

Role of perceived COVID-19 disruption, personality traits and risk perception in determining the investment behavior of retail investors: a hybrid regression-neural network approach

COVID-19's
role in retail
investors'
behavior

Received 27 January 2023
Revised 8 March 2023
15 April 2023
Accepted 12 June 2023

Arfat Manzoor

Department of Commerce, University of Kashmir, Srinagar, India

Andleebah Jan

Department of Management, Islamic University of Science and Technology, Awantipora, India

Mohammad Shafi

Department of Commerce, University of Kashmir, Srinagar, India

Mohammad Ashraf Parry

Department of Management, Islamic University of Science and Technology, Awantipora, India, and

Tawseef Mir

Department of Computer Science, Baba Ghulam Shah Badshah University, Jammu, India

Abstract

Purpose – This study aims to assess the impact of personality traits, risk perception and perceived coronavirus disease 2019 (COVID-19) disruption on the investment behavior of individual investors in the Indian stock market.

Design/methodology/approach – This study adopts a survey approach. The sample comprises 315 active retail investors investing in the Indian stock exchange. Two-stage analysis technique regression and Artificial Neural Network (ANN) were used for data analysis. Study hypotheses were tested through regression and ANN was adopted to validate the regression results.

Findings – Two regression models were modeled to test the research hypotheses. Findings showed that risk perception and COVID-19 disruption have a significant positive and neuroticism has a significant negative impact on short-term investment decisions, while the role of conscientiousness in determining short-term investment decisions was not found significant. Results also showed a positive impact of neuroticism and conscientiousness and a negative impact of risk perception on long-term investment decisions. The role of COVID-19 disruption was found negative but insignificant in predicting long-term investment decisions.

Practical implications – This study has practical implications for many parties like retail investors, financial advisors and policymakers. This study will assist the investors to realize that they do not always take rational financial decisions. This study will suggest the financial advisors to use the knowledge of behavioral finance in making the advisors' advisory and wealth management decisions. This study will also assist the policymakers to outline behaviorally well-informed policy decisions to protect the interests of investors.

Originality/value – India is one of the fast-growing economies in the world. India has a vast population of active investors and determining investors' investment behavior adds novelty to this study as developed economies have remained the main focus of previous studies. The other novel feature of this study is that this study tries to assess the impact of COVID-19 disruption along with personality traits and risk perception on



investment behavior. The other valuable factor of this study is the use of ANN to predict the relative importance of the exogenous variables.

Keywords COVID-19, Personality traits, Risk perception, Retail investors, ANN, Regression, Investment decisions

Paper type Research paper

1. Introduction

The field of traditional finance developed over the last few decades on the premise that people make rational decisions and make impartial predictions (Nofsinger, 2017). Traditional finance models the behavior of individual decision-makers as rational who use all the available information optimally. But researchers in the emerging discipline of behavioral finance stand against this notion and provide grounds that investors sometimes behave irrationally in making investment decisions. Hence, there can be psychological and behavioral factors behind investment decisions (Kourtidis *et al.*, 2011). In the field of Psychology, research within investor psychology is a new advancement which has grabbed the interest of investment professionals and psychologists. Behavioral finance has become a significant domain in finance from a cognitive perspective centering on the herding and disposition effects (Lai, 2019). Even so, a limited study is consecrated on the impact of personality traits on the investment behavior of individual investors. The present study enlarges the theory of planned behavior including the big-five personality traits to explore the impact of the personality traits of retail investors on their investment decisions. Besides the personality traits, also the effect of risk perception on the investment decisions of individual investors will be investigated. The impact of risk perception on a prudent investor's investment decisions is a new topic in the Behavioral Finance literature. Risk is an immanent constituent of all kinds of investment avenues. Risk is the chance of receiving less (or more) actual returns than predicted ones. Perception is the procedure by which an individual seeks superior elucidation of sensorial knowledge so that the investors can base their ultimate investment decision on their degree of proficiency and earlier learning. Risk perception is a rational or illogical belief held by a person or community concerning the probability of the happening of a risk, its size and regulating its influences is a vital fortune component which encourages sound decision-making in high-risk scenarios. The fact that each investor has a different risk tolerance and risk perception intricates the analysis of financial risk. An investor's risk perception is a key aspect that determines his or her financial decisions. To perceive risk, each individual acts differently and uniquely. Risk perception is not an objective estimate of an individual but gets influenced by one's thought processes. The importance of risk perception in investors' behavior is considered serious, especially in crucial and uncertain situations. Risk perception has a significant impact on financial decisions (Baghani and Sedaghat, 2016).

COVID-19 still seems to have a sustained influence on the world economy and financial markets (Ullah, 2022). As a result of the COVID-19 spreading across all continents, the larger part of investors' portfolios was faced with a financial deficit regardless of the truth that there are quite possibilities to gain from the current pandemic crisis. During economic booms, traditional investment tactics have been well-researched and documented. However, few studies have attempted to determine financial strategies to be employed during pandemics. Few studies have used an exploratory approach to examine investor behavior (Jaiyeoba and Haron, 2016). In reality, a careful literature assessment shows that there are few research documents available that examine the COVID-19 influence on individual investors' behavior especially in developing stock markets such as India's.

2. Literature review

The foundation of behavioral finance theory lies in psychology's pursuit to acknowledge how sentiments and cognitive distortions affect the behavior of individual investors (Kengatharan

and Kengatharan, 2014). According to Kasoga and Tegambwage (2022), the psychological traits of investors influence their investment decisions. A huge number of studies were carried out in the domain of behavioral finance from cognitive psychology which is related to thinking, perception and decision forming. Gitman and Joehnk (2008) in their study stated that academicians in behavioral finance hold the opinion that the investor's investment decisions get affected by various psychological factors. In addition to the heuristic biases (Jordan *et al.*, 2022) and the availability biases (Kengatharan and Kengatharan, 2014), personality traits and risk perception of investors also influence their investment behavior (Mayfield *et al.*, 2008). A similar study was conducted by (Yadav and Narayanan, 2021) in which they found a remarkable positive influence of personality traits on an individual's investment decisions. The association among variables of this study is backed by a vast literature.

2.1 Personality traits and investment behavior

Personality is the characteristic or combination of characteristics highlighting a personal aspect of a person and it convinces the investor to take risky or safe investment decisions (Becker *et al.*, 2012; Durand *et al.*, 2013). Fung and Durand (2014) Understanding the personality of investors is very imperative in predicting the investment performance of investors in the stock market. Many studies have been conducted in the field of behavioral finance showing an intense impact of personality traits on investment behavior (Raheja and Dhiman, 2018; Akhtar *et al.*, 2017). The other studies showing a considerable linkage of personality traits with investment behavior are (Nga and Yien, 2013; Rzeszutek *et al.*, 2015; Durand *et al.*, 2008; Sadi *et al.*, 2011; Jiang *et al.*, 2021; Priyadharshini, 2020).

2.2 Conscientiousness and investment behavior

Persons high on conscientiousness are "determined, well-organized, consistent, persistent and punctual and take higher risks less impulsively" (Mayfield *et al.*, 2008). Conscientious persons are diligently engaged in decision-making (Gunkel *et al.*, 2010) and some other researchers have shown a positive correlation between conscientiousness traits and trading behavior (Durand *et al.*, 2013). Conscientious individuals are independent of misbeliefs and thoughtfully choose their investment instruments (Costa and MacCare, 1992). This competence helps them to become particular about investment options and risk tolerance (Sadi *et al.*, 2011). Individuals who are high on conscientiousness are careful and believe in being prepared in advance and they do not believe in delusions in making their investment decisions. That is why they prefer long-term investment decisions over short-term (Mayfield *et al.*, 2008). Hamza and Arif (2019) hold a contradictory view of the insignificant impact of conscientiousness on investment decisions. Their findings were opposed by Khan and Abid Usman (2021) who advocates a significant association of conscientiousness with long-term investment decisions.

