OPTIMIZING INVESTMENT PERFORMANCE THROUGH ANALYSIS OF INVESTORS' BEHAVIORAL FACTORS

A Dissertation submitted to the Office of Dean, Faculty of Management in partial fulfillment of the requirements for the Master's Degree

By

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Certification of Authorship

I hereby corroborate that I have researched and submitted the final draft of dissertation entitled **"Optimizing Investment Performance Through Analysis of Investors' Behavioral Factors"**. The work of this dissertation has not been submitted previously for the purpose of the conferral of any degrees, nor it has been proposed and presented as part of the requirements for any other academic purposes.

The assistance and cooperation that I have received during this research work has been acknowledged. In addition, I declare that all information sources and literature used are cited in the reference section of the dissertation.

Sushil Parajuli
August 2025

Report of Research Committee

Mr. Sushil Parajuli has defended research proposal entitled **"Optimizing Investment Performance Through Analysis of Investors' Behavioral Factors"** successfully. The research committee has registered the dissertation for further progress. It is recommended to carry out the work as per suggestions and guidance of supervisor Dr. Dinesh Basnet and submit the thesis for evaluation and viva voce examination.

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We, the undersigned, have examined the dissertation entitled **"Optimizing Investment Performance Through Analysis of Investors' Behavioral Factors"** presented by Sushil Parajuli, a candidate for the degree of Master of Business Studies (MBS Semester) and conducted the Viva voce examination of the candidate. We hereby certify that the dissertation is worthy of acceptance.

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Sushil Parajuli

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Abbreviations

AGFI	Adjusted Goodness-of-Fit Index
AIC	Akaike Information Criterion
AMOS	Analysis of Moment Structures
BCC	Browne-Cudeck Criterion
BIC	Bayes Information Criterion
CAIC	Consistent Akaike Information Criterion
CAPM	Capital Asset Pricing Model
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
ECVI	Expected Cross-Validation Index
EFA	Exploratory Factor Analysis
GFI	Goodness-of-Fit Index
IFI	Incremental Fit Index
KMO	Kaiser-Meyer Olkin Measure of Sampling Adequacy
MBS	Master of Business Studies
MPT	Modern Portfolio Theory
NFI	Normed Fit Index
NPSE	Nepal Stock Exchange
PFI	Parsimonious Fit Index
RMR	Root Mean Square Residual
RMSEA	Root Mean Square Error of Approximation
RNI	Relative Non-centrality Index
SEM	Structural Equation Modeling
SPSS	Statistical Package for the Social Sciences
SRMR	Standardized Root Mean Square Residual
TLI	Tucker-Lewis Index
USBE	Umea School of Business
WRMR	Weighted Root Mean Residual

Abstracts

This research explores the impact of behavioral factors on investment decisions and Investment Performance at the Nepal Stock Exchange (NEPSE). The primary objective is to identify and analyze these factors to optimize Investment Performance in an emerging market context. The study employs a combination of quantitative and qualitative methods, including self-completion questionnaires and semi-structured interviews, to gather data from individual investors at NEPSE. Statistical techniques such as Factor Analysis, Cronbach's Alpha Test, and Structural Equation Modeling (SEM) are used for data analysis.

The findings reveal that behavioral factors such as heuristics (overconfidence, gambler's fallacy, anchoring, and availability bias), prospect factors (loss aversion, regret aversion, and mental accounting), market factors (price changes, market information, and past trends of stocks), and herding factors (following other investors' decisions) significantly influence investment decisions. Most behavioral factors have a moderate impact on investment decisions, with market factors having the highest influence. Heuristic and herding behaviors positively impact investment performance, while prospect behaviors also show a positive correlation.

The study concludes that understanding and managing these behavioral factors can significantly enhance investment performance. Recommendations for investors include maintaining balanced confidence, leveraging reliable investment partners, and considering prior losses for future decisions. The study contributes to the field of behavioral finance by providing empirical evidence on the impact of behavioral factors on Investment Performance in an emerging market context, offering practical insights for investors, financial advisors, and policymakers.

Keywords: Behavioral Finance, Investment Decisions, Investment Performance, NEPSE, Emerging Market

CHAPTER I

Introduction

Background of Study

In the ever-evolving landscape of finance, managing portfolio risk is essential for maintaining both profitability and stability. Investors continuously explore strategies to enhance returns while minimizing exposure to risk. Stock markets serve as a vital component of economic systems by enabling companies to secure funding and offering investors opportunities to build wealth. However, investment decisions are not always purely rational; they are frequently shaped by behavioral influences, which can lead to less-than-optimal portfolio outcomes. Behavioral finance, which merges psychological insights with financial theory, aims to explain how cognitive biases and emotional responses affect investor behavior. This research seeks to identify and evaluate these behavioral influences to improve portfolio outcomes.

A portfolio typically comprises a mix of financial instruments such as equities, bonds, commodities, currencies, and cash equivalents, along with their associated investment vehicles like mutual funds, ETFs, and closed-end funds. These portfolios may be self-managed by individual investors or overseen by financial professionals. Investors, whether individuals or institutions, allocate capital with the goal of earning returns. While individual investors manage their own funds, institutional investors, including banks, insurance firms, and pension funds, handle large-scale investments on behalf of clients. Investment refers to the act of allocating financial resources with the intention of earning a return or profit. Typical forms of investment include stocks, bonds, real estate, commodities, mutual funds, and exchange traded funds.

Contemporary portfolio management emphasizes diversification and the optimization of risk and return, building upon foundational theories and incorporating advanced tools like machine learning (Guerard, 2025). A sound investment strategy is one that is based on thorough analysis, aims to preserve capital, and seeks reasonable returns distinguishing it from speculative activities (Jagirdar & Gupta, 2024). This underscores the importance of systematic and data-driven approaches in selecting stocks strategically.

Investment plays a critical role in both personal financial growth and broader economic development. For individuals, it offers a pathway to wealth accumulation, goal

achievement, and financial security. At the macroeconomic level, investments stimulate growth by funding businesses, generating employment, and fostering innovation. They also serve as a hedge against inflation and help diversify income sources. Nonetheless, all investments carry inherent risks, which can be categorized into market, credit, liquidity, interest rate, and inflation risks. These risks can be mitigated through strategies such as diversification, asset allocation, hedging, diligent research, and continuous monitoring.

Stock markets act as centralized venues for the issuance, purchase, and sale of securities, thereby facilitating capital flow and liquidity within the economy (Madura, 2022). Beyond capital formation, stock markets also serve as indicators for corporate investment decisions, particularly in developing economies (Chen & Zhang, 2021). Public equity offerings, such as IPOs, remain a crucial mechanism for companies to raise funds for expansion and innovation (Bernstein, 2022). Investors are often interested in equities because they offer the possibility of sustained value growth, regular dividend payouts, and a hedge against inflation (Goldman Sachs Global Investment Research, 2024). Another key advantage of stock markets over other investment avenues is their liquidity (Jaswani, 2008). Many investors purchase stocks to gain ownership in companies, benefiting from both capital appreciation and dividends as the firms grow (Baker & Ricciardi, 2022). Some investors also acquire shares to gain influence over corporate decisions, particularly when they hold enough shares to secure a seat on the board of directors.

Investing in equities involves acquiring shares of publicly traded companies, offering the potential for substantial returns but also exposing investors to higher risks compared to other asset classes. Stock prices are influenced by a range of factors, including macroeconomic indicators, company performance, and investor sentiment. In Nepal, the Nepal Stock Exchange (NEPSE) serves as the primary platform for equity trading. NEPSE has experienced notable growth, reflecting the country's economic progress. However, it remains marked by high volatility and limited liquidity. The NEPSE index, which tracks listed companies, is sensitive to political developments, economic policies, and investor confidence.

NEPSE investors include both individuals and institutions. Individual investors often pursue short-term gains and are susceptible to market rumors and trends. Institutional investors, by contrast, typically adopt a long-term outlook and rely on fundamental

analysis. Investor behavior at NEPSE is shaped by various factors, including political stability, economic conditions, and prevailing market trends. A common behavioral pattern observed is herding, where investors mimic the actions of others rather than making independent decisions. This behavior can contribute to the formation of market bubbles and subsequent crashes.

Building a well-diversified investment portfolio is a key strategy for minimizing risk and reaching financial goals. By allocating funds across various asset categories and industries, diversification aims to stabilize returns. To enhance investment outcomes, several theoretical models are commonly applied, such as Modern Portfolio Theory, the Capital Asset Pricing Model, the Efficient Frontier framework, and Risk Parity. The decisions made by investors are shaped by a mix of psychological tendencies, economic conditions, market dynamics, and social influences.

Problem Statement

Investment decisions have long been considered rational processes, assuming that individuals make choices logically using all available data. Nevertheless, behavioral finance disputes this view, showing that emotional influences and cognitive biases frequently interfere with sound judgment. (Barberis & Thaler, 2021; Soll et al., 2024). These biases such as overconfidence, loss aversion, herding, and mental accounting can lead to suboptimal decisions and ultimately affect investment performance.

In emerging markets like Nepal, the influence of behavioral factors is even more pronounced due to market inefficiencies, limited financial literacy, and the dominance of informal information channels (Sharma et al., 2023; Lama, 2025). The Nepal Stock Exchange (NEPSE) is characterized by high volatility, low institutional participation, and sensitivity to political and economic events. These conditions create an environment where investor behavior is often driven by emotion, speculation, and social influence rather than fundamental analysis.

While global research has extensively explored behavioral finance in developed markets, there is a significant lack of empirical studies focusing on how these behavioral factors impact investment performance in Nepal. Most existing studies in the Nepalese context are either descriptive or limited in scope, lacking rigorous statistical validation or

theoretical grounding. Moreover, few studies have attempted to link behavioral biases directly with investment outcomes using robust analytical tools such as Structural Equation Modeling (SEM).

This study addresses this gap by empirically examining the behavioral factors that influence investment decisions and performance among NEPSE investors. It aims to provide evidence-based insights that can help investors make more informed decisions, support financial advisors in developing behaviorally aware strategies, and assist policymakers in designing investor education programs tailored to the Nepalese market.

The study also aims to provide answers to the following questions that have openly raised:

i. What are the key behavioral factors influencing investment decisions at NEPSE?
ii. How do these behavioral factors impact the Investment Performance of individual and institutional investors at NEPSE?

Objectives of the Study

The main objective of this study will be to find the optimal strategy to select stock to get maximum level of profit by lowering the portfolio risk. Accordingly, the specific objectives will be as follows:

i. To identify behavioral factors influencing investment decisions.
ii. To determine the impact levels of these factors on investment decisions and performance.

Hypotheses

Hypothesis H1: There is a positive relationship between herding and investment performance.

Hypothesis H2: There is a positive relationship between market and investment performance.

Hypothesis H3: There is a positive relationship between prospect and investment performance.

Hypothesis H4: There is a positive relationship between heuristic and investment performance.

Rationale of the study

The rationale for this study, "Optimizing Investment Performance through Analysis of Investors' Behavioral Factors," is grounded in the need to bridge the gap between traditional finance theories and the realities of investor behavior in emerging markets like Nepal. Traditional finance theories assume that investors are rational, and markets are efficient. However, behavioral finance challenges this assumption by incorporating psychological factors that influence investor behavior, leading to suboptimal investment decisions and affecting Investment Performance.

The Nepal Stock Exchange (NEPSE) is characterized by high volatility, limited liquidity, and significant political and economic influences. Investors at NEPSE, both individual and institutional, often exhibit behaviors driven by short-term gains, market rumors, and trends. This can lead to herd behavior, market bubbles, and crashes, further exacerbating the risks associated with stock market investments. Understanding these behavioral factors is crucial for developing strategies to optimize Investment Performance and enhance market stability.

Although behavioral finance has been extensively studied, its specific influence on investment outcomes in developing economies such as Nepal remains underexplored. Much of the existing literature centers on advanced markets, resulting in a lack of research that addresses the distinct conditions and prospects found in emerging economies. This research seeks to address that gap by examining how behavioral traits affect investment choices and performance within the NEPSE context.

The results of this investigation are expected to offer meaningful guidance to individual investors, financial consultants, and regulatory bodies. By pinpointing the behavioral elements that shape investment behavior and assessing their effects on performance, the study aims to support better decision-making. Financial professionals can apply these insights to craft customized strategies, and policymakers may use them to strengthen investor education and improve market functionality.

Investor education is crucial for mitigating the negative impacts of behavioral biases and promoting rational investment decisions. This study highlights the need for

comprehensive investor education programs that address the psychological factors influencing investment behavior. By enhancing investor education, the study aims to contribute to the overall stability and growth of the stock market.

This study also contributes to the field of behavioral finance by providing empirical evidence on the impact of behavioral factors on Investment Performance in an emerging market context. The insights gained from this study will be valuable for researchers and academics, furthering the understanding of investor behavior and its implications for financial markets.

In summary, the rationale for this study is to bridge the gap between traditional finance theories and the realities of investor behavior in emerging markets, provide practical insights for optimizing Investment Performance, enhance investor education and market efficiency, and contribute to the field of behavioral finance. By addressing these objectives, the study aims to improve investment outcomes for investors at NEPSE and contribute to the overall stability and growth of the stock market.

Limitations of the study

This research is being carried out as part of the requirements for the completion of a Master of Business Studies (MBS) degree. While this study aims to provide valuable insights into optimizing Investment Performance through the analysis of investors' behavioral factors, several limitations should be acknowledged:

i. This study is limited to the Nepal Stock Exchange (NEPSE), so the findings may not be applicable to other stock markets with different economic, political, or cultural contexts.
ii. It was challenging to access a wide and diverse group of investors for primary data collection, which may affect the representativeness of the sample.
iii. Self-reported questionnaires may have introduced recall or social desirability bias, affecting data accuracy.
iv. Since the study uses a cross-sectional design, it captures investor behavior at only one point in time and does not reflect changes over time.
v. The study focuses on selected behavioral factors, so other potentially relevant psychological or external influences may not have been considered.

By acknowledging these limitations, the study aims to provide a balanced perspective on its findings and encourage further research to address these challenges. Despite these limitations, the study contributes valuable insights into the role of behavioral factors in investment decisions and Investment Performance at NEPSE.

