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Providing a Prediction Model of Investment Decision Based on the Individual Characteristics of Investors using Artificial Intelligence

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ABSTRACT

Investment decisions are very important for managing current needs and future goals, and individuals and families spend considerable time and resources on financial planning, and much research has documented the importance of such decisions. These studies show the importance of evaluating the impact of personality characteristics on investment decisions. In the first part of this research, the correlation between representative parameters of individual characteristics (including psychological characteristics, personality characteristics and risk-taking attitude) with investment decisions has been done. The research statistical population is all investors. Sampling is available due to the unlimited statistical population. In the second part, the data related to the representative parameters of individual characteristics were used to predict investment decisions using data mining models of Artificial Neural Network (ANN), XGBoost and AdaBoost. Comparing the results of data mining algorithms showed that the best results are related to the XGBoost model. In this case, the R^2 is the highest and the MSE is the lowest compared to other cases. At the next level, the best results are obtained by the ANN with 1 hidden layer and 44 neurons. Finally, the weakest results are related to the AdaBoost model.

Keywords: Individual Characteristics, Psychological Characteristics, Personality Characteristics, Risk-Taking Attitude, Investment Decisions, Data Mining

1. Introduction

In the past few decades, extensive research has been conducted on the relationship between personality characteristics and investment decisions. Characteristics have been defined through various approaches, but the classic approach represented by the Big Five model (i.e., accountability, neuroticism, agreeableness, openness, and extroversion) has a broad research base. Through the Big Five, personality characteristics can be organized in a hierarchical form, which can be explained through a strong cross-validation questionnaire and has wide cross-cultural reproducibility (Jayawickreme et al., 2018). Although there have been numerous studies that have shown the role of personality characteristics in investment decision, there have been only a few studies that have analyzed the impact of personality characteristics on investment performance. In fact, there is very little information about the possible relationship between these personality characteristics and investment performance in the presence of other psychological characteristics (Akhtar and Das, 2020). The main factors affecting investors' decisions are cognition, mood and emotions, all of which are part of a person's personality. What distinguishes one person from another is a fraction of these variables in the person's personality (Quang et al., 2023). One of the important concepts regarding the investment decision and the risk level of investors is psychological factors such as personality, and their importance is clear in the entire decision-making process of investors (Lubis et al., 2015). Personality psychology is one of the branches of psychology. It is argued that personality is an important factor in determining behavior. Psychologists believe that business and investment decisions of investors are a human behavior that is related to the personality of investors (Sadiq and Amna, 2019). In financial markets, investors are customers or consumers. Therefore, investigating investors' behavior is important for financial institutions to devise appropriate strategies and market appropriate financial products or provide new financial products to investors in order to better satisfy their needs. To study the behavior of investors, researchers have largely accepted the concept of behavioral finance in the last decade (Mak & Ip, 2017). With the rapid development of the global economy, a large amount of unstructured and structured data is generated inside and outside the company. In the traditional financial decision analysis system, this unstructured data cannot be acquired and processed where the data is closely related and not continuously improved. With the rapid development of computer technology, the realization of many models and methods that were difficult has become simple and easy (Balducci and Marinova, 2018). Data warehouse and data mining technology can extract useful information and knowledge hidden in huge data that people do not already know, while artificial intelligence technology can simulate knowledge and reasoning ability for experts to solve complex problems (Gil et al., 2021). In this new operating environment, forecasting, analysis, control and scientific financial decision-making is especially important for companies. Due to the lack of intelligent financial decision support, the traditional methods of financial management can no longer respond to the rapid development of economic needs. With the advent of artificial intelligence, it has been applied in many fields such as smart electronic equipment, smart medical facilities, smart homes, smart control centers, etc. Research on the applied value and strategy of artificial intelligence technology in the financial field is useful for promoting the further development of the financial industry, promoting economic growth and improving economic efficiency (Ren, 2021).

Today, precise marketing and individualized services are the key strategies for companies to gain a competitive advantage in the era of big data. Answering to the question, "What is the relationship between the investment decision and the individual characteristics of investors in the financial market of Iran?" can directly affect the strategies of service providers. For example, based on clients' preference and risk tolerance, a brokerage firm can target them with a risky product. Based on this, gaining insight into the behavioral preferences of investors becomes a necessary action for companies to develop new customers, reduce management costs, provide individualized services, and gain competitive advantage (Lan et al., 2018). Recent developments in data science and machine learning have the potential to improve investment decisions. Rapid growth in machine learning algorithms and expansion of access to data at the micro level has occurred (Raschka et al., 2020). This data is the key to new developments. On the other hand, there are challenges to fully implement the investment. One of these challenges is the

changing nature of the investment landscape, where new products and services emerge and become available to the public quickly. These cases indicate the need for a comprehensive system. This system models the investment decisions of users using machine learning and can even predict their investment performance (Cabrera-Paniagua and Rubilar-Torrealba, 2021a). It can also help users to make more calculated and scientific financial decisions based on their individual characteristics.

The most important point in the financial industry is serving customers and providing them with more accurate and suitable services. The use of artificial intelligence technology in the financial industry will certainly promote intelligence and improve its efficiency. With the continuous improvement of information technology, if companies continue to adopt traditional financial decision-making methods, it will be difficult to increase their competitiveness. In the era of rapid development of science and technology, every industry should closely follow the footsteps of science and technology, which will bring changes in an industry or even an era (Ren, 2021). Artificial intelligence is transforming the strategy of financial players as they are forced to become more open and collaborative. Machine learning is a subset of artificial intelligence that uses statistical tools to learn from data and then use algorithms to solve problems (Ashta and Herrman, 2021). According to the mentioned points, this study makes it possible to predict financial behavior through the analysis of individual characteristics (psychological characteristics, personality characteristics, risk-taking attitude). The results of this research provide an answer to the question, "How can a predictive model of investment decision based on the individual characteristics of investors in financial markets be provided based on artificial intelligence?"

