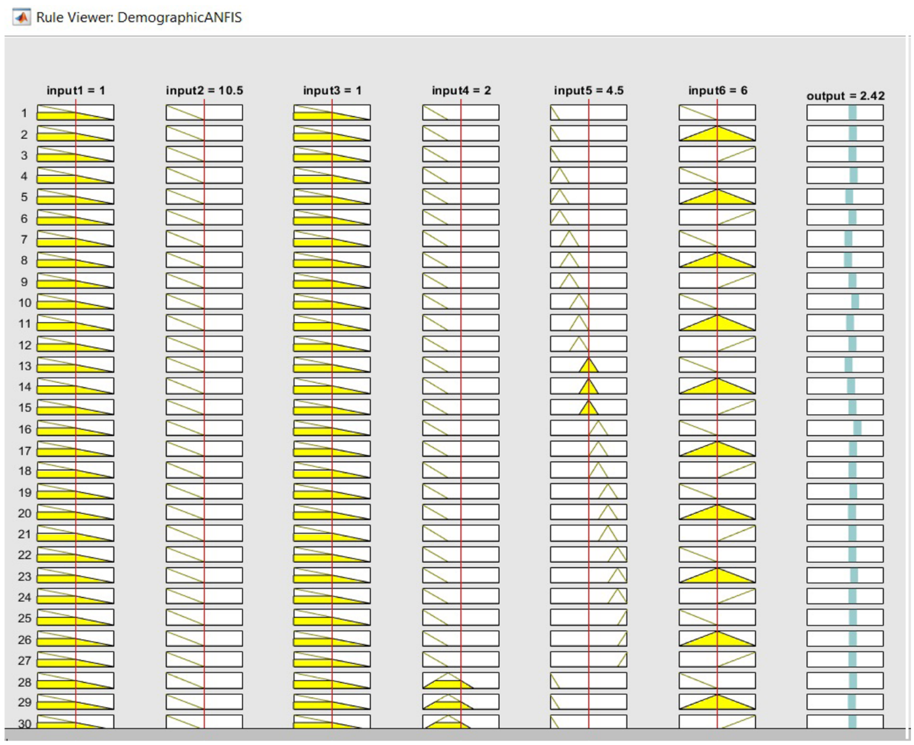


Fig. 15 The rule viewer of the opened DemographicANFIS system

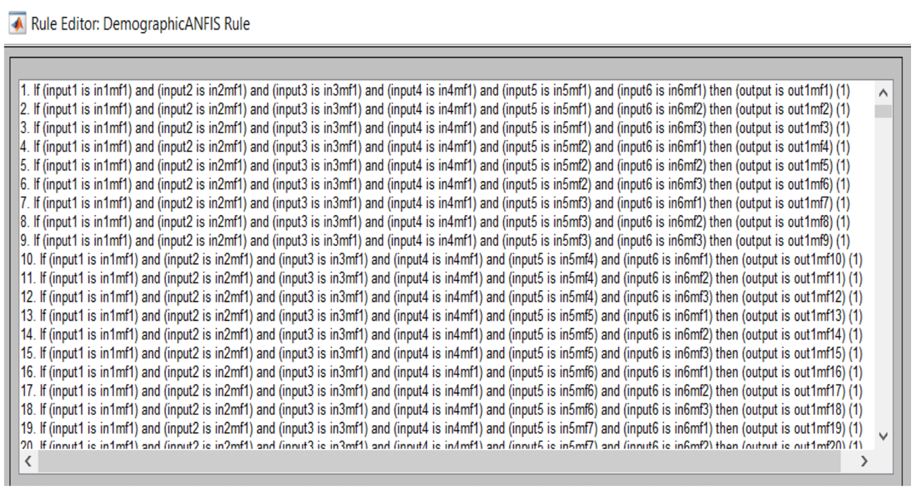


Fig. 16 A part of the rules in implemented DemographicANFIS system

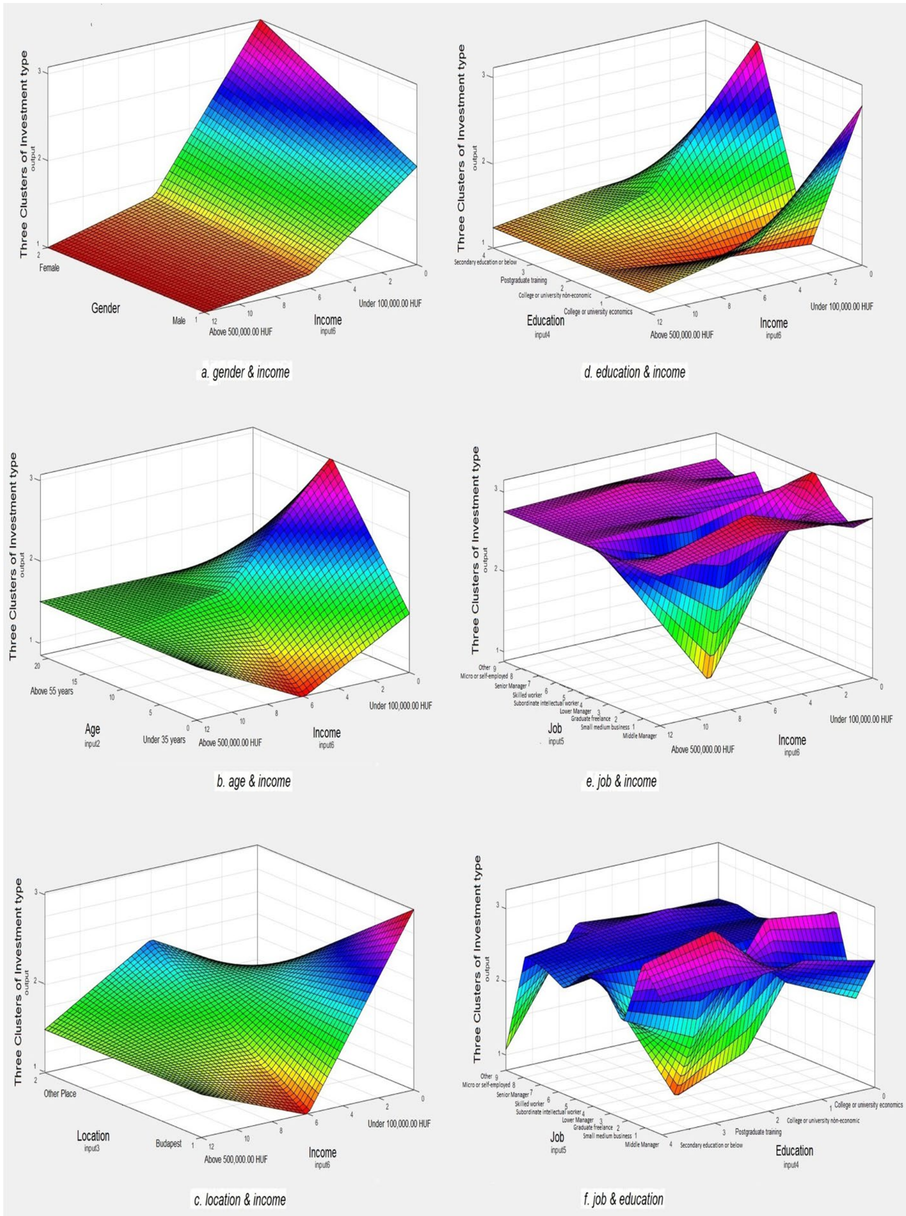


Fig. 17 Effectiveness of the relations of each pair of inputs on investment type cluster

```
Number of nodes: 2647
Number of linear parameters: 1296
Number of nonlinear parameters: 69
Total number of parameters: 1365
Number of training data pairs: 1542
Number of checking data pairs: 0
Number of fuzzy rules: 1296

[System]
Name='DemographicANFIS'
Type='sugeno'
Version=2.0
NumInputs=6
NumOutputs=1
NumRules=1296
AndMethod='prod'
OrMethod='probor'
ImpMethod='prod'
AggMethod='sum'
DefuzzMethod='wtaver'

[Input1]
Name='input1'
Range=[0 2]
NumMFs=2
MF1='in1mf1':'trimf',[-2 0.000333047420963386 1.99981415378178]
MF2='in1mf2':'trimf',[0.000442453779770493 2.0003330110654 4]