CHAPTER II

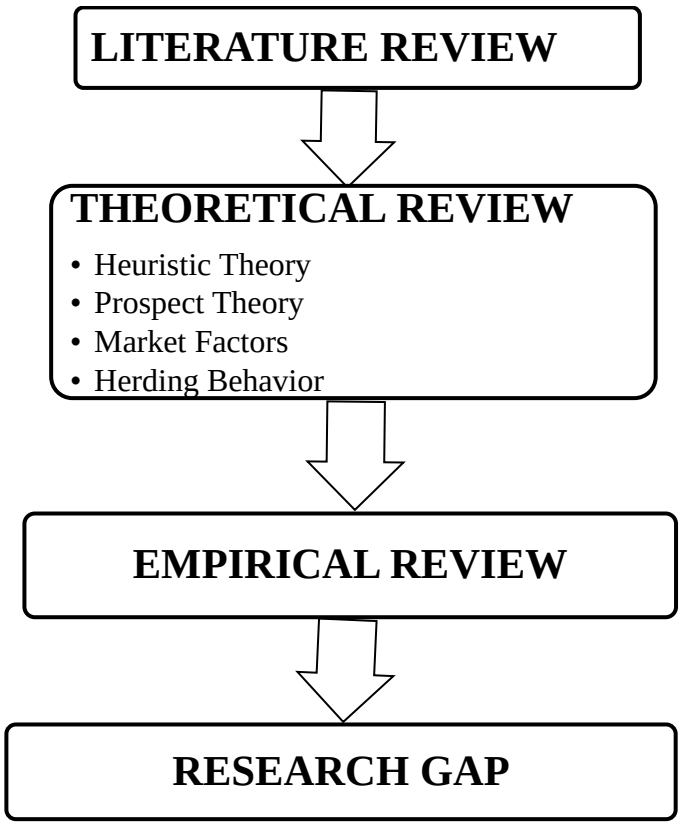
Literature Review

Introduction

This chapter explores the theoretical and empirical foundations of behavioral finance, emphasizing how mental and emotional factors influence investment decisions and performance particularly in the context of the Nepal Stock Exchange (NEPSE). It contrasts traditional finance, which assumes rational investor behavior, with behavioral finance, which incorporates cognitive biases and emotional influences. The chapter first discusses the theoretical shift from traditional to behavioral finance and its relevance in emerging markets like Nepal; the second introduces key behavioral theories such as heuristics, prospect theory, market anomalies, and herding behavior; the third reviews empirical studies from both global and Nepalese contexts; and the fourth identifies research gaps that justify the need for this study. The structure of the literature review is illustrated in the following figure.

Figure 1

The Literature Review Outline



Theoretical Review

Traditional financial theory is based on the belief that investors behave logically and that markets operate efficiently. A key concept within this framework, the Efficient Market Hypothesis (EMH), suggests that all known information is already incorporated into asset prices, thereby preventing investors from consistently achieving above-average returns when adjusted for risk (Barberis & Thaler, 2003). According to this view, investors are expected to make decisions logically, interpret information accurately, and update their beliefs using Bayesian principles. In such a framework, financial markets are considered efficient because any mispricing is quickly corrected by rational arbitrageurs. However, this idealized model has been increasingly challenged by empirical evidence showing persistent anomalies and irrational investor behavior.

Behavioral finance emerged as a response to these limitations, incorporating insights from psychology to explain why investors often deviate from rational decision-making. It argues that cognitive biases, emotional reactions, and mental shortcuts known as heuristics can lead to systematic errors in judgment (Ritter, 2003). These biases can distort asset prices, create market inefficiencies, and result in suboptimal investment outcomes. Behavioral finance has evolved into a robust field of study, supported by empirical research that documents phenomena such as overreaction to news, the disposition effect, and momentum trading (Frydman & Rangel, 2022; Daniel et al., 2021). While initially met with skepticism, behavioral finance is now widely accepted as a complement to traditional theories, offering a more realistic understanding of investor behavior and market dynamics.

In emerging markets like Nepal, the relevance of behavioral finance becomes even more pronounced. These markets are often characterized by limited regulatory oversight, low financial literacy, and high sensitivity to political and economic events. Investors in such environments frequently rely on informal sources of information, such as friends, family, and social media, rather than formal financial analysis (Sharma et al., 2023; Lama, 2025). Cultural factors, including collectivism and deference to authority, further reinforce behavioral tendencies like herding and overconfidence (Weber & Hsee, 2000). The Nepal Stock Exchange (NEPSE), for instance, exhibits high volatility, limited institutional participation, and a strong influence of market rumors and sentiment. These conditions create a fertile ground for behavioral biases to influence investment decisions and performance.

Behavioral finance categorizes these biases into several key groups that influence investor behavior. Among them, heuristic-driven biases simplify decision-making but often lead to errors. Prospect-related biases explain how investors perceive gains and losses asymmetrically. Market-related factors, though external, significantly shape investor reactions to price changes and information. Lastly, herding behavior reflects the tendency of investors to follow the crowd rather than rely on independent analysis. These behavioral dimensions are particularly relevant in the context of NEPSE, where investor decisions are often shaped more by psychological and social influences than by fundamental analysis.

Behavioral finance draws from psychological principles, proposing that individuals' decision-making is often influenced by various cognitive distortions (Ritter, 2003). These distortions are generally classified into two main types: those arising from heuristic-based thinking and those stemming from mental framing, as outlined in prospect theory (Waweru et al., 2008). Alongside these, herding tendencies and market-related influences are also discussed in the following sections.

Heuristic Theory

Heuristics are cognitive shortcuts that simplify decision-making, especially under uncertainty, by reducing complex judgments to more manageable mental rules (Salas-Velasco, 2024). These mental shortcuts, while efficient, can lead to systematic biases such as representativeness, availability, and anchoring first formalized by Kahneman and Tversky and still central to behavioral decision theory today (Kahneman & Tversky, 1974; Salas-Velasco, 2024).

Representativeness describes how closely an event mirrors the characteristics of its broader category or population. This cognitive shortcut can lead individuals to overemphasize recent experiences while overlooking long-term averages (Ritter, 2003). For instance, investors might assume a firm has strong long-term growth potential simply because of a few consecutive quarters of positive performance (Waweru et al., 2008). This bias is also linked to “sample size neglect,” where conclusions are drawn from insufficient data (Barberis & Thaler, 2003). In financial markets, this often results in investors pursuing trending stocks based on short-term gains, which can cause exaggerated reactions and eventual price corrections (Xie, Hua, Gao, & Tan, 2021).

The concept known as the "law of small numbers" suggests that individuals may mistakenly believe a limited sample accurately reflects the broader population, which can lead to the Gambler's Fallacy, a bias where people anticipate a reversal in random patterns (Tversky & Kahneman, 2021). Within financial markets, this bias is evident when investors incorrectly forecast market shifts, expecting that a series of gains or losses will soon reverse (Białkowski, Bohl, & Serwa, 2022). Furthermore, status quo bias may cause individuals to stick with familiar investment choices, even when more advantageous options are available (Imas, 2022).

Anchoring refers to the tendency to rely excessively on initial information when making decisions, which can distort judgment (Rezaei, Arab, & Mehregan, 2024). In investment contexts, this often occurs when investors base their evaluations on the original purchase price, causing current valuations to be influenced by past figures. This behavior leads to a narrow price expectation range and may result in insufficient response to new market developments. Anchoring is closely related to representativeness, as both involve a focus on recent experiences, with investors typically becoming more optimistic during market upswings and more pessimistic during downturns (Waweru et al., 2008).

Prospect Theory

Overconfidence occurs when individuals place too much trust in the accuracy of their own knowledge and abilities (DeBondt and Thaler, 1995; Hvide, 2002). Research has shown that this bias often leads to frequent trading among investors. For instance, financial analysts may delay updating their evaluations of a company even when there is clear evidence that their initial judgment is no longer valid (Evans, 2006). While overconfidence can enhance qualities such as persistence, decisiveness, and willingness to take risks, it may also contribute to improved professional outcomes. It can positively influence how others view a person's competence, which may support quicker career advancement and longer investment involvement (Oberlechner and Osler, 2004).

Availability bias refers to the tendency to rely heavily on information that is easy to access. In the context of stock trading, this bias is reflected in the preference for investing in domestic companies that are familiar or have readily available data, even when diversification would be a more effective strategy (Waweru et al., 2003).

This study includes five heuristic-related behavioral traits overconfidence, gambler's fallacy, availability bias, anchoring, and representativeness to examine their influence on investment decisions and outcomes among individual investors in the Nepal Stock Exchange.

Market Factors

Recent studies have shown that investor behavior plays a significant role in shaping financial markets. Psychological tendencies such as overconfidence, herding, and loss aversion are known to contribute to market volatility, pricing errors, and irregularities (Akin and Akin, 2024). According to behavioral finance, investors may respond disproportionately to news or price movements, extend past trends into future expectations, overlook fundamental stock indicators, or concentrate on trending stocks and seasonal patterns. These influences collectively affect how investment decisions are made.

Waweru et al. (2008) identified several market-related elements that impact investor choices, including price fluctuations, the availability of market information, historical stock performance, consumer preferences, reactions to price changes, and the underlying fundamentals of stocks. Shifts in stock prices, company fundamentals, or market news can trigger either exaggerated or muted investor responses. Empirical evidence supports the idea that such changes significantly influence investor behavior. Overreactions to news, as discussed by DeBondt and Thaler (1985) and Lai (2001), can lead to varied trading strategies and ultimately affect investment decisions.

Market information is particularly influential, often drawing investor attention to popular or high-profile stocks (Waweru et al., 2009). Events that capture attention, even without clear implications for future returns, can still shape investor behavior (Barber and Odean, 2000). Overconfidence also plays a role, as some investors rely heavily on the quality of information they possess when making investment choices, which may lead to excessive trading.

Stock price changes can influence investor behavior to some extent (Waweru et al., 2008). Many investors are more inclined to buy rather than sell stocks that have experienced significant price increases over the past two years. In this context, price movement acts as a trigger for investor attention (Odean, 1999). According to Capparelli et al. (2004), price

changes can also amplify herding behavior, where investors follow the actions of others. Additionally, investors may misjudge the expected returns in response to price shifts, which can further affect their decision-making (Waweru et al.).

A common tendency among investors is to focus on well-known or trending stocks (Waweru et al., 2008). Odean (1999) noted that investors often select stocks that capture their attention, and these choices are also influenced by personal preferences. Momentum investors may favor stocks with strong recent performance, while more rational investors might sell underperforming assets to manage tax liabilities. In contrast, behavioral investors may sell profitable stocks to avoid the emotional discomfort associated with realizing a loss (Waweru et al., 2008). Waweru also observed that investors frequently rely on technical analysis of past stock trends when making investment decisions.

Although market factors are typically considered external influences rather than behavioral ones, they still affect both behaviorally driven and rational investors in different ways. Therefore, excluding market factors from behavioral analysis would be incomplete. In line with Waweru et al. (2008), this study treats market-related elements as important contributors to investor decision-making in the stock market.

Herding Effect

In financial markets, herding refers to the behavioral tendency of investors to imitate the actions of others. Practitioners often examine this phenomenon closely, as reliance on collective behavior rather than individual analysis can lead to asset prices diverging from their intrinsic values, potentially causing missed investment opportunities. Scholars also emphasize the significance of herding, noting that it can affect stock price volatility and influence the assumptions used in risk and return modeling, which are central to asset pricing theories (Tan, Chiang, Mason, and Nelling, 2008).

From a behavioral standpoint, herding is associated with emotional influences such as conformity, alignment with group norms, internal conflict, preference for familiar environments, and the spread of informal information. Some investors may follow the crowd if they believe it provides access to dependable insights. In professional settings, such as among fund managers or analysts, performance is often judged in comparison to peers. In such cases, individuals with less confidence in their abilities may mimic more

successful colleagues to enhance their professional image (Kallinterakis, Munir, and Markovic, 2010).

Within the securities market, herding behavior is evident when investors base their decisions on the collective actions of others, such as buying or selling specific stocks. In contrast, informed investors who rely on independent analysis contribute to market efficiency. Herding, however, can lead to inefficiencies and is often linked to speculative bubbles. This behavior is likened to early human survival strategies, where individuals grouped together for safety due to limited knowledge of their surroundings (Caparrelli et al., 2004). Several factors influence herding, including confidence levels and investment size. Investors with greater confidence tend to rely more on their own judgment, while those with larger investments may follow others to feel more secure in their decisions. Herding remains a prominent behavioral pattern, especially in volatile environments such as cryptocurrency markets and developing stock exchanges (Bouri, Jain, and Roubaud, 2022).

According to Waweru, herding can stimulate trading activity and create momentum in the market. However, its influence may diminish when the cost of following the crowd outweighs the potential gains. Waweru et al. (2008) identified specific investment decisions that are affected by others, including buying and selling, stock selection, holding periods, and trade volumes. They concluded that decisions related to buying and selling are most influenced by herding, as it helps investors avoid regret. Other decisions, such as which stock to choose, how long to hold it, and how much to trade, appear to be less affected. These findings primarily reflect institutional investor behavior, which may differ from individual investors, who are generally more prone to herding. Therefore, this study investigates how herding influences individual investment decisions in the context of the Nepal Stock Exchange.

Summarize the behavioral factors influencing the investors' decision making:

To summarize, the behavioral influences on investor decision-making are categorized into four main groups: heuristic biases, prospect-related behaviors, market-driven factors, and herding tendencies. These categories are outlined in Table 1.

Table 1

Behavioral factors influencing investment decision making (Source: Waweru et al., 2008)

Group	Behavioral Variables
Heuristic Theory	- Representativeness - Overconfidence - Anchoring - Gambler's fallacy - Availability bias
Prospect Theory	- Loss aversion - Regret aversion - Mental accounting
Market	- Price changes - Market information - Past trends of stocks - Fundamentals of underlying stocks - Customer preference - Overreaction to price changes
Herding Effect	- Buying and Selling decisions of other investors - Choice of stock to trade with other investors - Volume of stocks to trade with other investors - Speed of herding

These groups provide a comprehensive overview of the behavioral factors that influence investor decisions in stock markets. As such, they are useful for identifying the behavior of both individual and institutional investors, regardless of whether the market is frontier, emerging, or developed.

Trading decisions and stock investment performance

Investment decisions in the stock market can take various forms, including buying and selling shares, selecting specific stocks, determining how long to hold them, and deciding the quantity to trade. Among these, buying and selling are particularly significant, as they

are closely linked to other decisions and have a strong influence on overall investment outcomes.

i. **Selling decision:**

Recent findings suggest that investors are generally reluctant to sell assets that have dropped below their purchase price, a behavioral pattern known as the disposition effect, which remains a key topic in behavioral finance (Joshipura, Joshipura, and Sharma, 2024). This tendency is also supported by research showing that individuals are more inclined to sell stocks that have gained in value while holding onto those that have declined (Gödker, Odean, and Smeets, 2024). From a rational perspective, this behavior is difficult to justify, as it implies that investors sell profitable stocks not because they anticipate a downturn, but due to emotional biases. Odean observed that the average return on sold stocks tends to be higher than that of those retained.

When investors sell at a loss, they often expect to receive a better price than what others are asking. However, market corrections typically determine the final price. Genesove and Mayer (2001) noted that investors facing losses tend to sell at relatively higher prices than others. According to prospect theory, individuals who experience gains in the early part of the trading day tend to take fewer risks later, while those who incur losses may become more risk-seeking (Coval and Shumway, 2000). The disposition effect, which reflects this behavior, is closely related to momentum in stock returns. Investors often sell stocks that have been appreciated, which can initially slow price growth and later lead to higher returns. Conversely, when investors hold onto losing stocks, they may only sell once a target price is reached, potentially causing a temporary price increase followed by a decline (Grinblatt and Han, 2001).

ii. **Buying decision:**

Quispe-Torreblanca et al. (2025) explored the factors that influence investors when selecting stocks to purchase. Unlike selling, which often focuses on profitable stocks, buying decisions may involve both previously successful and underperforming stocks. These choices are frequently driven by attention effects. Given the vast number of listed securities, investors often choose stocks that stand

out, typically due to recent performance, whether positive or negative (Shen and Wang, 2023).