2- Theoretical foundations and research background

2-1- Personality theory

A person's thoughts, actions and behavior are guided by his personality characteristics (Allport and Vernon, 1930). Although there are several theories about personality, there is a consensus among researchers that personality represents a complete system of characteristics of a person, and that people differ in their thoughts, processes, feelings, emotions, and resulting behaviors, and that personality is one of the strongest predictors of emotional and physical well-being of people (Manner, 2017). The big five personality characteristics (called the five-factor model of McCrae and Costa, 1997) have been one of the most widely used classifications of characteristics in organizational behavior and personnel psychology. These characteristics include: openness to experience, accountability, extroversion, agreeableness and emotional stability. Particularly in the case of behavioral finance, personality characteristics were associated with short- and long-term investment choices (Mayfield et al. 2008; Durand et al. 2008) and mutual fund investments. It was also found that people with high extroversion and openness to experience have high risk tolerance. In contrast, people with neuroticism tend to be risk averse (Oehler et al., 2018; Arvindh Rajasekar et al., 2022). Psychological characteristics determine individual financial behavior (Baker et al., 2021). Personality characteristics are central to understanding a person (Parks-Leduc et al., 2015) and explain how people receive, process, and act on information. Second, the five-factor personality characteristic model provides the possibility of examining the influence of individual characteristics on risk capacity, risk aversion and risk-taking behavior in investment decisions. Third, it is essential to understand how personality characteristics influence the complex relationships between risk capacity, investment preferences, and investment strategies, and influence individuals' financial well-being (Arvindh Rajasekar et al., 2022).

2-2- Psychological characteristics and investment decision

Personality can be defined through two general approaches, i.e. inter-individual characteristics, which is the way in which people communicate with each other, and dispositional characteristics, i.e. a person's behavior due to his or her internal characteristics. These characteristics have been used to study the behaviors and emotions shown by an individual (Hogan et al., 1996). Shefrin and Statman (2000) organized these psychological phenomena under three specific themes, namely discovery bias, frame dependence, and inefficient markets. Investors' risk-taking attitude has been investigated from different

perspectives. One prominent perspective is through the analysis of stability in decision making under risk and uncertainty (Tversky and Kahneman, 1992). This study showed that there is a possible effect of personality characteristics on risk perception (Sitkin and Pablo, 1992). On the other hand, overconfidence can be defined as overestimating the accuracy of one's knowledge (Dittrich et al., 2005). Specifically, overconfidence is the positive deviation of accuracy confidence, meaning that people are generally confident of accuracy. It has been observed that investors trade with overconfidence (Odean, 1998, 1999) and overreact to public signals (Daniel et al., 1998). Overconfidence is also related to many personality characteristics, for example, people who are extraverted or tend to experience are often positively related to overconfidence (Pallier et al., 2002). In addition, individuals who are neurotic or agreeable have low levels of overconfidence (Wolf & Grosch, 1990; Schaefer et al., 2004).

Studies have also shown that there is a large gap between an individual's predicted and actual investment behavior (Merkle and Weber, 2014). Financial theories, such as portfolio theory, assume that the investor creates expectations about his risk and return and chooses a portfolio based on his expectations and risk preference (Markowitz, 1952). Therefore, it can be said that investors should always invest in a well-diversified investment regime and trade less. But instead, it has been observed that individual investors generally have undiversified portfolios (Goetzmann and Kumar, 2008), trade frequently (Barber and Odean, 2000) and speculate in the stock market (Kumar, 2009). It has also been observed that investors generally adopt investment strategies that are far from the mean-variance optimization strategy (Grinblatt and Keloharjo, 2000). Studies have analyzed these deviations from the perspective of psychological biases (Odean, 1999).

2-3- Personality characteristics and investment decision

Personality captures the foundation of each person (Fung and Durand, 2014). Personality is defined as "the way a person interacts, reacts, and behaves with others and is often expressed through measurable characteristics" (Crysel et al., 2013). Many researchers have stated that their intellect and behavior are defined through their personality (Sadiq and Amna, 2019). In some studies, the Big Five Personality Factor (BFF) model has been used. This model is mostly used to study people's personality. Allport and Odebert (1936) developed this model. This model describes five personality characteristics: openness to experience, extraversion, neuroticism, conscientiousness, and agreeableness (Lee & Ashton, 2004; Weller & Thulin, 2012).

Extroverted people are energetic, active, social and friendly (Pak and Mahmood, 2015; Sediq and Khan, 2019). Such people are hopeful, optimistic and extroverted. A study conducted by Mayfield et al. (2008) on undergraduate business students found that extroverts invested in the stock market and had a negative relationship with risk aversion bias. Another study conducted by Tauni et al. (2017) found that extraversion positively moderates the relationship between information seeking and investment decisions (Reddy Jain and Deepasha Sharma, 2022).

Agreeableness characteristics show that people are considerate, cooperative, selfless and philanthropic (Mount et al., 2005; Sadiq and Khan, 2019). Such people show individual sympathy towards others. A study conducted by Joyce and Yien (2013) showed that personality characteristic compatibility dominates financial decision-making including social responsibility investment and risk aversion bias. The characteristics of neuroticism indicate poor cognitive skills, critical thinking, and poor conceptual understanding, making people anxious and fearful (Pak and Mahmood, 2015). Tauni et al. (2017) showed that neuroticism moderates the relationship between information seeking and trading frequency. This ability of individuals makes them very particular about their investment choices. Therefore, there is a negative relationship between accountability and financial risk (Pak and Mahmood, 2015). Tauni et al. (2017) found a positive relationship between information seeking and trading frequency. However, the extent to which an individual's characteristics influence financial decision-making has yet to be explored. The present study examines the answer by analyzing the personality characteristics of an Indian investor. Durand et al. (2013) have shown that personality characteristics affect two psychological biases: the desire effect and the availability bias. The divestiture effect means that the investor is reluctant to sell that asset that has lost its value and has more prospects for

sale that should increase its weight (Shefrin and Statman, 1985). Availability bias refers to the investor's tendency to rely on an immediate event that the mind can easily retrieve to make a decision or to choose a mental shortcut to make a decision (Marx and Weber, 2012). Therefore, these studies provide insight into how personality characteristics influence investment decision-making. Understanding individual personality characteristics helps predict and clarify individual decisions (Fung and Durand, 2014).

