Development of an Investment Recommender System Using Factor Analysis, ANFIS, and MMNN

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Abstract : The main goal is to present two investment recommender systems (IRS), by combining clustering, factor analysis, Adaptive Neuro Fuzzy Inference System (ANFIS), and Multimodal Neural Network (MNN). The aim is to merge each method with advanced techniques to improve the precision and efficiency of investment recommendations. To develop and implement the IRS, clustering and factor analysis are initially used to detect patterns and connections among variables aiding in grouping individuals into several categories. Then ANFIS is developed in MATLAB using data derived from factor analysis to prove rules for recommending clusters of investment types. Furthermore, MNN was created using Python making use of TensorFlow and Keras libraries using same data for ANFIS. This network is pre-trained with data to predict investment types. The performance of both models is assessed by metrics RMSE and MSE on test data to gauge their accuracy of recommendations. An assessment of the IRSs illustrates its effectiveness in offering investment recommendations. Both models highlight promising performance as shown by the error rates on the test data. By combining clustering, factor analysis, ANFIS and MNN a holistic strategy appears for tailoring investment advice. This approach effectively merged methods with innovative machine learning (ML) and deep learning (DL) techniques. This paper proposes the personalized IRSs that are useful for investment advice. By integrating clustering, factor analysis, ANFIS, and MNN, IRS provides a unique approach with using Explainable artificial intelligence (XAI) to increase the accuracy of investment recommendations. These systems use the strengths of each method in combining them.

Keywords: Investment Recommender System, Clustering, Factor Analysis, Adaptive Neuro-Fuzzy Inference System (ANFIS), Multi-Modal Neural Network (MMNN), Machine Learning, Deep Learning, Personalized Investment, Explainable artificial intelligence (XAI).

1 INTRODUCTION

In the digital landscape, it is essential for individuals to make informed investment choices to manage their finances effectively. The intricate and unpredictable nature of markets creates challenges for investors in spotting available investment opportunities [1]. Artificial intelligence (AI), machine learning (ML), and deep learning (DL) are increasingly being used in this field [2]. These methods can analyze volumes of data to detect patterns and offer personalized investment advice based on individual preferences and investors profile. One important approach in this domain is the development of recommender systems that use AI algorithms to give personalized investment advice [4]. These systems consider factors such as demographics, investment goals, risk tolerance levels, and market trends to provide tailored recommendations for investors based on their needs [4]. The goal is to improve decision making processes, boost portfolio performance and reduce risks using data analysis and predictive modeling techniques. This paper introduces a framework for developing the IRS by combining techniques, with clustering, factor analysis, adaptive neuro fuzzy inference systems (ANFIS), and multimodal neural network (MNN) approaches. “Multimodality refers to the presence of multiple modalities, where a "modality" denotes a specific type of input or output, including video, image, audio, text, proprioception, and so forth [5]. In this study, MNN encompasses the concept of multimodality stemming from the presence of diverse methodologies. The spectrum of inputs or outputs is not confined to formats like video, image, sound, or text; instead, it can embrace various categories within a single data form. “An ANFIS is a kind of artificial neural network that is based on Takagi–Sugeno fuzzy inference system” [6]. We combined data analysis techniques to pinpoint elements that affect investment choices. Then, ANFIS was used for crafting rule-based suggestions and utilized MNN for forecasting and assessment. This study aims to offer an understanding of creating and implementing IRS by delving into the systems structure, parts, and execution methods. Additionally test outcomes and performance reviews highlight the effectiveness and precision of the suggested methods, in creating tailored investment advice and aiding in making informed decisions within markets.

2 BACKGROUND AND RELATED WORKS

Lately, there have been advancements in investment development and associated areas influenced by shifts in market dynamics and investor choices. Various research works have delved into personalized investment system enhancements. The past few years have seen progress in predicting stock market trends thanks to methodologies incorporating neural networks and DL strategies. Zhang and colleagues [7] presented a method for recommending works of art in shopping platforms that focused on different preferences of system users. The approach they used was related to the use of correlation graphs based on the keywords used by users. This system provided suggestions related to personal collections of works of art. This method emphasized the importance of considering user interactions and preferences in recommendation systems. Huang and Vakharia [8] introduced the RCA-BiLSTM-DQN model, which harnesses DL to enhance prediction accuracy by using multi-temporal stock data and reverse cross attention. In addition, Hou [9] proposed a model using DL methods to predict user investment behaviors. Bansal and colleagues [10] also introduced a learning-based model for predicting stock market trends by combining temporal stock data and inverse attention. Researchers also showed how ensemble learning methods, combined with investor sentiment, can lead to stock index predictions [11]. In addition, a study introduced an integrated approach using learning methods focusing on investor sentiment characteristics for stock index forecasting. These diverse methodologies emphasize the importance of combining diverse learning approaches in analysis and forecasting, which underscores the value of computational techniques and behavioral insights for informed decision making in financial markets. Chen and colleagues [12] developed a system for recommending educational content for sports using C for clustering. In another study, Singh, and his team [13] unveiled a real-time question answering system in MSX Sales Copilot to increase sales productivity. Iftikhar and colleagues [14] proposed a reinforcement learning recommender system that used Markov decision processes to adjust to changing user preferences. Takayanagi and colleagues [15] presented a Personalized Dynamic Recommender System for Investors (PDRSI), recognizing how investor preferences are influenced by online platforms and social media conversations. PDRSI combines individual investor characteristics and temporal environmental factors to provide customized investment suggestions. Their system, evaluated using RMSE, proves the superiority of the hybrid model over traditional ANN approaches. Through the application of K means clustering and Markowitz's Modern Portfolio In their work, Bian, and colleagues [16] introduced Feynman, a federated learning-based advertising platform that aims to improve mobile app recommendations while addressing privacy issues. Asemi and colleagues [17] proposed an ANFIS recommender system specifically designed for investment recommendations. By analyzing investors demographic information and feedback, the model gives personalized investment advice for investors. Asemi and colleagues [18] introduced an automated IRS based on an ANFIS algorithm. Their model considered weighty decision factors like the value of the system and expected returns to offer customized investment advice. Saini and Vaz [19] proposed a hybrid recommendation system for personalized investment portfolios, using user-based collaborative filtering and Sharpe ratio optimization. Chen and colleagues [20] introduced a trend-aware investment target recommendation system using sequential records and heterogeneous relation graphs, achieving impressive results compared to baseline methods. Ahmadiyah and colleagues [21] presented an IRS for agriculture peer-to-peer lending websites, using Decision Tree algorithms with a high accuracy rate. Yue [22] proposed FAI, a recommendation system for investors based on Euclidean Distance of TF-IDF value, aiming to enhance startup financing efficiency and providing unprecedented convenience to investors through a mini-program. SheidaeiNarmigi and colleagues [23] explored portfolio optimization strategies, aiming to minimize investment risk while maximizing profit. Aljunid and Huchaiah [24] suggested a multimodal DL method to tackle issues related to implicit feedback data in recommendation systems. These research findings collectively highlight the progress of IRS, underscoring the importance of integrating ML, data analysis and user centered methods for delivering personalized investment guidance. In this paper, authors aimed to introduce the advanced models for personalized investment recommendations by potential investors' data sources and sophisticated modeling techniques ANFIS and MNN.