[Input2]
Name='input2'
Range=[0 21]
NumMFs=3
MF1='in2mf1':'trimf',[-10.5 -0.00243999954277444 10.5009016647353]
MF2='in2mf2':'trimf',[-0.00426113799422104 10.4975598614319 21.0000001229014]
MF3='in2mf3':'trimf',[10.5 21 31.5]

[Input3]
Name='input3'
Range=[0 2]
NumMFs=2
MF1='in3mf1':'trimf',[-1.99999999514709 0.00624622576903484 2.00002374077672]
MF2='in3mf2':'trimf',[-0.00193069552001991 2.00622273541233 4]

[Input4]
Name='input4'
Range=[0 4]
NumMFs=4
MF1='in4mf1':'trimf',[-1.33333333137059 0.00293171412369073 1.34204420573551]
MF2='in4mf2':'trimf',[-0.00200680495691898 1.33725182401531 2.66765409107521]
MF3='in4mf3':'trimf',[1.33432343993649 2.66834094973322 3.99885323149771]
MF4='in4mf4':'trimf',[2.66872624331244 4.00068503268348 5.33333333333333]

[Input5]
Name='input5'
Range=[0 9]
NumMFs=9
MF1='in5mf1':'trimf',[-1.125 0.000129835998789197 1.12603591835356]