2-4- Investor risk and investment decision

Each person has a risk profile that governs his behavior when investing in uncertain situations. Risk preference, which is also known as risk tolerance, is the amount of risk that a person is ready to accept in exchange for return (Pompian, 2016). A person with a high degree of risk aversion constantly wants to avoid risk in their investment choices, even if they have to suffer a loss for it, and will never be ready to invest in risky assets (Nga and Ken Yien, 2013). Individual financial investment can be divided into two categories: long-term financial investment and short-term financial investment. People's long-term financial investment goals include long-term products to meet long-term financial needs. While people's short-term financial investments are related to meeting financial needs in the near future (Thuy et al., 2021). Unlike pessimistic investors, it has been proven that investors with high risk tolerance will outperform the stock portfolio (Akhtar and Das, 2020). Risk tolerance is an important factor that affects financial decisions, savings and investment choices, because it is able to accurately assess individual risk behavior and allocate investment tools according to the level of risk that the investor can tolerate. In Massol et al. (2015), it was found that psychological biases such as overconfidence and cognitive dissonance positively affect students' risk tolerance. Other empirical studies showed that risk tolerance is also determined by the level of education, whether the higher the tolerance, the higher the level of study that investors are in (Ramudzuli and Muzindutsi, 2015).

2-5- Application of artificial intelligence in the financial field

With the development of economic globalization and the gradual complexity of the market environment, companies should pay attention to financial management in the increasingly competitive environment. It is necessary to develop a scientific and effective system to support financial decisions. The more comprehensive the simulation thinking of artificial intelligence technology, the more it can replace simple repetitive tasks that require humans. For example, the smart navigation menu can provide individualized services suitable for people according to the needs of different people, to solve simple and repetitive questions without human resources. The ANN algorithm of artificial intelligence technology provides a reliable possibility for financial decision making. Smart use of AI technology in financial decision-making will definitely have a big impact on the financial industry. Smart finance is mainly driven by the core AI technology, which empowers all participants and business links in the financial industry, and highlights the important role of AI technology in product innovation, process reengineering and service improvement in the financial industry. Participants include not only companies that provide AI technology services to financial institutions, but also traditional financial institutions, emerging financial formats and essential regulatory agencies in the financial industry. In terms of scope, internet finance and smart finance belong to financial technology. Smart finance is developed on the basis of Internet financing, which shows that the degree of integration and innovation of finance and science and technology is higher than Internet financing. In applied technology, the created financial analysis model is improved according to the characteristics of the industry. An expert model base has been established, so that information sources can be effectively used in the operational decision-making of companies, and timely and comprehensive information for scientific and correct leadership decision-making is provided (Jiaping Ren, 2021).

2-6- Research background

Sekscinska et al. (2023), in a research to investigate investment decisions in response to profit and loss with the common role of psychological and demographic variables, presented four models that predict people's willingness to invest and accept investment risks. In a research, Jian et al. (2023) investigated the role of investors' personality characteristics on their investment intention. The

findings of this study showed that the personality characteristics of an investor are related to financial literacy and investment intention, but it is insignificant with overconfidence bias.

Rajasekar et al. (2023) examined the relationship between five big personality characteristics and investment behavior. The results showed that (1) personality characteristics (extroversion, emotional stability, accountability, agreeableness, and openness to experience) are positively related to investment attitude and investment strategy. Zulhajmi and Rafik (2022) showed that extroversion positively affects the probability of students investing in the stock market because their risk tolerance moderates it. Paniagua and Torrealba (2021a), in studying a new artificial autonomous system, put a lot of effort to support investment decisions using the personality characteristic model approach. Jiaping Ren (2021) in a research entitled "Financial Investment Decision Making Based on Artificial Intelligence Algorithm" found that traditional financial decision support cannot meet the intelligent development needs of companies and therefore the use of artificial intelligence improves accuracy, automation and timeliness of financial decision-making. Thuy and Ngoc (2021) investigated the influence of individual characteristics on risk preferences and investment decisions of Vietnamese investors and believed that Vietnam's financial investment market, especially the stock market, has overcome the issue of Covid-19. Thomas et al. (2020) provided a research framework for analyzing financial behavior using machine learning classification through analyzing handwritings. The results of 7 handwriting features were evaluated with machine learning techniques on 112 samples collected through an individual questionnaire.

Das and Akhtar (2020) investigated investor personality and investment performance from the perspective of psychological characteristics. The findings showed that the personality characteristics of individual investors are related to financial risk tolerance, financial overconfidence and perceived investment performance. Sekscinska et al. (2020) found that narcissism explained the general orientation to take financial risks, the orientation for investment risks, and gambling risks, regardless of whether the reward was a significant gain or no financial loss. Chen et al. (2019) investigated the effect of investor personality in predicting investment performance using statistical models and machine learning. Their results showed that investors' personality affects short-term and long-term trading performance. Ting-Hsuan Chen et al. (2018) in the article "Investigating the predictive power of investor personality in predicting investment performance using machine learning models" found that investors who have the characteristics of extroversion and openness are likely to invest more profit in long-term conditions.