Attention-grabbing stocks appear to have less influence on selling decisions, as investors can only sell what they already own. In contrast, buying decisions offer a broader selection, allowing individuals to choose from a wide range of options. This explains why attention plays a more prominent role in purchasing than in selling (Shen and Wang, 2023). Quispe-Torreblanca et al. (2025) demonstrated that buying decisions are more influenced by attention than selling decisions. They identified high-attention stocks using criteria such as unusually high trading volumes, extreme returns, and recent news coverage. Their findings showed that individual investors were more likely to buy these stocks than to sell them.

In summary, behavioral finance suggests that investor psychology affects both buying and selling decisions in different ways, which in turn influences market trends and individual investment performance (Almansour et al., 2023).

iii. **Investment performance:**

Some critics of behavioral finance argue that irrational investors who perform poorly will eventually be eliminated from the market. However, recent research suggests that overconfident investors despite their tendency to ignore financial advice and engage in suboptimal investment behavior can still influence market dynamics and may not be immediately penalized, as their confidence often leads to aggressive decision-making that can yield short-term gains (Sharma, Kumar, Jain, & Kaur, 2025). Overconfidence often leads individuals to overrate the accuracy of their private information, resulting in narrow subjective probability estimates. This bias encourages more assertive trading compared to rational investors, with the expectation of higher returns despite increased risk exposure (Soll, Palley, Klayman, and Moore, 2024). While extreme levels of under confidence or overconfidence may not persist over time, moderate overconfidence can be sustained and may even outperform purely rational behavior (Wang, 2001).

Anderson, Henker, and Owen (2005) also found that individual investors who engage in more frequent trading may achieve better returns than those who trade less. Interestingly, stocks that see the largest increase in individual ownership

often yield negative abnormal returns, while those with the greatest decline in ownership may produce positive abnormal returns. Kim and Nofsinger (2003) examined buying and selling patterns and found that stocks with increased individual ownership were typically past winners. Surprisingly, stocks with reduced ownership were also past winners. This contradicts momentum trading theory but aligns with the disposition effect, where investors tend to sell profitable stocks and hold onto losing ones.

Lin and Swanson evaluated investment performance using three types of return measures: raw returns, returns adjusted for risk, and returns adjusted for momentum. These were assessed across five-time frames daily, weekly, monthly, quarterly, and annually. Their findings suggest that investors often achieve strong performance in the short term, largely driven by momentum rather than risk-taking. However, this advantage tends to diminish over longer periods. The implication is that short-term gains are more likely the result of increased demand for previously successful stocks or reduced demand for underperformers, rather than superior information. Investors may benefit from understanding and applying momentum strategies, such as purchasing stocks that have recently performed well and selling those that have not. These behaviors can cause short-term price increases for winning stocks and declines for losing ones, but the effect does not persist over longer periods. Lin and Swanson (2003) concluded that short-term performance is primarily influenced by momentum among winning stocks, suggesting that investor buying behavior introduces new information into the market, which can be profitable over a short horizon but not over extended periods.

The influence of overconfidence on investment performance can be assessed through return rates and trading experience. Return rate, or profit, serves as an objective measure of performance and is often compared to the returns of peers. Trading experience, defined by how long an investor has been active in the market, is another important factor. Oberlechner and Osler (2004) found that while overconfidence does not necessarily improve profitability, it can affect how long individuals remain engaged in trading.

There are various ways to evaluate stock investment performance. Previous studies have primarily relied on secondary data from market results (Lin and Swanson, 2003; Kim and Nofsinger, 2003). In contrast, this study uses self-reported data, asking investors to assess their own performance. Following the approach of Oberlechner and Osler (2004), this research measures return rates from both objective and subjective perspectives. Subjective evaluation involves comparing actual returns to personal expectations, while objective evaluation compares actual returns to the market average. Additionally, this study includes satisfaction with investment decisions as a performance indicator. Some investors may feel content with their decisions even if their profits are modest, while others may feel dissatisfied despite earning higher returns. Therefore, both return rate and satisfaction level are used to assess investment performance in this study.

Empirical Review

The empirical foundation of behavioral finance has grown steadily over the past few decades, yet its application in emerging markets like Nepal remains relatively underexplored. While extensive research has been conducted in developed economies such as the United States, the United Kingdom, and parts of Europe studies focusing on investor psychology in developing contexts are still limited. These developed market studies often benefit from robust datasets, advanced analytical tools, and well-established financial infrastructures, which are not always available in frontier markets like NEPSE.

In Nepal, behavioral finance research is still in its early stages. The Nepal Stock Exchange (NEPSE) is characterized by high volatility, limited liquidity, and a strong influence of political and macroeconomic factors. Investors often rely on informal sources of information, such as social media, peer networks, and market rumors, which increases their susceptibility to cognitive biases. Moreover, the lack of formal investor education and financial literacy programs further exacerbates the problem, making it difficult for individuals to make rational investment decisions (Sharma et al., 2023; Lama, 2025).

Empirical studies from other Asian markets provide useful parallels. For instance, research from China and South Korea has shown that investors frequently engage in behaviors such as chasing past performance, holding onto losing stocks, and mimicking others' trades patterns that are consistent with biases like overconfidence, herding, and

loss aversion (Kim & Kim, 2022; Xia & Madni, 2024). These findings suggest that similar behavioral tendencies may be present among Nepalese investors, though localized studies are needed to confirm this.

The current study addresses this gap by focusing specifically on the behavioral factors that influence investment decisions and performance in NEPSE. It builds upon foundational theories such as heuristics and prospect theory (Kahneman & Tversky, 1979) and incorporates empirical insights from global research to assess their relevance in the Nepalese context. The study also utilizes primary data collected from individual investors through structured questionnaires, allowing for a direct analysis of behavioral patterns and their impact on investment outcomes.

In summary, while global literature on behavioral finance is expanding, there remains a significant gap in empirical research focused on emerging markets like Nepal. This study contributes to filling that gap by providing evidence on how behavioral biases shape investment decisions and performance in NEPSE, offering practical insights for investors, financial advisors, and policymakers.

The following articles listed on Table 2 are reviewed for the Literature review.

Table 2

Literature Review

Date	Author	Article Title	Objective	Methodology	Finding
2023	Dongmei Jing and 4 others	Optimal Selection of Stock Portfolios Using Multi-Criteria Decision-Making Methods	The primary purpose of this study was comprehensive modeling for the optimal section of stock portfolios.	Multi-criteria decision-making methods. This method is based on fundamental analysis ratios and uses the UTA method to classify stocks from the best to the worst and consider the investor's risk-taking ability.	One of the ways to manage and mitigate investment risk is to form a stock portfolio and diversify all types of assets. Current cumulative return methods represent safe investments for the analyzed period, and the aggression profile obtains more profit with more risk.

2024	Adrian Eriksson, Erik Peterson	Comparative Analysis of Portfolio Optimization Strategies	Approach 1: Risk is used by diversifying the portfolio. Approach 2: To minimize the risk is to exclusively regard stocks with low correction.	Theoretical foundations and mathematical formulations.	Two distinct approaches to modeling robust portfolio optimization, comparing their efficacy in balancing the return and the risk.
2020	Jia LU, Noor Muhammad Shazemeen and Raimonda MARTINKUTE-KAULIENE	Portfolio Decision Using Time Series Prediction and Multi-Objective Optimization	To find a straightforward method for portfolio decision applicable to strong-form and weak-form efficient markets.	A methodology for portfolio decision based on the Nonlinear Autoregressive Exogenous Model and multi-objective optimization.	Investment strategy based on the predicted market trend is crucial to portfolio decision. Results prove that the Shannon entropy and correlation coefficient criteria combined for the prediction presented a rational judgement on the market trend.
2020	Van-Dai Ta, CHUAN-MING Liu and Direselign Addis Tadesse	Portfolio Optimization-Based Stock Prediction Using Long-Short Term Memory Network in Quantitative Trading	Analyzing financial historical data based on statistical techniques, which is known as a type of time series analysis with limited achievements.	In order to construct an efficient portfolio, multiple portfolio optimization techniques, including equal-weighted modeling (EQ), simulation modeling Monte Carlo simulation (MCS) and optimization modeling men variant optimization (MVO), are used to improve the Investment Performance.	A prediction model that combines a strategic prediction based on historical data with a dynamic prediction, based on valuation, momentum, and spillover, should be extensively investigated in order to minimize the risk-return-offs.

2042	Fernando Anuno, Mara Madaleno and Elisabete Vieira	Testing of Portfolio Optimization by Timor-Leste Portfolio Investment Strategy on the Stock Market	The objective of the study is to analyze the performance of optimized portfolio in minimizing risk and achieving maximum returns in the dynamics of equity portfolio in the international capital market.	Markowitz's portfolio analysze methodology.	The empirical findings of the study indicate that the correlation matrix showed that JPM has a very strong positive correlation with one of the twenty assets.

Research Gap

Despite the growing body of literature in behavioral finance, most empirical studies have focused on developed markets, leaving a significant gap in understanding how behavioral factors influence investment decisions and performance in emerging economies like Nepal. In these markets, investor behavior is shaped by unique challenges such as limited access to reliable information, low financial literacy, and high sensitivity to political and economic fluctuations. These conditions amplify the impact of psychological biases yet remain underrepresented in academic research (Kim & Nofsinger, 2008; Sharma et al., 2023).

In the context of NEPSE, investors particularly individuals often rely on informal sources such as peer advice, social media, and market rumors. This reliance increases susceptibility to biases like herding, overconfidence, and loss aversion. While some studies have acknowledged these tendencies, few have systematically measured their impact on investment performance using robust analytical tools. Moreover, existing research in Nepal tends to focus on traditional finance models, overlooking the behavioral dimensions that are increasingly relevant in volatile and information-scarce environments. Another gap lies in the lack of localized behavioral finance frameworks tailored to Nepal's market structure and investor profile. Most behavioral models are derived from Western contexts and may not fully capture the cultural and institutional nuances of Nepalese investors. For example, collectivist cultural traits and informal investment networks may reinforce certain biases that are less prevalent in individualistic societies.

This research aims to fill these gaps by empirically analyzing the behavioral factors of heuristics, prospect theory, market dynamics, and herding behavior, and their impact on investment decisions and performance at NEPSE. Utilizing primary data and employing statistical methods such as factor analysis and structural equation modeling, the study aspires to deliver a thorough understanding of investor psychology in Nepal. The anticipated results are expected to provide valuable insights for investors, financial advisors, and policymakers, thereby aiding in the formulation of more effective strategies for investor education and market regulation.

CHAPTER III

Research Methodology

Introduction

This chapter presents the methodological framework adopted to investigate the influence of behavioral factors on investment decisions and performance among individual investors at the NEPSE. The research methodology outlines the design, sampling strategy, data collection instruments, and analytical techniques used to achieve the study's objectives. It ensures that the research is conducted systematically, with a focus on reliability, validity, and contextual relevance.

Behavioral finance research requires a methodological approach that captures psychological patterns and decision-making behaviors in a quantifiable manner. Therefore, this study employs a quantitative research design supported by statistical tools to analyze behavioral variables such as heuristics, prospect theory, market factors, and herding behavior. These variables are measured using structured questionnaires and analyzed through techniques like Exploratory Factor Analysis (EFA), Cronbach's Alpha reliability testing, and Structural Equation Modeling (SEM), which are widely recognized in behavioral finance studies (Schreiber et al., 2006; Liu, Wu & Zumbo, 2010).

Given the unique characteristics of NEPSE such as high volatility, limited institutional participation, and strong influence of informal information sources the methodology is tailored to reflect the behavioral tendencies of Nepalese investors. The chapter also explains the rationale for selecting a cross-sectional design, the sampling method used to ensure representativeness, and the tools applied to validate the research model. By integrating established behavioral finance frameworks with localized data collection and analysis, this methodology aims to provide robust insights into investor psychology in an emerging market context.

Research Design

The research design acts as the framework for executing this study, directing the methods of data collection, analysis, and interpretation. This study adopts a quantitative research design with a cross-sectional approach, which is appropriate for examining behavioral patterns among investors at a specific point in time. A cross-sectional design enables the researcher to capture a snapshot of investor behavior and its relationship with investment

performance, without requiring long-term observation (Saunders, Lewis, & Thornhill, 2023).

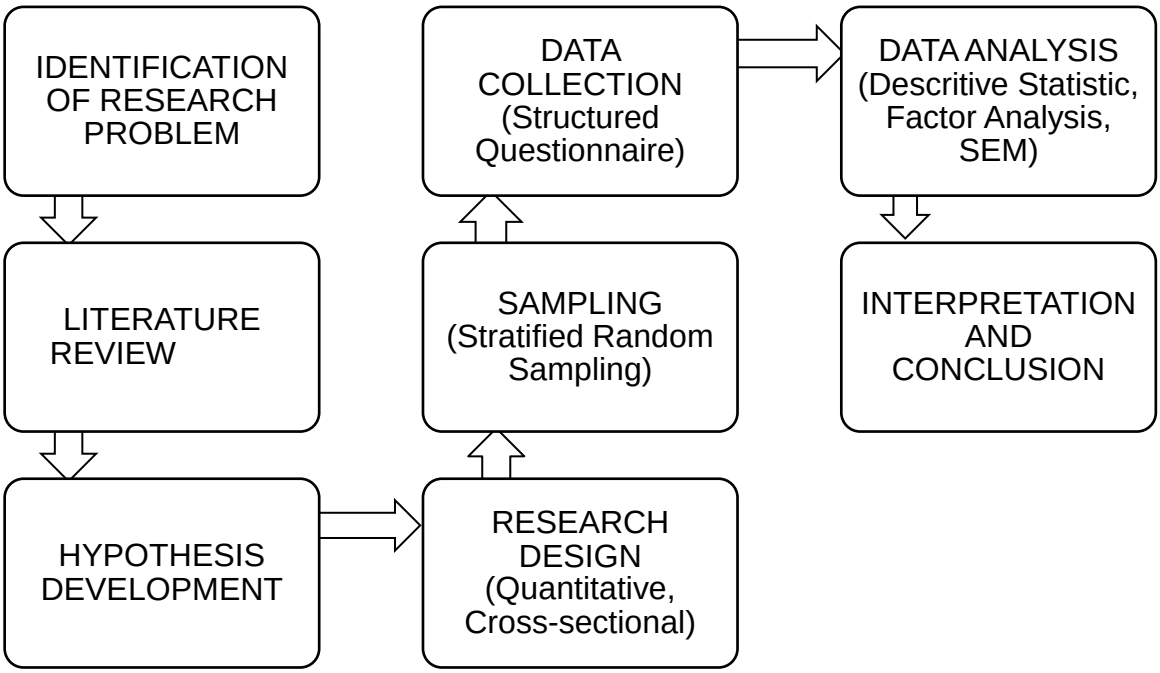
The study is explanatory in nature, aiming to identify and measure the influence of behavioral factors namely heuristic, prospect, market, and herding on investment decisions and performance. This design is particularly suitable for behavioral finance research, where the goal is to test theoretical constructions using empirical data (Creswell & Creswell, 2018). The research also incorporates hypothesis testing, allowing for the validation of proposed relationships between behavioral variables and investment outcomes.