3 METHODS

3.1. System Design

System design involves a comprehensive approach to system design that uses advanced computational techniques for system development [25]. A set of advanced methods and techniques have been used in the current IRS's design. To do this, the data of the earlier research, which includes the responses of 1542 people to the investment questionnaire on the Hungarian portfolio website, has been used. This questionnaire was developed as part of the GINOP project in collaboration with Corvinus University of Budapest [18]. The data contain information about financial standing, investing experiences, managerial traits, and other investment-related information. To improve the investment suggestions, data clustering and data factor analysis techniques were combined in the construction of the investment recommender system (IRS). The IRS is designed with consideration for the following crucial processes:

3.2 Preparation Data (Clustering and Factor Analysis)

In the first step, in preparation data, clustering techniques are used to find distinct segments [26] within the dataset based on similarities in managerial characteristics, financial status, investment experiences, and other relevant factors. Then, factor analysis methodologies apply to extract underlying factors influencing [27] in investment decisions, such as demographic information, personality traits, and investment experiences.

3.3 ANFIS Implementation

In the later phase, ANFIS functions as a rule-based inference system to produce tailored investment suggestions. ANFIS utilizes data trained on outputs obtained from clustering and factor analysis stages to refine recommendation precision. So, the system employs a novel method centered on crucial factors [28]. XAI used to explain the generated rules.

3.4 ANFIS Model Training and Testing

During this stage, input-output pairs extracted from factor analysis and clustering are employed to fine-tune parameters, thereby enhancing recommendation accuracy via RMSE. This process entails training the model to minimize prediction errors, assessing its performance through validation, and evaluating its ability [4], [28].

3.5 MNN Implementation

Develops an MNN architecture incorporating layers like Long Short-Term Memory (LSTM) and Dense layers to personalize investment recommendations [25]. In the MNN architecture, layers such as LSTM and dense layers are combined [20]. At this stage, by implementing the MNN neural network, input, and output data of ANFIS, which was prepared based on clustering and factor analysis, is trained, and further improves the accuracy and predictability of investment.

3.6 MNN Model Training and Evaluation

After implementing MNN, training, and fine-tuning the neural network model using training data, it is necessary to perform validation to perfect parameters to improve prediction accuracy. Therefore, the performance of this model is evaluated using the mean squared error (MSE) measure to evaluate its effectiveness in predicting investment types.

3.7 Prediction on New Data

In this step, the trained MNN model is used to predict investment types for new data inputs. This provides real-time recommendations based on pre-analyzed factors. In this step, investment recommendations are created using the mapping between predicted values and investment product clusters. This helps investors in their decision-making processes.

In the end we evaluate how well an IRS, created using ANFIS and MNN models performs. We analyze clustered data and factors used in both models to provide investment suggestions. The effectiveness of these recommendations is then assessed based on accuracy and efficiency measures. This study examines how well both models predict types of investments to figure out which one is superior, for the recommendation system. By incorporating diversity and advanced methods the proposed systems present a foundation for creating investment advice. Through world testing and performance assessments these systems highlight their ability to enhance investment decision making processes and perfect portfolio performance in the market.

4 RESULTS

Implementations: The IRS is put into action by bringing the system design to life using computational tools and methods. This part describes the actions taken to put into practice parts of the system such as preparing data creating models, training, and assessing performance.

4.1 Clustering

The first step involves preprocessing the raw data obtained from the Portfolio website questionnaire. This includes data cleaning, normalization, and transformation to ensure uniformity and compatibility for later analysis. Standard techniques such as data imputation for missing values, outlier detection, and feature scaling are applied to prepare the dataset for data analysis. Cluster Analysis was done by JMP using K-Means for seven categories. Descriptions of the three clusters for demographic data (input) are as the following:

Cluster 1: *This cluster comprises predominantly male individuals aged between 40 and 64, residing in diverse locations ranging from rural areas to highways. Their educational backgrounds vary, spanning from high school diplomas to college and university degrees. Occupationally, this cluster represents a wide spectrum, including individuals in management positions as well as laborers.*

Cluster 2: *This cluster consists mainly of male individuals aged between 20 and 59, predominantly located in urban areas and along highways. Their educational levels vary similarly, ranging from high school diplomas to college and university degrees. Occupationally, this cluster is characterized by most employees and managers.*

Cluster 3: *This cluster composed primarily of male individuals spanning ages 20 to 69, mostly residing in urban areas and along highways. Their educational backgrounds vary from high school diplomas to university degrees. Occupationally, this cluster exhibits diversity, including individuals in management roles as well as laborers. These descriptions are based on the main characteristics of each cluster, such as gender, age range, location, education, and occupation of individuals in each cluster.*

Descriptions of the three clusters for key decision factors data (input) are as the following:

Cluster 1: *This cluster comprises results indicating that the most important factors in investors' decision-making include banking algorithms, banking advice, and the opinions of others like themselves, such as family and friends. This group holds positive views regarding environmental values and the importance of flexibility in investment within those values.*

Cluster 2*: This cluster includes results where the majority consider the most important factors in investment decision-making to be the opinions of family and friends and social influences. This group also affirms the importance of environmental values and flexibility in investment.*

Cluster 3: *This cluster represents results typically associated with investors who have high self-confidence and often make investment decisions without external influences. They are often not seeking high returns on socially and environmentally responsible investments and prefer financial returns above all else.*

The key decision factors clusters demonstrate that there are different investment attitudes and patterns in society, which may be shaped by individual values, beliefs, and experiences. Descriptions of the three clusters for personality traits data (input) are as the following. These descriptions provide a general overview of the behaviors and needs of customers in each of the three main clusters.

Cluster 1: *This cluster comprises customers who exhibit high-frequency purchases with substantial monetary values. These individuals or businesses are likely high-income, showing strong loyalty and satisfaction with the products or services offered. Their consistent spending patterns indicate a high level of engagement and a willingness to invest in quality. To maintain their loyalty, personalized offers and rewards programs tailored to their preferences and purchase history can be highly effective marketing strategies.*

Cluster 2: *This cluster consists of customers who make occasional purchases with moderate monetary values. This cluster represents middle-income individuals or small businesses with varying levels of engagement. While some customers in this cluster are moderately active, others display more sporadic buying behavior. Their purchasing patterns suggest a degree of price sensitivity or fluctuating needs. Targeted promotions during peak buying periods or incentives for repeat purchases can help encourage more consistent engagement from this cluster.*

Cluster 3: *This cluster includes customers with infrequent purchases and low monetary values. These individuals may have limited purchasing power or alternative preferences. Their buying patterns indicate minimal engagement with the products or services offered, possibly due to budget constraints or lack of interest. To increase engagement from this cluster, targeted discounts, personalized product recommendations, or efforts to understand their specific needs and preferences may be necessary. Additionally, expanding the product range to cater to different budget segments could help attract more customers from this cluster.*

Descriptions of the three clusters for experiences data (input) are as the following:

Cluster 1 *Relatively Low Digital Flexibility: This cluster consists of customers who own smartphones and have access to mobile internet. Most of them have made online purchases in the past 3 months. They do not use password management services. They are subscribers to online services like Spotify, Apple Music, and Netflix. They are often recognized as normal bank customers. The majority have expressed satisfaction with their bank. They are willing to trust robotic recommendations for investment decisions. They may consider switching to better digital banking services.*

Cluster 2 *Medium Digital Flexibility: This cluster includes customers who own smartphones and have access to mobile internet. Some of them have not made online purchases in the past 3 months. They do not use password management services. They are subscribers to online* *services like Spotify, Apple Music, and Netflix. They may be recognized as normal or private bank customers. Some have expressed satisfaction with their bank. Most of them do not trust robots for investment decisions. They might consider digital banking services for betterment.*