H1a. Conscientiousness has a significant negative impact on STID.

H1b. Conscientiousness has a significant positive impact on LTID.

2.3 Neuroticism and investment behavior

Neurotic persons are "pessimistic, depressed, anxious and exhibit more fear of uncertainty and ambiguity" (McCrae and Costa, 1997). Niszcota (2014) discovered that neurotic individuals fear riskiness and prefer to evade offshore equities. In a similar study, Jiang *et al.* (2021) observed that neurotic individuals intend to invest less income in equities. Analytical capacity, abstract thoughts, reasoning and notional understanding are all lacking in neurotic people. These inadequacies predispose neurotic people to fear failure and anxiety while

making risky decisions (Young *et al.*, 2012). Pak and Mahmood (2015) identified that neuroticism is associated with risky behavior. Neurotic people are not emotionally stable and have a gloomy outlook on financial decisions (Oehler and Wedlich, 2018; Noe and Vulkan, 2017). Neurotic individuals do not want to change their investments regularly since they are pessimistic (Zeb *et al.*, 2020).

H2a. Neuroticism has a significant negative effect on STID.

H2b. Neuroticism has a significant positive effect on LTID.

2.4 Risk perception and investment behavior

Literature has revealed numerous extrinsic and intrinsic factors that remarkably influence investors' investment behavior. The former involves condition composing and the feature of knowledge (Steul, 2006), however, the last involves personality traits and financial literacy (Sadi *et al.*, 2011; Riaz *et al.*, 2012). There is a small number of studies considering the influence of risk perception. Studies about the contribution of risk perception revealed that individuals with high-risk perception hold risk-free assets in their financial portfolios and display short-term investment behavior (Oehler *et al.*, 2017; Virlics, 2013). Investors who show better risk perception make better investment decisions (Waheed *et al.*, 2020). Some researchers revealed that individuals with less risk perception take the high risk (i.e. opt for those decisions which have a high chance of getting fewer returns than expected) (Kahneman and Lovallo, 1993; MacCrimmon and Wehrung, 1990). Some researchers also believe that risk perception has no impact on investment decisions (Mulyani *et al.*, 2021). While their view was criticized by Mankuroane *et al.* (2022) who found a negative significant correlation between short-term investment decisions and risk perception and advocated that more the risk perception level, the fewer short-term investment decisions an investor will take.

H3a. Risk perception has a significant positive impact on STID.

H3b. Risk perception has a significant negative impact on LTID.

2.5 COVID-19 disruption and investment behavior

The COVID-19 pandemic has shaken the globe and surprised everyone. The COVID-19 pandemic extends the support to behavioral finance by criticizing traditional finance which assumes markets to be well organized and investors to be rational. Excessive fluctuations in stock prices are not entirely justified by traditional finance (Aslam *et al.*, 2020). The COVID-19 pandemic has proved that market participants behave irrationally and also justifies the inefficiency of stock markets globally (Bansal, 2020). With the bad economic conditions due to the deadly COVID-19 pandemic, investors have become more careful and try to be very rational in carrying out investment activities (Parveen *et al.*, 2021). Pandemic reactions can be associated with personality traits (Kohút *et al.*, 2021). This view was supported by (Bogg and Milad, 2020; Zajenkowski *et al.*, 2020) who demonstrated that organized and friendly individuals display elevated conformity with COVID-19 guidelines more than social, anxious and adventurous individuals. Apart from this, COVID-19 pandemic also changed the behavior of investors towards their investment decisions.

H4a. Perceived COVID-19 disruption has a positive significant impact on STID.

H4b. Perceived COVID-19 disruption has a negative significant impact on LTID.

As literature supports the influence of COVID-19 on investment behavior, the study of this important factor throughout the pandemic period adds more value to the current study.

To attain the objective of this study, we have developed a double-layered hybrid model and to the best of our information, previous researchers have not adopted this approach. We presented the non-linear model (ANN) and linear model (regression) for the analysis and compared the results to know the deviances in the results of the linear and non-linear models [Figure 1](#) depicts the proposed model of the study.

3. Research methodology

The current study endeavors to utilize a two-staged research methodology (see [Figure 2](#)) [Figure 2](#) depicts a self-explanatory flowchart. Regression analysis is used in the initial stage to test the hypothesized routes in the intended research model. The regression analysis is only capable of assessing linear associations between decision variables and it may overgeneralize the intricacies engaged in the process of decision-making in some circumstances. This regression flaw is resolved by the sturdiness of Neural Network (NN) modeling which can assess both linear and non-linear associations between decision factors. As a result, NN modeling was used in the second step to rank the main variables and validate the regression results.

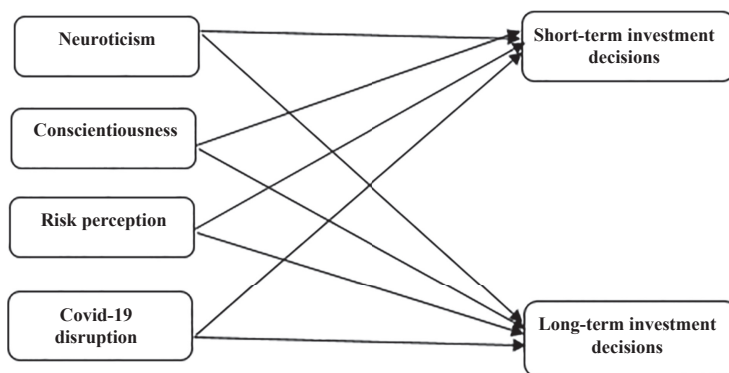
3.1 Purpose of the study

The main purpose of the study is to analyze the impact of personality traits, risk perception and COVID-19 disruption on the investment behavior of individual investors.

3.2 Sample

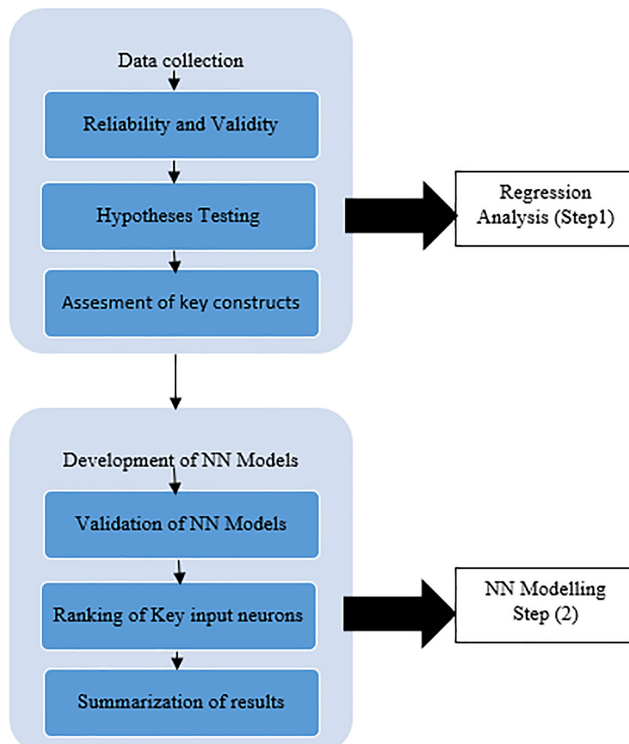
The selected sample for the present study includes individual investors trading in Indian stock markets. Only active individual investors of North India who are engaged in the investment activities were targeted. This research study used the multi-stage sampling method. Under the multi-stage sampling method, North India was divided into north, central and south zones based on geographical location. The north zone includes Jammu and Kashmir, Ladakh and Himachal Pradesh. The central zone includes Delhi and Punjab. The south zone includes Haryana, Uttar Pradesh and Rajasthan. For each zone, one area was selected randomly. Jammu and Kashmir for the north zone, Delhi for the central zone and Uttar Pradesh for the south zone were selected.