To ensure methodological rigor, the study integrates established statistical techniques such as EFA to identify latent behavioral constructs, Cronbach's Alpha to assess the reliability of measurement scales, and SEM to evaluate the strength and direction of relationships among variables. These tools are widely used in behavioral finance research and provide a robust framework for analyzing complex behavioral patterns (Schreiber et al., 2006).

Given the context of NEPSE, an emerging market characterized by volatility, limited institutional participation, and strong influence of informal information sources, the chosen research design is both practical and contextually relevant. It allows for the collection of data from a diverse group of individual investors and supports the development of insights that are grounded in both theory and local market dynamics.

Figure 2

Research Design Flowchart



This figure illustrates the sequential steps followed in the research process from identifying the research problem to interpreting the results ensuring a systematic approach to analyzing behavioral factors influencing investment decisions at NEPSE.

Population and sample, and sampling design

The population for this study comprises individual investors actively participating in the Nepal Stock Exchange (NEPSE). These investors include a diverse group ranging from students and corporate employees to self-employed and foreign employees. Given the behavioral nature of the study, it was essential to select a sample that reflects the heterogeneity of NEPSE participants in terms of investment experience, background, and exposure to financial information.

To ensure representativeness and minimize sampling bias, the study employed a stratified random sampling technique. The population was divided into four distinct strata based on investor type: students, corporate staff, self-employed, and foreign employees. From each stratum, respondents were randomly selected to participate in the survey. This method allowed for proportional representation of each group and enhanced the generalizability of the findings.

A total of 600 questionnaires were disseminated via online platforms such as Google Forms, utilizing social media channels including Facebook, WhatsApp, and Viber. Of

these, 390 valid responses were collected, yielding a response rate of 65%, which is deemed satisfactory for behavioral finance research conducted through self-administered surveys (Bryman & Bell, 2011).

The distribution of questionnaires across different investor groups is presented in the table below:

Table 3

Questionnaires distributed according to different population groups

S. No	Group	Number of questionnaires sent	% of number of questionnaires sent
1	Student	150	25%
2	Corporate Staff	250	42%
3	Self-employed	125	21%
4	Foreign Employee	75	13%

The majority of responses were collected from corporate staff, who generally possess a moderate to high level of financial awareness and access to investment resources. However, the inclusion of students and full-time investors ensures that the sample captures a broad spectrum of behavioral tendencies. Although foreign employees represent a smaller portion of the sample, their inclusion adds diversity and reflects the growing interest of non-resident investors in NEPSE.

This sampling approach ensures that the findings of the study are reflective of the broader investor population in Nepal and provides a reliable basis for analyzing the behavioral factors influencing investment decisions and performance.

Nature and Sources of data, and the instrument of data collection

Among the different methods for data collection, including structured interviews, semi-structured interviews, unstructured interviews, self-completion questionnaires, observation, and group discussions, the self-completion questionnaire was chosen for gathering quantitative data in this research.

Self-completion questionnaires are widely recognized as one of the most common tools in quantitative research. In this method, respondents independently complete the questionnaire without the presence of an interviewer. This approach was chosen for several reasons. Firstly, since the research questions are clearly defined, the use of a

questionnaire ensures standardized data, which is easier to process and analyze. Secondly, the absence of an interviewer during completion reduces the risk of interviewer bias. Additionally, this method is more cost-effective compared to alternatives like face-to-face interviews, which can be expensive and time-consuming. Self-completion questionnaires also allow for efficient distribution, enabling researchers to reach a large number of respondents simultaneously (Bryman & Bell, 2011). Given that the target respondents are investors who may have limited availability, this method offers flexibility, allowing them to respond at their convenience. Furthermore, it may encourage more honest responses, especially when sensitive information is involved, as there is no direct interaction with a researcher (Bryman & Bell, 2011).

Self-completion questionnaires can be categorized into two types based on distribution: postal questionnaires and delivery-collection questionnaires (Saunders et al., 2023). Bryman and Bell (2011) also describe these two options. The first involves sending questionnaires to selected respondents and requesting them to return the completed forms by mail or submit them to designated individuals or locations. The second involves personally delivering the questionnaire to each respondent and collecting it immediately after completion (Saunders et al., 2023). For this study, the first method was adopted due to geographical distance between the researcher and participants. Questionnaires were distributed via Google Forms using various social media platforms such as Facebook, WhatsApp, and Viber.

Although distributing questionnaires through intermediaries may introduce bias due to limited control over respondent selection, steps were taken to minimize this risk. First, investors were clearly informed about the concept of random sampling and instructed on how to select respondents accordingly. Second, they were asked to strictly follow the instructions provided. These measures helped reduce potential bias and improve the reliability of the data.

In conclusion, this study collected quantitative data through self-completion questionnaires distributed to individual investors. The responses gathered offer foundational insights into the behavioral factors influencing investment decisions.

Design of Measurements and Questionnaire

The questionnaire is organized into three primary sections: demographic information, behavioral influences on investment choices, and investment results. The demographic section utilizes both nominal and ordinal scales. Nominal scales are applied for

categorizing data, while ordinal scales serve the dual purpose of classification and establishing a ranking order of responses (Ghauri & Gronhaug, 2010). The specific measurements used in this section are outlined in Table 4.

Table 4

Types of measurements for personal information

Individual Information	Questions	Types of measurements
Classifying: Gener, Marital status, Security company, Attendance of security course	Questions 1, 3, 8, 9	Nominal Scale
Classifying and ranking orders of: Age, Educational level, Years of working, Income, Attendance time of stock market, Amount of Investment.	Questions 2, 4, 5, 6, 7, 10, 11	Ordinal Scale

This study is grounded in key behavioral finance theories, including heuristic theory, prospect theory, and other frameworks that examine how psychological factors influence investor decision-making. These theories, as discussed by Waweru et al. (2008) and other scholars referenced in the literature review, were used to develop a set of questions aimed at identifying the behavioral influences on both investment decisions and performance.

To gather responses, the study employed a six-point Likert scale, a commonly used tool for measuring attitudes and opinions (Fisher, 2010). Respondents were asked to indicate their level of agreement with statements related to behavioral influences on their investment choices and outcomes. The scale ranged from 1 to 6, where 1 represented "strongly disagree" and 6 represented "strongly agree," with intermediate levels reflecting varying degrees of agreement or disagreement.

The six-point scale was chosen to minimize central tendency bias, which is more common in five-point or seven-point scales where respondents often select the midpoint. The questionnaire was reviewed and approved by the research supervisor before finalization. A copy of the questionnaire is included in **Appendix 1**.

Table 5

Measurement of the 6 Likert scale

Group	Dimensions	Questions	Measurements

Behavioral	Heuristic:		6-point Likert
	iv. Representativeness	Questions 12 – 13	
	v. Overconfidence	Question 14	
	vi. Anchoring	Question 15 - 16	
	vii. Gambler's fallacy	Question 17	
	viii. Ability bias	Question 18 - 19	
	Prospect:		6-point Likert
	ix. Loss aversion	Questions 20 -21	
	x. Regret aversion	Questions 22 – 23	
	xi. Mental accounting	Questions 24 - 25	
	Market:		6-point Likert
	xii. Price changes	Questions 26 - 31	
	xiii. Market information		
	xiv. Past trends of stocks		
	xv. Fundamentals of underlying stocks		
	xvi. Customer preference		
	xvii. Overreaction to price changes		
	Herding:		6-point Likert
	xviii. Following the others' trading actions (buying and selling, choice of stock, volume of stock and speed of herding)	Questions 32 - 35	
Investment Performance	Investment Performance:		6-point Likert
	xix. Return rate and satisfaction of investment decisions	Questions 36 - 38	

Methods of analysis

The data collected for this study was analyzed using SPSS and AMOS software. Initially, the dataset was cleaned by removing responses that contained excessive missing values or showed signs of biased ratings. Several statistical methods were then applied to meet the research objectives, including descriptive statistics, factor analysis, Cronbach's alpha reliability testing, and structural equation modeling.

Descriptive Statistics:

Basic statistical measures such as mean, median, mode, variance, and standard deviation were used to summarize the demographic characteristics of the respondents. These statistics also helped assess the influence of behavioral variables on investment performance. Only the variables that passed the exploratory factor analysis and reliability

testing were included in this part of the analysis. This approach was used to evaluate the extent to which behavioral traits affect investment decisions at the Nepal Stock Exchange.

Factor Analysis

Factor analysis is a multivariate technique used to uncover the underlying structure within a dataset by identifying groups of related variables, known as factors (Ghauri and Gronhaug, 2010). Questionnaire items were grouped into domains that shared similar characteristics (O'Brien, 2007). Two types of factor analysis were considered: exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). EFA was used to identify the latent constructs within the behavioral and performance-related variables from questions 12 to 38. CFA was used to validate the factor structure based on theoretical expectations (Liua and Salvend, 2009). EFA also helped eliminate items that did not meet the required analytical standards.

The criteria used in EFA included factor loadings, the Kaiser-Meyer-Olkin (KMO) measure, total variance explained, and eigenvalues. Factor loadings represent the correlation between each item and its corresponding factor. A loading above 0.5 is considered meaningful, especially with a sample size of 100 or more (Hair et al., 1998). The KMO value, which assesses the adequacy of the sample for factor analysis, should fall between 0.5 and 1.0, with a significance level below 0.005 (Ali, Zairi, and Mahat, 2006). The total variance explained should exceed 50 percent to ensure that the retained factors account for a substantial portion of the data (Hair et al., 1998). Eigenvalues indicate the amount of variance explained by each factor and should be greater than 1 to be considered valid (Leech, Barrett, and Morgan, 2005). All EFA procedures were conducted using SPSS.

Cronbach's Alpha Test

To assess the internal consistency of the measurement scales, Cronbach's alpha was applied to the continuous variables, including those measured using the six-point Likert scale. This test evaluates how consistently respondents answered related items (Helms, Henze, Sass, and Mifsud, 2006). Cronbach's alpha is widely used in behavioral and social science research to determine reliability (Liu, Wu, and Zumbo, 2010). Given the nature of this study and the use of Likert-type items, Cronbach's alpha was appropriate for evaluating the reliability of the factors identified through EFA.

A Cronbach's alpha value of 0.7 or higher is generally considered acceptable, although values above 0.6 may also be deemed sufficient in exploratory research (Cheung et al., 2024; Shelby, 2011). In addition, corrected item-total correlations were examined, with values above 0.3 indicating acceptable consistency (Shelby, 2011). These thresholds were selected because the behavioral finance constructs used in this study are relatively new to investors in Nepal. The significance level for the F-test in Cronbach's alpha was set at 0.05 or lower. Both SPSS and AMOS were used to perform the reliability analysis.

Structural Equation Modeling (SEM):

SEM combines confirmatory factor analysis and multiple regression to examine relationships among latent variables (Schreiber et al., 2006). In this study, SEM was used to validate the behavioral factors identified through EFA and Cronbach's alpha and to estimate their influence on investment performance. The model tested the hypotheses H1 through H4 presented in Chapter 1.

AMOS software was used to conduct the SEM analysis. Model fit was evaluated using several indices. According to Alsberg, Bowers, Renk, and McKinney (2008), a model is considered acceptable if the root mean square error of approximation (RMSEA) is 0.10 or lower, the comparative fit index (CFI) is 0.90 or higher, and the parsimonious fit index (PFI) is at least 0.60. Schreiber et al. (2006) provided a comprehensive set of criteria for assessing SEM model fit, which are summarized in Table 6.

Table 6

Criteria for an accepted SEM (Source: Schreiber, et al., 2006)

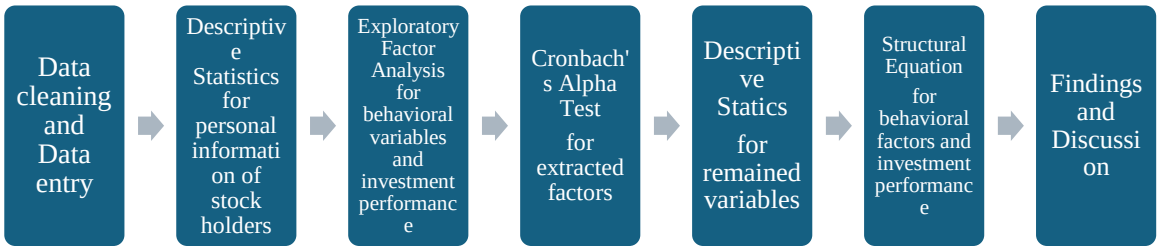
Indexes	**Shorthand**	**General rule for acceptable fit**
Absolute/predictive fit		
Chi-square	χ^2	Ratio of χ^2 to df ≤ 2 or 3
Akaike information criterion	AIC	Smaller the better
Browne-Cudeck criterion	BCC	Smaller the better
Bayes information criterion	BIC	Smaller the better
Consistent AIC	CAIC	Smaller the better
Expected cross-validation index	ECVI	Smaller the better

Figure 3

The process of data analysis

Comparative fit		
Normed fit index	NFI	≥ .95 for acceptance
Incremental fit index	IFI	≥ .95 for acceptance
Tucker-Lewis's index	TLI	≥ .95 for acceptance
Comparative fit index	CFI	≥ .95 for acceptance
Relative no centrality fit index	RNI	≥ .95, similar to CFI
Parsimonious fit		
Parsimony-adjusted NFI	PNFI	Very sensitive to model size
Parsimony-adjusted CFI	NCFI	Sensitive to model size
Parsimony-adjusted GFI	PGFI	Closer to 1 the better
Other		
Goodness-of-fit index Adjusted GFI	GFI	≥ .95
Adjusted Goodness of Fit Index	AGFI	≥ .95
Root means square residual	RMR	Smaller, the better
Standardized RMR	SRMR	≤.08
Weighted root mean residual	WRMR	<.90
Root means square error of approximation	RMSEA	<.06 to .08

In this research, the criteria for an accepted SEM, outlined in Table 6, are utilized to evaluate the model fit of the collected data. A summary of the data processing and analysis is illustrated in Figure 3.



