Journal of Informatics Education and Research
ISSN: 1526-4726
Vol 5 Issue 2 (2025)

Deciphering Behavioural factors influencing the decision making of investors:
A TISM- MICMAC approach

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Abstract Purpose

This study aims to investigate recent advancements in behavioural finance, specifically focusing on the presence of behavioural biases that influence investors' decision-making processes. Additionally, it assesses the feasibility of behavioural finance as a widely recognized evolution beyond traditional finance. By investigating the cognitive and emotional biases that influence individual investors during the process of making investment decisions and their portfolio choices, this study intends to highlight the substantial effect these biases have on investment outcomes. Through a detailed examination of biases, the research seeks to provide a deeper understanding of how these factors contribute to suboptimal decisions, ultimately affecting market efficiency and financial stability.

Design/methodology/approach

To explore the logical interconnections between various factors and to identify behavioural biases that influence investment decision-making among investors, we applied the Total Interpretive Structural Modeling (TISM) and MICMAC (Matrice d'Impacts Croisés Multiplication Appliquée à un Classement) methodologies. Furthermore, the study explores the cross-interconnection of these biases and the hierarchical levels of various enablers that contribute to portfolio performance. Using a structured analytical approach, the research uncovers how certain biases and enablers interact, either amplifying or mitigating the impact on investment decisions. By identifying eleven key behavioural factors that profoundly affect individual investors' decision-making procedures and the profitability of their portfolios, this study pushes the theoretical, methodological, and practical limits of previous research.

Findings

This study identifies and analyses the key variables that can have a major influence on how individual investors make decisions, focusing on the role of behavioural biases. Both cognitive and emotional biases are found to be major obstacles to effective investment decisions, often leading to misinformed financial choices. Through critical path analysis, the study establishes a sequential connection between cognitive biases (F4), financial expertise (F3), risk tolerance (F1), individual investors (F10), and portfolio performance (F2). The findings provide valuable insights into the complex dynamics of investor behaviour, offering guidance for investors, financial advisors, and policymakers on improving portfolio management and decision-making strategies.

Originality/value

This research provides a fresh insight into the topic of behavioural finance by focusing on low-income investors in emerging economies. Unlike previous studies that primarily address investors in developed markets, this research highlights the unique behavioural biases and market anomalies specific to a developing economy. Furthermore, the research underscores the importance of consulting specialists among self-directed investors, adding a new dimension to the understanding of advisory roles in emerging markets.

Keywords
Behavioural finance, Behavioural bias, Individual investor, Investment, Portfolio performance

Introduction

In the past, substantial research has been carried out by proponents of conventional finance, particularly around concepts like economic utility theory, which posits that investors act rationally and understand how to maximize returns. According to conventional finance, rationality is a key assumption for investors (Baker & Filbeck, 2013). Over the past few decades, financial researchers have conducted a plethora of research emphasizing the necessity of having a foundation in the financial markets based on investor rationality. Traditional finance rests on four foundational pillars: the Arbitrage Pricing Theory (Modigliani & Millar), the Capital Asset Pricing Model (Sharpe, Linter, and Black), the Option Pricing Theory (Black, Scholes, and Merton), and the Markowitz Principle of Portfolio Management (Badola et al., 2024; Kumar & Goyal, 2015). Adherents of conventional finance also uphold the Efficient Market Hypothesis (EMH), which asserts that capital markets operate efficiently, allowing investors to make optimal investment decisions under the assumption of information symmetry. However, researchers in the past have found discrepancies between theoretical investor behaviour and actual practices (Raut, 2020).

Conventional finance assumes that investors behave rationally, but in reality, they often rely on rules of thumb rather than reason. It has been observed that established financial models do not fully account for or predict all financial outcomes (Aggarwal, 2022), and they neglect to clarify certain factors that influence an investor's stock selection. Emotional factors often drive investment decisions, leading to irrational market behaviour and inefficiencies (Zahera & Bansal, 2018). This demonstrates the significance of behavioural finance, which recognizes that investors are not always logical.; rather, they are human beings prone to irrational decision-making (Mushinada, 2020). Numerous empirical studies in financial markets have demonstrated that investment decisions are not solely based on traditional finance theories but are also influenced by behavioural factors like risk appetite, cognitive errors, and emotional sensitivity (Joshi et al., 2022; Jokar & Daneshi, 2018; Waweru et al., 2008).

Research in behavioural finance has identified various behaviours that deviate from rationality, typically categorized into emotional biases, cognitive biases, and the theory of bounded rationality (Ahmad et al., 2017). "Bounded rationality" refers to decision-making based on incomplete information, influenced by factors such as heuristics and procrastination (Munro, 2009). Such irrational decision- making often stems from a lack of reliable and comprehensive information. Conventional finance has mainly disregarded how human behaviour affects investment choices (Weixiang et al., 2022), and these anomalies in traditional finance have paved the way for the development of behavioural finance.

In recent decades, conventional finance has increasingly been supplemented by behavioural finance. The 1970s marked the beginning of empirical research that laid the foundation for behavioural finance (Truc, 2022). This field of study focuses on the impact of psychology, emotions, and cognitive errors on how investors make financial decisions. Behavioural finance seeks to understand how these factors influence the behaviour of individual investors, whose investment decisions, in turn, impact the broader market and economy. Despite being well-informed and conducting thorough research, investors may still act irrationally due to the persistent fear of future losses. The study of behavioural finance enhances decision-making processes (Mittal et al., 2022), and the literature suggests that specific behavioural biases significantly influence investors' decisions.