In total 370 survey questionnaires were distributed and 325 completed the questionnaire (i.e., with a response rate of 87.83%). However, 10 questionnaires were found incomplete and were excluded. Therefore, 315 questionnaires were included in the final analysis. Out of 315



Source(s): Authors own creation

Figure 1.
Proposed
research model



Source(s): Authors own creation

Figure 2.
Regression-NN
modeling Flow chart

participants, 68.3% were male and 31.7% were females. 14.2% of the participants were having an annual income of fewer than 2 lakhs, 42% were having 2 to 4 lakh, 35.2% respondents were having 4 to 6 lakh annual income and 8.6% of respondents were having annual income of more than 6 lakhs. Interestingly, a large number of the participants were in the age group of 20–40 years (72.4%) indicating the interest of younger generations in the investment market. Concerning occupation, most of the sample participants (43.5%) were from the private employee category. Further, 50.4% of the respondents were married and 49.6% were unmarried. In addition, the majority of the respondents were graduates (53.3%), followed by post-graduates (30.5%), undergraduates (13%) and professional class (3.2%).

3.3 Methods and procedure

The respondents initially filled up the demographic information (gender, age, income and marital status). Then they put answers in questionnaires evaluating personality traits, risk perception and perceived COVID-19 disruption in a countervailed way accompanied by the investment questionnaire. In 185 survey queries, questions related to the exogenous variables come earlier than the queries of investment decisions and in further 185 survey instruments the investment queries came earlier than the personality, risk perception and perceived COVID-19 disruption queries. This countervailing demonstration of survey instruments can lessen the attainable impact that could change the reactions (Hogarth and Einhorn, 1992). For instance, if participants fill up the investment queries initially, they may have distinct

responses to the ensuing personality (e.g. being extra anxious) and risk perception (e.g. more or less risky) survey instruments. Alternatively, if people fill in the personality traits, risk perception and perceived COVID-19 disruption queries initially, they may have prejudices on the investment perceptions (e.g. more or less attracted towards STID). To measure all the 27 survey items: Neuroticism (5 items), Conscientiousness (4 items), Risk perception (4 items), perceived COVID-19 disruption (4 items), STID (5 items) and LTID (5 items) standard scales were adopted from existing studies. For measuring the two personality traits (neuroticism and conscientiousness) (Mayfield *et al.*, 2008), scale was used. The Mayfield *et al.* (2008) scale of personality contains 23 items. As this study only includes neuroticism and conscientiousness that is why only 9 items were adopted, 4 items of conscientiousness and 5 items of neuroticism. Risk perception was measured in this study by the scale of Blais and Weber (2006). Perceived COVID-19 disruption was measured by the scales of (Byun and Sternquist, 2011; Zsido *et al.*, 2020; Ling *et al.*, 2020). Investment decisions that act as a dependent variables in this study were measured by the scale of Mayfield *et al.* (2008) who segregated the investment decisions into short-term and long-term. All items in the study instrument were demarcated utilizing a Five point Likert scale as suggested by (Sharma *et al.*, 2019a, b) with a 1 representing “strongly disagree” and 5 “strongly agree” with exception of demographic variables. The indicators in the survey instrument were only available in English. An obligatory question was posed at the start of the survey instrument: “Are you investing in the stock market?” respondents giving a positive response to this question were only allowed to fill out the survey instrument. Table 1 provides the demographic profile of the study sample.

4. Data analysis and results

4.1 Factor analysis

Factor analysis has been employed to define the dimensions of the factors impacting the investment behavior of retail investors. The Kaiser-Meyer-Olkin (KMO) value was obtained to be 0.861 over the suggested value of 0.5 (Kaiser, 1974) and Bartlett’s test of sphericity was

Demographic variable	Category	Number of respondents	Percentage
Gender	Male	215	68.3
	Female	100	31.7
Income (yearly)	Less than 2 lakh	45	14.2
	2 to 4 lakh	132	42
	4 to 6 lakh	111	35.2
	Above 6 lakh	27	8.6
Occupation	Govt. Employee	98	31.1
	Private employee	137	43.5
	Other	80	25.4
Marital status	Married	159	50.4
	Unmarried	156	49.6
Education	Undergraduate	41	13.0
	Graduate	168	53.3
	Post graduate	96	30.5
	Professional	10	3.2
Age (years)	Below 20	22	7.0
	20 to 40	228	72.4
	40 to 60	57	18.1
	Above 60	8	2.5

Source(s): Authors' own creation

Table 1.
Sample structure

also noticed significant ($\chi^2 = 11,528.50, p < 0.05$) specifying that the study sample was sufficient for factor analysis. Factor scores of the measuring items of the constructs are presented in [Table 2](#). The study only includes the items having loadings greater than 0.5 ([Hair et al., 2017](#)). Finally, 4 factors with 17 items each having Eigen value greater than 1 ([Table 2](#)) were retained with a total variance of 76.16%.

4.2 Reliability and validity

The evaluation model was assessed for composite reliability and construct validity. Construct validity was evaluated by evaluating both convergent and discriminant validity.

Composite reliability: The table shows that all four constructs have achieved the suggested composite reliability threshold limit of 0.7 ([Hair et al., 2017](#)).

Convergent validity: Standardized factor loadings, construct reliability (CR) and average variance extracted (AVE) were calculated to test the convergent validity of the constructs. [Hair et al. \(2010\)](#) recommended that standardized factor loadings be 0.50 or greater, the AVE be greater than 0.5 and CR be more than 0.7. [Table 2](#) shows the factor scores of all items are more than the threshold limit of 0.5 and range from 0.699 to 0.911. [Fornell and Larcker’s \(1981\)](#) criterion has been used to calculate the AVE. The AVE values (see [Table 3](#)) of all the study variables were found well above the set limit of 0.5 (NER: 0.769, CON: 0.608, RP: 0.777 and PCD: 0.534), which indicates that model has no convergent validity issue.

Discriminant validity: Discriminant validity tests the uniqueness of the variables. This study adopts the [Fornell and Larcker’s \(1981\)](#) criterion according to which the square root of the AVE of a variable should be greater than its association with other constructs. In addition to this criterion, AVE and maximum square variance (MSV) criterion set by [Hair et al. \(2010\)](#) was also used to rule out any discriminant validity issue.

[Table 3](#) shows that the values of MSV are less than the values of AVE for all constructs. Results in [Table 4](#) also show that the square root of AVE of constructs is more than their correlation with other constructs which rules out any discriminant validity problem.

Items	Component			
	1	2	3	4
neur1	0.870			
neur2	0.878			
neur3	0.883			
neur4	0.842			
neur5	0.911			
cons1			0.848	
cons2			0.720	
cons3			0.699	
cons4			0.841	
RP1		0.895		
RP2		0.898		
RP3		0.828		
RP4		0.902		
P1				0.715
P2				0.765
P3				0.718
P4				0.723
Eigen Value	6.640	2.749	2.051	1.509
% of variance	39.056	16.170	12.063	8.874

Table 2.
Factor loadings

Source(s): Authors’ own creation

4.3 Hypothesis testing

Regression analysis was used to test the study hypotheses. Regression analysis adopts a linear approach and predicts the linear relations among the decision variables. Two regression models were modeled. In the model first, neuroticism, conscientiousness, risk perception and perceived COVID-19 disruptions were used as exogenous variables and short-term investment decisions as endogenous variables. In the second model, long-term investment decision acts as an endogenous variable and neuroticism, conscientiousness, risk perception and perceived COVID-19 disruptions as exogenous variables.