Cluster 3 *High Digital Flexibility: This cluster consists of customers who own smartphones and have access to mobile internet. Some of them have not made online purchases in the past 3 months. They use password management services. They are subscribers to online services like Spotify, Apple Music, and Netflix. They may be recognized as special bank customers. The majority have expressed satisfaction with their bank. They trust robotic recommendations for investment decisions. They prefer digital banking services to enhance their services.*

These descriptions of the experiences data clusters provide insights into the digital flexibility of customers across three different clusters, which can be valuable for banks and fintech companies to tailor their services to meet the needs and preferences of their customers. Descriptions of the three clusters for financial situation data (input) are as the following:

Cluster 1 *Strong Financial Status: Individuals in this cluster generally have a strong financial standing and regularly manage their expenses and savings diligently. They are often able to allocate budget for enjoying travels and entertainment, and frequently indulge in extra spending for such activities. These individuals tend to have minimal concerns regarding their daily affairs and overall are content with their financial situation.*

Cluster 2 *Moderate Financial Status: Individuals in this cluster may face some day-to-day financial challenges, but overall, their financial situation appears to be good. They typically have savings for specific goals such as purchasing a car or a house, or even for international travels. Some individuals in this cluster might have concerns about the future of their children, but generally they are satisfied with their situation and manage financial matters well.*

Cluster 3 *Weak Financial Status: Individuals in this cluster usually struggle with daily financial issues and may find it difficult to allocate additional funds for enjoying life or attending to important matters. They may harbor significant concerns about the future and may feel hopeless about their situation, with life being very challenging due to financial constraints. Some individuals in this cluster may even refrain from saving or planning for their future and focus solely on getting by day-to-day.*

Descriptions of the three clusters managerial traits data (input) are as the following:

Cluster 1: *Individuals in this cluster tend to lean towards rational thinking and precise planning. They often draw from their past experiences in decision-making and generally have fewer fantasies about life. These individuals may prefer to plan and execute their plans in environments such as home or workplace. Their planning may revolve around daily activities and be limited to near-term timeframes.*

Cluster 2*: Members of this cluster appear to be more inclined towards flexibility and adaptation to their surroundings. They may be influenced by factors such as stress and anxiety in decision-making. These individuals may prefer planning and executing their plans in environments like home or workplace where there are fewer time constraints. Their planning may be determined by priorities and immediate needs.*

Cluster 3: *Individuals in this cluster seem to be less planned and more inclined towards adapting to environmental conditions. They probably pay less attention to past points and experiences in their decision-making. These individuals may be less inclined to plan and more influenced by their immediate circumstances. Their planning might be more reactive and less structured.*

Descriptions of the three clusters for investment type experiences (output) are as the following:

Cluster 1 *Stock Market Investors: This group of customers shows the most interest in investing in financial markets such as the stock market. They may have a high level of experience and knowledge in investment and are mostly seeking high returns with medium to high risk. They may be familiar with technical analysis and financial news and prefer to continuously monitor their investments and make decisions based on their own analysis.*

Cluster 2 *Banking Investors: This group of customers seeks minimal ways to invest and preserve their capital. They may be interested in depositing in banks, investing in mutual funds, or purchasing shares of large companies. They tend to reduce their investment risk and adapt to regional risks and financial conditions.*

Cluster 3 *Unconventional Investors: This group of customers seeks unconventional and high-yield investments. They may invest in diverse assets such as art, real estate, gold, and ancient coins. They may have less knowledge and experience in financial investment but are looking for attractive investment opportunities with high returns.*

Table 1 shows summarizing the clusters across various categories. It provides a concise overview of the characteristics of each cluster across different dimensions.

Cluster	Demographic Data	Decision Factors Data	Personality Traits Data	Experiences Data	Financial Situation Data	Managerial Traits Data	Investment Type Experiences
	Input	Input	Input	Input	Input	Input	Output
1	Predominantly male individuals aged 40-64, diverse locations, varying education & occupation	Banking algorithms, banking advice, opinions of others, positive views on environmental values	High-frequency purchases, substantial monetary values, high loyalty & satisfaction	Relatively low digital flexibility, use of smartphones but not password management services	Strong financial status, allocate budget for travel & entertainment	Lean towards rational thinking & precise planning	Stock market investors, seeking high returns with medium to high risk
2	Predominantly male individuals aged 20-59, urban & highway locations, varying education & occupation	Opinions of family and friends, social influences, importance of environmental values	Occasional purchases, moderate monetary values, varying engagement	Medium digital flexibility, use of smartphones but not password management services	Moderate financial status, savings for specific goals, some concerns about future	Inclined towards flexibility and adaptation, influenced by stress and anxiety	Banking investors, seek minimal ways to invest and preserve capital
3	Predominantly male individuals aged 20-69, urban & highway locations, varying education & occupation	High self-confidence, less influenced by external factors, prioritize financial returns	Infrequent purchases, low monetary values, minimal engagement	High digital flexibility, use of smartphones and password management services	Weak financial status, struggle with daily financial issues, significant concerns about future	Less planned, more inclined towards adapting to environmental conditions	Unconventional investors, seek high-yield investments in diverse assets

Table 1: Summarizing the clusters across different categories

4.2. Factor Analysis for recommender system's inputs

Factor Analysis has done by JMP using suitable techniques and methods as the following. The factor analysis results indicate the relationships between different clusters or categories of input variables and the underlying factors influencing them. Table 1 shows the Standard Score Coefficients. These coefficients show the strength and direction of the relationship between each input category and the underlying factors (Factor 1 to Factor 6). Higher absolute values indicate a stronger association with the corresponding factor. Table 2 shows the Standard Score Coefficients. These coefficients show the strength and direction of the relationship between each input category and the underlying factors (Factor 1 to Factor 6). Higher absolute values indicate a stronger association with the corresponding factor.

Table 2: Relationships between input categories and underlying factors

Clusters/ Categories	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6
Demographic	-0.001	0.707	-0.0002	-0.004	-0.001	0.002
Decision Key Factors	0.001	0.001	0.0004	0.001	0.00007	0.707
Personality Traits	0.707	-0.0004	0.004	-0.0001	-0.0009	0.0009
Experiences	0.004	-0.0001	0.708	0.0001	0.0021	0.001

Clusters/ Categories	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6
Financial	-0.001	-0.004	0.0001	0.707	-0.003	0.001
Managerial Traits	-0.002	-0.001	0.002	-0.003	0.707	-0.001

Table 3 shows the Variance explained by each factor. This table shows the amount of variance explained by each factor. It indicates how much of the total variance in the input data is accounted for by each factor. A higher percentage suggests that the factor is more influential in explaining the variability in the data. Tables 4 & 5 show the Significance Test. This test evaluates whether there are common factors among the input variables. A significant result ($p < 0.05$) suggests that at least one common factor exists, meaning that the variables are not entirely independent.

Table 3: Amount of variance explained by each underlying factor

Factor	Variance	Percent	Cum Percent
Factor 1	0.5087	8.479	8.479
Factor 2	0.5071	8.451	16.930
Factor 3	0.5067	8.445	25.375
Factor 4	0.5066	8.443	33.818
Factor 5	0.5062	8.437	42.255
Factor 6	0.5037	8.395	50.650

Table 4: Evaluation of common factors among input variables

Test	DF	ChiSquare	Prob>ChiSq
H0: no common factors.	15	61.020	<.0001*
HA: at least one common factor			

Table 5: Evaluation of all factors among input variables

Test	DF	Criterion	Chi Square	Prob > ChiSq
H0: 6 factors are sufficient.	-6	0.000	0.000	.
HA: more factors are needed.				