Academicians such as Woo et al. (2020) and Metawa et al. (2019) have also noted that traditional financial models, frequently fall short of effectively capturing the swings in financial markets and

instead concentrate on time series analysis of prices, dividends, and earnings. Similarly, Strömbäck et al. (2017) emphasized the significant role that psychological factors play in the decision-making processes of individual investors.
Thus, following research questions are addressed in the study:

a. To examine the behavioural biases of individuals while making an investment decision and their portfolio decisions.
b. Cross-interconnection and levels of enablers contribute to the portfolio performance of individual investors.

The remainder of the document is structured as follows: Section 2 covers the literature review; Section 3 discusses the research methods; Section 4 presents the analysis and results; Section 5 discusses the study's implications and discussion; and Section 6 offers conclusion and scope for further research.

Literature Review:

An alternate method for modelling asset prices is provided by behavioural finance (Ángeles et al., 2020). In contrast to conventional finance, this method assumes that markets are inefficient and that strategies based on past data can provide profits (Krishnan & Periasamy, 2022). According to the asset pricing methodology based on behavioural finance, in a complex and uncertain environment, investors' decisions are influenced by emotional and intuitive factors, choice bracketing, cognitive shortcuts, and decision heuristics (Beshears et al., 2018; Barberis, 2018; Stracca, 2004). Behavioural finance provides a more cohesive explanation for the investment returns and their unpredictability in the stock markets by integrating investor behaviour into the models. It has proven successful in predicting sudden market

shocks. This field has the potential to more accurately forecast asset price volatility and could gain further popularity as an accepted concept for future research on asset pricing. In the current literature review section, we explore and deliberate the recent literature on asset pricing research through the lens of behavioural finance. The discussion is bifurcated as:

a. Investor Decision-Making and Behavioural Biases
b. Selection of investment and behavioural factors affecting investment behaviour

2.1 Investor Decision-Making and Behavioural Biases

Investor behaviour significantly influences decision-making in the stock market, often leading to irrational choices (Padmavathy, 2024). Addressing these behavioural influences is crucial, as traditional finance has struggled to explain market anomalies, inefficiencies, and irrational behaviour (Joshi et al., 2022). To tackle this irrationality, behavioural psychologists and finance theorists have conducted extensive studies and research (King & Kay, 2020). By integrating traditional economics and finance with behavioural and cognitive-emotional aspects, behavioural finance rationalizes the financial inefficiencies of financial markets arising due to investor's irrational behaviour (Sharma et al., 2021).
Daniel Kahneman and Amos Tversky, pioneers in behavioural finance (Vaid & Chaudhary, 2022), laid the foundation of behavioural finance in the 1960s through extensive research. Kahneman & Tversky, 2013) demonstrated that individuals do not typically use statistical methods in decision-making; instead, they depend on a limited set of heuristics (Szollosi & Newell, 2020). Their findings revealed that potential losses have a greater impact on individuals than comparable gains and that people assign different weights to gains, losses, and probabilities (Zhao et al., 2021).
The influence of behavioural elements such as heuristics, cognitive dissonance, greed, and fear, on investing outcomes has been noted by researchers in the past (Shah et al., 2018). Aigbovo &

Ilaboya (2019) demonstrated that behavioural biases like herding, overconfidence, and reinforcement bias have a more pronounced effect on individual investors than on institutional ones. Parveen et al. (2019) further explained how behavioural finance accounts for irrational financial decisions, showing that biases like anchoring, overconfidence, herd behaviour, overreaction, underreaction, and loss aversion contribute to such irrationality.

Various financial characteristics and biases—including loss aversion, hindsight bias, anchoring, endowment effect, disposition effect, and mental accounting—hinder individuals from making sound financial decisions (Sharma & Kumar, 2022). Moreover, Sabir et al. (2004) noted that the herding effect leads investors to follow the crowd, while Kartin & NAHDA (2021) observed that investors often display excessive confidence in their past gains and investment skills, causing them to overestimate their knowledge and underestimate risks.

Selection of Factors

The study initially considered sixteen variables. After consulting with experts, eleven variables were selected from the existing literature, ensuring that each one had a unique significance and impact on investor decision-making. The method of purposive sampling was applied to select fifteen experts, each with a minimum of five years of experience in equity market trading. The experts discussed these factors using a Likert scale (where 5 represents the most significant and 1 is the least important). Only those factors that received an average importance score of three or higher from multiple experts were included in this study (Table 1).

Table 01: Key factors selected for the study:

Sl.No.	Factors	Variable name		References
1	F1	Risk tolerance	The degree of uncertainty a person is ready to take on when making a financial choice.	Murhadi et al., 2023; Rai et al., 2021; Bayar et al., 2020
2	F2	Portfolio performance	Portfolio performance is the term used for describing the outcomes of an investor's investments. It generally involves evaluating a portfolio's yield to that of a benchmark portfolio.	Bacon (2023); Cunha et al., 2021; Zhang et al., 2020
3	F3	Financial Expertise	The knowledge of investing effectively. Financially literate investors are more likely to indulge in irrational behaviour as compared to others.	Ahmad (2024), Weixiang (2022); Tran (2020)
4	F4	Cognitive biases	Cognitive (behavioural) psychology studies cognition, i.e. mental processes that regulate human behaviour.	Ishfaq et al. 2020; Ahmad (2020); Khan (2020); Novianggie & Asandimitra (2019)