MF2='in5mf2':'trimf',[8.33373538882956e-05 1.1241002468386 2.2463782754096]
MF3='in5mf3':'trimf',[1.12470673176409 2.24781007956832 3.37267224716138]
MF4='in5mf4':'trimf',[2.2494192826356 3.37722967512196 4.50422036500721]
MF5='in5mf5':'trimf',[3.37772553584201 4.50703482738974 5.62790095552386]
MF6='in5mf6':'trimf',[4.50457684557055 5.62802266062106 6.74968949973325]
MF7='in5mf7':'trimf',[5.62375818688295 6.74822748983581 7.87467050988712]
MF8='in5mf8':'trimf',[6.74599701793529 7.87383117113062 8.99926799292603]
MF9='in5mf9':'trimf',[7.87484961347295 8.99998119438774 10.125]

[Input6]
Name='input6'
Range=[0 12]
NumMFs=3
MF1='in6mf1':'trimf',[-6 0.000309741878187414 5.99738707320999]
MF2='in6mf2':'trimf',[0.0140390606608012 6.0003097862919 12]
MF3='in6mf3':'trimf',[6 12 18]

[Output1]
Name='output'
Range=[0 3]
NumMFs=1296
```

Figure 18 depicts the DemographicANFIS's organizational structure as the proposed investment recommender system.