Table 6 shows the Measures of Fit. These measures assess how well the chosen factor structure fits the data. Lower values for measures such as AIC and BIC indicate better fit, while values close to 1 for indices like Tucker and Lewis's Index suggest good fit.

Table 6: Assessment of the fit between the chosen factor structure and the data

Measures of Fit	Fit Index
Chi-Square without Bartlett's Correction	0.000
AIC	12.000
BIC	44.045
Tucker and Lewis's Index	1.326
Root Mean Square Error of Approximation	.

Table 7 shows the Measures of Factor Scores. These measures indicate the reliability of the factor scores derived from the analysis. The multiple R and multiple R-square values show the strength of the relationship between the observed variables and the derived factors. Table 8 shows the Rotated Factor Loading. This table displays the rotated factor loadings, which represent the correlation between each input variable and each factor after rotation. Variables with high loading values (absolute value > 0.3) are considered important for interpreting the factors.

Table 7: Reliability of the derived factor scores

Factor	Multiple R	Multiple R Square	Minimum Correlation
Factor 1	0.707	0.500	-0.0002*
Factor 2	0.707	0.500	-0.0000*
Factor 3	0.707	0.500	-0.0000*
Factor 4	0.707	0.500	0.0001*
Factor 5	0.707	0.500	-0.0000*
Factor 6	0.707	0.500	0.0001*

Table 8: Correlation between input variables and rotated factors

Clusters/ Categories	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6
Personality Traits	0.71	0.038	-0.01	0.072	0.049	0.006
Demographic	0.04	0.71	-0.07	-0.003	0.019	0.02
Experiences	-0.01	-0.07	0.71	-0.03	-0.024	0.02
Financial	0.07	-0.003	-0.03	0.71	0.021	0.005
Managerial Traits	0.05	0.02	-0.02	0.02	0.71	-0.05
Decision Key Factors	0.01	0.02	0.02	0.005	-0.05	0.71

- Suppress Absolute Loading Value Less Than 0.3 & Dim Text 0.4

Figure 1 shows the Factor Loading Plot. The Factor Loading Plot displays the relationship between variables and factors. Each variable is represented by a point, and the distance and direction from the origin (0,0) indicate its loading on different factors. This plot helps visualize how variables contribute to each factor and identify patterns or clusters of variables that load heavily on certain factors.

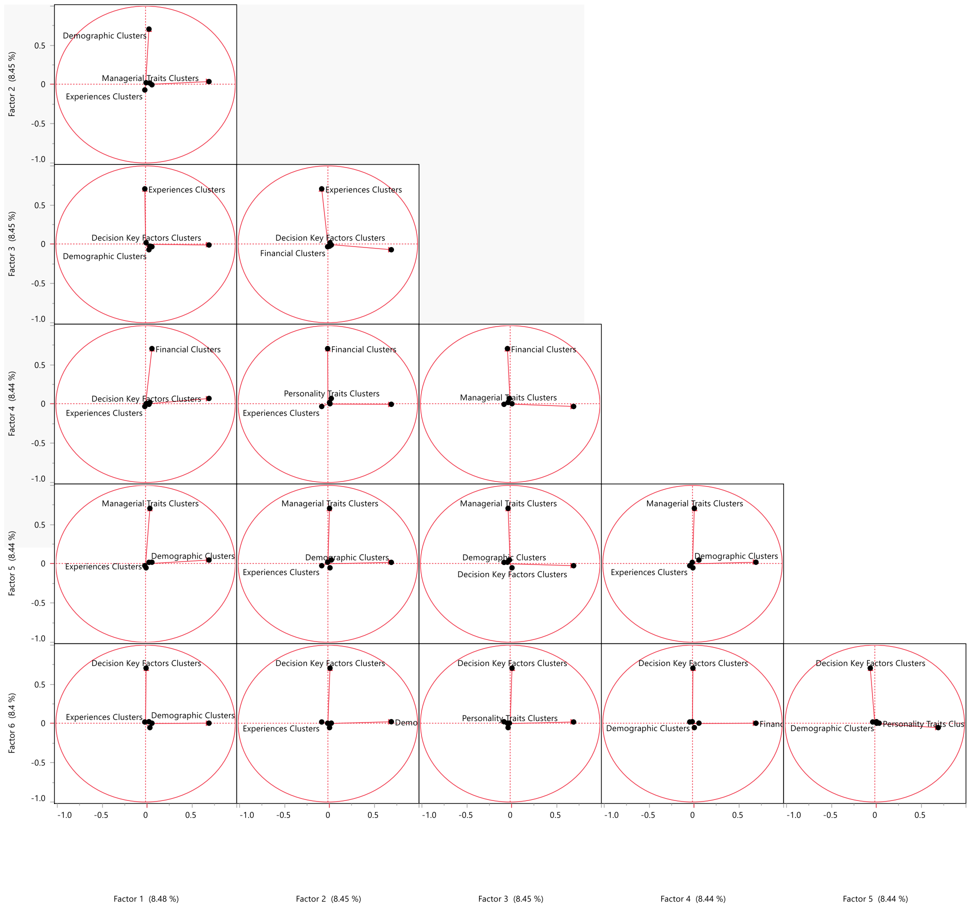


Figure 1: **Relationship between variables and factors**

The Score Plot (figure 2) displays the scores of observations on different factors extracted from the factor analysis. Each observation is represented by a point in the plot, with its position indicating its score on each factor. This plot helps visualize the distribution of observations in the factor space and identify any patterns or clusters among them based on their factor scores.

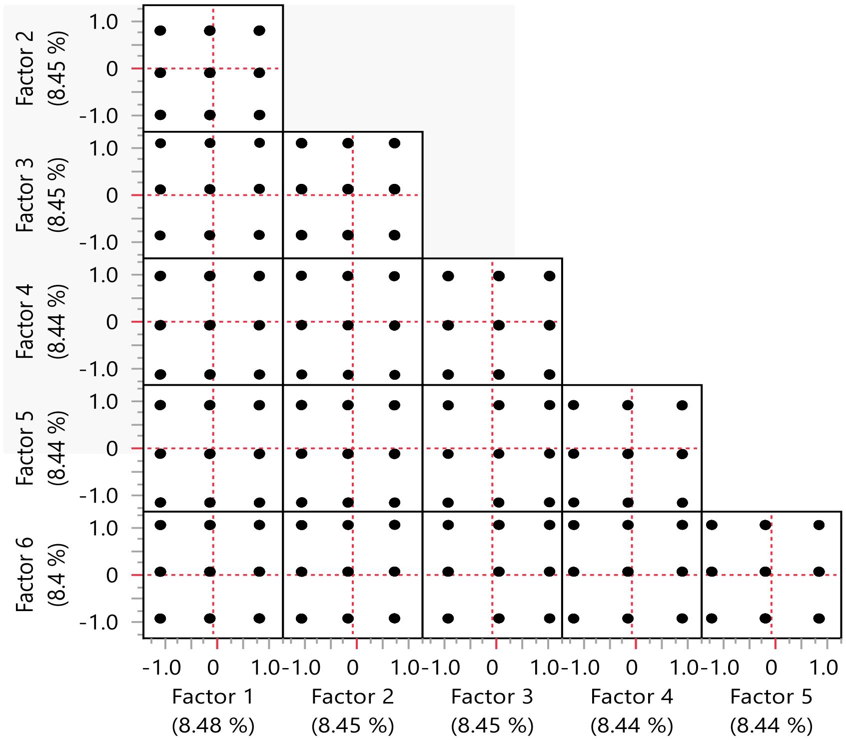


Figure 2: Scores of observations on different factors extracted from the factor analysis