5	F5	Emotional biases	A mental state occurs due to intuitive decisions rather than reasonable judgment.	Armansyah (2022); Akinkoye & Bankole (2020); Khilar & Singh (2020); Novianggie & Asandimitra (2019)
6	F6	Herding	It describes how people behave when they choose to follow a group or the crowd instead of forming their own opinions and decisions because they think the majority is always correct.	Mand et al., 2023; Choijil et al., 2022; Komalasar et al., 2022; Chang et al., 2020
7	F7	Heuristics	Mental short cuts, often known as rules of thumb, are utilized to quickly arrive at a workable answer.	Ahmad (2024); Goyal etal., 2023; Kasoga (2021); Khan et al., 2021
8	F8	Risk perceptions	Interpretation of risk which is different from estimates/thoughts/ reality. It is a factor in cognitive bias.	Maharani & Saputra (2021); Ahmad & Shah (2020); Pflueger et al., 2020
9	F9	Diversifications	Portfolio diversification helps in constructing alternative investment assets that would have the ability to endure financial losses.	Almeida & Gonçalves (2022); Letho et al., 2022; Koumou (2020); Gulshirin & Abdulazizovich (2022)
10	F10	Individual investor	An individual who invests after evaluating his/her past trading experiences and trying to achieve a higher risk-reward ratio.	Weixiang et al., 2022; Din et al., 2021; Choi & Robertson (2020);
11	F11	Investment objectives	The goal of any investor or asset manager is to maximize the investment return generating a cash flow stream.	Cunha (2021); Hani (2020); Rahman (2020)

3. Methodology:

3.1. Details of the respondents:

The survey was conducted online from August 2023 to December 2023. The questionnaire was distributed to 45 individuals who have been actively involved in stock investment and trading for the past five years. By the end of December 2023, all 45 responses had been received, but only 30 were deemed suitable for analysis, as 15 were discarded due to random responses and incomplete data.

3.2 Total Interpretive Structural Modeling and MICMAC (TISM-MICMAC) Analysis

To explore the logical interconnections between various factors and to identify behavioral biases that influence investment decision-making among investors, we applied the Total Interpretive Structural Modeling (TISM) and MICMAC (Matrice d'Impacts Croisés Multiplication Appliquée à un Classement) methodologies.

The Interpretive Structural Modeling (ISM) technique, introduced by Warfield in 1973, enables the creation of complex system diagrams using a set of variables. Researchers have incorporated this concept and its analytical framework in their studies. TISM, an extension of ISM developed by Sushil in 2012, further identifies the logic of interdependence among variables.
The TISM hierarchy is particularly useful for managers and strategic decision-makers, providing guidance in addressing complex organizational challenges (Singh and Sushil, 2013). In another study, Bag (2016) highlighted that TISM is valuable when multiple components are required to solve a complex problem. MICMAC analysis, on the other hand, was developed to categorize components based on their interactions with one another. Gandhi (2015) integrated TISM with MICMAC to examine factors with high driving power that demand careful consideration in the context of an organization's ERP application systems.

4. **Result and findings**:

Table 02 provides the contextual link between each pair of components, which was constructed based on expert responses. The majority technique with 50% of the responses has been employed to determine the contextual correlations between the components (Mondal and Chakrabarti, 2021).

Table 02: SSIM (Structural Self-Interaction Matrix):

.	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11
F1		V	A	O	A	A	A	X	X	O	V
F2			A	A	A	A	A	O	A	A	A
F3				O	A	X	X	V	V	O	V
F4					X	V	O	V	V	O	V
F5						V	O	V	V	V	V
F6							X	V	V	O	V
F7								V	V	V	O
F8									X	V	V
F9										V	V

F10											**X**
F11											

To create an initial reachability matrix, SSIM is modified (Table 03) by replacing 0 or 1 with the transformation criteria.

Table 03: IRM (Initial Reachability Matrix)

	F1	**F2**	**F3**	**F4**	**F5**	**F6**	**F7**	**F8**	**F9**	**F10**	**F11**
F1	**1**	**1**	**0**	**0**	**0**	**0**	**0**	**1**	**1**	**0**	**1**
F2	**0**	**1**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
F3	**1**	**1**	**1**	**0**	**0**	**1**	**1**	**1**	**1**	**0**	**1**
F4	**0**	**1**	**0**	**1**	**1**	**1**	**0**	**1**	**1**	**0**	**1**
F5	**1**	**1**	**1**	**1**	**1**	**1**	**0**	**1**	**1**	**1**	**1**
F6	**1**	**1**	**1**	**0**	**0**	**1**	**1**	**1**	**1**	**0**	**1**
F7	**1**	**1**	**1**	**0**	**0**	**1**	**1**	**1**	**1**	**1**	**0**
F8	**1**	**0**	**0**	**0**	**0**	**0**	**0**	**1**	**1**	**1**	**1**
F9	**1**	**1**	**0**	**0**	**0**	**0**	**0**	**1**	**1**	**1**	**1**
F10	**0**	**1**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**1**	**1**
F11	**0**	**1**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**1**	**1**

The connection is updated for each new transitivity when the transitivity rule is tested in the direct reachability matrix. If the transitivity connection is significant, it is indicated as 1* in Table 4.