Sadigh and Amna (2019), in a research entitled "The influence of personality characteristics on risk tolerance and investors' decision-making", investigated the relationship between personality characteristics, risk tolerance and investment decisions and highlighted the importance of personality characteristics in determining risk. Oehler et al. (2018) studied the influence of investors' personality on investment decisions with empirical evidence on extroversion and neuroticism. They found that extroversion and neuroticism significantly affect people's behavior in the experimental property market. In a research, Shiroyeh pour et al. (2022) analyzed the impact of innovative biases on investment decisions and market efficiency for future policy making. The research findings showed that biases of overconfidence, representativeness, accessibility, anchoring and adjustment have a significant effect on market efficiency. Nayeb Mohseni et al. (2021) tried to develop a behavioral model of individual investors' decision-making in the Iranian capital market. The findings of the research showed that the causal factors affecting investors' decision-making include regret, greed, fear, cognitive dissonance, reputation effect, mental anchor, self-documentation, loss aversion, gambling pleasure, investment thinking, mass behavior, having an outlook, image-making, false excitement, false self-confidence, bias towards the past, novelty, mental accounting, empowerment, trading asymmetry, similarity error, amber effect, gambler's illusion, motivation, time horizon, initial profit effect, experience, age, gender and analysis. Zeinivand et al. (2021) investigated the behavioral biases and decisions of real and legal investors based on technical information in the Tehran Stock Exchange. The results showed that the behavioral patterns of real and legal investors had different effects on their investment decisions in the levels of resistance and support. Also, behavioral trends among real investors have more predictive power than their

investment decisions. Aghajani et al. (2020) studied the relation between behavioral types and investment decisions with self-efficacy mediation. The results showed that the behavioral types of change-avoidant, accumulative, independent and follower have a significant effect on self-efficacy and investors' decisions and the effect of self-efficacy on investors' decisions. Abdul Rahimian et al. (2018) identified the factors influencing the decision-making behavior of real investors and presented a related model using a mixed research approach (evidence from the Tehran Stock Exchange). In other words, the most fundamental factor in investors' behavior is culture. The theory of creation, which considers emotional distortions to precede cognitive distortions, was not confirmed.

3- Methodology

This study is practical in terms of purpose and descriptive correlational in terms of method. The research population is all investors. Sampling is available due to the unlimited statistical population. Accordingly, considering the unlimited statistical population, the default sample size was estimated to be 384 people. Convenient sampling method is applied. In this research, both methods of collecting information, i.e. library methods and field studies, are used. In this research, the investment decision model is presented based on the individual characteristics of investors in financial markets using artificial intelligence. For this purpose, the first part includes the identification of individual characteristics related to investment decisions. Then the second part includes the examination of the relationship between individual characteristics (such as: psychological characteristics, personality characteristics, risk-taking attitude) and investment decisions among potential private investors in a developing country, such as Iran. This study provides valuable insights to investment experts and policy makers to understand investor behavior in developing countries. After identifying and analyzing the important components, it is time for the third part of the research. For this purpose, using artificial intelligence, the individual's investment decision is modeled and predicted based on the finalized individual characteristics. For this purpose, components related to individual characteristics (such as: psychological characteristics, personality characteristics, risk-taking attitude) are used as input to the data mining model. The output is the individual's investment decisions.

After identifying the effective components, these components are used in data mining models such as ANN, XGBoost and AdaBoost. Then, with the help of artificial intelligence, people's investment decisions are predicted.

3-1- Data preprocessing

In this section, an attempt is made to prepare the data of the research dataset for training the model. For this purpose, first, all rows of the dataset were checked for missing data. Less than 10 cases of the data had no value, which were valued with the average values of the corresponding question.

The next point is related to the coding of columns with label values. For this purpose, these columns were valued with the help of numbers instead of labels. In this way, this column can be used in model training. The data used in this research had no problem in this regard and all the values were numerical.

The final item is the normalization of column values. For this purpose, the column values were normalized between 0 and 1. Equation 1 shows the way of normalization. In this way, maximum and minimum values were calculated for each column. Then, based on equation 1, normal values were calculated for each line.

(1)

$$z = \frac{x - X_{min}}{X_{max} - X_{min}}$$

By pre-processing the data, it becomes easier to interpret and use them. This process makes it possible to use string data in the model training process. Data preprocessing also ensures that there are no missing values due to human or system error. Finally, the advantage of linear normalization (Relation 1) used in the research is that it preserves the relationships between the original data values.

3-2- ANN

Nowadays, using ANNs has become common in various fields of human needs (Wu & Feng, 2018). A good advantage of using ANNs is that it can provide models that are easy to use and more accurate than complex natural systems with larger inputs. ANN is a very new and useful model for problem solving and machine learning. ANN is an information management

model that resembles the functioning of the biological nervous system of the human brain.

The layers of the neural network are independent from each other. That is, a specific layer can have any number of nodes. This arbitrary number of nodes is called bias node. Bias nodes are always equal to one. In analogy, bias nodes are like offset in linear regression, which is as y = ax + b, in which "a" is the independent coefficient of "x" and "b" is called the slope. A main function of the bias is to provide a fixed value for the node to be trained on, in addition to the regular inputs received by the network node. When NN is used as a classifier, input and output nodes correspond to input features and output classes. However, when NN is used as an approximation function, it generally has one input and one output node. However, the number of designed hidden nodes is much more than the input nodes (Abidun et al., 2018).

3-3- XGBoost algorithm

XGBoost is a machine learning algorithm that belongs to the group learning category, specifically the gradient boosting framework. It uses decision trees as base learners and uses regularization techniques to increase the generalization of the model. Known for its computational efficiency, feature importance analysis, and handling of missing values, XGBoost is widely used for tasks such as regression, classification, and ranking. This tool is used to combat overfitting as well as support differentiable loss functions (Luo et al., 2021).

3-4- AdaBoost algorithm

AdaBoost algorithm is one of the boosting classification algorithms that can upgrade a group of weak classifiers to a strong classifier. These algorithms usually first use a base classifier algorithm whose classification ability is better than random guessing, i.e. a process that trains a base classifier from initial training examples. Then the weight of the sample is adjusted according to the base classification result. This causes more attention to be paid to samples that are misclassified. Then, the set examples are used to train a next level learner. After iteration, weights are added to these base learners to form the final classifier (Wang et al., 2019).

3-5- Evaluation of the data-mining model

There are several approaches to compare the performance of classifiers. MSE is a measure of predictive performance that can never have a negative value (values close to zero are better). MSE accounts for the bias and variance of the prediction model (how much the predictions differ from one data sample to another). MSE measures the distance from the mean (how close the mean of the predicted value is to the observation). The relevant formula is given in the following relation.