The results depicted in Table 5 indicate that neuroticism ($\beta = -0.707, p < 0.05$) has a negative significant effect on STID. However, it was observed that conscientiousness ($\beta = 0.052, p > 0.05$) has a positive but not noteworthy influence on STID. Hence, H2a is

Constructs	α	CR	AVE	MSV
PCD	0.712	0.821	0.534	0.031
RP	0.945	0.933	0.777	0.324
NER	0.947	0.943	0.769	0.324
CON	0.840	0.860	0.608	0.267

Note(s): •PCD perceived COVID-19 disruption, RP: risk perception, NER: neuroticism, CON: conscientiousness

• α : Cronbach's alpha, CR: composite reliability, AVE: average variance extracted and MSV: maximum shared variance

Source(s): Authors' own creation

Table 3.
Reliability and
convergent validity

Constructs	PCD	RP	NER	CON
PCD	0.731			
RP	0.040	0.881		
NER	-0.129	-0.569	0.877	
CON	0.176	0.190	-0.517	0.780

Note(s): •PCD: perceived COVID-19 disruption, RP: risk perception, NER: neuroticism and CON: conscientiousness

Source(s): Authors' own creation

Table 4.
Discriminant validity

Model 1: Short-term investment decisions			Model 2: Long-term investment decisions		
Relationship	Beta	<i>p</i> value	Relationship	Beta	<i>p</i> value
RP → STID	0.116	0.014	RP → LTID	-0.250	0.001
PCD → STID	0.134	0.002	PCD → LTID	-0.067	0.246
NER → STID	-0.707	0.000	NER → LTID	0.590	0.000
CON → STID	0.052	0.218	CON → LTID	0.122	0.006
R Square = 0.758			R Square = 0.725		

Note(s): •PCD: perceived COVID-19 disruption, RP: risk perception, NER: neuroticism, CON: conscientiousness, STID: short-term investment decisions and LTID: long-term investment decisions

• $p^* < 0.05$

Source(s): Authors' own creation

Table 5.
Regression results

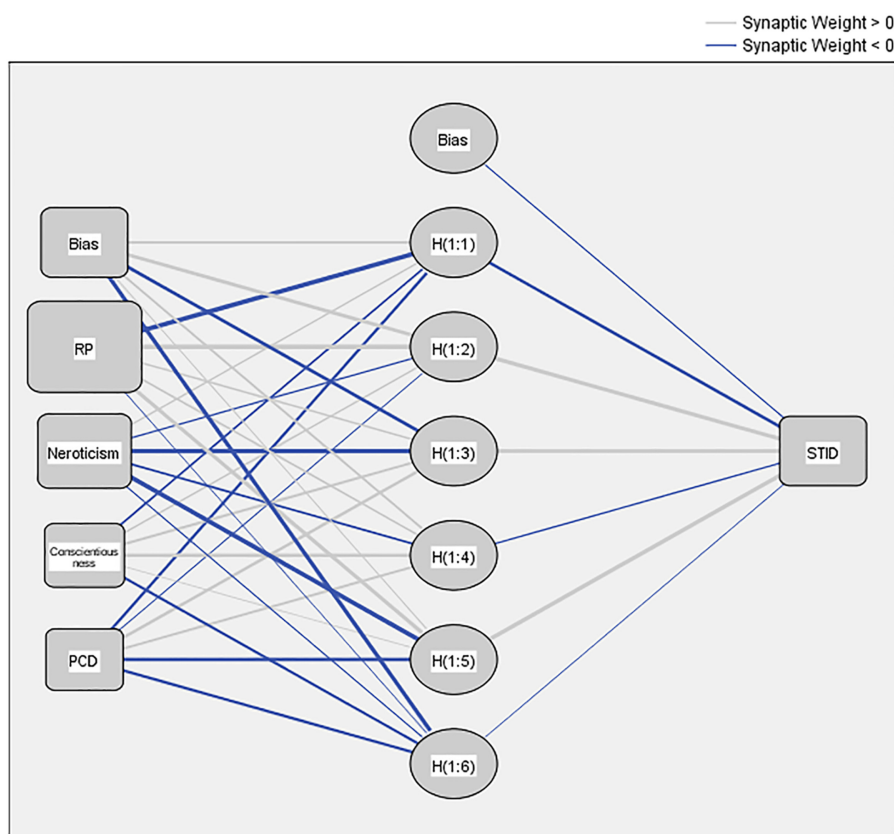
supported but H1a is not supported. The regression table shows that the risk perception ($\beta = 0.116, p < 0.05$) and perceived COVID-19 disruption ($\beta = 0.134, p < 0.05$) have a notable positive impact on STID. Hence, H3a and H4a are supported. The coefficient of the determination (R^2) of the model is 0.758 demonstrating that a total of 75.8% variance in STID is explained by these four variables. The significance of the measurements is represented by standardized beta coefficients (Clemes *et al.*, 2008). The results also show the positive and significant impact of neuroticism ($\beta = 0.590, p < 0.05$) and conscientiousness ($\beta = 0.122, p < 0.05$) on LTID. Hence, H2b and H1b are supported and accepted. Results also show the negative significant impact of risk perception ($\beta = -0.250, p < 0.05$) on LTID. However, it was found that perceived COVID-19 disruption ($\beta = -0.067, p > 0.05$) has a negative but insignificant impact on LTID. Hence, H3b is accepted but H4b is not supported by the results. The coefficient of determination (R^2) of the model is 0.725, demonstrating that a total of 72.5% variance in long-term investment decisions is explained by these four constructs.

4.4 Artificial neural network (ANN)

In this stage, similar to Liébana-Cabanillas *et al.* (2017), we took the exogenous variables of the regression models as the input neurons for the ANN model. Irregular data dissemination and the continuance of non-linear associations between the external and interior antecedents are arguments for using the ANN. ANN supports unbalancing models, in which a drop in one factor is not required to be recouped by an expansion in another. The ANN analysis was carried out with the help of International Business Machine Corporation's Statistical Package for the Social Sciences (IBM's SPSS) neural network module. Parallel to the regression analysis, two ANN models (Figures 3 and 4) were developed, one for short-term investment decisions and other for long-term investment decisions. Multilayer Perceptrons and Hyperbolic Tangent activation functions were used for the input and hidden layers and identity functions for output layers (Sharma *et al.*, 2019a, b). In ANN it is even possible to minimize the error through various series of the learning process which ultimately improves the prediction rate (Idrissi *et al.*, 2019). 90% of the samples were allocated for the training procedure and the remaining 10% was used for the testing procedure. To dodge the possibility of over-fitting, we adopted a ten-fold cross-validating approach and found the root mean square of errors (RMSE) (Ooi and Tan, 2016). Table 6 and Table 7 indicate that the average RMSE values of the training and evaluating processes are comparatively small for both the models (model 1: RMSE training = 0.109, RMSE testing = 0.085) model 2 (RMSE training = 0.136, RMSE testing = 0.102), which confirms the excellent model fit.

4.4.1 Sensitivity analysis. To assess the divining potential of each input neuron, we executed sensitivity analysis which was calculated by averaging the comparative relevance of the input neurons acquired from NN models (Chong, 2013). The significance of variables examine the normalized significance, which might be represented as the proportion of comparative significance to its greatest comparative significance and is typically conveyed in percentages (Sharma *et al.*, 2017; Yadav *et al.*, 2016). Table 8 summarizes the average comparative significance and normalized comparative significance found from both the NN models.

The results in Table 8 show that neuroticism (0.378) is the key predictor of short-term investment decisions followed by risk perception (0.347) and conscientiousness (0.175). The importance of perceived COVID-19 disruption (0.101) in predicting short-term investment decisions was minimum. The result indicates that neuroticism (0.439) is the most significant influencer of long-term investment decisions followed by risk perception (0.297), conscientiousness (0.160) and again perceived COVID-19 disruptions (0.150) was ranked last in predicting the long-term investment decisions.