Table 4: FRM (Final Reachability Matrix)

	F1	**F2**	**F3**	**F4**	**F5**	**F6**	**F7**	**F8**	**F9**	**F10**	**F11**
F1	**1**	**1**	**0**	**0**	**0**	**0**	**0**	**1**	**1**	**1***	**1**
F2	**0**	**1**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
F3	**1**	**1**	**1**	**0**	**0**	**1**	**1**	**1**	**1**	**1***	**1**

F4	1*	1	1*	1	1	1	1*	1	1	1*	1
F5	1	1	1	1	1	1	1*	1	1	1	1
F6	1	1	1	0	0	1	1	1	1	1*	1
F7	1	1	1	0	0	1	1	1	1	1	1*
F8	1	1*	0	0	0	0	0	1	1	1	1
F9	1	1	0	0	0	0	0	1	1	1	1
F10	0	1	0	0	0	0	0	0	0	1	1
F11	0	1	0	0	0	0	0	0	0	1	1

The process of level partitioning is used to understand the location of factors at each level (Kumar et al., 2019). The antecedent set and reachability set are determined using the FRM to find level partitions (Table 5). After each portioned level is determined, a conical matrix (Table 6) is created.

Table 05: Level partitions

Factors	Reachability Set	Antecedent set	Intersection	Level
F2	2	1,2,3,4,5,6,7,8,9,10,11	2	First Level
F10	10,11	1,3,4,5,6,7,8,9,10,11	10,11	Second Level
F11	10,11	1,3,4,5,6,7,8,9,10,11	10,11	Second Level
F1	1,8,9	1,3,4,5,6,7,8,9	1,8,9	Third Level
F8	1,8,9	1,3,4,5,6,7,8,9	1,8,9	Third Level
F9	1,8,9	1,3,4,5,6,7,8,9	1,8,9	Third Level
F3	3,6,7	3,4,5,6,7	3,6,7	Fourth Level

F6	**3,6,7**	**3,4,5,6,7**	**3,6,7**	**Fourth Level**
F7	**3,6,7**	**3,4,5,6,7**	**3,6,7**	**Fourth Level**
F4	**4,5**	**4,5**	**4,5**	**Fifth Level**
F5	**4,5**	**4,5**	**4,5**	**Fifth Level**

Table 06: Canonical matrix

The conical matrix (Table 5), which assembles all elements into a single portioned level, is used to validate level partitions and assist in the development of the TISM digraph.

	F2	**F10**	**F11**	**F1**	**F8**	**F9**	**F3**	**F6**	**F7**	**F4**	**F5**
F2	**1**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
F10	**1**	**1**	**1**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
F11	**1**	**1**	**1**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
F8	**1***	**1**	**1**	**1**	**1**	**1**	**0**	**0**	**0**	**0**	**0**
F9	**1**	**1**	**1**	**1**	**1**	**1**	**0**	**0**	**0**	**0**	**0**
F1	**1**	**1***	**1**	**1**	**1**	**1**	**0**	**0**	**0**	**0**	**0**
F3	**1**	**1***	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**0**	**0**
F6	**1**	**1***	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**0**	**0**
F7	**1**	**1**	**1***	**1**	**1**	**1**	**1**	**1**	**1**	**0**	**0**
F4	**1**	**1***	**1**	**1***	**1**	**1**	**1***	**1**	**1***	**1**	**1**
F5	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1***	**1**	**1**