Factor analysis results for the clusters in different categories are as follows:

Demographic Clusters: *Factor analysis on demographic clusters reveals common factors among demographic traits. These factors include aspects such as age, gender distribution, geographic locations, and educational and occupational diversity. The analysis suggests that certain demographic characteristics tend to cluster together, indicating potential correlations or shared attributes within specific demographic groups.*

Decision Key Factors Clusters: *The factor analysis conducted on decision key factors clusters identifies underlying factors influencing decision-making processes related to investments. These factors encompass various elements such as reliance on banking algorithms, advice from family and friends, social influences, and consideration of environmental values. By understanding these key decision factors, the recommendation system can tailor investment suggestions to align with users' preferences and decision-making criteria.*

Personality Traits Clusters*: Analysis of personality traits clusters reveals common traits or behavioral tendencies among users. These traits may include levels of self-confidence, adaptability to environmental conditions, tendencies towards rational decision-making versus flexibility, and susceptibility to stress and anxiety. Understanding these personality traits can help personalize investment recommendations and engagement strategies to better resonate with users' individual characteristics.*

Experiences Clusters*: Factor analysis on experiences clusters uncovers patterns in users' investment experiences and behaviors. These patterns may involve frequency and monetary values of investment activities, digital flexibility in utilizing financial services, financial stability or challenges, and the level of planning or adaptability in investment strategies. By recognizing these patterns, the recommendation system can offer tailored suggestions that address users' specific investment experiences and needs.*

Financial Clusters: *The factor analysis conducted on financial clusters highlights commonalities in users' financial situations. These may include factors such as overall financial status (strong, moderate, weak), savings habits, concerns about future* *financial stability, and attitudes towards risk-taking. Understanding these financial clusters allows the recommendation system to offer suitable investment options that align with users' financial circumstances and risk preferences.*

Managerial Traits Clusters: *Analysis of managerial traits clusters reveals underlying managerial characteristics shared among users. These traits may encompass aspects such as decision-making styles (rational, adaptive), digital literacy and flexibility, and attitudes towards planning and improvisation. Recognizing these managerial traits enables the recommendation system to provide tailored investment advice that resonates with users' managerial preferences and tendencies.*

By comprehensively analyzing these clusters across different categories, the recommendation system can enhance its ability to provide personalized investment recommendations and engagement strategies that cater to users' diverse preferences, behaviors, and characteristics. Table 9 shows an interpretation of the factor analysis results in a tabular format. This table summarizes the key factors extracted from the factor analysis across different clusters in each category. Factor 1 encompasses a broad range of demographic, decision-making, personality, experiential, financial, and managerial traits. Factor 2 highlights specific decision-making factors, attitudes towards investment flexibility, susceptibility to stress, and financial behaviors. Factor 3 mainly focuses on digital flexibility in financial services utilization. By identifying these features, recommendation algorithms were designed in a way that takes fundamental characteristics into account and provides the best suggestions for users. For example, by determining important managerial or financial features through factor analysis, recommendation algorithms were improved based on these features to offer more accurate suggestions. Utilizing these two methods effectively enabled the design of patterns and algorithms required for the recommendation system, allowing for the optimal utilization of user participation.

Table 9: Interpretation of the factor analysis results

	Demographic Clusters	Decision Key Factors Clusters	Personality Traits Clusters	Experiences Clusters	Financial Clusters	Managerial Traits Clusters
Factor 1	Age distribution, gender, geographic locations, educational and occupational diversity	Reliance on banking algorithms, advice from family and friends, social influences	Levels of self-confidence, adaptability, decision-making styles	Frequency and monetary values of investment activities, digital flexibility	Overall financial status, savings habits, concerns about future financial stability	Decision-making styles, digital literacy, attitudes towards planning
Factor 2	-	Environmental values, flexibility in investment, opinions of others like themselves	Susceptibility to stress and anxiety, tendencies towards rational decision-making	-	Attitudes towards risk-taking, savings habits, financial stability	-
Factor 3	-	-	-	Digital flexibility in utilizing financial services	-	-

4.3 System Development based on the Factor Analysis and creating Inputs for ANFIS

In the data analysis process, "grouping based on analyzed factors" or "grouping using multivariate analysis tools" was performed to determine the inputs for the recommender system implementation for investment recommendation. Initially, in the factor analysis stage, various factor analysis methods were used to identify patterns and relationships among variables or clusters. These factors were determined based on changes in the data and their relationships. After identifying the analysis factors, individuals can be grouped into different groups based on these factors. For example, we formed three different groups. For each of these groups, a five-point scale was considered to help evaluate each individual based on different characteristics identified in each group. Based on the information obtained from grouping and scaling, inputs for the implementation of the recommender system were determined. The output of the inference was also considered the clustering of investment types.

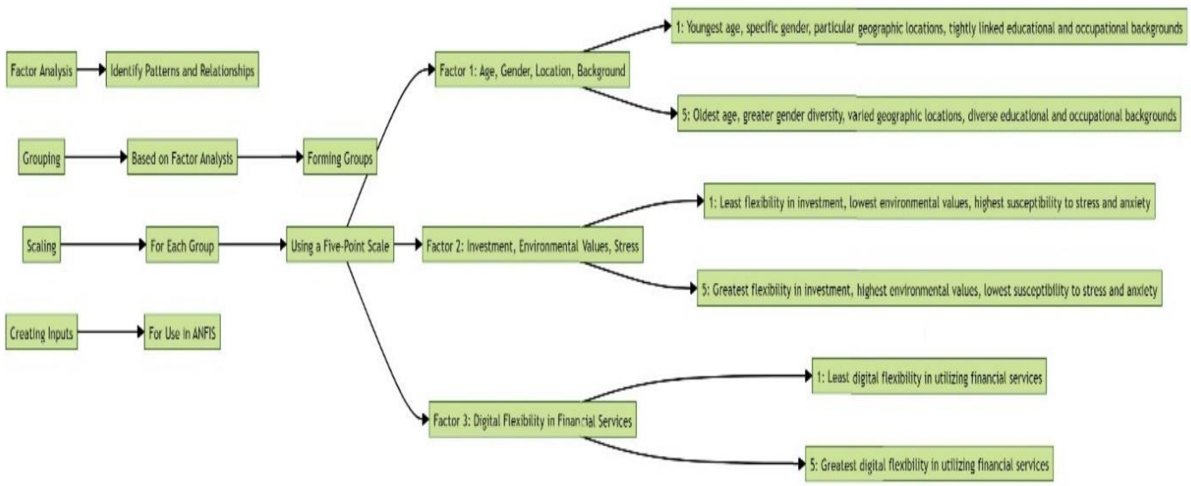


Figure 3. Developing investment recommender system based on analyzed factors and generating ANFIS inputs

In this pattern (Figure 3), we start with factor analysis to identify important patterns and relationships. Then, using these factors, we divide individuals into different groups and consider a five-point scale for each group. Finally, we create inputs for use in ANFIS.