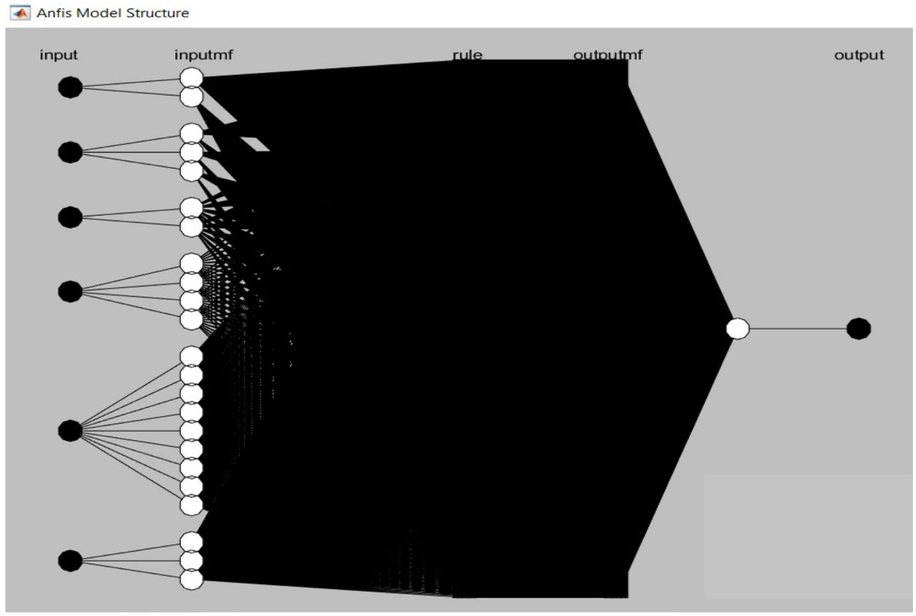


Fig. 18 Structure of DemographicANFIS (investment recommender system)

Discussion

The aim of this study is to design a novel model for investment recommender systems that utilize demographic and investment preference data of potential investors. To provide guidance and support the investor's choice, the model employs a fuzzy neural inference solution and investment type selection. Seven group agents were considered in the design of the investment recommender system. The ANFIS system categorizes customers based on six demographic traits using six input factors. The output of the ANFIS system, which corresponds to three clusters of investment types, is referred to as a factor.

The first cluster of investment types comprises a significant number of respondents with a total of 592 individuals. This cluster was given the top ranking and includes government securities, mutual funds, and listed stock/equity as the best investment options. These individuals have not made any stock market investments in the previous 3 years and did not regularly monitor or follow the stock's performance. Many of them did not own any government bonds. The second cluster, which includes 406 respondents, is in second place. The appropriate investment products for this cluster are listed stock/equity, mutual funds, voluntary pension funds, and government securities. These individuals have invested in the stock market within the last 3 years and regularly kept an eye on and followed the stock's performance. Many of them had investments in government bonds. The third cluster, with 340 respondents, is in third place. The appropriate investment products for this cluster are listed stock/equity, voluntary pension funds, and government securities. These individuals made an investment in the stock market in the previous 3 years and regularly checked in on and followed the stock's performance. However, many of them had no investment in government bonds.

The results indicate that each cluster's respondents shared specific characteristics and investment preferences, providing valuable insights for an investment recommendation. The results show that a DemographicANFIS investment recommender system was created using 2647 nodes. This system consists of a total of 1365 parameters, with 1296 being linear and 69 non-linear. Machine learning techniques were utilized to generate 1542 training data pairs for the system. The system ultimately produced 1296 fuzzy rules for investment recommendations. In order to fully assess the effectiveness of the system, it is important for users to test it in real-world settings. As users interact with the system, new fuzzy rules can be generated using feedback from potential or actual investors and expert knowledge. One example of how the first rule in the system was generated and interpreted is provided:

Rule 1 (example): The recommended investment type for a male under 34 years old living in Budapest, with a degree in economics, a middle management job, and a monthly income of less than 100,000 HUF, is a combination of stocks, mutual funds, and government securities. This investment strategy is appropriate for this individual as they may have limited experience in the stock market and are not actively monitoring stock performance. Additionally, they may not have previously invested in government bonds.