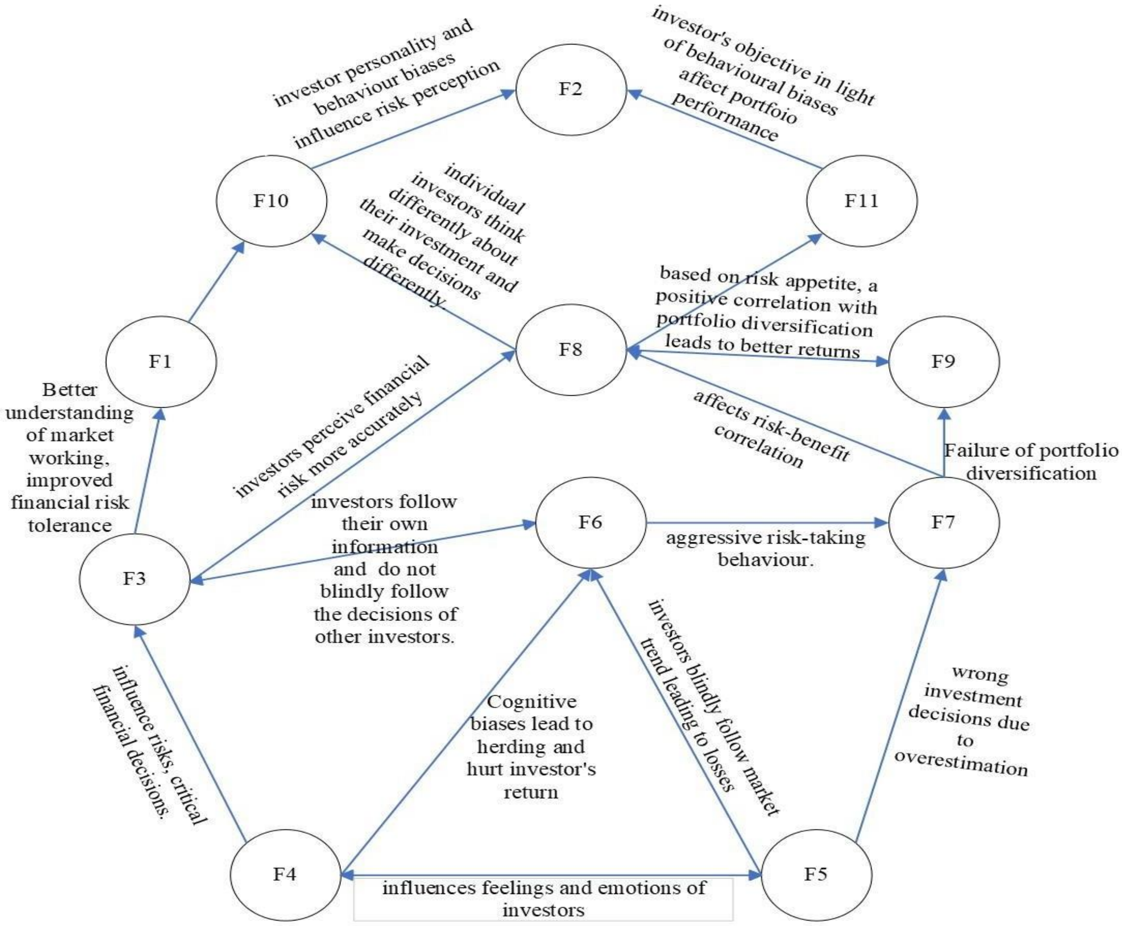

Figure 01: TISM digraph on investors' behavioral biases

Cross-Impact Relationship Among Factors:

There exists a close relationship between the cognitive dissonance theory and the impact of behavioural factors on stock investment decision-making. This theory posits that individuals view themselves as “smart, nice people,” and they have a tendency to dismiss or ignore data that contradicts this belief about themselves (March, 2006). Our analysis framework is thus based on cognitive dissonance, as described by psychologists, rather than the rational behaviour assumed in Bayesian decision theory. Remarkably, we observed that most investors base their investment decisions on their projections regarding future investments (Jones, 2014). The theoretical framework is outlined in Figure 1.

Although behavioural finance variables have been the subject of many studies, the majority of them have concentrated on developed markets (Odean, 1999; Caparrelli et al., 2004; Fogel and Berry, 2006), with emerging and frontier economies receiving very less attention (Sochi, 2018; Akhter and Ahmed, 2013). In their study, Akhter and Ahmed (2013) found several variables that influence investment decisions, including media influence, prior success, and recommendations from brokers, friends and family. Similarly, Sochi (2018) found significant evidence of biases like representativeness, overconfidence, anchoring, gambler’s fallacy, loss aversion, regret aversion, and mental accounting in investment decisions.

Overconfident investors often engage in excessive trading, overestimating their abilities, skills, and knowledge. Past successful decisions can create a false sense of confidence in future decisions, leading to over-hopefulness and underestimation of investment risks. Individual investors in the

stock market are also influenced by the information they receive when selecting and identifying stocks. Information availability can cause investor preferences to change, and the relationship between overconfidence and investment decision-making is heavily influenced by risk perception.
In financial markets, risk perception is evident when investors avoid stocks that have previously performed poorly, which reflects their dissatisfaction. Investors' risk perception indirectly influences their risk tolerance, which directly impacts investment decisions. Cognitive biases, arising from heuristics or mental shortcuts, often exacerbate these perceptions by emphasizing fears stemming from a lack of information or control. Improving financial knowledge by better understanding risk perception can lead to more informed investment decisions and potentially higher returns.
Emotional biases can also cause investors to make poor decisions, negatively affecting their returns. Such biases often result in irrational behaviours like buying high and selling low, contrary to successful investment strategies. Individuals with lower financial literacy in general make flawed judgments that yield lower returns, those with higher financial literacy are more likely to make wise investment decisions, such as effectively saving for retirement and planning for it.
Emotions—especially greed and fear—have a big influence on investing decisions. Fear can cause panic selling and a shift away from long-term investing techniques during market downturns. Emotion may outweigh logical reasons when making investment decisions, as demonstrated by the herd mentality bias that occurs when investors follow the behaviour of others rather than performing their own independent analysis.
Unrealistic investment objectives that disregard the risk-return trade-off are unlikely to yield favourable portfolio returns. A detailed analysis of investment objectives is crucial for achieving a fair balance between risk and return, thereby enhancing portfolio performance.
Cognitive bias, an unconscious and often uninformed bias, can significantly impact financial decision- making. Behavioural biases influence most investment decisions, leading to illogical conclusions and misinterpreting risks. Cognitive biases, shaped by personal values, memory, socialization, and other attributes, often result in short-term decisions that deviate from an investor's long-term financial goals.

Table 07: Driving-dependency Analysis:
The row total and column sum represent the driving force and dependency, respectively, in Table 6. Based on the total rows and columns, all the elements can be grouped into four categories and increased driving power factors are highly effective and intrinsically independent.