4.4 System Development based on the Factor Analysis and creating Inputs for ANFIS

This section includes a detailed description of the design of the ANFIS system, including its architecture, components, algorithms, and data structures of the proposed investment recommender system. Figure 3 is a composite figure, consisting of several subplots. One subplot illustrates the input and output variables in the ANFIS system, showcasing the relationship between the input variables and the corresponding output. Another subplot depicts the membership functions of the input and output variables, demonstrating how the fuzzy sets are defined and utilized within the system. Additionally, there is a subplot displaying the training error of the ANFIS model after implementation, providing insights into the convergence and optimization process during the training phase. ANFIS comprises multiple layers, each serving a distinct purpose. The first layer, the fuzzification layer, converts crisp input data into fuzzy sets using membership functions. The second layer, the rule layer, evaluates the firing strength of each fuzzy rule by combining the membership grades of input variables. Next, the normalization layer scales the firing strengths to ensure proper weighting. Subsequently, the defuzzification layer aggregates the weighted outputs of the rules to generate a crisp output. Finally, the output layer yields the system's output, providing investment recommendations based on the input variables. Throughout these stages, ANFIS adapts its parameters using hybrid learning algorithms, such as backpropagation and gradient descent, to refine its predictive capabilities and optimize the investment recommendations (Figure 4). Attachment 4 shows five sample rules generated by ANFIS.

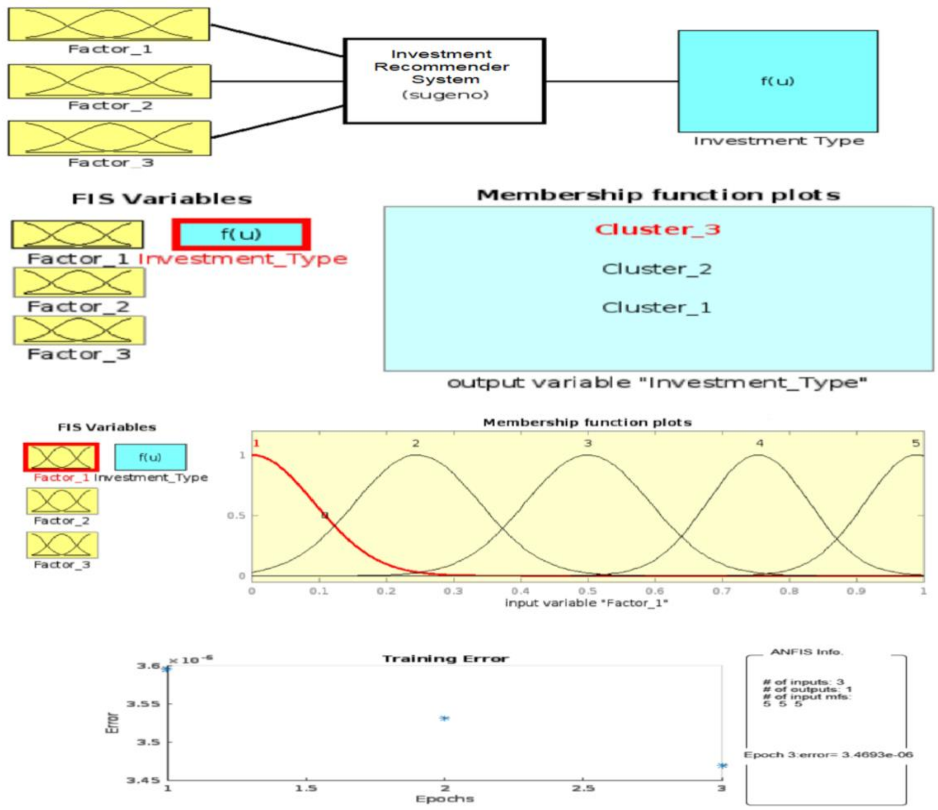


Figure 4: Implementation IRS by ANFIS in MATLAB

Here are five sample rules generated by ANFIS. These rules are a kind of XAI in investment advising:

Rule 1*: If Age, Gender, Location, Background (Factor 1) are in group 5 AND Investment, Environmental Values, Stress (Factor 2) are low AND Digital Flexibility in Financial Services (Factor 3) is moderate, then recommend Cluster 1: Stock Market Investors. This rule suggests that individuals who are relatively older, have specific demographic characteristics, and moderate digital flexibility, but exhibit low stress and environmental values tend to belong to Cluster 1, characterized by their interest in the stock market.*

Rule 2: *If Age, Gender, Location, Background (Factor 1) are in group 1 AND Investment, Environmental Values, Stress (Factor 2) are high AND Digital Flexibility in Financial Services (Factor 3) is high, then recommend Cluster 2: Banking Investors. This rule indicates that individuals with certain demographic characteristics, high investment orientation, and high digital flexibility are likely to belong to Cluster 2, focused on conservative banking investments.*

Rule 3: *If Age, Gender, Location, Background (Factor 1) are in group 3 AND Investment, Environmental Values, Stress (Factor 2) are moderate AND Digital Flexibility in Financial Services (Factor 3) is high, then recommend Cluster 2: Banking Investors. Here, individuals with specific demographic characteristics, moderate investment tendencies, and high digital flexibility are associated with Cluster 2, suggesting their preference for secure banking investments.*

Rule 4: *If Age, Gender, Location, Background (Factor 1) are in group 4 AND Investment, Environmental Values, Stress (Factor 2) are low AND Digital Flexibility in Financial Services (Factor 3) is high, then recommend Cluster 2: Banking Investors. This rule implies that individuals characterized by certain demographic traits, low investment inclination, and high digital flexibility tend to align with Cluster 2, emphasizing their interest in secure banking investments.*

Rule 5*: If Age, Gender, Location, Background (Factor 1) are in group 2 AND Investment, Environmental Values, Stress (Factor 2) are moderate AND Digital Flexibility in Financial Services (Factor 3) is low, then recommend Cluster 1: Stock Market Investors. This rule indicates that individuals with specific demographic characteristics, moderate investment tendencies, and low digital flexibility are likely to belong to Cluster 1, reflecting their interest in stock market investments.*

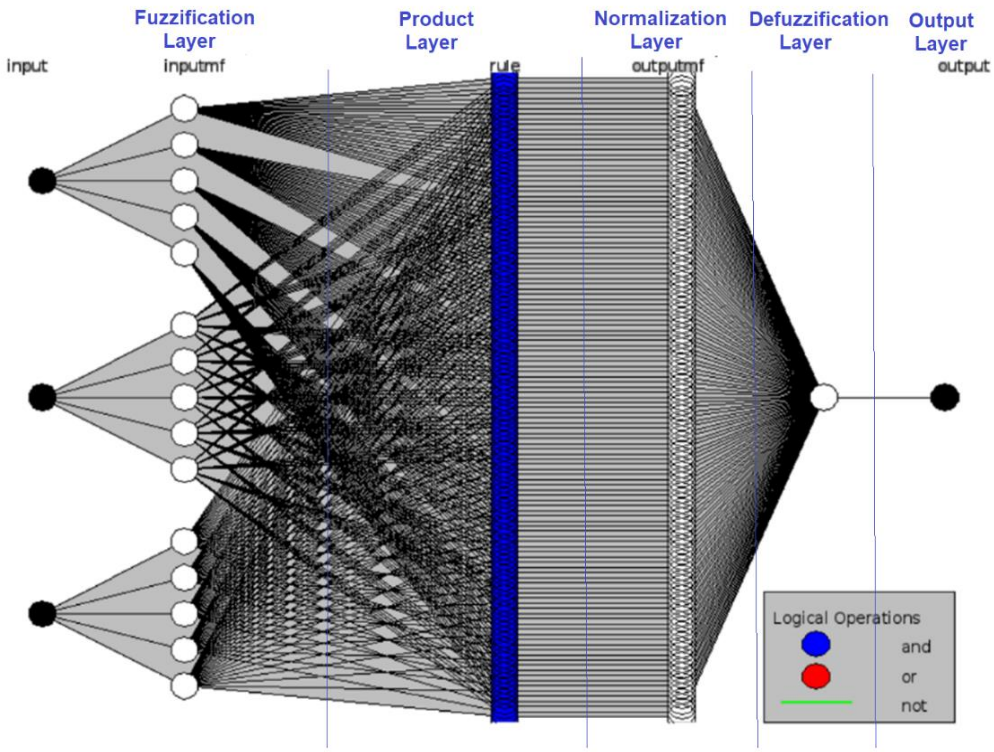


Figure 5: Model Architecture of ANFIS for IRS

ANFIS info:

Number of nodes: 286
Number of linear parameters: 125
Number of nonlinear parameters: 30
Total number of parameters: 155
Number of training data pairs: 10
Number of checking data pairs: 0
Number of fuzzy rules: 125

***Start training ANFIS** ...*

1 3.46926e-06
2 3.40944e-06

Designated epoch number reached. ANFIS training completed at epoch 2.