(2)

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_{i,observ} - y_{i,pred})^2$$

The coefficient of determination (R^2) is a statistical metric that indicates how much of the variation in a dependent variable can be attributed to the independent variable(s) in a regression model.

4- Results

In this section, the results of artificial neural network training and group learning models are presented. For this purpose, first, different modes of the artificial neural network structure are tested. Then the best mode is selected based on 2 MSE indicators and coefficient of determination. Finally, group learning models are developed and the obtained results are compared with artificial neural network.

4-1- Investigating relationships between parameters

In this section, the input and output data of data mining models are introduced. In this research, 58 questions affecting the prediction of investment decision, i.e. questions QX1 to QX58 were selected as input to the data-mining model. Also, 6 investment decision parameters (QY1 to QY6) were selected as outputs of the data mining model (Appendix 1).

Table 1 shows the degree of correlation between input parameters and output parameters, i.e. investment decision. For this purpose, Pearson's correlation coefficient was used. The value of this coefficient changes between -1 and 1, where 1 means full positive correlation, 0 means no correlation and -1 means full negative correlation. As can be seen, the conditions for different columns are very different.

Some entries have very low correlation (such as questions 28 and 29) and others have more correlation (such as questions 44 and 45).

Table 1: The degree of correlation between the input and output parameters of the data-mining model

	QY6	QY5	QY4	QY3	QY2	QY1
QX1	-0.2730	-0.2707	-0.3019	-0.2999	-0.3021	-0.2453
QX2	-0.2676	-0.2671	-0.2652	-0.2628	-0.2648	-0.2658
QX3	-0.2472	-0.2443	-0.2708	-0.2682	-0.2701	-0.2381
QX4	-0.2446	-0.2387	-0.2445	-0.2431	-0.2430	-0.2503
QX5	0.3775	0.3673	0.5234	0.5198	0.5292	0.3509
QX6	0.3906	0.3871	0.5894	0.5979	0.6072	0.3616
QX7	0.4027	0.4102	0.4553	0.4739	0.4734	0.3754
QX8	0.3778	0.3970	0.4511	0.4700	0.4695	0.3519
QX9	0.4019	0.4098	0.4403	0.4638	0.4586	0.3761
QX10	0.1548	0.1617	0.2383	0.2404	0.2376	0.1298
QX11	0.1536	0.1506	0.0837	0.0847	0.0868	0.1418
QX12	0.2931	0.3061	0.4024	0.4201	0.4146	0.2717
QX13	0.1544	0.1583	0.0017	-0.0051	-0.0081	0.1630
QX14	0.1862	0.1812	0.0572	0.0510	0.0480	0.1967
QX15	0.1800	0.1852	0.0994	0.1080	0.0982	0.1778
QX16	0.1992	0.2016	0.1512	0.1627	0.1538	0.1898
QX17	0.0794	0.0787	-0.0032	-0.0089	-0.0143	0.0920
QX18	0.1019	0.1165	0.0032	0.0264	0.0183	0.1029
QX19	0.0784	0.0926	0.0247	0.0473	0.0394	0.0793
QX20	0.0484	0.0522	-0.1162	-0.1102	-0.1194	0.0577
QX21	0.1393	0.1565	0.0184	0.0451	0.0364	0.1438
QX22	0.0131	0.0164	-0.1071	-0.1184	-0.1107	0.0212
QX23	0.1140	0.1108	0.1338	0.1171	0.1232	0.0968
QX24	0.1386	0.1450	0.1042	0.0964	0.1075	0.1367
QX25	0.2232	0.2267	0.0493	0.0709	0.0614	0.2005
QX26	0.2000	0.2002	0.0976	0.1085	0.0991	0.1725
QX27	0.1136	0.1159	-0.0109	-0.0119	-0.0079	0.1163
QX28	-0.0525	-0.0507	0.0385	0.0266	0.0346	-0.0432
QX29	-0.0764	-0.0754	0.0384	0.0255	0.0312	-0.0617
QX30	-0.0845	-0.0862	0.0535	0.0540	0.0597	-0.0778
QX31	-0.0851	-0.0831	0.0322	0.0202	0.0260	-0.0670
QX32	-0.0902	-0.0925	0.0386	0.0387	0.0444	-0.0851
QX33	0.1427	0.1563	0.0826	0.1012	0.1002	0.1149
QX34	0.0959	0.1071	0.0561	0.0660	0.0706	0.1013
QX35	0.2241	0.2217	0.1532	0.1588	0.1514	0.1936
QX36	0.0864	0.0973	0.0492	0.0645	0.0633	0.0577
QX37	0.2328	0.2328	0.1652	0.1761	0.1747	0.2160
QX38	0.3400	0.3408	0.2096	0.2225	0.2210	0.3141
QX39	0.3708	0.3836	0.2242	0.2498	0.2458	0.3592
QX40	0.3624	0.3745	0.2185	0.2408	0.2393	0.3438
QX41	0.3356	0.3528	0.2117	0.2330	0.2313	0.3207
QX42	0.3519	0.3293	0.1908	0.1885	0.1841	0.3424
QX43	0.3118	0.2888	0.1477	0.1498	0.1452	0.3130
QX44	0.4001	0.3835	0.2365	0.2350	0.2306	0.3484