Hidden layer activation function: Hyperbolic tangent

Output layer activation function: Identity

Source(s): Authors own creation

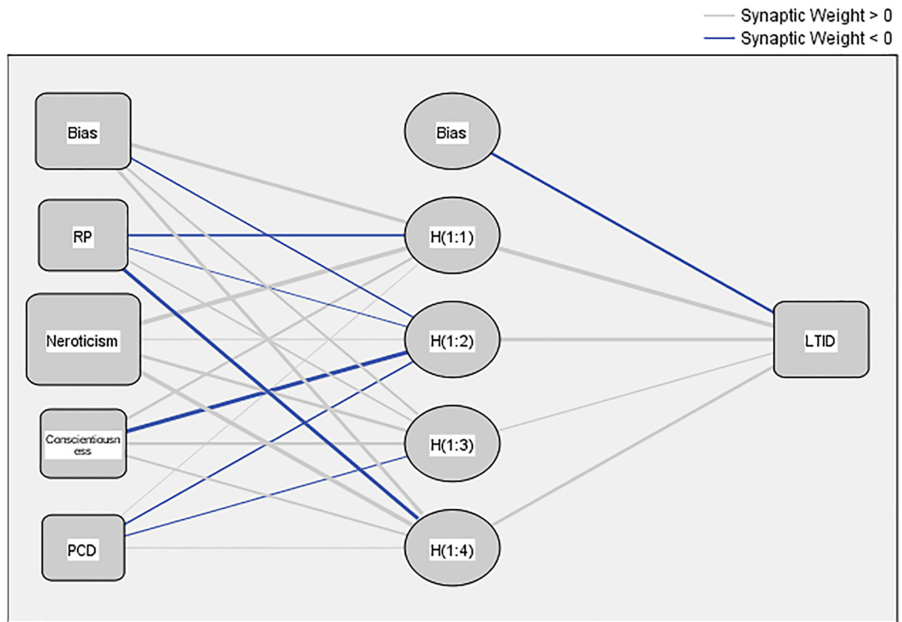
Figure 3.
ANN model 1

4.5 Comparison between the results

A comparison was made between the findings of the regression analysis and the results of ANN. Table 9 compares the results of regression and ANN (all two models) based on the strength of beta coefficients and relative normalized importance.

For model 1, Table 9 shows that ANN gives the highest rank to neuroticism (rank 1) and the same rank (rank 1) is given to neuroticism by regression. Interestingly, the ranking of risk perception (regression rank: 3, ANN rank: 2), perceived COVID-19 disruption (regression rank: 2, ANN rank: 4) and conscientiousness (regression rank: 4, ANN rank 3) were found to be asymmetric. For model 2, Table 9 indicates the similarity between the results of regression analysis and ANN. Both analysis techniques give rank 1 to neuroticism, rank 2 to risk perception, rank 3 to conscientiousness and rank 4 to perceived COVID-19 disruption in predicting long-term investment decisions.

The variance between results obtained by the regression analysis and the NN model in model 1 can be indicated by the non-linear and non-recoupable feature and the much advanced estimation ability of the NN model.



Hidden layer activation function: Hyperbolic tangent

Output layer activation function: Identity

Source(s): Authors own creation

Figure 4. ANN model 2

Network	Sample size training	Sample size testing	Total sample	RMSE training	RMSE Testing
1	285	30	315	0.115	0.105
2	286	29	315	0.114	0.100
3	280	35	315	0.117	0.088
4	275	40	315	0.112	0.076
5	285	30	315	0.104	0.082
6	270	39	315	0.101	0.066
7	284	31	315	0.103	0.082
8	277	38	315	0.106	0.084
9	288	27	315	0.106	0.090
10	283	32	315	0.110	0.081
Mean				0.109	0.085
S.D				0.005	0.011

Table 6. RMSE model 1 (short-term investment decisions)

Note(s): •RMSE: root mean square error
Source(s): Authors' own creation

5. Discussion

Based on the summary of results provided in the preceding sub-sections, it is possible to conclude that the research model intended in the current study had a high divining potential in assessing the impact of personality traits, risk perception and COVID-19 disruption on investment decisions of individual investors. This was further proved by the terms of

COVID-19's
role in retail
investors'
behavior

Network	Sample size training	Sample size testing	Total sample	RMSE training	RMSE Testing
1	277	38	315	0.169	0.136
2	285	30	315	0.164	0.141
3	286	29	315	0.155	0.083
4	280	35	315	0.105	0.070
5	275	40	315	0.119	0.076
6	284	31	315	0.122	0.097
7	275	40	315	0.141	0.102
8	283	32	315	0.124	0.108
9	278	37	315	0.123	0.094
10	285	30	315	0.143	0.114
Mean				0.136	0.102
S.D				0.021	0.023

Note(s): ●RMSE: root mean square error
Source(s): Authors' own creation

Table 7.
RMSE model 2 (long-term investment decisions)

Network	Model 1: Short-term investment decisions				Model 2: Long-term investment decisions			
	PCD	RP	NER	CON	PCD	RP	NER	CON
N1	0.104	0.425	0.338	0.133	0.068	0.377	0.330	0.226
N2	0.174	0.419	0.361	0.046	0.166	0.336	0.387	0.111
N3	0.057	0.193	0.509	0.241	0.106	0.228	0.555	0.110
N4	0.136	0.457	0.262	0.145	0.128	0.227	0.525	0.121
N5	0.033	0.251	0.506	0.210	0.044	0.314	0.544	0.098
N6	0.107	0.414	0.296	0.183	0.065	0.294	0.454	0.188
N7	0.052	0.276	0.406	0.266	0.113	0.321	0.307	0.259
N8	0.142	0.302	0.340	0.216	0.111	0.310	0.454	0.125
N9	0.124	0.343	0.398	0.135	0.053	0.354	0.482	0.110
N10	0.080	0.387	0.362	0.171	0.193	0.209	0.349	0.248
Average Importance	0.101	0.347	0.378	0.175	0.150	0.297	0.439	0.160
Normalized importance (%)	0.267	91.798	100	0.462	0.341	67.653	100	0.364

Note(s): PCD: perceived COVID-19 disruption, RP: risk perception, NER: neuroticism and Con: conscientiousness

Source(s): Authors' own creation

Table 8.
Sensitivity analysis

Model 1: Short-term investment decisions				Model 2: Long-term investment decisions			
Constructs	Rank (regression)	Rank (ANN)	Matched	Construct	Rank (regression)	Rank (ANN)	Matched
RP	3	2	No	RP	2	2	YES
NER	1	1	YES	NER	1	1	YES
PCD	2	4	No	PCD	4	4	YES
CON	4	3	No	CON	3	3	YES

Note(s): ●PCD: perceived COVID-19 disruption, RP: risk perception, NER: neuroticism, CON: conscientiousness and ANN: artificial neural network

Source(s): Authors' own creation

Table 9.
Comparison of results

coefficient of determination (R^2) for STID (75.8%) and LTID (72.5%), which shows that the research model used in this study is quite capable of meeting the objectives of the study. In addition to regression analysis, the results of neural networks were used to rank the independent variables in this study. Furthermore, neural network modeling offered evidence to support and validate the regression results.

The findings of this study support the hypotheses. The role of neuroticism in predicting STID is supported by the regression results. The role of neuroticism in predicting STID was found negatively significant. However, its role in predicting the LTID was found positive and significant. On the other hand, the regression results displayed a significant positive impact of conscientiousness on LTID. These results were found consistent with the results of Dickason Koekemoer *et al.* (2020) and Husnain (2019), who advocated that neuroticism and conscientiousness predict the investment decisions of investors. However, this study contradicts the findings of Sadiq and Azad (2019), who in their research found an insignificant impact of neuroticism on long-term investment decisions.