*Minimal training **RMSE = 3.40944e-06***

4.4. MNN Implementation

This section explains the details about the implementation of the Multi-Model Neural Network, including scripts, libraries, tools, and technologies used. Also, it includes the evaluation of the system's performance, effectiveness, and efficiency by presenting experimental results. After implementing ANFIS as a pre-trained model, a MMNN implemented for predicting the investment type based on pre-analyzed factors. The implementation and evaluation process of the prediction model using neural networks was conducted in several steps:

Multimodal Neural Network Pretraining: In this stage, a MMNN was pre-trained. This network consisted of layers such as LSTM and Dense, trained using ANFIS training data related to three factors and investment type outputs.

In:
```
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, LSTM
from tensorflow.keras.optimizers import SGD

# Step 1: Load the data
df = pd.read_excel("Main_ANFIS.xls")
X = df.iloc[:, :3].values
y = df.iloc[:, 3].values

# Step 2: Normalize the data
scaler = StandardScaler()
X = scaler.fit_transform(X)

# Step 3: Split the data
n_samples = len(X)
train_idx = int(n_samples * 0.7)
val_idx = int(n_samples * 0.15)
X_train, y_train = X[:train_idx], y[:train_idx]
X_val, y_val = X[train_idx:train_idx+val_idx], y[train_idx:train_idx+val_idx]
X_test, y_test = X[train_idx+val_idx:], y[train_idx+val_idx:]
```

Initializing Neural Network Weights: In this stage, the neural network was initialized, and an LSTM model architecture with a Dense layer for predicting the investment type was implemented.

```
# Step 4: Initialize the network
model = Sequential()
model.add(LSTM(units=64, input_shape=(3, 1)))
model.add(Dense(units=1))
```

Model Training and Fine-tuning: Next, the neural network was trained using the training data and then fine-tuned using validation data.

```
# Step 5: Train the network
X_train = X_train.reshape(-1, 3, 1)
X_val = X_val.reshape(-1, 3, 1)
X_test = X_test.reshape(-1, 3, 1)
model.compile(optimizer=SGD(learning_rate=0.01), loss='mse')
model.fit(X_train, y_train, epochs=100, validation_data=(X_val, y_val))

# Step 6: Validate the network
y_val_pred = model.predict(X_val)
val_mse = np.mean((y_val_pred - y_val)**2)
print("Validation MSE:", val_mse)
```

```
# Step 7: Fine-tune the network
model.compile(optimizer=SGD(learning_rate=0.001), loss='mse')
model.fit(X_train, y_train, epochs=50, validation_data=(X_val, y_val))
```

Model Evaluation: In this stage, the model's performance was evaluated using test data, examining the MSE to assess the overall performance of the model in predicting the investment type.

```
# Step 8: Evaluate the network
y_test_pred = model.predict(X_test)
test_mse = np.mean((y_test_pred - y_test)**2)
print("Test MSE:", test_mse)
```

Result Test MSE is 0.0011995050086818341. A low test MSE indicates that your model is performing well on the test data, which is a good sign. However, it's important to keep in mind that a low test MSE doesn't necessarily mean that our model is perfect. Thus, the other metrics considered such as accuracy or precision to solve the problem. Now that we have a pre-trained neural network model, we can use it for making predictions on new data. To do this, we can use the prediction method of the Keras model object, which takes an input array of the same shape as the training data and returns the predicted output values. Here, new_data is a numpy array with two new input samples, which we normalize using the same scaler object that was used to normalize the training data. We then reshape the new data to have the same shape as the training data and use the prediction method of the model to obtain the predicted output values. Finally, we print the predictions to the console.

Prediction on New Data: Finally, the trained model was used to predict on new data input. Then, using the equation created to estimate the investment product cluster, the recommended investment type was determined for each new data point.

In:

```
# Load the new data
new_data = np.array([[1.2, 0.8, 0.9], [0.4, -0.6, -0.3]])

# Normalize the new data
new_data = scaler.transform(new_data)

# Reshape the new data
new_data = new_data.reshape(-1, 3, 1)

# Make predictions on the new data
predictions = model.predict(new_data)

print(predictions)
```

Out:

```
[[1.059356]
 [1.055637]]
```

In:

```
# Define the mapping between predicted values and investment products
mapping = {0: "Investment Product Cluster 1", 1: "Investment Product Cluster 2", 2: "Investment Product Cluster 3"}

# Obtain the predicted values for the new data
predictions = model.predict(new_data)

# Convert the predicted values to integer indices using argmax
indices = np.argmax(predictions, axis=1)
```

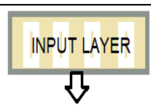
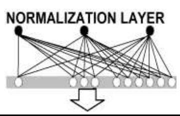
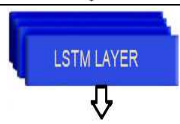
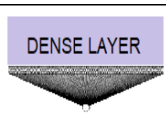
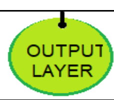
```
# Use the mapping to obtain the recommended investment product for each input sample
recommendations = [mapping[idx] for idx in indices]

# Print the recommendations to the console
print(recommendations)

Out:
['Investment Product Cluster 1', 'Investment Product Cluster 1']
```

○

This process demonstrated that the proposed model for the investment recommender system, after training and tuning, is capable of accurately predicting the investment type based on the desired factors and can perform well on new data with good accuracy. Based on the provided implementation process, here's the structured model architecture of MMNN model (Table 10) with total params: 17,480, trainable params: 17,473, and non-trainable params: 7.

○ .

Table 10: Model Architecture of MMNN for IRS

	Layer Type	Output Shape	Param#	Description
	input_1 (InputLayer)	[(None, 3)]	0	Shape: (3,) Represents the input factors related to the investment decision.
	normalization_layer (Normalization)	(None, 3)	7	StandardScaler is used to normalize the input data.
	lstm (LSTM)	(None, 3)	17408	Units: 64 Input Shape: (3, 1) LSTM layer with 64 units, capable of capturing temporal dependencies in the input data.
	dense (Dense)	(None, 64)	65	Units: 1 Activation Function: Linear (default) Fully connected dense layer for predicting the investment type.
		(None, 1)		Units: 1 Output layer providing the predicted investment type.

This model architecture suggests a sequential flow of data through the layers, starting with input factors, passing through LSTM and Dense layers for learning and prediction, and finally outputting the predicted investment type. The model is trained using MSE loss and Stochastic Gradient Descent (SGD) optimizer. After training and fine-tuning, the model demonstrates good performance in predicting the investment type based on the provided factors. For predicting on new data, the model is used to make predictions, and then a mapping is applied to interpret the predicted values into specific investment product clusters. Finally, the recommended investment product for each input sample is obtained based on the highest predicted value. This structured model architecture encapsulates the steps involved in training, fine-tuning, and predicting with the MMNN for investment recommendation.