	QY6	QY5	QY4	QY3	QY2	QY1
QX45	0.3988	0.3878	0.2210	0.2190	0.2097	0.3689
QX46	0.3815	0.3646	0.2427	0.2407	0.2362	0.3289
QX47	0.3952	0.3903	0.2284	0.2266	0.2222	0.3546
QX48	0.4330	0.4199	0.2972	0.2888	0.2847	0.3984
QX49	0.4034	0.4000	0.2741	0.2736	0.2693	0.3812
QX50	0.4193	0.4166	0.2782	0.2784	0.2743	0.3995
QX51	0.4081	0.4047	0.2832	0.2896	0.2876	0.3811
QX52	0.3787	0.3754	0.2721	0.2786	0.2764	0.3597
QX53	0.3916	0.3881	0.2677	0.2741	0.2720	0.3638
QX54	0.1525	0.1552	0.0018	-0.0008	0.0020	0.1554
QX55	0.1542	0.1567	0.0114	0.0086	0.0114	0.1566
QX56	0.1314	0.1364	0.0093	0.0114	0.0193	0.1568
QX57	0.1431	0.1568	0.0139	-0.0027	0.0127	0.1535
QX58	0.1303	0.1309	0.0185	0.0146	0.0168	0.1269
QY1	0.9359	0.9416	0.3736	0.3785	0.3787	1.0000
QY2	0.4201	0.4251	0.9842	0.9926	1.0000	0.3787
QY3	0.4198	0.4248	0.9810	1.0000	0.9926	0.3785
QY4	0.4245	0.4194	1.0000	0.9810	0.9842	0.3736
QY5	0.9758	1.0000	0.4194	0.4248	0.4251	0.9416
QY6	1.0000	0.9758	0.4245	0.4198	0.4201	0.9359

4-2- ANN results

To train the ANN in this research, the settings in Table 2 were applied. As can be seen, the type of optimizer, loss function and activation function used are Nadam, Mean Squared Error and Relu respectively. Also, a hidden layer and the number of 1-64 neurons in the hidden layer have been used. Also, the distribution of training and test data was determined as 80% and 20%, respectively.

As can be seen in Table 3, the best results are related to the mode of 1 hidden layer and 44 neurons. In this case, the coefficient of determination is the highest and the MSE is the lowest compared to other cases. The results of Table 3 showed that the MSE values for training and test data are 0.061236 and 0.420368, respectively. Also, the coefficient of determination values for training and test data are 0.9391 and 0.6128, respectively.

Table 2: Settings available in this research for ANN training

Type of parameter	Value
Neural Network Type	Sequential
Hidden Layer	1
hiddenSizes	1-64
Optimizer	Nadam
Loss	Mean Squared Error
trainRatio	0.80
testRatio	0.20
Activation function	ReLU
Epochs	500
batch_size	8
Early stop	Reaching 99.99% the coefficient of determination in test data

Table 3: Comparison of the results of the coefficient of determination and MSE of the ANN with 1 to 64 neurons and 1 hidden layer

Number of neurons in the hidden layer	Coefficient of determination		MSE level	
	Training	Test	Training	Test
1	0.3965	0.3745	0.601264	0.693765
2	0.3967	0.3754	0.600122	0.693207
3	0.3936	0.3769	0.604618	0.691068
4	0.4579	0.3952	0.542256	0.678064
5	0.5680	0.4418	0.430027	0.625786
6	0.4556	0.3930	0.544608	0.678097
7	0.5275	0.3924	0.473250	0.681913
8	0.6377	0.4452	0.350225	0.620156
9	0.5156	0.4007	0.490487	0.674848
10	0.6531	0.4210	0.345524	0.649662
11	0.5713	0.3479	0.422284	0.730015
12	0.6811	0.3984	0.306612	0.674610
13	0.6822	0.4190	0.311084	0.655600
14	0.6542	0.4072	0.333389	0.667493
15	0.6530	0.4217	0.335532	0.655219
16	0.5979	0.4115	0.391541	0.659994
17	0.7036	0.4318	0.288579	0.636916
18	0.7113	0.4915	0.280932	0.564657
19	0.7718	0.4923	0.225132	0.569172
20	0.7129	0.5302	0.268235	0.522249
21	0.8790	0.4751	0.118448	0.592737
22	0.7236	0.4573	0.265151	0.603362
23	0.8261	0.5036	0.168937	0.559174
24	0.7426	0.3911	0.247494	0.678157
25	0.7356	0.3933	0.264548	0.685289
26	0.7998	0.5439	0.197867	0.511353
27	0.7833	0.5050	0.208337	0.549569
28	0.7445	0.4402	0.249198	0.626376
29	0.8945	0.5156	0.103739	0.543677
30	0.8162	0.4605	0.184374	0.609805
31	0.8796	0.4909	0.117581	0.571391
32	0.8731	0.4341	0.121738	0.630519
33	0.8901	0.5481	0.106250	0.507303
34	0.7972	0.4466	0.199516	0.622501
35	0.9028	0.3865	0.096486	0.682365
36	0.8503	0.4767	0.141313	0.586251
37	0.8971	0.5504	0.099788	0.498918
38	0.8747	0.5235	0.127273	0.533482
39	0.9533	0.5354	0.045183	0.513667
40	0.9410	0.5932	0.060056	0.450989
41	0.9433	0.4964	0.056053	0.553436
42	0.9503	0.4957	0.048413	0.557388
43	0.9207	0.4897	0.076902	0.564237
44	0.9391	0.6128	0.061236	0.420368
45	0.9050	0.5536	0.095427	0.497680

Number of neurons in the hidden layer	Coefficient of determination		MSE level	
	Training	Test	Training	Test
46	0.9180	0.4967	0.077679	0.555487
47	0.9450	0.5401	0.055517	0.508420
48	0.8866	0.4775	0.110891	0.582414
49	0.9445	0.6065	0.054144	0.443660
50	0.9322	0.5365	0.067311	0.515594
51	0.9435	0.6125	0.054662	0.430403
52	0.9302	0.6028	0.070334	0.443820
53	0.9716	0.5937	0.028379	0.457679
54	0.9558	0.6100	0.042618	0.439588
55	0.9104	0.3384	0.091996	0.729645
56	0.9451	0.5708	0.053595	0.480780
57	0.9321	0.6066	0.067406	0.439695
58	0.9662	0.4095	0.032371	0.645048
59	0.9667	0.5230	0.032371	0.532700
60	0.9421	0.5537	0.058481	0.506146
61	0.9592	0.5368	0.039678	0.511585
62	0.9752	0.4849	0.025006	0.575011
63	0.9644	0.5771	0.036218	0.470596
64	0.9671	0.5962	0.032068	0.450896

4-3- XGBoost model results

In this part, the XGBoost model is trained using the research data set. Considering that XGBoost model training has a set of parameters. For this purpose, the obtainable values of these parameters are presented in Table 4. The uniform function returns a value uniformly between low and high. The quniform function returns a value like round (uniform(low,high) / q) * q. The choice function selects a value from the set of defined values.