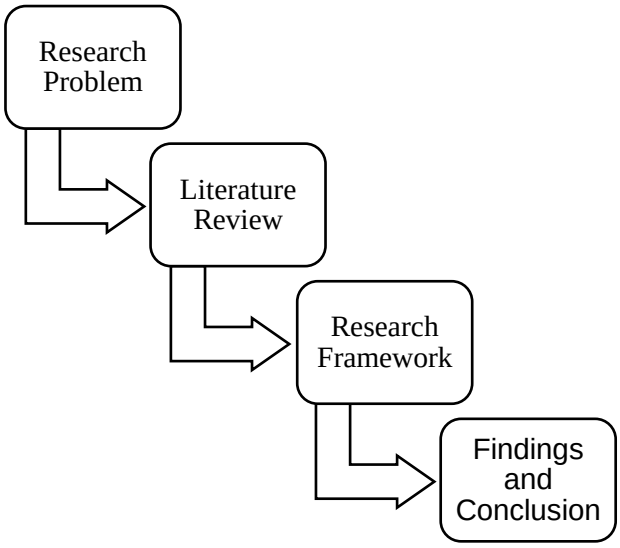
Research framework and definition of variables

The research framework provides a structured representation of the connection between behavioral factors and investment performance. It is developed based on the theoretical foundations of behavioral finance and empirical findings from previous studies. The framework assumes that investor behavior is influenced by four key behavioral dimensions: heuristic factors, prospect factors, market factors, and herding behavior. These behavioral factors are treated as independent variables, while investment performance is considered the dependent variable.

The framework is designed to test the extent to which each behavioral factor influences investment performance among individual investors at NEPSE. It also supports hypothesis testing through Structural Equation Modeling (SEM), allowing for the evaluation of direct and indirect effects of behavioral biases on investment outcomes.

Figure 4

Research Framework Diagram



Definition of Variables

Independent Variables: Herding, Market, Prospect, Heuristic

This is the variable that is manipulated or categorized to observe its effect on another variable. In the context of the research, the independent variables are the investors' behavioral factors such as Herding, Market, Prospect and Heuristic. These factors are manipulated or categorized to observe their effect on Investment Performance.

i. **Heuristic Factors**: These refer to mental shortcuts or simplified decision-making strategies used by investors. In this study, heuristic factors include:
    a. Overconfidence: The tendency of investors to overestimate their knowledge or predictive ability.
    b. Anchoring: Relying heavily on initial information (e.g., purchase price) when making decisions.
    c. Availability Bias: Making decisions based on readily available or recent information.

   d. Gambler's Fallacy: Expecting a reversal in stock trends based on past sequences.

ii. **Prospect Factors**: Derived from prospect theory, these factors describe how investors perceive gains and losses:
   a. Loss Aversion: The tendency to avoid losses more strongly than acquiring equivalent gains.
   b. Regret Aversion: Avoiding decisions that could lead to future regret.
   c. Mental Accounting: Treating each investment separately rather than as part of a portfolio.

iii. **Market Factors**: These are external influences that affect investor decisions:
   a. Price Changes: Sensitivity to recent stock price movements.
   b. Market Information: Influence of news, announcements, and data on decision-making.
   c. Past Trends: Use of historical stock performance to guide current decisions.

iv. **Herding Behavior**: The tendency of investors to follow the actions of others rather than relying on their own analysis. This includes:
   a. Mimicking others' buying/selling decisions.
   b. Following the crowd in stock selection and trading volume.

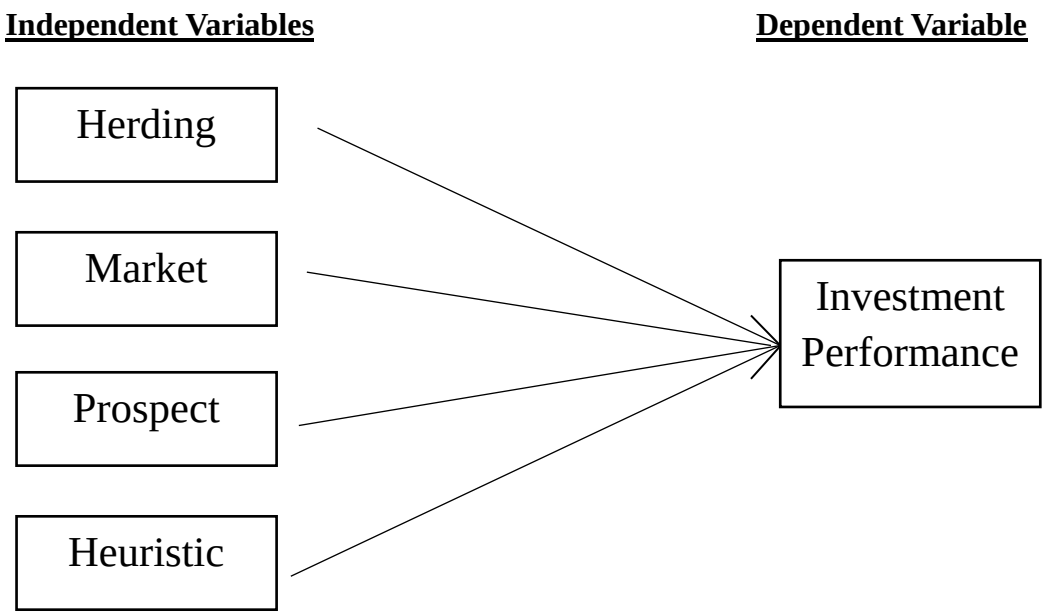
Dependent Variable:

This is the variable that is measured to see if it is affected by changes in the independent variable. For this research, the dependent variable is Investment Performance, which can be measured by metrics like returns on investment, risk-adjusted returns, and portfolio volatility. It is the outcome that is influenced by the independent variables.

i. **Investment Performance**: This refers to the outcome of investment decisions measured through:
   a. Return Rate: The actual return compared to expected or market average.
   b. Satisfaction Level: The investor's subjective evaluation of their investment decisions.

Figure 5

Dependent and Independent Variables


Independent Variables
Dependent Variable
Herding
Market
Prospect
Heuristic
Investment Performance

CHAPTER IV

Results and Discussion

Results

Out of 600 questionnaires distributed to individual investors at the Nepal Stock Exchange through email and social media platforms, 390 valid responses were received. This results in a response rate of 65 percent, which is considered moderately high for a survey conducted via mail. The demographic and investment-related characteristics of these 390 respondents such as gender, age, duration of market participation, and total investment amount are described in the following section.

Figure 6

Sample distributions of Gender, Age, and Time for attending stock market

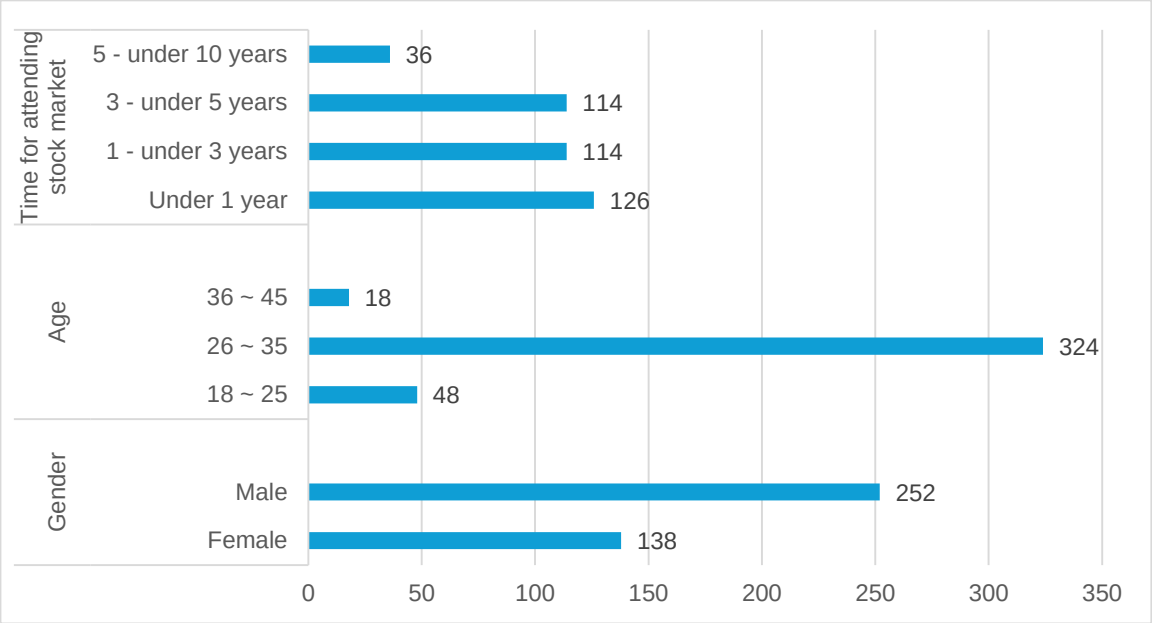


Figure 6 illustrates that male investors make up a larger portion of the sample, accounting for approximately 65 percent, while female investors represent about 35 percent. This gender distribution may indicate a potential gender bias in the study. The majority of respondents fall within the 26 to 35 age group, comprising 83 percent of the total sample. Additionally, 12 percent are aged between 18 and 25, and only 5 percent fall within the 36 to 45 age range. These figures suggest that a significant share of NEPSE investors are under the age of 35, meaning the study primarily reflects the behaviors of younger investors.

Regarding market experience, a large portion of participants have been involved in stock trading for less than five years. Specifically, 32 percent have participated for under one year, 29 percent for one to less than three years, and another 29 percent for three to less than five years. Only 9 percent have been active in the market for more than five but fewer than ten years. These statistics indicate that the sample closely represents the current investor base at NEPSE. The growing accessibility of online trading platforms and the influence of social media in recent years have contributed to a surge in new investors entering the market.

Figure 7

Proportion of respondents attending the course in Stock Exchange

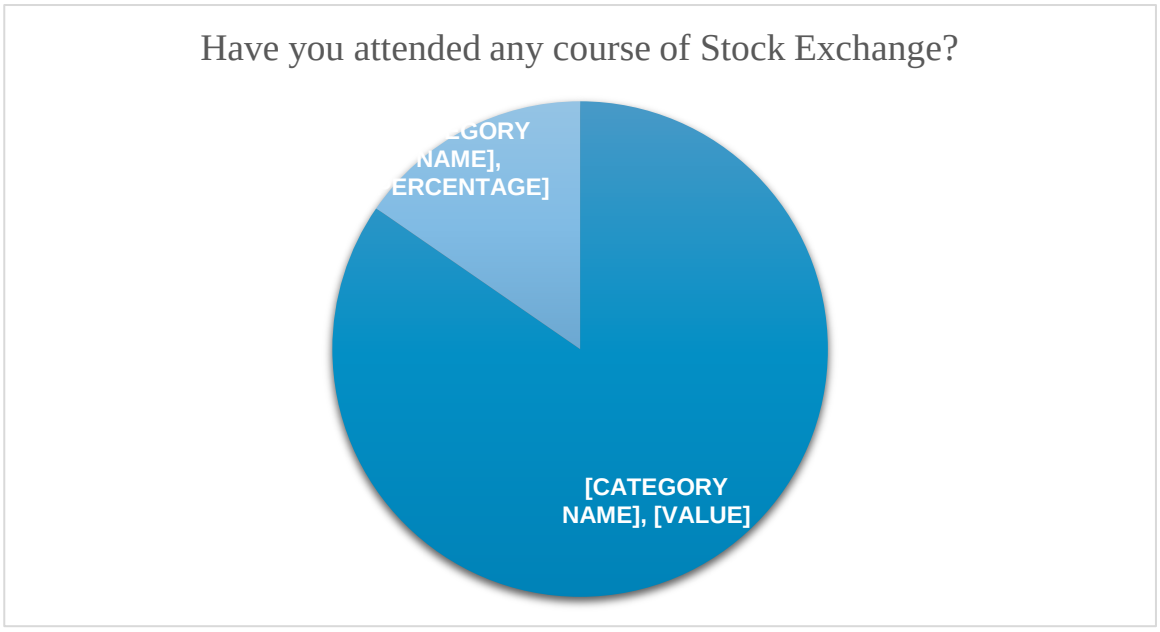
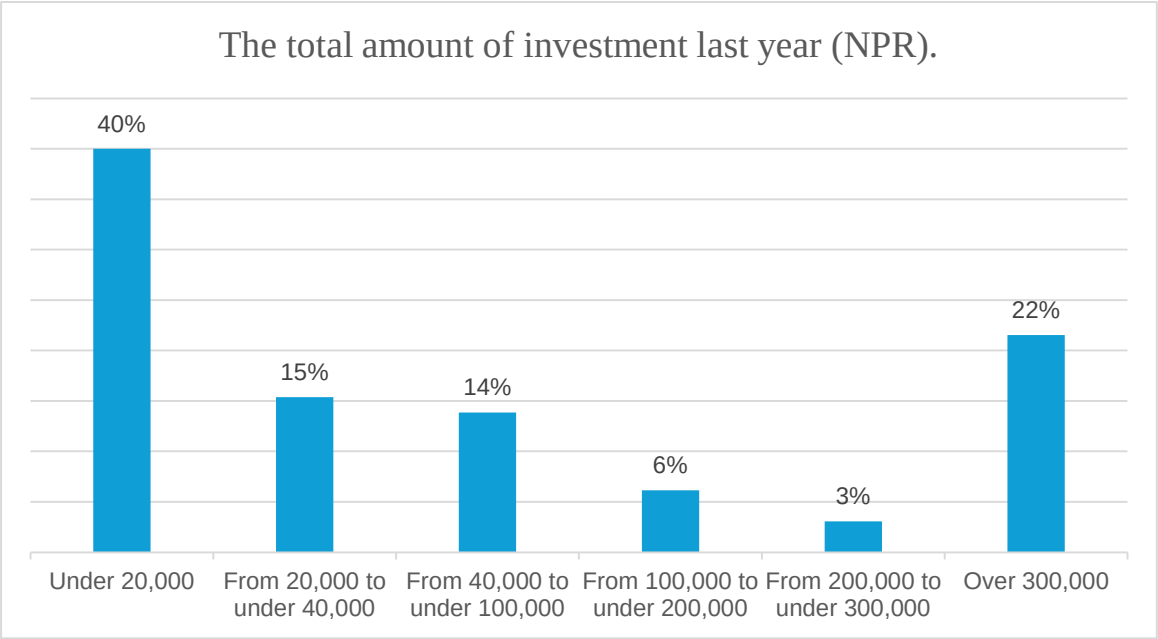


Figure 7 indicates that only 15 percent of the individual investors surveyed have completed a stock trading course, while the remaining 85 percent have not received any formal training in this area.

Figure 8

Percentages of respondents with their ranges of last-year investment



Although the respondents reported investment amounts ranging from NPR 20,000 to over NPR 300,000 in the past year, a larger portion of them invested less than NPR 200,000. Specifically, 15 percent invested between NPR 20,000 and NPR 40,000, 14 percent between NPR 40,000 and NPR 100,000, 6 percent between NPR 100,000 and NPR 200,000, and 3 percent between NPR 200,000 and NPR 300,000. Additionally, 22 percent of participants reported investing more than NPR 300,000 during the same period, as shown in Figure 7.