4.5 Comparison of ANFIS & MMNN Performance

The ANFIS model managed to achieve a training RMSE of 3.41, within two epochs showing that it learned well from the training data. In contrast the MNN produced a test MSE of 0.0012 showing performance on the test data as shown in Table 9. While the networks low test MSE suggests overall performance it is important to also consider metrics such as accuracy and precision. Each model has its strengths; ANFIS is skilled at capturing relationships with minimal parameters while the neural network offers flexibility in handling various data patterns. The explainability of ANFIS results is an advantage to consider when deciding between the two models based on needs and tradeoffs about simplicity and adaptability, within an IRS.

Table 11. Comparison of ANFIS and MMNN Performance

Model	Test RMSE	Test MSE
ANFIS	3.40944e-06	-
MMNN	-	0.0011995050086818341

5. DISCUSSION

The document presents an approach for creating an IRS using advanced computational methods. It draws on research by authors such as Zaizi and colleagues [25] and Asemi and colleagues [18] emphasize the significance of using computational techniques and existing data for analysis. The systems design begins with data clustering and factor analysis to find segments in the dataset and uncover factors influencing investment choices building upon prior studies by Fereydooni and colleagues [26] and Istanti & Lestari [27] that prove the effectiveness of these methods in detecting patterns and relationships among variables. By integrating ANFIS and MNN the system enhances its ability to provide tailored recommendations with ANFIS generating suggestions based on input output pairs derived from factor analysis and clustering as shown in the work of Asemi and colleagues [28]. Thorough evaluation during both training and testing phases including metrics like RMSE and MSE along with validation aligns with established practices, for assessing recommendation systems advocated by Mondal and colleagues [29] and Mohammadifar and colleagues [30]. Recent studies conducted by Zhang and colleagues [3], [7] and Soori and colleagues [2] have explored the application of AI and ML in decision-making processes. Zhang and colleagues [7] introduced a recommendation approach tailored for e-commerce platforms, emphasizing the importance of accommodating diverse user preferences through algorithmic solutions. Similarly, Soori and colleagues [2] underscored the increasing use of AI and ML techniques to analyze market trends and offer investment guidance, aligning closely with the themes discussed in the article. In another study by Huang and Vakharia [8], as mentioned, they introduced an RCA BiLSTM DQN model that used learning techniques to improve forecasting accuracy using multitemporal stock data and reversal of mutual attention. Also, Qian and colleagues [31] presented the MDGNN framework, and their goal was to address the multifaceted nature of stock market data through a dynamic graph and transformer structure. These studies show that there has been satisfactory progress in the use of networks and DL to predict stock market trends and confirm the use of these techniques in current research. These studies open promising ways to apply these techniques in financial decision-making strategies. In addition, Hou [9] proposed a model using DL methods to predict user investment behaviors. On the other hand, Bansal, and colleagues [10] introduced a learning-based model for predicting stock market trends by combining temporal stock data and inverse mutual attention. These studies show how sophisticated computational techniques are used in market analysis to understand intricacies and uncover insights about investor behavior aligning with the conclusions of this research. Researchers such as Saifudin and Widiyaningtyas [32], Son and colleagues [33], and Chen and colleagues [20] have also made contributions. They highlighted approaches for developing tailored recommender systems across various domains, including sports education and content recommendations. The research highlighted in these studies underscores how different fields, like intelligence, finance and data science come together in IRS. By combining insights from areas the importance of investment is highlighted, showing the potential of advanced modeling methods, like ANFIS and MNN in addressing the challenges of modern investment decision making. Furthermore, in this study, when comparing ANFIS and MNN we can see the strengths and weaknesses of each method. ANFIS shows learning from training data, with parameters while MNN demonstrates superior performance on test data showing its ability to handle different data patterns. In the end the system design creates a foundation for investment advice by combining clustering and factor analysis in ANFIS and MNN methods. This provides insights into how effective tradeoffs exist for making informed decisions in designing and implementing systems, in dynamic financial markets.

6 CONCLUSION

In conclusion the creation and application of the IRS stands for a step in using computational methods to improve investment decision making processes. By incorporating techniques like factor analysis, ANFIS and MNN this study highlights the feasibility and efficacy of generating customized investment suggestions. By using real world data from the Portfolio website questionnaire in Hungary the system has been. Validated to offer tailored investment guidance based on demographic attributes, financial status, and investment backgrounds. The combination of clustering and factor analysis methods helps pinpoint patterns and relationships in the data helping suggestions. ANFIS boosts recommendation accuracy by capturing relationships and decision rules from the data while MNN captures temporal dependencies to enhance prediction accuracy. Empirical validation confirms the system's ability to predict investment types with MSE indicating its reliability. Potential future enhancements may involve designing a user interface incorporating expert input for feedback and boosting user interaction. Additionally structuring inputs using a Fuzzy Inference System across user profiles and market information domains while providing confidence levels for recommendations could further improve the system's effectiveness in delivering investment advice. Through improvements, the IRS can empower users to pursue their financial goals' evolving financial landscapes. In accordance with the current research approach, implementing scoring or gamification activities based on user participation metrics, such as the frequency of investment recommendations and content sharing, can effectively encourage users to engage actively. Enhanced user participation facilitates the utilization of more current and relevant data by the system. To foster active engagement, the designed system incorporates diverse tools like scoring and ranking mechanisms. Furthermore, the study delves into designing an intuitive and visually appealing user interface to enhance user participation experience. Through this interface, users can effortlessly access information and participate in various activities. For future research endeavors, it is advised to structure the inputs of the investment recommendation system using a FIS (Fuzzy Inference System) across two principal domains. The first domain can be dedicated to user profile-related categories, as explored in this study. The second domain can encompass market information, encompassing aspects such as market performance across different investment types, economic indicators, industry trends, sentiment analysis of news, among others. The outputs can be categorized into two main sections as well. The first section should provide recommendations for buying, selling, holding investments, and diversifying them, while the second section should focus on suggesting confidence levels for investment, classified into three scales: high, medium, and low. These input-output structures serve as the foundation for the fuzzy inference system to generate recommendations grounded in fuzzy logic rules and membership functions. This system processes inputs, applies fuzzy logic operations, generates pertinent outputs, and furnishes investment recommendations and confidence levels for each recommendation.

DECLARATIONS

- Funding: No Funding
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- 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 of Participation: Not Applicable
- Availability of data and materials: Data was collected in partnership with the Corvinus University of Budapest in the 1.3.1-VKE-2018-00007 GINOP project. According to the Consortia agreement and the Head of the project's consent, project data can be used for additional research and publications by the authors.
- Authors Contributions: A.A. led the conceptualization, design, and execution of the study, and drafted the main manuscript text. A.A. developed the Adaptive Neuro-Fuzzy Inference System (ANFIS) in MATLAB, performed the clustering and factor analysis, and contributed to the implementation of the Multimodal Neural Network (MNN) using Python, TensorFlow, and Keras libraries. A.A. also assisted in the analysis and interpretation of the data. Ad.A.contributed significantly to the methodology, specifically in the development of the ANFIS in MATLAB and the performance of the clustering and factor analysis. A.K. supervised the overall project, provided critical revisions, and contributed to the conceptual framework of the study. A.K. ensured the integrity and accuracy of the research. All authors reviewed and approved the final manuscript.
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