In this research, the Python programming language was used to train the XGBoost model, and in particular, two popular libraries, xgboost and Hyperopt, were used. The data used in this research was divided into 80% for training and 20% for testing. Considering that in training the XGBoost model, a comprehensive search (with the help of Hyperopt) was used on the specified parameter values (Table 4) for the XGBoost model to determine the optimal values. Hyperopt is a powerful Python library for hyperparameter optimization developed by James Bergstra. Hyperopt uses a form of Bayesian optimization for parameter tuning that allows you to obtain the best parameters for a given model. This library helps to determine the optimal values for the model through predefined meta-parameters. Therefore, in the end, the best parameters (Table 4) can be selected from the listed meta-parameters. Table 5 shows the results of the coefficient of determination and MSE with the research data set in the XGBoost algorithm.

Table 4: Adjustable parameter values and optimal values in XGBoost algorithm

Adjustable parameter	Values	Optimum value
n_estimators	hp.choice('n_estimators', np.arange(50, 200, 10))	100
max_depth	hp.choice('max_depth', np.arange(3, 18, 1))	15
Gamma	hp.choice('gamma', np.arange(0, 9, 0.01))	0.02
learning_rate	hp.uniform('reg_lambda', 0, 1)	0.05

Table 5: Comparison of the results of the coefficient of determination and MSE in the XGBoost algorithm

Coefficient of determination		MSE value	
Training	Test	Training	Test
0.9954	0.6256	0.004883	0.345239

4-4- AdaBoost model results

In this section, the AdaBoost model is trained using the research data set. Considering that AdaBoost model training has a set of parameters. For this purpose, the obtainable values of these parameters are presented in Table 6.

In this research, the Python programming language was used to train the AdaBoost model, and in particular, two popular libraries, sklearn.ensemble and Hyperopt, were used. The data used in this research was divided into 80% for training and 20% for testing. Considering that in training the AdaBoost model, a comprehensive search (with the help of Hyperopt) was used on the specified parameter values (Table 6) for the AdaBoost model to determine the optimal values. Therefore, in the end, the best parameters (Table 6) can be selected from the listed meta-parameters. Table 7 shows the results of the coefficient of determination and MSE with the research data set in the AdaBoost algorithm.

Table 6: Adjustable parameter values in AdaBoost algorithm

Adjustable parameter	Values	Optimum value
n_estimators	hp.quniform('n_estimators',50,200,10)	100
learning_rate	hp.uniform('learning_rate',0.01,1)	0.2

Table 7: Comparison of the results of the coefficient of determination and MSE in AdaBoost algorithm

Coefficient of determination		MSE value	
Training	Test	Training	Test
0.6081	0.4260	0.418821	0.522182

4-5- Comparing the results

In this section, the results of data mining algorithms are compared. As can be seen in Table 8, the best results are related to the XGBoost model. In this case, the coefficient of determination is the highest and the MSE is the lowest compared to other cases. At the next level, the best results are obtained by the ANN with 1 hidden layer and 44 neurons. Finally, the weakest results are related to the AdaBoost model.

Investment decisions are the most important financial decisions that an individual, company or organization takes to exploit its existence to secure its interests in a period. Sometimes these decisions fall within the strategic decisions of an individual, company or organization. Investment decisions are a vital aspect of managing individual finances and achieving financial goals. However, the process of choosing the right savings and investment products can be complex and challenging because it involves evaluating a wide range of factors including risk tolerance, investment horizon and individual circumstances. In recent years, there has been a growing interest in the development of individualized investment recommendation systems that can help investors make better investment decisions. One of the key factors that influence investment decisions is individual characteristics (Asemi et al., 2023). For this purpose, in this research, the prediction model of investment decision is presented based on individual characteristics (including psychological characteristics, individual characteristics and risk-taking attitude) of investors was done using artificial intelligence. In order to implement the data mining model for investment decision prediction, three models XGBoost, AdaBoost and ANN were used.

Table 8: Comparison of the results of the coefficient of determination and MSE of data mining algorithms

Model	Coefficient of determination		MSE value	
	Training	Test	Training	Test
ANN	0.9391	0.6128	0.061236	0.420368
XGBoost	0.9954	0.6256	0.004883	0.345239
AdaBoost	0.6081	0.4260	0.418821	0.522182

5- Discussion and conclusion

To train the ANN, the optimizer, loss function, and activation function used are Nadam, Mean Squared Error, and Relu, respectively. Also, a hidden layer and the number of 1-64 neurons in the hidden layer have

been used. Also, the distribution of training and test data was determined as 80% and 20%, respectively. In the implementation of the investment decision prediction model using artificial intelligence, 58 inputs and 6 outputs were used, and the best results were related to the mode of 1 hidden layer and 44 neurons. In this case, the coefficient of determination is the highest value and the MSE value is the lowest compared to other cases. The results showed that the MSE values for the training and test data are 0.061236 and 0.420368, respectively. Also, the coefficient of determination values for training and test data are 0.9391 and 0.6128, respectively.

For XGBoost model training, 4 parameters n_estimators, max_depth, gamma and learning_rate were set. The optimal values of n_estimators, max_depth, gamma and learning_rate parameters are equal to 100, 15, 0.02 and 0.05 respectively. Also, the distribution of training and test data was determined as 80% and 20%, respectively, and in order to compare the results of the XGBoost model, the coefficient of determination and MSE were calculated for the training and test data, and the coefficient of determination in the training data section was equal to 0.9954. And in the test data section, it is equal to 0.6256. Also, MSE in the training data section was equal to 0.004883 and in the test data section was equal to 0.345239.