Overall, the sample primarily consists of investors aged 26 to 35 who are relatively new to the stock market. This is understandable given that NEPSE is a relatively young exchange and Nepal's capital market is still considered to be in a pre-emerging phase. The sample also includes individuals who have completed stock trading courses, indicating a certain level of awareness and knowledge about investing.

4.1 Factor analysis of behavioral variables influencing the individual investment decisions and the variables of investment performance

Questions 12 to 35 in the questionnaire, labeled as variables X1 through X24, were designed to assess the extent to which behavioral factors influence individual investment decisions at NEPSE. Meanwhile, questions 36 to 38, coded as Y1 to Y3, were intended to capture how investors evaluate their own investment performance.

Exploratory Factor Analysis (EFA) was applied to both sets of variables X1 to X24 for behavioral traits and Y1 to Y3 for performance evaluation to determine the underlying factor structure. The analysis followed the criteria outlined in Chapter 3 to ensure the validity of the results. After several iterations of removing variables that did not meet the required standards, the remaining items were grouped into six distinct factors: five representing behavioral dimensions and one representing investment performance.

The final EFA results showed strong statistical validity, with an eigenvalue of 1.007, a Kaiser-Meyer-Olkin (KMO) measure of 0.728 (significance level = 0.000), and a total variance explained of 68.32 percent. All factor loadings exceeded the threshold of 0.5. These results confirm that the factor analysis was appropriate and statistically sound. A summary of the findings is presented in Table 6, with detailed SPSS output provided in **Appendix 2.**

Table 7

Factor analysis for behavioral variables and investment performance

Factors	Variables	Factor Loadings					
		F1	F2	F3	F4	F5	F6
Herding	X21: Other investors' decisions of choosing stock types have impact on your investment decisions.	0.634					
	X22: Other investors' decisions of the stock volume have impact on your investment decisions.	0.875					
	X23: Other investors' decisions of buying and selling stocks have impact on your	0.831					

	investment decisions.					
	X24: You usually react quickly to the changes of other investors' decisions and follow their reactions to the stock market.	0.823				
Prospect	X10: After a prior loss, you become more risk averse.		0.668			
	X11: You avoid selling shares that have decreased in value and readily sell shares that have increased in value.		0.641			
	X13: You tend to treat each element of your investment portfolio separately.		0.748			
	X14: You ignore the connection between different investment possibilities		0.569			
Market	X15: You consider carefully the price changes of stocks that you intend to invest in.			0.782		
	X17: Market information is important for your stock investment.			0.837		
	X18: You put the past trends of stocks under your consideration for your investment.			0.738		
Overconfidence and Gambler's fallacy	X3: You believe that your skills and knowledge of stock market can help you to outperform the market.				0.808	
	X6: You are normally able to anticipate the end of good or poor.				0.838	
Anchoring and Ability bias	X5: You forecast the changes in stock prices in the future					0.554

	based on the recent stock prices	
	X7: You prefer to buy local stocks than international stocks because the information of local stocks is more available.	0.556
Investment Performance	Y1: The return rate of your recent stock investment meets your Expectation.	0.870
	Y2: Your rate of return is recently equal to or higher than the average return rate of the market.	0.830
	Y3: You feel satisfied with your investment decisions in the last year (including selling, buying, choosing stocks, and deciding the stock volumes).	0.776

As illustrated in Table 7, the behavioral variables associated with herding, prospect, and market dimensions were each consolidated into distinct and coherent factors. In contrast, the heuristic-related variables were split into two distinct categories: overconfidence gambler's fallacy and anchoring–availability bias. This outcome slightly diverges from the initial expectation that all behavioral variables would align under four primary categories herding, prospect, market, and heuristic as proposed by Waweru et al. (2008). Nevertheless, the findings largely align with the conceptual framework outlined in Chapter 3 under the Methods of Analysis, which anticipated that behavioral influences on investment decisions at the Nepal Stock Exchange would be categorized into four overarching groups.

The analysis ultimately identified five behavioral dimensions that significantly affect the investment decisions of individual investors at NEPSE. Within the herding category, all four original questionnaire items (questions 32 to 35, coded X21 to X24) were retained following factor analysis. For the market dimension, three out of six initial items

(questions 26 to 31, coded X15 to X20) were validated. Similarly, four of the six prospect-related items (questions 20 to 25, coded X9 to X14) were preserved. Regarding heuristic variables, only four of the original eight items (questions 12 to 19, coded X1 to X8) met the criteria for inclusion, and these were further divided into the two aforementioned subgroups.

Additionally, Table 7 indicates that all three items related to investment performance (questions 36 to 38, coded Y1 to Y3) were validated through factor analysis and grouped into a single construct. This suggests that Factor 6 (F6) effectively represents the investment performance dimension, while Factors F1 through F5 correspond to the various behavioral constructs identified.

4.2 Reliability assessment of measurement using Cronbach's Alpha

This section applies Cronbach's Alpha to evaluate the internal consistency of the items grouped under each factor identified through factor analysis. The purpose of this test is to ensure that the measurement items are dependable for subsequent analysis. The outcomes of the Cronbach's Alpha test are presented in Table 8.

Table 8

Cronbach's Alpha Test for items of factors

Factors	Variables	Cronbach's Alpha	Corrected Item-total Correlation	Cronbach's alpha if Item deleted	F (sig.)
Herding	X21	0.85	0.58	0.85	45.72 (<.001)
	X22		0.76	0.78	
	X23		0.72	0.79	
	X24		0.72	0.79	
Prospect	X10	0.72	0.408	0.72	34.91 (<.001)
	X11		0.649	0.57	
	X13		0.509	0.57	
	X14		0.479	0.67	
Market	X15	0.831	0.63	0.83	32.58 (<.001)
	X17		0.77	0.68	
	X18		0.68	0.77	
Overconfidence	X3	0.85	0.75	-	9.28

and Gambler's fallacy	X6		0.75	-	(.002)
Anchoring and Ability bias	X5	0.63	0.45	-	64.22 (<.001)
	X7		0.45	-	
Investment Performance	Y1	0.85	0.66	0.85	3.02 (.05)
	Y2		0.83	0.7	
	Y3		0.68	0.83	

According to the table, all factors exhibit Cronbach's Alpha values exceeding 0.6, and the corrected item total correlations for each item are above 0.30. Furthermore, the Cronbach's Alpha value for each factor decreases when any individual item is removed, and the significance level of the F test for each factor, which assesses the appropriateness of using Cronbach's Alpha for the dataset, is below 0.05 (refer to Chapter 3 for further explanation of these indicators). These results confirm that the items under the factors Herding, Prospect, Market, Overconfidence and Gambler's Fallacy, Anchoring and Availability Bias, and Investment Performance—are sufficiently reliable for further statistical procedures, including Structural Equation Modeling, to examine the relationships among the variables. Additional details regarding the Cronbach's Alpha calculations performed using SPSS are available in **Appendix 3**.

4.3 Influence Levels of Behavioral Variables on Investment Decisions and Evaluation of Investment Performance

The extent to which behavioral variables affect investment decisions has been determined by calculating the average scores of each variable based on the responses. Similarly, the evaluation of investment performance is based on the mean scores derived from participants' assessments of each performance-related item. In this section, only those variables that satisfied the criteria established through factor analysis and the Cronbach's Alpha reliability test are considered for analysis within the context of NEPSE. Since a six-point scale was used to assess the influence of each variable, the average scores serve as indicators of their respective impact levels on investment decision-making. The interpretation of these mean values follows the guidelines below:

- Mean values are below 2 indicate a very low level of influence.
- Mean values between 2 and 3 indicate a low level of influence.
- Mean values between 3 and 4 indicate a moderate level of influence.

- Mean values between 4 and 5 indicate a high level of influence.
- Mean values above 5 indicate a very high level of influence.

4.3.1 Influence of Heuristic Variables on investment decision making

As previously discussed, the heuristic-related variables were categorized into two distinct groups: Overconfidence and Gambler's Fallacy, and Anchoring and Availability Bias. The effects of these categories are presented in the following table:

Table 9

Influence of Heuristic Variables on investment decision-making

Factors	Variables	Mean	Std. Deviation
Overconfidence and Gambler's fallacy	X3: You believe that your skills and knowledge of stock markets can help you to outperform the market.	3.68	1.46
	X6: You are normally able to anticipate the end of good or poor market returns at the NEPSE.	3.52	1.31
Anchoring and Availability bias	X5: You forecast the changes in stock prices in the future based on the recent stock prices.	3.75	1.28
	X7: You prefer to buy local stocks than international stocks because the information of local stocks is more available.	4.29	1.26

According to the literature review, the heuristic dimension includes behavioral traits such as representativeness, overconfidence, gambler's fallacy, anchoring, and availability bias. However, in this study, the representativeness variable did not meet the reliability criteria and was therefore excluded from the list of behavioral factors influencing individual investor decisions at NEPSE. The variables representing overconfidence (X3), gambler's fallacy (X6), and anchoring (X5) demonstrated moderate influence on investment decisions, with average scores of 3.68, 3.52, and 3.75 respectively. In contrast, the availability bias variable (X7) showed a strong influence, with a mean score of 4.29. Among all heuristic variables, availability bias emerged as the most influential factor affecting investor decisions. This suggests that individual investors at NEPSE often depend on familiar and easily accessible sources of information when making investment

choices. Such sources may include advice from friends, family members, or locally available information, rather than insights from international or less familiar channels. Table 10 presents the summarized results of the influence of heuristic variables on investment decision making.

Table 10

Results of Impact of Heuristic Variables on investment decision making

Factors	Variables	Results
Overconfidence and Gambler's fallacy	X3	Moderate Impact
	X6	Moderate Impact
Anchoring and Availability bias	X5	Moderate Impact
	X7	High Impact

4.3.2 Influence of Prospect Variables on the investment decision making

Table 11

Influence of Prospect Variables on the investment decision-making

Factors	Variables	Mean	Std. Deviation
Prospect	X10: After a prior loss, you become more risk averse.	3.68	1.395
	X11: You avoid selling shares that have decreased in value and readily sell shares that have increased in value.	4.15	1.42
	X13: You tend to treat each element of your investment portfolio separately.	3.91	1.29
	X14: You ignore the connection between different investment possibilities.	3.4	1.41

Within the prospect dimension, all three behavioral tendencies loss aversion, regret aversion, and mental accounting are represented by variables that influence how investors make decisions in the stock market. At NEPSE, individual investors exhibit moderate

levels of loss aversion (X10) and mental accounting (X13 and X14), with average scores of 3.68, 3.91, and 3.4 respectively. In contrast, regret aversion (X11) demonstrates a stronger influence, with a higher mean score of 4.15. Notably, investors show a strong inclination to evaluate each component of their investment portfolio independently, as reflected in the score for X11. In practice, the elements of a portfolio are interconnected and collectively shape investment decisions. Treating these components in isolation may lead to less effective decision-making and could negatively affect overall investment performance. Table 12 presents the summarized results of the influence of prospect-related variables on investment decision making.

Table 12

Result of Impact of Prospect Variables on investment decision making

Factors	Variables	Results
Prospect	X10	Moderate Impact
	X11	High Impact
	X13	Moderate Impact
	X14	Moderate Impact

4.3.3 Influence of Market Variables on investment decision making

The market-related variables that shape individual investment decisions at NEPSE include stock price fluctuations, market information, and historical stock trends. These factors and their effects are summarized in the following table:

Table 13

Influence of Market Variables on investment decision-making

Factors	Variables	Mean	Std. Deviation
Market	X15: You consider carefully the price changes of stocks that you intend to invest in.	4.15	1.47

	X17: Market information is important for your stock investment.	4.65	1.55
	X18: You put the past trends of stocks under your consideration for your investment.	4.54	1.34

According to the data, the market dimension has a strong influence on investor decision making, as reflected in the average scores for stock price changes (X15), market information (X17), and past stock trends (X18), which are 4.15, 4.65, and 4.54 respectively. This indicates that investors tend to carefully consider various forms of market data, including general updates, historical price movements, and current price shifts, before making investment choices. The relatively high standard deviations associated with these variables suggest that some investors place particularly strong emphasis on market-related information when deciding where to invest. Table 14 provides a detailed summary of the influence of market variables on investment decision making.

Table 14

Result of Impact of Market Factor on investment decision making

Factors	**Variables**	**Results**
Market	X15	High Impact
	X17	High Impact
	X18	High Impact

4.3.4 Influence of Herding Variables on the investment decision making

Table 15

Influence of Herding Variables on Investment Decision Making

Factors	**Variables**	**Mean**	**Std. Deviation**

Herding	X21: Other investors' decisions of choosing stock types have impact on your investment decisions.	4.17	1.24
	X22: Other investors' decisions of the stock volume have impact on your investment decisions.	4.05	1.32
	X23: Other investors' decisions of buying and selling stocks have impact on your investment decisions.	3.82	1.39
	X24: You usually react quickly to the changes of other investors' decisions and follow their reactions to the stock market.	3.49	1.44

As shown in Table 11, individual investors at NEPSE tend to moderately follow the trading actions of other investors. They often take into account the decisions of others when selecting stock types (X21, mean score 4.17) and determining the volume of stocks to trade (X22, mean score 4.05). Additionally, the buying and selling choices made by peers (X23, mean score 3.82) also influence their own decisions. However, the speed at which investors react to changes in others' behavior (X24, mean score 3.49) appears to have a relatively lower impact compared to the other herding-related variables. Table 16 summarizes the influence of herding variables on investment decision making.

Table 16

Result of Impact of Herding Factor on investment decision making

Factors	**Variables**	**Results**
Herding	X21	High Impact
	X22	High Impact
	X23	Moderate Impact
	X24	Moderate Impact

Overall, the behavioral variables across the four main categories; Heuristic (split into two subgroups), Prospect, and Herding exhibit either moderate or high levels of influence on the investment decisions of individual investors at NEPSE.

Specifically, the market-related variables (X15, X17, and X18), one heuristic variable (X7), one prospect variable (X11), and two herding variables (X21 and X22) are identified as having strong impacts on decision making.

These findings largely support the framework discussed in Chapter 3 under the Methods of Analysis section, which proposed that behavioral factors significantly affect investment decisions in the context of the Nepal Stock Exchange.

However, the relatively high standard deviations observed across all behavioral variables suggest notable differences in how respondents perceive the influence of these factors. For instance, the average score for price change (X15) is 4.15, with a standard deviation of 1.47, indicating that some investors may rate its impact as high as approximately 5.5.