The nonlinear monolithic graphs in Fig. 17a–f present investment-type recommendations based on a pair of demographic factors, with the membership points of the investment-type clusters represented on the z-axis. The x-axis and y-axis represent the membership points of the demographic characteristics of a cluster of investment types. For example, Fig. 17a illustrates the respondents' membership in investment types according to their gender and income. It shows that as income increases, more men become investors, with potential investors with monthly incomes below 100,000 forints primarily in the second type of investment cluster and those with monthly incomes of more than 500,000 forints primarily in the third type of investment cluster. Similarly, Fig. 17b shows that potential investors around the age of 45 with a monthly income of fewer than 100,000 forints are in the third cluster of the investment type, while those of the same age with a monthly income of about 300,000 forints are in the second cluster. Figure 17c demonstrates that potential investors living in Budapest and earning less than HUF 100,000 per month belong to the third investment type cluster, while those living elsewhere and earning roughly HUF 300,000 per month belong to the second investment cluster. Figure 17e illustrates that potential investors in the third cluster of investment type have a middle manager job and make less than 100,000 forints per month. Figure 17f shows that the first cluster of investment types includes potential investors with postgraduate degrees and lower manager jobs, while the third cluster of investment types includes potential investors who hold lower manager jobs but have a college or university degree. Figure 17d illustrates that potential investors with any level of education and a monthly income of more than 500,000 forints are assigned to the first cluster of investment type. Overall, these graphs suggest that different demographic factors and characteristics can influence an individual's investment preferences and recommendations. These clusters of investment types can be used to guide potential investors in selecting investment products such as government securities, mutual funds, stocks/shares on stock exchanges, and voluntary pension funds.

In comparison, previous research in the field of investment recommender systems has focused on various aspects to improve the accuracy and relevance of investment recommendations. One study proposed a system to improve customer loyalty, while another proposed a model based on unique hedge funds that consider multiple factors such as modern-day yields and historic performance. Another proposed system incorporates the use of agents and an algorithm to improve the accuracy of the recommender system. Some studies focused on improving customer loyalty and utilizing various factors, such as modern-day yields, historic performance, and diversification by industry. Another proposed system incorporates the use of agents and an algorithm to improve the accuracy of the recommender system, while another proposed model is based on association rule mining. However, this study differs in its focus on utilizing demographic information and investment preferences to generate personalized recommendations for potential investors and making use of the ANFIS system for grouping and analyzing data. Paranjape-Voditel and Umesh [23] proposed a recommender system based on association rule mining. Tejeda-Lorente et al. [35] proposed a recommender system that relates to unique hedge funds that consider multiple factors, such as modern-day yields, historic performance, and diversification by industry. Hernández et al. [14] proposed a system that incorporates the use of agents and an algorithm to improve the accuracy of the recommender system. Tarnowska et al. [34] presented a recommender system for improving customer loyalty. Kovács, Ko, and Asemi [18] examined the use of a two-stage clustering method for identifying the investment patterns of potential retail banking customers. The study uses a combination of neural-network-based Kohonen self-organizing maps (SOMs) and hierarchical clustering to analyze data from an online investment survey. The research found that by using this method, investment patterns could be identified, and customer clusters could be described based on their investment preferences and current financial assets. The study also found that the customers had different perceptions of different financial instruments and portfolios, which suggested that different communication strategies might be required for different types of investment products. Additionally, it highlighted that risk and yield were perceived differently when considering financial stability. Overall, the study contributes to the field by demonstrating the benefits of using a two-stage clustering method, which allows for the simultaneous use of both categorical and numerical variables, in identifying investment patterns of retail banking customers. This can help in improving marketing policy and strategic planning in the retail banking industry. The literature review of Asemi and Ko [4] examines the current state of investment recommender systems and the use of customer investment service feedback to improve the accuracy and relevance of investment recommendations. The authors propose a new business model for an investment recommender system that utilizes fuzzy neural inference solutions and customized investment services. The authors' proposed model is based on the ANFIS system and is designed to support investment companies, individual investors, and fund managers in their investment decisions. The model identifies seven group factors to implement the proposed investment system model through the customer or potential investor data set. These 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. Overall, the proposed business model aims to improve the accuracy and relevance of investment recommendations by utilizing customer investment service feedback and fuzzy neural inference solutions. The literature review highlights the lack of similar models in the field and the potential benefits of the proposed model for investment companies, individual investors, and fund managers. This paper differs from these previous studies in its utilization of customer investment service feedback and fuzzy neural inference solutions to generate personalized investment recommendations. Moreover, the authors use the ANFIS system, which is a combination of the neural network and fuzzy logic, to group and analyze data which is something that the previous papers have not proposed. Additionally, the authors have considered a more comprehensive set of factors, including demographic data which can influence the investor's decision-making process and make the recommendations more personalized. This system has several innovations The role of potential investors is the subject of its first innovation. that the model's initial inputs are gathered from regular users who are thought of as potential investors. The second novel aspect of this research is the proposed ANFIS system's reliance on professional knowledge. This implies that investment experts can add rules to this system in addition to those that are intelligently generated by it. This study's third innovation is based on getting feedback. Investors and experts both provide feedback, and the system can be improved as a result. The proposed system's ability to operate based on erroneous or incomplete data is another innovation. Most information systems must deal with this issue.