The third model investigated was the AdaBoost model, which used two parameters n_estimators and learning_rate for training, and the optimal value of the parameters related to trib is 100 and 0.2. Also, the distribution of training and test data was determined as 80% and 20%, respectively, and in the AdaBoost model, in order to compare the results of the coefficient of determination and MSE for the training and test data, the coefficient of determination in the training data section was calculated as 0.6081 and in the test data section it is equal to 0.4260. Also, MSE in the training data section was equal to 0.418821 and in the test data section was equal to 0.522182.

By comparing the coefficient of determination in the training and test data in the three mentioned models, it can be stated that the coefficient of determination in the training and test data of XGBoost model, ANN and AdaBoost model respectively have coefficients It was determined more to less that the best results are related to the XGBoost model. In this case, the coefficient of determination is the highest and the MSE is the lowest compared to other cases. At the next level, the best results are obtained by the ANN with 1 hidden layer and 44 neurons. Finally, the weakest results are related to the AdaBoost model.

Finally, according to the results of the research, it is suggested to use the feature selection process in future researches to improve the results of data-mining algorithms. It is also possible to perform the feature selection process by modern meta-heuristic algorithms such as binary gray wolf.

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Appendix 1: Research Questionnaire

Variable	Dimension	Component	Source
Risk-taking attitude	Risk avoidance	I am not willing to take risks when choosing stocks or investing.	Bashir, T., Shah, H., & Khan, R. Z. (2019)
		I prefer a low risk/decent return investment with consistent performance to one that offers higher risk/higher return.	
		I would rather stick with an investment strategy that has known problems than risk trying a new investment strategy that has unknown problems, even if the new investment strategy has high returns.	
		I see risk in investment as a situation that should be avoided at all costs.	
	Short term investment intention	I plan to invest in an index every year.	
		I plan to invest at least half of my investment money in the stock market.	
		I plan to participate in portfolio management activities at least twice a week.	
		I plan to do my own investment research instead of using outside advice.	
		I am going to compare my portfolio performance with professional managers.	
	Long term investment intention	I plan to save at least 10% of my gross income for investment/savings/retirement purposes.	
		I plan to have a portfolio that focuses on multiple asset classes (i.e, stocks, bonds, cash, real estate, etc.).	
		I plan to participate in investment training courses.	Hamza, N., & Arif, I. (2019)
Individual characteristics	Extroversion	I see myself as a talkative person.	
		I see myself as a friendly person.	
		I see myself as an energetic person.	
		I see myself as a person who creates a lot of enthusiasm.	
		I see myself as a person who likes to communicate.	
	Acceptance (Agreeableness)	I see myself as a person who tends to take care of others.	
		I see myself as a useful and selfless person.	
		I see myself as a person who initiates agreement with others.	
		I see myself as a person who has a forgiving nature.	
		I see myself as a person who is generally trusted.	
	Accountability	I see myself as a person who does a job perfectly.	
		I see myself as a person who takes care of things.	
		I see myself as a reliable person.	
		I see myself as a person who tends to organize.	
		I see myself as a person who tends to be active.	
	Neurosis (emotional instability)	I see myself as someone who is depressed right now.	
		I see myself as a person who has no tolerance and cannot tolerate stress.	
		I see myself as a person who can be tense.	
		I see myself as a person who is very worried.	
		I see myself as a person who is emotionally unstable and easily upset.	
	Openness	I see myself as a person who presents new ideas.	
		I see myself as a person who is curious about different things.	
		I see myself as a person with innovative intelligence and a deep thinker.	
		I see myself as a person who has an active imagination.	
		I see myself as an innovative person.	
Psychological characteristics	Risk perception	I see the word "risk" with the idea of "opportunity" as well.	Hunjra , A. I., Qureshi, S., & Riaz, L. (2016)
		I look at risk in investment as a situation that should be avoided.	
		I show my willingness to take risks in financial decisions.	
		Where there is risk, it is much more acceptable to limit the risk to my potential for benefit from the risk.	
	Problem framework	I feel that the loss of investment is felt more than the profit.	
		I will invest in situations where there is a fairly high potential to earn a return on my investment.	
		If I am asked to choose between a 50% chance of losing 1000 Rials and a 50% chance of losing nothing, I will choose the risky option.	
		An investment is risky if there is a 50% chance that my investment will underperform.	
		If I was given 10,000 Rials and had to choose between two options: a guaranteed profit of 500 Rials or a 50-50 chance of winning 1,000 Rials or nothing, I would prefer the first option. the tenth	
		If I want to choose between "sure increase of 1000 Rials" and "50-50 chance	

Variable	Dimension	Component	Source
		of losing 1000 Rials and losing nothing", I prefer the second option.	
	Risk orientation	I avoid risk when choosing stocks for investment.	
		I generally look for safer investments, even if that means lower returns.	
		I am willing to accept significant investment risk for significant returns.	
		I prefer to invest in low risk / high yield stocks with stable performance.	
		I'd rather take a chance with higher risk investments than increase the amount I save.	
		I am ready to choose the possibility of initial losses in order to get more returns in the future.	
	Information asymmetry	The lack of knowledge about certain investments affects the investment decision.	
		There is no information asymmetry in stock markets.	
		Information asymmetry has a big impact on my investment decision.	
		I think that people who believe that they have more knowledge of risk and risky situations tend to take more financial risks.	
		I think people fail to recognize omissions in the risk information they receive.	
Investment decision		Fluctuations in the stock market do not concern me.	Hunjra , A. I., Qureshi, S., & Riaz, L. (2016)
		I plan to put at least half of my investment money in the stock market.	
		I think that the benefits offered by the company to make a risky investment affect the investment decision.	
		I choose riskier options to ensure financial security.	
		I choose riskier alternatives to maximize potential profit.	
		My investments in stocks have shown increasing income/cash flow growth over the past 5 years.	