In addition, while evaluating the influence of risk perception on investment decisions, we found a positive and strong influence of risk perception on STID and a negative significant impact on LTID. These findings imply that investors belonging to North India perceive STID as riskier than LTID. As STID provide immediate returns (Ignashkina *et al.*, 2022) to the investors but the chance of loss is also very high. So, investors perceive high risk in taking STID than LTID. These results are in line with the results of existing studies of Mayfield *et al.* (2008) and Mankuroane *et al.* (2022). However, the findings of this study contradict the findings of Sadiq and Azad (2019), who in their study found a negative significant impact of risk behavior on both short-term and long-term investment decisions.

In this study, we further tested the impact of perceived COVID-19 disruption on investment behavior. The results revealed the positive and significant impact of perceived COVID-19 disruption on the STID of individual investors. Additionally, no significant influence of perceived COVID-19 disruption was found on the investment decisions made for a longer period. These findings imply that because of the COVID-19 pandemic, investors prefer STID more than LTID. They might feel high risk and insecurity in making LTID during the pandemic as it engulfs the whole world and affects their financial position severely. Therefore, investors might feel fear of investing in long-term securities.

5.1 Conclusion

This study tested the influencing role of two personality traits (neuroticism, conscientiousness), risk perception of investors and perceived COVID-19 disruption in predicting the investment behavior of investors. It was found that all these input variables have a significant role in predicting investment behavior. This study used a two-staged research approach to examine and validate the intended research model (Trigkas and Liapis, 2020). The proposed research model was evaluated and the research hypotheses were tested using regression analysis and then these results were validated by NN models. The findings of this study contradict the results of many existing studies (Shukla *et al.*, 2020; Kumar and Goyal, 2015; Zahera and Bansal, 2018) which gave more weight to behavioral biases in predicting the investment behavior and unexplored the role of many other psychological factors like personality and risk behavior. This study explored the predicting role of these factors and suggests that decision-makers must give these factors equal weight.

5.2 Theoretical implications

The current research has many significant theoretical research implications. This work has significantly contributed to the existing literature on behavioral finance in emerging nations particularly India, a rapidly growing economy. Many research models are exploring the

determinants of the investment behavior of investors. However, the research model debated in this study is still broad, it explores the impact of personality traits, risk perception and perceived COVID-19 disruption on investment decisions. The current study has used an innovative research methodology that combines regression and a neural network approach. To examine the effect of exogenous factors on endogenous factors, regression analysis was executed. The neural network technique, on the other hand aided in confirming the regression results and ranking input neurons based on their predictive strength.

5.3 Practical implications

This study will assist investors to realize that they do not always take rational financial decisions. It will also help them to understand that their risk perception has an important role in their financial decision-making, personality traits and even by the perceived COVID-19 disruptions, which they should consider before engaging in the investment decision-making process. This study firmly suggests that financial advisors should use the knowledge of behavioral finance in making their advisory and wealth management decisions. Financial advisors ought to understand the personality traits of their clients and their way of perceiving the risk they are prone to. The advisory association may become stronger by understanding clients' psychology as it helps to determine the expected outcomes and gives a lot of insights into the investment behavior of retail investors. This study also aids the policymakers like the government to create awareness among investors and to frame policies keeping in view the psychological approach together with the financial literacy for making investment decisions and avoiding an inappropriate level of risk perception. Policymakers must outline behaviorally well-informed policy decisions to protect the interests of investors.

5.4 Limitations

Any research is a process and therefore, can never be complete. The current study too has some limitations. First, the current research was undertaken in India and the sample was drawn from the country's northern region. Future studies should take a large sample from the entire country. Secondly, this study was bounded to the investors of a single country; a cross-country analysis can be preferred to draw a more valid conclusion regarding the investment behavior of investors and make comparisons between the results from different countries. Thirdly, it will be interesting to use mediators and moderators as these factors may be checked for their indirect effect also. Finally, it would be fascinating to see future research studies comparing the outcomes of the intended model in this study from diverse gender and age groups.

References

- Akhtar, F., Thyagaraj, K.S. and Das, N. (2017), "The impact of social influence on the relationship between personality traits and perceived investment performance of individual investors: evidence from Indian stock market", *International Journal of Managerial Finance*, Vol. 14 No. 1, pp. 130-148.
- Aslam, F., Mohmand, Y.T., Ferreira, P., Memon, B.A., Khan, M. and Khan, M. (2020), "Network analysis of global stock markets at the beginning of the coronavirus disease (Covid-19) outbreak", *Borsa Istanbul Review*, Vol. 20, pp. S49-S61.
- Baghani, M. and Sedaghat, P. (2016), "Effect of risk perception and risk tolerance on investors' decision making in tehran stock exchange", *International Academic Journal of Accounting and Financial Management*, Vol. 3 No. 9, pp. 45-53.
- Bansal, T. (2020), "Behavioral finance and COVID-19: cognitive errors that determine the financial future", *SSRN*, Vol. 3595749, doi: [10.2139/ssrn.3595749](https://doi.org/10.2139/ssrn.3595749).

-
- Becker, A., Deckers, T., Dohmen, T., Falk, A. and Kosse, F. (2012), "The relationship between economic preferences and psychological personality measures", *Annual Review of Economics*, Vol. 4 No. 1, pp. 453-478.
- Blais, A.R. and Weber, E.U. (2006), "A domain-specific risk-taking (DOSPERT) scale for adult populations", *Judgment and Decision making*, Vol. 1 No. 1, pp. 33-47, doi: [10.1017/S1930297500000334](https://doi.org/10.1017/S1930297500000334).
- Bogg, T. and Milad, E. (2020), "Slowing the spread of COVID-19: demographic, personality, and social cognition predictors of guideline adherence in a representative US sample", *PsyArXiv*, Vol. 10, pp. 1-26.
- Byun, S.E. and Sternquist, B. (2011), "Fast fashion and in-store hoarding: the drivers, moderator, and consequences", *Clothing and Textiles Research Journal*, Vol. 29 No. 3, pp. 187-201.
- Chong, A.Y.L. (2013), "Predicting m-commerce adoption determinants: a neural network approach", *Expert Systems with Applications*, Vol. 40 No. 2, pp. 523-530.
- Clemes, M.D., Gan, C., Kao, T.H. and Choong, M. (2008), "An empirical analysis of customer satisfaction in international air travel", *Innovative Marketing*, Vol. 4 No. 2, pp. 49-62.
- Costa, P.T Jr. and MacCare, R.R. (1992), *Revised NEO Personality Inventory and NEO Five-Factor Inventory Professional Manual*, Psychological Assessment Resources, FL.
- Dickason Koekemoer, Z., Makhubu, S. and Ferreira, S.J. (2020), "Personality traits and investment decisions in South Africa", *Gender and Behaviour*, Vol. 18 No. 2, pp. 15364-15371.
- Durand, R.B., Newby, R. and Sanghani, J. (2008), "An intimate portrait of the individual investor", *The Journal of Behavioral Finance*, Vol. 9 No. 4, pp. 193-208.
- Durand, R., Newby, R., Tant, K. and Trepongkaruna, S. (2013), "Overconfidence, overreaction and personality", *Review of Behavioral Finance*, Vol. 5 No. 2, pp. 104-133.
- Fornell, C. and Larcker, D.F. (1981), "Evaluating structural equation models with unobservable variables and measurement error", *Journal of Marketing Research*, Vol. 18 No. 1, pp. 39-50.
- Fung, L. and Durand, R.B. (2014), "Personality traits", *The Psychology of Financial Planning and Investing*, pp. 99-115.
- Gitman, L.J. and Joehnk, M.D. (2008), *Fundamentals of Investing*, 10th ed., Pearson Education, Boston.
- Gunkel, M., Schlaegel, C., Langella, I.M. and Peluchette, J.V. (2010), "Personality and career decisiveness: an international empirical comparison of business students' career planning", *Personnel Review*, Vol. 39 No. 4, pp. 503-524.
- Hair, J.F., Black, W.C., Babin, B.J. and Anderson, R.E. (2010), *Multivariate Data Analysis*, 7th ed., Prentice Hall, Upper Saddle River, NJ.
- Hair Jr, J.F., Matthews, L.M., Matthews, R.L. and Sarstedt, M. (2017), "PLS-SEM or CB-SEM: updated guidelines on which method to use", *International Journal of Multivariate Data Analysis*, Vol. 1 No. 2, pp. 107-123, doi: [10.1504/IJMDA.2017.087624](https://doi.org/10.1504/IJMDA.2017.087624).
- Hamza, N. and Arif, I. (2019), "Impact of financial literacy on investment decisions: the mediating effect of big-five personality traits model", *Market Forces*, Vol. 14 No. 1, pp. 43-60.
- Hogarth, R.M. and Einhorn, H.J. (1992), "Order effects in belief updating: the belief-adjustment model", *Cognitive Psychology*, Vol. 24 No. 1, pp. 1-55.
- Husnain, B. (2019), "Effect of neuroticism, conscientiousness on investment decisions. Mediation analysis of financial self-efficacy", *City University Research Journal*, Vol. 9 No. 1, pp. 15-26.
- Idrissi, T.E., Idri, A. and Bakkoury, Z. (2019), "Systematic map and review of predictive techniques in diabetes self-management", *International Journal of Information Management*, Vol. 46, pp. 263-277.
- Ignashkina, A., Rinne, K. and Suominen, M. (2022), "Short-term reversals, returns to liquidity provision and the costs of immediacy", *Journal of Banking and Finance*, Vol. 138, doi: [10.1016/j.bankfin.2022.106430](https://doi.org/10.1016/j.bankfin.2022.106430).