Conclusion

In conclusion, this research suggested an automated recommender system to give investors investment-related suggestions. These suggestions are based on information about the investors' demographics. The system is built on a novel, intelligent methodology that makes use of ANFIS and six demographic factors. Additionally, this system operates with partial data. Based on comments made by investors using the system, it is also possible to put expert judgments into practice. According to the findings, the suggested system is a solid method for making recommendations regarding the kind of investment or investment products based on demographic traits.

What matters is that two categories of new rules for the proposed investment recommender system are defined by investment experts using their knowledge. When an expert decides that it is necessary to eliminate one or more variables from a generated rule, that rule falls under a certain category. As a result, the expert can modify one or more of the six variables in each rule the system generates and produce a new rule. Rules that are not produced by the system fall into the second category. Not all the rules that can be created based on the available variables are necessarily generated by the proposed investment recommender system. As previously mentioned, this system may function using fuzzy logic and incomplete or inaccurate data. Consequently, a new rule that incorporates all the variables and is not currently generated by the system can be added to it based on feedback from investors who use the system and the opinions of experts.

This system attempts to address the issue of incomplete or inaccurate data by using the function described for it. One of the system's drawbacks is that it only takes potential investors' demographic information into account. As system inputs, these data are also constrained to six variables. Another drawback is that only a few investment types are clustered together and viewed as the system's output. Naturally, the rules produced by the system will alter as the characteristics of potential investors are changed as inputs and as investment types are altered as an output of the system. Other traits of potential investors may be considered as system inputs in the future. Additionally, it is recommended that experts conduct future research in intelligently producing knowledge-based rules so that these rules can be intelligently added to the system based on experts' judgment.

Acknowledgements

We would like to thank Ms. Asefeh Asemi from Khurzouk Municipality in interpretation of some parts of primer data that were gathered from customers.

Author contributions

Asefeh Asemi acted as the main researcher, Adeleh Asemi provided guidance as the research advisor, and Andrea Ko served as the research supervisor. All authors read and approved the final manuscript.

Funding

Open access funding provided by Corvinus University of Budapest.

Availability of data and materials

Original data was collected in partnership with the Corvinus University of Budapest, the Dorsum company, and the Portfolio in the 1.3.1-VKE-2018–00007 project in the Hungarian language. According to the consortium agreement and the head of the project's consent, project data can be used for additional research and publications by the authors. The authors translated, cleaned, and prepared it for this research. New data available at Asemi, Asefeh (2022), "Data for Adaptive Neuro-Fuzzy Inference System for Customizing Investment Type based on the Potential Investors' Demographics", Mendeley Data, V1, https://doi.org/10.17632/93dmwj5yhk.1

Declarations

Ethics approval and consent to participate

This article does not contain any studies with human or animal participants performed by any of the authors.

Consent for publication

Not applicable

Competing interests

Work at the Corvinus University of Budapest helped design and develop the survey in conjunction with commercial companies (Dorsum and Portfolio).

Received: 5 April 2022 Accepted: 17 May 2023
Published online: 28 May 2023

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