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	Driving Power
F1	1	1	0	0	0	0	0	1	1	1*	1	6
F2	0	1	0	0	0	0	0	0	0	0	0	1
F3	1	1	1	0	0	1	1	1	1	1*	1	9
F4	1*	1	1*	1	1	1	1*	1	1	1*	1	11
F5	1	1	1	1	1	1	1*	1	1	1	1	11

F6	1	1	1	0	0	1	1	1	1	1*	1	9
F7	1	1	1	0	0	1	1	1	1	1	1*	9
F8	1	1*	0	0	0	0	0	1	1	1	1	6
F9	1	1	0	0	0	0	0	1	1	1	1	6
F10	0	1	0	0	0	0	0	0	0	1	1	3
F11	0	1	0	0	0	0	0	0	0	1	1	3
Dependence	8	11	5	2	2	5	5	8	8	10	10	

Here, all of the variables (factors) are divided into four groups based on driving force and dependence: autonomous, dependence, linkage, and independence variables (Figure 2). Using the midpoint as the boundary, the graph is split into four equal quadrants (11 / 2 = 5.5 scale). The following four quadrants are shown in Table 7:

Figure 2: MICMAC Readings

Strong	11	IV	F4,F5									III
	10											
	9					F3,F6,F7						
	8											
	7											
	6								F1,F8,F9			
	5	I										II
	4											
	3										F10,F11	
	2											
	1		Weak						Strong			F2
Weak		1	2	3	4	5	6	7	8	9	10	11

Table 7: MICMAC clusters and associate factors

Cluster I	Autonomous Factors	Nil
Cluster II	Dependent factors	F2; F10; F11
Cluster III	Linkage factors	F1;F8; F9
Cluster IV	Independent Factors	F3;F4;F5;F6;F7

Autonomous Variables (Cluster I): These are interdependent variables with weak driving forces, indicating a minimal correlation with other factors. As shown in Figure 2, Cluster I contains no variables, highlighting the close interrelationship among variables in this analysis.
Dependence Variables (Cluster II): This cluster includes factors with high reliance but low driving force. Specifically, factors F2 (cognitive biases), F10 (individual investors), and F11 (portfolio performance) are positioned in this cluster. Figure 2 illustrates that these elements are situated at the higher levels of the model (Levels I and II) and are influenced by other variables.
Linkage Variables (Cluster III): Factors in this quadrant exhibit both strong dependence and driving power. These variables are critical as their influence extends to all other factors. As depicted in Figure 2, F1 (herding), F8 (investment objectives), and F9 (diversification) are categorized in this cluster, indicating their crucial role in the model.
Independent Variables (Cluster IV): This cluster features variables with high driving strength but low dependency. The five variables—F3 (emotional biases), F4 (heuristics), F5 (risk tolerance), F6 (risk perception), and F7 (financial expertise)—are positioned in Cluster IV. These variables, located at the bottom of the model, exert a strong influence on portfolio performance.

5. **Discussion and Conclusion**:

Behavioural biases represent systematic deviations from rational judgment and decision-making. Retail investors, who are individual participants in financial markets, are particularly susceptible to behavioural biases, which can significantly influence their investment decisions. Often, retail investors underestimate their own knowledge and forecasting abilities, leading them to trade excessively and assume higher risks. They frequently experience the grief of losses more strongly than the joy of winnings, which might lead them to hold onto losing investments in the hopes of recovering those losses. Furthermore, they might anchor all of their assessments on a single, insignificant piece of information.

Retail investors frequently focus on recent events or trends rather than long-term fundamentals when making decisions. The presentation of information can also impact their choices, leading them to react differently to the same data based on its framing. Investors might categorize their investments based on arbitrary criteria rather than considering their overall portfolio, and they may overestimate their control over outcomes, leading to speculative trading or market timing strategies that are unlikely to succeed. Addressing these biases can help retail investors make more informed decisions and avoid common financial pitfalls.

Investors might also ignore contradictory evidence that challenges their existing beliefs about an investment, resulting in less balanced decision-making. Emphasizing recent market trends can lead them to buy assets that have already appreciated significantly and sell those that have recently declined, often resulting in buying high and selling low. Using arbitrary criteria for categorizing investments can lead to inefficient asset allocation and suboptimal capital use.

Key variables that significantly impact retail investors' decision-making were identified. Behavioural biases, both cognitive and emotional, are major obstacles to effective investment decisions. Additionally, a lack of financial expertise often drives investors towards herd behaviour and reliance on heuristics, contributing to misinformed financial choices.

Critical path analysis identified a sequence: F4 (cognitive biases) → F3 (financial expertise) → F1 (risk tolerance) → F10 (individual investors) → F2 (portfolio performance). This analysis suggests that understanding and managing cognitive biases (F4) is essential at the grassroots level to improve investors' financial expertise (F3) and enhance their risk tolerance (F1). Once these factors are well-integrated, individual investors (F10) are more likely to achieve better portfolio performance (F2).

6. **Implications of the study**:

Theoretical Implications

The findings contribute to the existing body of knowledge in behavioural finance by identifying eleven distinct behavioural characteristics that significantly influence investment decisions. This expands the theoretical framework of behavioural finance, particularly in the context of developing markets, where previous research has been limited. The study emphasizes the need for a deeper understanding of how these biases create market inefficiencies and affect portfolio performance. By integrating these insights, researchers can further refine models that explain investor behaviour and market anomalies.

Social Implications

The study highlights how important it is for low-income investors to have access to professional advice and financial literacy. These investors tend to set significant emphasis on risk-sharing and savings, demonstrating a collective approach to money management that can strengthen the resilience of the community. Customized educational programs can be created to empower these people and help them make better financial decisions by identifying the behavioural biases that influence their decision- making. This will enhance their overall financial well-being.