- Jaiyeoba, H.B. and Haron, R. (2016), "A qualitative inquiry into the investment decision behaviour of the Malaysian stock market investors", *Qualitative Research in Financial Markets*, Vol. 8 No. 3, pp. 246-267.
- Jiang, Z., Peng, C. and Yan, H. (2021), "Personality differences and investment decision-making", doi: [10.2139/ssrn.3580364](https://doi.org/10.2139/ssrn.3580364).
- Jordan, S.L., Palmer, J.C., Daniels, S.R., Hochwarter, W.A., Perrewé, P.L. and Ferris, G.R. (2022), "Subjectivity in fairness perceptions: how heuristics and self-efficacy shape the fairness expectations and perceptions of organisational newcomers", *Applied Psychology*, Vol. 71 No. 1, pp. 103-128.
- Kahneman, D. and Lovallo, D. (1993), "Timid choices and bold forecasts: a cognitive perspective on risk taking", *Management Science*, Vol. 39 No. 1, pp. 17-31.
- Kaiser, H.F. (1974), "An index of factorial simplicity", *Psychometrika*, Vol. 39 No. 1, pp. 31-36.
- Kasoga, P.S. and Tegambwage, A.G. (2022), "Psychological traits and investment decisions: the mediation mechanism of financial management, behavior-evidence from the Tanzanian stock market", *Journal of Money and Business*, Vol. 2 No. 2, pp. 213-227.
- Kengatharan, L. and Kengatharan, N. (2014), "The influence of behavioral factors in making investment decisions and performance: study on investors of Colombo Stock Exchange, Sri Lanka", *Asian Journal of Finance and Accounting*, Vol. 6 No. 1, p. 1.
- Khan, N. and Abid Usman, M.F.J. (2021), "The impact of investor's personality traits over their investment decisions with the mediating role of financial self efficacy and emotional biases and the moderating role of need for cognition and the individual mood in Pakistan stock exchange", *Multicultural Education*, Vol. 7 No. 8, pp. 766-775.
- Kohút, M., Kohútová, V. and Halama, P. (2021), "Big Five predictors of pandemic-related behavior and emotions in the first and second COVID-19 pandemic wave in Slovakia", *Personality and Individual Differences*, Vol. 180, 110934.
- Kourtidis, D., Šević, Ž. and Chatzoglou, P. (2011), "Investors' trading activity: a behavioural perspective and empirical results", *The Journal of Socio-Economics*, Vol. 40 No. 5, pp. 548-557.
- Kumar, S. and Goyal, N. (2015), "Behavioural biases in investment decision making—a systematic literature review", *Qualitative Research in Financial Markets*, Vol. 7 No. 1, pp. 88-108.
- Lai, C.P. (2019), "Personality traits and stock investment of individuals", *Sustainability*, Vol. 11 No. 19, p. 5474.
- Liébana-Cabanillas, F., Marinković, V. and Kalinić, Z. (2017), "A SEM-neural network approach for predicting antecedents of m-commerce acceptance", *International Journal of Information Management*, Vol. 37 No. 2, pp. 14-24, doi: [10.1016/j.ijinfomgt.2016.10.008](https://doi.org/10.1016/j.ijinfomgt.2016.10.008).
- Ling, Y., Xu, S.B., Lin, Y.X., Tian, D., Zhu, Z.Q., Dai, F.H., Wu, F., Song, Z.G., Huang, W., Chen, J., Hu, B.J., Wang, S., Mao, E.Q., Zhu, L., Zhang, W.H. and Lu, H.Z. (2020), "Persistence and clearance of viral RNA in 2019 novel coronavirus disease rehabilitation patients", *Chinese Medical Journal*, Vol. 133 No. 09, pp. 1039-1043.
- MacCrimmon, K.R. and Wehrung, D.A. (1990), "Characteristics of risk taking executives", *Management Science*, Vol. 36 No. 4, pp. 422-435.
- Mankuroane, E., van Heerden, W., Ferreira-Schenk, S. and Dickason-Koekemoer, Z. (2022), "Psychological and behavioural drivers of short-term investment intentions", *International Journal of Economics and Financial Issues*, Vol. 12 No. 4, pp. 19-27.
- Mayfield, C., Perdue, G. and Wooten, K. (2008), "Investment management and personality type", *Financial Services Review*, Vol. 17 No. 3, pp. 219-236.
- McCrae, R.R. and Costa, P.T., Jr (1997), "Personality trait structure as a human universal", *American Psychologist*, Vol. 52 No. 5, p. 509.
- Mulyani, E., Fitra, H. and Honesty, F.F. (2021), "Investment decisions: the effect of risk perceptions and risk propensity for beginner investors in west sumatra", in *Seventh Padang International Conference on Economics Education, Economics, Business and Management, Accounting and Entrepreneurship (PICEEBA 2021)*, Atlantis Press, pp. 49-55.