4.3.5 Investment Performance

Table 17

The results of investment performance

Factors	Variables	Mean	Std. Deviation
Investment Performance	Y1: The return rate of your recent stock investment meets your expectation	3.42	1.36
	Y2: Your rate of return is recently equal to or higher than the average return rate of the market.	3.52	1.23
	Y3: You feel satisfied with your investment decisions in the last year (including selling, buying, choosing stocks, and deciding the stock volumes).	3.54	1.32

Table 12 indicates that the investment outcomes generally align with the expectations of individual investors. The average return rates are moderate when compared both to personal expectations (Y1, mean score 3.42) and to the overall market average (Y2, mean score 3.52). Additionally, investors reported a moderate level of satisfaction with their investment decisions over the past year, including actions such as buying, selling, selecting stocks, and determining trade volumes (Y3, mean score 3.54). These findings

suggest that there is room for improvement in investment performance, which could be achieved by addressing the influence of behavioral factors.

5.4 Influences of Behavioral Factors on Investment Performance

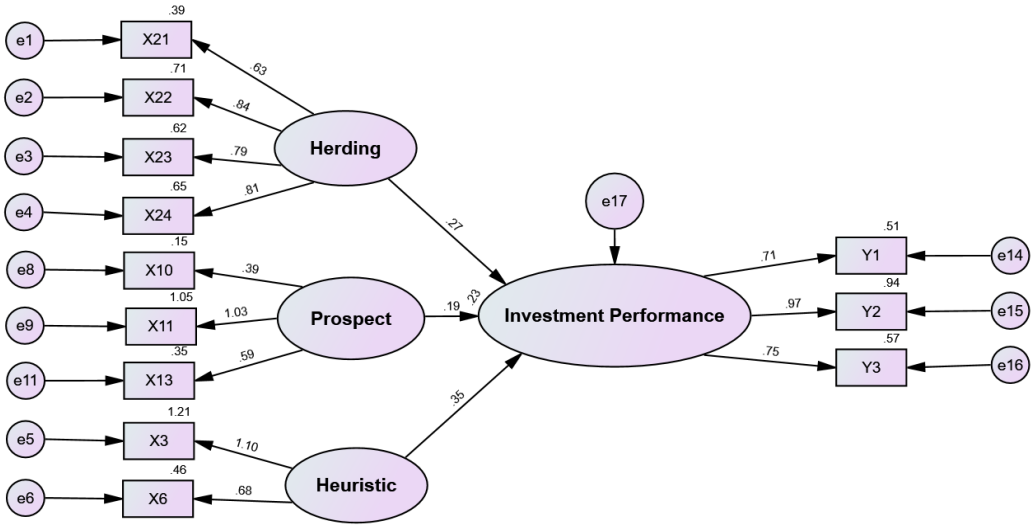
This section uses Structural Equation Modeling (SEM) to examine the relationships among the variables. SEM integrates multiple regression analysis with factor analysis into a single framework. One component of SEM, known as Confirmatory Factor Analysis (CFA), is used to validate whether the factors and their associated variables (identified earlier through Exploratory Factor Analysis) are appropriate for inclusion in the structural model. The other component, multiple regression, estimates the strength of the relationships between the behavioral factors (independent variables) and investment performance (dependent variable). The SEM results generated using AMOS are illustrated in Figure 9.

The model demonstrates a strong fit, with the following indicators: Goodness of Fit Index (GFI) = 0.95, Tucker Lewis Index (TLI) = 0.96, Comparative Fit Index (CFI) = 0.95, Root Mean Square Error of Approximation (RMSEA) = 0.08, CMIN divided by degrees of freedom = 2.25, and a p-value of 0.00. These values meet the criteria for a well-fitting model as outlined in Table 6 of Chapter 3, confirming the model's predictive validity for the data collected. Additional SEM output details are available in **Appendix 4**.

Figure 9 displays the factor loadings, regression weights between variables, and the proportion of variance explained by each factor. The model identifies three behavioral dimensions that significantly influence investment performance: Herding (X21, X22, X23, X24), Prospect (X10, X11, X13), and Heuristic (X3, X6). All factor loadings exceed 0.5, confirming the convergent validity of the measurement model. Among these, heuristic behaviors specifically overconfidence (X3) and gambler's fallacy (X6) have the strongest positive effect on investment performance, with a regression coefficient of 0.35 (significance level = 0.00). Herding behaviors also show a positive influence, with a coefficient of 0.27 (significance level = 0.00). Prospect-related behaviors, including loss aversion (X10), regret aversion (X11), and mental accounting (X13), contribute positively as well, with a regression coefficient of 0.19 (significance level = 0.00). Collectively, these three behavioral dimensions account for 23 percent of the variation in investment performance among individual investors at NEPSE.

Figure 9

Structural Equation Modeling for Behavioral Factors and Investment Performance



Key Findings from the Diagram:

i. Heuristic Factor has the strongest positive impact on investment performance (regression weight = 0.35).
ii. Herding Factor also positively influences performance (regression weight = 0.27).
iii. Prospect Factor has a moderate positive impact (regression weight = 0.19).

The Market factor was excluded from the Structural Equation Modeling (SEM) analysis of investment performance. Although it had a strong influence on investment decision-making (with mean scores above 4), it did not exhibit a statistically significant regression weight with investment performance. As a result, it was omitted from the SEM path diagram (Figure 9). Therefore, hypothesis H2 is not supported.

The findings indicate that investment performance can be enhanced by simultaneously improving heuristic, herding, and prospect behaviors. Interestingly, although market variables significantly influence investment decision making, they do not have a notable impact on investment performance. The Structural Equation Modeling (SEM) results support hypotheses H1, H3, and H4, which propose that behavioral factors Heuristic, Prospect, Herding, and Market have a positive relationship to investment performance.

In summary, the four hypotheses presented in Chapter 1 have undergone testing. The results of these hypothesis evaluations are consolidated in the table below.

Table 18

The results of hypothesis tests

Hypotheses	Contents of Hypotheses	Findings	Contents of findings
H1	There is a positive relationship between Herding and Investment Performance.	The findings support H1	The results given by SEM support the hypothesis H1 that mentions that Heuristic Factor has the strongest positive impact on investment performance (regression weight = 0.35).
H2	There is a positive relationship between Market and Investment Performance.	The findings do not support H2	While these had a high influence on decision-making, they did not significantly impact investment performance. This suggests that reacting to market signals alone doesn't guarantee better returns.
H3	There is a positive relationship between Prospect and Investment Performance.	The findings support H3	Prospect Factor has a moderate positive impact (regression weight = 0.19).
H4	There is a positive relationship between Heuristic and Investment Performance.	The findings support H3	Herding Factor also positively influences performance (regression weight = 0.27).

Discussion

This section interprets the findings of the study in light of behavioral finance theories and empirical results. It explores how various psychological and market-related factors influence investment decisions and performance among individual investors at the Nepal Stock Exchange (NEPSE). The discussion is structured into three thematic areas: Behavioral Factors, Investment Performance, and the Effect of Behavioral Factors on Investment Performance.

Behavioral Factors

The first objective of the study was to identify the behavioral factors that influence investment decisions of individual investors at the Nepal Stock Exchange (NEPSE). Based on the results of factor analysis and reliability testing, four major behavioral dimensions were confirmed: Heuristic, Prospect, Market, and Herding.

The heuristic factors were divided into two subgroups: overconfidence–gambler's fallacy and anchoring–availability bias. Among these, availability bias had the strongest influence (mean = 4.29), indicating that investors tend to rely on easily accessible and familiar information, such as advice from friends or local news, rather than conducting independent analysis. Overconfidence (mean = 3.68), anchoring (mean = 3.75), and gambler's fallacy (mean = 3.52) showed moderate influence, suggesting that while investors believe in their own judgment, they also tend to base decisions on recent trends or expect reversals in market patterns.

The prospect factors, which include loss aversion, regret aversion, and mental accounting, also influenced investment decisions. Regret aversion had a high impact (mean = 4.15), showing that investors are more likely to sell winning stocks to avoid future regret, even if it means holding onto losing ones. Mental accounting (mean = 3.91) and loss aversion (mean = 3.68) had moderate impacts, indicating that investors often treat each investment separately and become more cautious after experiencing losses.

The market factors had the highest overall influence on investment decisions. Market information (mean = 4.65), past trends (mean = 4.54), and price changes (mean = 4.15) were all rated highly. This suggests that NEPSE investors are highly responsive to external signals and rely heavily on market data and trends when making investment decisions.

The herding factors also showed significant influence. Investors tend to follow others in choosing stock types (mean = 4.17) and volumes (mean = 4.05), though they are less reactive to rapid changes in peer behavior (mean = 3.49). This indicates a cautious form of herding, where investors seek validation from others but still exercise some level of independent judgment.

These findings fulfill the first objective by clearly identifying the behavioral factors that shape investment decisions at NEPSE.

Table 19

Influence Levels of Behavioral Factors on Investment Decisions

Factor Group	Variable	Mean Score	Impact Level
Heuristic	Availability Bias	4.29	High
	Overconfidence	3.68	Moderate
	Anchoring	3.75	Moderate
	Gambler's Fallacy	3.52	Moderate
Prospect	Mental Accounting	3.91	Moderate
	Loss Aversion	3.68	Moderate
	Regret Aversion	4.15	High
Market	Price Changes	4.15	High
	Market Information	4.65	High
	Past Trends	4.54	High
Herding	Stock Type Decisions	4.17	High
	Volume Decisions	4.05	High
	Buy/Sell Decisions	3.82	Moderate
	Reaction Speed	3.49	Moderate

The table illustrates that market variables and availability bias exert the strongest influence on investment decisions. Regret aversion and certain herding behaviors also

play a significant role. Most other factors have moderate impacts, indicating a nuanced behavioral landscape among NEPSE investors.

Investment performance

The second objective of the study was to determine the impact levels of behavioral factors on investment performance. Investment performance was measured using three indicators: return rate (Y1), comparison with market average (Y2), and satisfaction with investment decisions (Y3). All three indicators showed moderate levels:

i. Return rate vs. expectation: 3.42
ii. Return rate vs. market average: 3.52
iii. Satisfaction with decisions: 3.54

These results suggest that while investors are moderately satisfied with their performance, there is room for improvement. The moderate scores reflect the challenges of investing in an emerging market like NEPSE, where volatility, limited information, and behavioral biases can affect outcomes.

Effect of behavioral factors on investment performance

This study reveals that behavioral factors specifically heuristics, herding tendencies, and prospect-related biases have a meaningful and positive effect on the investment performance of individual investors at NEPSE. Each of these behavioral dimensions contribute in a unique way to how investors make decisions and manage their portfolios, ultimately shaping their financial outcomes. To evaluate the extent of these influences, Structural Equation Modeling (SEM) was employed. The SEM analysis confirmed that the three behavioral categories heuristic, herding, and prospect each have a statistically significant and positive relationship with investment performance. The regression coefficients representing the strength of these relationships are summarized in Table 20.

Table 20

The influence levels of Heuristics, Herding and Prospect

Behavioral Factor	Relationship with Investment Performance	Regression Coefficient
Heuristics	Positively associated	0.35
Herding	Positively associated	0.27
Prospect	Positively associated	0.19

Heuristic behaviors, particularly overconfidence and gambler's fallacy, were found to have the strongest positive impact on investment performance. Overconfident investors tend to believe in their ability to outperform the market based on their knowledge and experience. This confidence often leads to quicker and more decisive actions, which can be advantageous in a volatile market like NEPSE, where timing is crucial. Research supports this view, suggesting that moderate overconfidence can enhance trading activity and improve returns (Wang, 2001; Anderson et al., 2005).

However, overconfidence also has potential downsides. Overconfident investors may underestimate risks, overtrade, or hold unrealistic expectations about returns. Studies by Gottesman and Morey (2024) and Kim & Nofsinger (2003) show that such investors are more likely to pursue risky strategies, such as trading in volatile assets like cryptocurrencies, and may hold onto losing stocks too long. Therefore, while overconfidence can be beneficial when balanced, excessive confidence may lead to poor investment outcomes.

Herding, or the tendency to follow the actions of other investors, also showed a positive correlation with investment performance. In emerging markets like Nepal, where reliable information is limited and market transparency is low, herding can serve as a practical strategy. When many investors act in the same direction, it can create momentum or a "wave" in the market. Those who recognize and ride this wave early may benefit from short-term gains.

Moreover, herding increases trading volume and market liquidity, allowing investors to enter and exit positions more easily. This is particularly important in NEPSE, where liquidity can be a constraint. However, investors must be cautious not to follow the crowd blindly. As Lutje (2009) notes, while herding investors aim to match their peers, non-herding investors strive to outperform them. Thus, understanding when to follow and when to lead is key to maximizing returns.

Prospect theory-related behaviors such as loss aversion, regret aversion, and mental accounting also positively influence investment performance, though their effects are more nuanced.

Loss aversion encourages investors to be more cautious after experiencing losses. This often leads to more thorough analysis and risk-averse behavior, which can protect against further losses. However, excessive caution may delay decision-making and cause investors to miss profitable opportunities. Gao, Lin, and Savor (2022) suggest that loss aversion can lead to more prudent investment behavior when balanced appropriately.

Regret aversion is common among NEPSE investors. It manifests in the tendency to sell winning stocks quickly to realize gains while holding onto losing stocks in the hope of a rebound. This behavior is driven by the desire to avoid the emotional pain of realizing a loss. While this can sometimes preserve capital, it may also result in portfolios filled with underperforming assets. Interviews with NEPSE managers revealed that investors often hesitate to sell at a loss due to low market liquidity and the psychological discomfort of admitting failure. Timely decision-making, especially selling at peak prices, is essential to avoid long-term losses.

Mental accounting refers to the tendency of investors to treat each investment as a separate mental account rather than viewing the portfolio as a whole. This can lead to inefficient diversification and missed opportunities. For example, if one stock is closely linked to another through supply chains or market trends, changes in one may affect the other. Investors who fail to recognize these relationships may not respond effectively to market shifts. A more integrated approach to portfolio management can help investors make better-informed decisions and improve overall performance.

Interestingly, market factors, despite having the highest influence on decision-making, did not have a significant impact on investment performance. This suggests that reacting to market signals alone does not guarantee better returns, and that internal behavioral traits may play a more critical role in shaping outcomes. These findings support hypotheses H1, H3, and H4, while H2 is not supported.

In conclusion, the discussion confirms that behavioral factors significantly influence both investment decisions and performance at NEPSE. The findings are consistent with the research objectives and hypotheses defined in Chapter I. While market variables and availability bias dominate decision-making, heuristic and herding behaviors have the most substantial impact on performance. Prospect-related behaviors also contribute positively, though their effects are more nuanced. These insights highlight the importance

of understanding investor psychology in emerging markets and suggest that improving behavioral awareness can lead to better investment outcomes.

CHAPTER V

Summary and Conclusion

Summary

This research examines how behavioral factors impact investment choices and outcomes for individual investors at the NEPSE. Utilizing theories from behavioral finance, the study highlights four primary categories of behavioral influences: heuristics (which encompass overconfidence, gambler's fallacy, anchoring, and availability bias), prospect factors (including loss aversion, regret aversion, and mental accounting), market factors (such as price fluctuations, market information, and historical stock trends), and herding behavior (the tendency to follow the decisions of other investors).