Practical Implications

From a practical standpoint, the study's conclusions have important real-world implications for a range of stakeholders, including market regulators, investment businesses, wealth management firms, and hedge funds. These organizations can use the knowledge gathered from the study to create plans of action that deal with the biases found. Investment firms can design marketing campaigns that are aimed at individual investors and that relate to their personality traits. Wealth management firms can execute educational programs that improve clients' financial literacy and assist them in identifying and reducing their preconceived ideas. To improve market efficiency, regulators and policymakers may establish frameworks that promote investor awareness.

The study emphasizes that stakeholders can improve investment strategies, maximize overall investment levels, enhance profits, and eliminate losses by concentrating on behavioural aspects. To enable the financial markets to operate more effectively, it advocates a preventative approach to managing behavioural anomalies.

References:

1. *Advances*, *1*(1), 25-48.
2. Aggarwal, D. (2022). Defining and measuring market sentiments: A review of the literature. *Qualitative Research in Financial Markets*, *14*(2), 270-288.
3. Ah Mand, A., Janor, H., Abdul Rahim, R., & Sarmidi, T. (2023). Herding behavior and stock market conditions. *PSU Research Review*, *7*(2), 105-116.
4. Ahmad, M. (2024). The role of recognition-based heuristics in investment management activities: are expert investors immune?–A systematic literature review. *Qualitative Research in Financial Markets*, *16*(3), 401-422.
5. Ahmad, M., & Shah, S. Z. A. (2020). Overconfidence heuristic-driven bias in investment

decision- making and performance: mediating effects of risk perception and moderating effects of financial literacy. *Journal of Economic and Administrative Sciences*, *38*(1), 60-90.
6. Aigbovo, O., & Ilaboya, O. J. (2019). Does behavioural biases influences individual investment decisions. *Management Science Review*, *10*(1), 68-89.
7. Ainia, N. S. N., & Lutfi, L. (2019). The influence of risk perception, risk tolerance, overconfidence, and loss aversion towards investment decision-making. Journal of Economics, Business, & Accountancy Ventura, 21(3), 401-413.
8. Akinkoye, E. Y., & Bankole, O. E. (2020). Effect of emotional biases on investor's decision making in Nigeria. International Journal of Business and Management Future, 4(1), 33-39.
9. Almeida, J., & Gonçalves, T. C. (2022). Portfolio diversification, hedge and safe-haven properties in cryptocurrency investments and financial economics: a systematic literature review. *Journal of Risk and Financial Management*, *16*(1), 3.
10. Ángeles López-Cabarcos, M., M Pérez-Pico, A., & López Perez, M. L. (2020). Investor sentiment in the theoretical field of behavioural finance. *Economic research-Ekonomska istraživanja*, *33*(1), 2101- 2228.
11. Badola, S., Sahu, A. K., & Adlakha, A. (2024). A systematic review on behavioral biases affecting individual investment decisions. *Qualitative Research in Financial Markets*, *16*(3), 448-476.
12. Bapat, D. (2020), "Antecedents to responsible financial management behavior among young adults: moderating role of financial risk tolerance", International Journal of Bank Marketing, Vol. 38 No. 5,
13. Chang, C. L., McAleer, M., & Wang, Y. A. (2020). Herding behaviour in energy stock markets during the Global Financial Crisis, SARS, and ongoing COVID-19. *Renewable and Sustainable Energy Reviews*, *134*, 110349.
14. Choi, J. J., & Robertson, A. Z. (2020). What matters to individual investors? Evidence from the horse's mouth. *The Journal of Finance*, *75*(4), 1965-2020. Rau, P. R., & Yu, T. (2024). A survey on ESG: investors, institutions and firms. *China Finance Review International*, *14*(1), 3-33.
15. Choijil, E., Méndez, C. E., Wong, W. K., Vieito, J. P., & Batmunkh, M. U. (2022). Thirty years of herd behavior in financial markets: A bibliometric analysis. *Research in International Business and Finance*, *59*, 101506.
16. Cunha, F. A. F. D. S., Meira, E., & Orsato, R. J. (2021). Sustainable finance and investment: Review and research agenda. *Business Strategy and the Environment*, *30*(8), 3821-3838.
17. Din, S. M. U., Mehmood, S. K., Shahzad, A., Ahmad, I., Davidyants, A., & Abu-Rumman, A. (2021).
18. George O. Aragon and Wayne E. Ferson (2007), "Portfolio Performance Evaluation", Foundations and Trends® in Finance: Vol. 2: No. 2, pp 83-190.
19. Goyal, P., Gupta, P., & Yadav, V. (2023). Antecedents to heuristics: decoding the role of herding and prospect theory for Indian millennial investors. *Review of Behavioral Finance*, *15*(1), 79-102.
20. Gulshirin, J., & Abdulazizovich, X. U. B. (2022, March). INCREASING THE EFFICIENCY OF INVESTMENT IN THE DEVELOPMENT OF EXPORT DIVERSIFICATION IN THE REGION.
21. Hani, L. Y. B. (2020). A study of financial planning and investment of individual. *Int. J. Sci. Res*, *9*(11), 1268-1272.
22. Heuristic biases and investment decisions: multiple mediation mechanisms of risk tolerance and financial literacy—a survey at the Tanzania stock market. *Journal of Money and Business*, *1*(2), 102- 116.
23. Hossain, T., & Siddiqua, P. (2022). Exploring the influence of behavioral aspects on stock

investment decision-making: a study on Bangladeshi individual investors. *PSU Research Review*, (ahead-of- print).