-
- Nga, J.K. and Yien, L.K. (2013), "The influence of personality trait and demographics on financial decision making among Generation Y", *Young Consumers*, Emerald Group Publishing, Vol. 14, pp. 230-243.
- Niszczoła, P. (2014), "Cross-country differences in personality and the foreign bias in international equity portfolios", *The European Journal of Finance*, Vol. 20 No. 10, pp. 934-956.
- Noe, T.H. and Vulkan, N. (2017), "The role of personality in financial decisions and financial crises", *Preparing for the next financial crisis*. Cambridge University Press.
- Nofsinger, J.R. (2017), *The Psychology of Investing*, 6th ed., Routledge, New York.
- Oehler, A., Horn, M. and Wendt, S. (2017), "Brexit: Short-term stock price effects and the impact of firm-level internationalization", *Finance Research Letters*, Vol. 22, pp. 175-181, doi: [10.1016/j.frl.2016.12.024](https://doi.org/10.1016/j.frl.2016.12.024).
- Oehler, A. and Wedlich, F. (2018), "The relationship of extraversion and neuroticism with risk attitude, risk perception, and return expectations", *Journal of Neuroscience, Psychology, and Economics*, Vol. 11 No. 2, p. 63.
- Ooi, K.B. and Tan, G.W.H. (2016), "Mobile technology acceptance model: an investigation using mobile users to explore smartphone credit card", *Expert Systems with Applications*, Vol. 59, pp. 33-46.
- Pak, O. and Mahmood, M. (2015), "Impact of personality on risk tolerance and investment decisions: a study on potential investors of Kazakhstan", *International Journal of Commerce and Management*, Vol. 25 No. 4, pp. 370-384.
- Parveen, S., Satti, Z.W., Subhan, Q.A., Riaz, N., Baber, S.F. and Bashir, T. (2021), "Examining investors' sentiments, behavioral biases and investment decisions during COVID-19 in the emerging stock market: a case of Pakistan stock market", *Journal of Economic and Administrative Sciences*, Vol. ahead-of-print.
- Priyadharshini, S.U. (2020), "Influence of Big 5 personality traits on the investment decisions of retail investors-an empirical approach", *PalArch's Journal of Archaeology of Egypt/Egyptology*, Vol. 17 No. 9, pp. 9725-9736.
- Raheja, S. and Dhiman, B. (2018), "Does investor personality determine their risk tolerance?", *Journal of Engineering and Applied Sciences*, Vol. 5 No. 7, pp. 439-448.
- Riaz, L., Hunjra, A.I. and Azam, R.I. (2012), "Impact of psychological factors on investment decision making mediating by risk perception: a conceptual study", *Middle-East Journal of Scientific Research*, Vol. 12 No. 6, pp. 789-795.
- Rzeszutek, M., Szyszka, A. and Czerwonka, M. (2015), "Investors' expertise, personality traits and susceptibility to behavioral biases in the decision making process", *Contemporary Economics*, Vol. 9 No. 3, pp. 237-352.
- Sadi, R., Asl, H.G., Rostami, M.R., Gholipour, A. and Gholipour, F. (2011), "Behavioral finance: the explanation of investors' personality and perceptual biases effects on financial decisions", *International Journal of Economics and Finance*, Vol. 3 No. 5, pp. 234-241.
- Sadiq, M. and Azad, R. (2019), "Impact of personality traits on investment intention: the mediating role of risk behaviour and the moderating role of financial literacy", *Journal of Finance and Economics Research*, Vol. 4, pp. 1-18, doi: [10.20547/jfer1904101](https://doi.org/10.20547/jfer1904101).
- Sharma, S.K., Sharma, H. and Dwivedi, Y.K. (2019a), "A hybrid SEM-neural network model for predicting determinants of mobile payment services", *Information Systems Management*, Vol. 36 No. 3, pp. 243-261.
- Sharma, S., Oli, N. and Thapa, B. (2019b), "Electronic health-literacy skills among nursing students", *Advances in Medical Education and Practice*, Vol. 10, p. 527.
- Sharma, L.K., Vishal, V. and Singh, T.N. (2017), "Developing novel models using neural networks and fuzzy systems for the prediction of strength of rocks from key geomechanical properties", *Measurement*, Vol. 102, pp. 158-169, doi: [10.1016/j.measurement.2017.01.043](https://doi.org/10.1016/j.measurement.2017.01.043).

- Shukla, A., Rushdi, D., Jamal, N., Katiyar, D. and Chandra, R. (2020), "Impact of behavioral biases on investment decisions: a systematic review", *International Journal of Management*, Vol. 11 No. 4, pp. 68-76.
- Steul, M. (2006), "Does the framing of investment portfolios influence risk-taking behavior? Some experimental results", *Journal of Economic Psychology*, Vol. 27 No. 4, pp. 557-570.
- Trigkas, S.J. and Liapis, K.J. (2020), "Assessing artificial neural networks (ANNS) adequacy against econometric models for decision making approaches in banking industry", *Business Performance and Financial Institutions in Europe: Business Models and Value Creation Across European Industries*, pp. 105-116.
- Ullah, S. (2022), "Impact of covid-19 pandemic on financial markets: a global perspective", *Journal of the Knowledge Economy*, pp. 1-22, doi: [10.1007/s13132-022-00970-7](https://doi.org/10.1007/s13132-022-00970-7).
- Virlics, A. (2013), "Investment decision making and risk", *Procedia Economics and Finance*, Vol. 6, pp. 169-177.
- Waheed, H., Ahmed, Z., Saleem, Q., Din, S.M.U. and Ahmed, B. (2020), "The mediating role of risk perception in the relationship between financial literacy and investment decision", *International Journal of Innovation, Creativity and Change*, Vol. 14 No. 4, pp. 112-131.
- Yadav, A. and Narayanan, G.B. (2021), "Do personality traits predict biasedness while making investment decisions?", *International Journal of Accounting and Finance Review*, Vol. 6 No. 1, pp. 19-33.
- Yadav, N., Yadav, A. and Kim, J.H. (2016), "Numerical solution of unsteady advection dispersion equation arising in contaminant transport through porous media using neural networks", *Computers and Mathematics with Applications*, Vol. 72 No. 4, pp. 1021-1030, doi: [10.1016/j.camwa.2016.06.014](https://doi.org/10.1016/j.camwa.2016.06.014).
- Young, S., Gudjonsson, G.H., Carter, P., Terry, R. and Morris, R. (2012), "Simulation of risk-taking and its relationship with personality", *Personality and Individual Differences*, Vol. 53 No. 3, pp. 294-299, doi: [10.1016/j.paid.2012.03.014](https://doi.org/10.1016/j.paid.2012.03.014).
- Zahera, S.A. and Bansal, R. (2018), "Do investors exhibit behavioral biases in investment decision making? A systematic review", *Qualitative Research in Financial Markets*, Vol. 10 No. 2, pp. 210-251.
- Zajenkowski, M., Jonason, P.K., Leniarska, M. and Kozakiewicz, Z. (2020), "Who complies with the restrictions to reduce the spread of COVID-19?: personality and perceptions of the COVID-19 situation", *Personality and Individual Differences*, Vol. 166, 110199.
- Zeb, A., ur Rehman, F., Imran, M., Ali, M. and Almansoori, R.G. (2020), "Authentic leadership traits, high-performance human resource practices and job performance in Pakistan", *International Journal of Public Leadership*, Vol. 16 No. 3, pp. 299-317.
- Zsido, A.N., Teleki, S.A., Csokasi, K., Rozsa, S. and Bandi, S.A. (2020), "Development of the short version of the spielberger state—trait anxiety inventory", *Psychiatry Research*, Vol. 291, 113223.

Further reading

- Anna, I., Rinne, K. and Suominen, M. (2022), "Short-term reversals, returns to liquidity provision and costs of immediacy", *Journal of Banking and Finance*, Vol. 138, doi: [10.1016/j.jbankfin.2022.106430](https://doi.org/10.1016/j.jbankfin.2022.106430).
- Dwivedi, Y.K., Kapoor, K.K., Williams, M.D. and Williams, J. (2013), "RFID systems in libraries: an empirical examination of factors affecting system use and user satisfaction", *International Journal of Information Management*, Vol. 33 No. 2, pp. 367-377.
- Hussain, B., Sato, H., Miwa, T. and Morikawa, T. (2020), "Influence of personality traits on aberrant driving behaviors: a comparison of Japanese, Chinese, and Vietnamese drivers", *Journal of Safety Research*, Vol. 75, pp. 178-188.

Varshney, V., Varshney, A., Ahmad, T. and Khan, A.M. (2017), "Recognising personality traits using social media", in *2017 IEEE International Conference on Power, Control, Signals and Instrumentation Engineering (ICPSI)*, IEEE, pp. 2876-2881.

Yadav, R.K. (2020), "PSO-GA based hybrid with Adam Optimization for ANN training with application in Medical Diagnosis", *Cognitive Systems Research*, Vol. 64, pp. 191-199.

Corresponding author

Arfat Manzoor can be contacted at: shaducum59@gmail.com