24. Hossain, T., & Siddiqua, P. (2022). Exploring the influence of behavioral aspects on stock investment decision-making: a study on Bangladeshi individual investors. *PSU Research Review*, (ahead-of- print).
25. In *Conference Zone* (pp. 277-281).
26. Jones, R. C. (2014). Making better (investment) decisions. *The Journal of Portfolio Management*, *40*(2), 128-143.
27. Joshi, C. S., Badola, S., & Chopra, G. (2022). Behavioural Bias: Does it Affect an Investor's Rationality?. *SCMS Journal of Indian Management*, *19*(4), 128-142.
28. Khan, I., Afeef, M., Jan, S., & Ihsan, A. (2021). The impact of heuristic biases on investors' investment decision in Pakistan stock market: moderating role of long term orientation. *Qualitative Research in Financial Markets*, *13*(2), 252-274.
29. King, M., & Kay, J. (2020). *Radical uncertainty: Decision-making for an unknowable future*. Hachette UK.
30. Komalasari, P. T., Asri, M., Purwanto, B. M., & Setiyono, B. (2022). Herding behaviour in the capital market: what do we know and what is next?. *Management Review Quarterly*, *72*(3), 745-787.
31. Koumou, G. B. (2020). Diversification and portfolio theory: a review. *Financial Markets and Portfolio Management*, *34*(3), 267-312.
32. Krishnan, P., & Periasamy, M. N. (2022). Testing of Semi–Strong Form of Efficiency: an Empirical Study on Stock Market Reaction Around Dividend Announcement. *International Journal of Professional Business Review: Int. J. Prof. Bus. Rev.*, *7*(2), 8.
33. Leković, M. (2020). Cognitive biases as an integral part of behavioral finance. Economic Themes, 58(1), 75-96.
34. Letho, L., Chelwa, G., & Alhassan, A. L. (2022). Cryptocurrencies and portfolio diversification in an emerging market. *China Finance Review International*, *12*(1), 20-50.
35. Maharani, A., & Saputra, F. (2021). Relationship of investment motivation, investment knowledge and minimum capital to investment interest. *Journal of Law, Politic and Humanities*, *2*(1), 23-32.
36. March, J. G. (2006). Rationality, foolishness, and adaptive intelligence. *Strategic management journal*, *27*(3), 201-214.
37. Mittal, S. K. (2022). Behavior biases and investment decision: theoretical and research framework. *Qualitative Research in Financial Markets*, *14*(2), 213-228.
38. Padmavathy, M. (2024). Behavioral Finance and Stock Market Anomalies: Exploring Psychological Factors Influencing Investment Decisions. *Shanlax International Journal of Management*, *11*(S1), 191- 97.
39. Pflueger, C., Siriwardane, E., & Sunderam, A. (2020). Financial market risk perceptions and the macroeconomy. *The Quarterly Journal of Economics*, *135*(3), 1443-1491.
40. pp. 1177-1194.
41. Rahman, M., & Gan, S. S. (2020). Generation Y investment decision: an analysis using behavioural factors. *Managerial Finance*, *46*(8), 1023-1041.
42. Sabir, S. A., Mohammad, H. B., & Shahar, H. B. K. (2019). The role of overconfidence and past investment experience in herding behaviour with a moderating effect of financial literacy: evidence from Pakistan stock exchange. Asian Economic and Financial Review, 9(4), 480-490.
43. Sachdeva, M., & Lehal, R. (2023). The influence of personality traits on investment decision-making: a moderated mediation approach. *International Journal of Bank Marketing*, *41*(4), 810-834.
44. Sahoo, S. K., & Goswami, S. S. (2023). A comprehensive review of multiple criteria decision-

making (MCDM) Methods: advancements, applications, and future directions. *Decision Making*

45. Shantha, K. V. A., Xiaofang, C., & Gamini, L. P. S. (2018). A conceptual framework on individual investors' learning behavior in the context of stock trading: An integrated perspective. Cogent economics & finance, 6(1), 1544062.
46. Sharma, D., Misra, V., & Pathak, J. P. (2021). Emergence of behavioural finance: a study on behavioural biases during investment decision-making. *International Journal of Economics and Business Research*, *21*(2), 223-234.
47. The impact of behavioral biases on herding behavior of investors in Islamic financial products. *Frontiers in Psychology*, *11*, 600570.
48. Truc, A. (2022). Forty years of behavioral economics. *The European Journal of the History of Economic Thought*, *29*(3), 393-437.
49. Vaid, A. J., & Chaudhary, R. (2022). Review paper on impact of behavioral biases in financial decision-making. *World Journal of Advanced Research and Reviews*, *16*(2), 989-997.
50. Weixiang, S., Qamruzzaman, M., Rui, W., & Kler, R. (2022). An empirical assessment of financial literacy and behavioral biases on investment decision: Fresh evidence from small investor perception. *Frontiers in psychology*, *13*, 977444.
51. Weixiang, S., Qamruzzaman, M., Rui, W., & Kler, R. (2022). An empirical assessment of financial literacy and behavioral biases on investment decision: Fresh evidence from small investor perception. *Frontiers in psychology*, *13*, 977444.
52. Zhang, W. (2020). Application of crowd thought and herd behavior in economic investment. *Revista Argentina de Clinica Psicologica*, *29*(1), 328.
53. Zineb, M. I. H. R. A. J., & Abdelouahed, A. M. (2024). Behavioral Finance: How to Reveal and Overcome Investor Bias?. *African Scientific Journal*, *3*(22), 834-834.