Using a quantitative approach, data was collected through self-administered questionnaires from 390 NEPSE investors. The analysis employed Exploratory Factor Analysis (EFA), Cronbach's Alpha, and Structural Equation Modeling (SEM) to assess the reliability and impact of these behavioral factors on investment decisions and performance.

It was observed that while all behavioral factors moderately influence investment decisions, market-related variables exert the strongest impact. However, in terms of investment performance, heuristic behaviors particularly overconfidence and gambler's fallacy demonstrate the most significant positive effect, followed by herding and prospect-related behaviors. Interestingly, market factors, despite their strong influence on decision-making, do not significantly affect investment performance.

The study concludes that enhancing awareness and management of behavioral biases can lead to improved investment outcomes. It recommends that investors maintain balanced confidence, critically assess market information, and reflect on past investment experiences to make more informed decisions. This research contributes to the growing field of behavioral finance in emerging markets by offering empirical insights relevant to investors, financial advisors, and policymakers in Nepal.

Conclusion

This research has effectively addressed its core questions and objectives, offering meaningful insights into the behavioral factors that influence investment decisions and performance at the Nepal Stock Exchange (NEPSE). The findings underscore the relevance of behavioral finance in emerging markets and its potential to enhance investment outcomes.

The study identified five key behavioral factors that shape the investment decisions of individual investors at NEPSE: Herding, Market, Prospect, Overconfidence and Gambler's Fallacy, and Anchoring and Availability Bias. The herding factor includes four behavioral aspects: following others' decisions regarding buying and selling, selecting types of stocks, determining trade volumes, and the speed of reaction to others' actions. The market factor comprises three elements: stock price fluctuations, market-related information, and historical stock trends. The prospect factor includes loss aversion, regret aversion, and mental accounting. Heuristic behaviors are divided into two categories: overconfidence and gambler's fallacy and anchoring and availability bias. These findings provide partial support for Hypothesis H1.

Most behavioral variables from the four categories Heuristic (with two subgroups), Prospect, and Herding exert moderate influence on investment decisions at NEPSE. A few variables, such as gambler's fallacy and the speed of herding, show relatively lower influence. On the other hand, three market-related variables (price changes, market information, and past trends) and one prospect-related variable (mental accounting) demonstrate a strong influence on decision making. These results do not fully support Hypothesis H2, which proposed that all behavioral factors would have a high level of influence on investment decisions.

Only three behavioral dimensions were found to significantly affect investment performance: Herding (including buying and selling, stock selection, trade volume, and reaction speed), Prospect (including loss aversion, regret aversion, and mental accounting), and Heuristic (specifically overconfidence and gambler's fallacy). Among these, heuristic behaviors had the strongest positive effect on investment performance, followed by herding and then prospect-related behaviors. These outcomes support Hypothesis H3, which posits that all behavioral factors positively influence investment performance.

Implication of the study

This research presents a comprehensive overview of how behavioral factors influence both investment decisions and performance among individual investors at the Nepal Stock Exchange. Unlike earlier studies in Nepal that primarily relied on traditional finance approaches focusing on supply and demand dynamics in the securities market, this study adopts the perspective of behavioral finance.

It stands out as one of the few investigations in Nepal that applies behavioral finance to understand stock investment behavior. By incorporating a broad range of behavioral dimensions, this study offers a more complete assessment of their effects on individual investors, whereas previous research often examined only a limited set of behavioral traits. This contributes to expanding the relevance and application of behavioral finance in frontier and emerging markets.

The six-point scale used to measure behavioral factors was validated through Factor Analysis and Cronbach's Alpha, confirming the reliability of behavioral finance tools in the context of NEPSE. Additionally, the method used to evaluate investment performance was based on self-assessment by investors, focusing on return rates and satisfaction levels. This approach differs from earlier studies that relied on secondary market data, and it demonstrates that Likert-scale measurements can be effectively used to study behavioral finance in Nepal's stock market.

Beyond individual investors, the findings of this study can be valuable to financial institutions for market analysis and forecasting. Companies that raise capital through public offerings may also benefit by using these insights to better understand investor behavior and develop strategies to attract investment.

Future research is encouraged to validate these findings using larger and more diverse samples. It would also be beneficial to explore the behavior of institutional investors and refine behavioral finance measurement tools to better suit the specific characteristics of Nepal's securities market.

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Appendix

Appendix 1: Questionnaire

I. Personal Information

1. Gender
   - Male
   - Female

2. Age
   - 18 ~ 25
   - 26 ~ 35
   - 36 ~ 45
   - 46 ~ 55
   - Over 55

3. Marital Status
   - Single
   - Married
   - Divorced

4. Education level
   - High school and lower
   - Undergraduate
   - Bachelor
   - Master
   - PhD degree
   - Others

5. Years of working
   - Under 5 years
   - 5 - 10 years
   - Over 10 years

6. Please estimate your average monthly income (NPR)
   - Under 200
   - 20000 - under 40000
   - 40000 - under 70000
   - More than 70000

7. How long have you attended the stock market
   - Under 1 year
   - 1 - under 3 years
   - 3 - under 5 years
   - 5 - under 10 years
   - Over 10 years

8. Please name the security company that you are holding an account for stock investment.

9. Have you attended any course of Stock Exchange?
   - Yes
   - Not yet

10. The total amount of money (EUR) that you have invested at Nepal Stock Market.
    - Under 200000
    - From 200000 to under 400000
    - From 400000 to under 1000000
    - From 1000000 to under 20000000
    - From 2000000 to under 3000000
    - Over 3000000

11. The total amount of money (NPR) that you have invested at the Nepal security market during the last year.
    - Under 200000
    - From 200000 to under 400000
    - From 400000 to under 1000000
    - From 1000000 to under 20000000
    - From 2000000 to under 3000000
    - Over 3000000

II. Behavioral Factors Influencing Your Investment Decisions

Please evaluate the degree of your agreement with the impacts of behavioral factors on your investment decision making:

Factors	**Extremely disagree**	**Highly disagree**	**Somewhat disagree**	**Somewhat agree**	**Highly agree**	**Extremely agree**
12. You buy 'hot' stocks and avoid stocks that have performed poorly in the recent past.	1	2	3	4	5	6
13. You use trend analysis of some representative stocks to make investment decisions for all stocks that you invest.	1	2	3	4	5	6
14. You believe that your skills and knowledge of stock market can help you to outperform the market.	1	2	3	4	5	6
15. You rely on your previous experiences in the market for	1	2	3	4	5	6

your next investment.						
16. You forecast the changes in stock prices in the future based on the recent stock prices.	1	2	3	4	5	6
17. You are normally able to anticipate the end of good or poor market returns at the Ho Chi Minh Stock Exchange.	1	2	3	4	5	6
18. You prefer to buy local stocks than international stocks because the information of local stocks is more available.	1	2	3	4	5	6
19. You consider the information from your close friends and relatives as the reliable reference for your investment decisions.	1	2	3	4	5	6
20. After a prior gain, you are more risk seeking than usual.	1	2	3	4	5	6
21. After a prior loss, you become more risk averse.	1	2	3	4	5	6
22. You avoid selling shares that have decreased in value and readily sell shares that have increased in value.	1	2	3	4	5	6
23. You feel more sorrow about holding losing stocks too long than about selling winning stocks too soon.	1	2	3	4	5	6
24. You tend to treat each element of your investment portfolio separately.	1	2	3	4	5	6
25. You ignore the connection between different investment possibilities.	1	2	3	4	5	6
26. You consider carefully the price changes of stocks that you intend to invest in.	1	2	3	4	5	6
27. You have the over-reaction to price changes of stocks.	1	2	3	4	5	6
28. Market information is important for your stock investment.	1	2	3	4	5	6
29. You put the past trends of stocks under your consideration for your investment.	1	2	3	4	5	6
30. You analyze the	1	2	3	4	5	6

companies' customer preference before you invest in their stocks.						
31. You study about the market fundamentals of underlying stocks before making investment decisions.	1	2	3	4	5	6
32. Other investors' decisions of choosing stock types have impact on your investment decisions.	1	2	3	4	5	6
33. Other investors' decisions of the stock volume have impact on your investment decisions.	1	2	3	4	5	6
34. Other investors' decisions of buying and selling stocks have impact on your investment decisions.	1	2	3	4	5	6
35. You usually react quickly to the changes of other investors' decisions and follow their reactions to the stock market.	1	2	3	4	5	6

III. Your Investment Performance

Please give your opinions about the levels of agreement for the following statements:

Statements	**Extremely disagree**	**Highly disagree**	**Somewhat disagree**	**Somewhat agree**	**Highly agree**	**Extremely agree**
36. The return rate of your recent stock investment meets your expectation.	1	2	3	4	5	6
37. Your rate of return is equal to or higher than the average return rate of the market.	1	2	3	4	5	6
38. You feel satisfied with your investment decisions in the last year (including selling, buying, choosing stocks, and deciding the stock volumes).	1	2	3	4	5	6

Appendix 2: Factor analysis for behavioral variables and investment performance

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.758
Bartlett's Test of Sphericity	Approx. Chi-Square	4587.353
	df	153
	Sig.	<.001

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.53	36.276	36.276	6.53	36.276	36.276	3.417	18.983	18.983
2	2.271	12.616	48.892	2.271	12.616	48.892	3.238	17.986	36.969
3	1.878	10.432	59.324	1.878	10.432	59.324	3.056	16.976	53.945
4	1.484	8.243	67.567	1.484	8.243	67.567	2.452	13.622	67.567
5	0.937	5.205	72.772						
6	0.91	5.054	77.826						
7	0.723	4.016	81.842						
8	0.652	3.623	85.464						
9	0.585	3.252	88.717						
10	0.377	2.095	90.811						
11	0.329	1.827	92.639						
12	0.302	1.679	94.318						
13	0.268	1.488	95.806						
14	0.214	1.19	96.995						
15	0.182	1.012	98.007						
16	0.153	0.849	98.856						
17	0.111	0.618	99.474						
18	0.095	0.526	100						

Extraction Method: Principal Component Analysis.

Rotated Component Matrix[a]

	Component			
	1	2	3	4
Y1: The return rate of your recent stock investment meets your expectation.				.870
Y2: Your rate of return is equal to or higher than the average return rate of the market.				.830
Y3: You feel satisfied with your investment decisions in the last year (including selling, buying, choosing stocks, and deciding the stock volumes).				.776
X3: You believe that your skills and knowledge of stock market can help you to outperform the market.		.808		
X5: You forecast the changes in stock prices in the future based on the recent stock prices.		.554		
X6: You are normally able to anticipate the end of good or poor market returns at the Nepal Stock Exchange.		.838		
X7: You prefer to buy stocks based on their available information.		.556		
X10: After a prior loss, you become more risk averse.		.668		
X11: You avoid selling shares that have decreased in value and readily sell shares that have increased in value.	.641			
X13: You tend to treat each element of your investment portfolio separately.	.748			
X14: You ignore the		.569		

connection between different investment possibilities.				
X15: You consider carefully the price changes of stocks that you intend to invest in.	.782			
X17: Market information is important for your stock investment.	.837			
X18: You put the past trends of stocks under your consideration for your investment.	.738			
X21: Other investors' decisions of choosing stock types have impact on your investment decisions.			.634	
X22: Other investors' decisions of the stock volume have impact on your investment decisions.			.875	
X23:Other investors' decisions of buying and selling stocks have impact on your investment decisions.			.831	
X24: You usually react quickly to the changes of other investors' decisions and follow their reactions to the stock market.			.823	

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.[a]
a. Rotation converged in 6 iterations.

Appendix 3: Cronbach's Alpha Test for items of factors

Cronbach's Alpha	N of Items
.851	2

Item Statistics

	Mean	Std. Deviation	N
X3: You believe that your skills and knowledge of stock market can help you to outperform the market.	3.68	1.460	390
X6: You are normally able to anticipate the end of good or poor market returns at the Nepal Stock Exchange.	3.52	1.304	390

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
X3: You believe that your skills and knowledge of stock market can help you to outperform the market.	3.52	1.700	.745	.
X6: You are normally able to anticipate the end of good or poor market returns at the Nepal Stock Exchange.	3.68	2.132	.745	.

ANOVA

		Sum of Squares	df	Mean Square	F	Sig
Between People		1297.200	389	3.335		
Within People	Between Items	4.615	1	4.615	9.284	.002
	Residual	193.385	389	.497		
	Total	198.000	390	.508		
Total		1495.200	779	1.919		

Grand Mean = 3.60

Reliability Statistics

Cronbach's Alpha	N of Items
.626	2

Item Statistics

	Mean	Std. Deviation	N
X5: You forecast the changes in stock prices in the future based on the recent stock prices.	3.75	1.279	390
X7: You prefer to buy stocks based on their available information.	4.29	1.263	390

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
X5: You forecast the changes in stock prices in the future based on the recent stock prices.	4.29	1.596	.455	.
X7: You prefer to buy	3.75	1.636	.455	.

stocks based on their available information.				

ANOVA

		Sum of Squares	df	Mean Square	F	Sig
Between People		914.585	389	2.351		
Within People	Between Items	56.538	1	56.538	64.222	<.001
	Residual	342.462	389	.880		
	Total	399.000	390	1.023		
Total		1313.585	779	1.686		

Grand Mean = 4.02

Reliability Statistics

Cronbach's Alpha	N of Items
.720	4

Item Statistics

	Mean	Std. Deviation	N
X10: After a prior loss, you become more risk averse.	3.68	1.395	390
X11: You avoid selling shares that have decreased in value and readily sell shares that have increased in value.	4.15	1.419	390
X13: You tend to treat each element of your investment portfolio separately.	3.91	1.299	390

X14: You ignore the connection between different investment possibilities.	3.40	1.403	390

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
X10: After a prior loss, you become more risk averse.	11.46	10.861	.408	.717
X11: You avoid selling shares that have decreased in value and readily sell shares that have increased in value.	10.98	9.023	.649	.569
X13: You tend to treat each element of your investment portfolio separately.	11.23	10.574	.509	.659
X14: You ignore the connection between different investment possibilities.	11.74	10.281	.479	.676

ANOVA

		Sum of Squares	df	Mean Square	F	Sig
Between People		1610.631	389	4.140		
Within People	Between Items	121.292	3	40.431	34.906	<.001
	Residual	1351.708	1167	1.158		
	Total	1473.000	1170	1.259		
Total		3083.631	1559	1.978		

Grand Mean = 3.78

Reliability Statistics

Cronbach's Alpha	N of Items
.831	3

Item Statistics

	Mean	Std. Deviation	N
X15: You consider carefully the price changes of stocks that you intend to invest in.	4.15	1.472	390
X17: Market information is important for your stock investment.	4.65	1.546	390
X18: You put the past trends of stocks under your consideration for your investment.	4.54	1.338	390

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
X15: You consider carefully the price changes of stocks that you intend to invest in.	9.18	7.123	.629	.826
X17: Market information is important for your stock investment.	8.69	6.013	.769	.684
X18: You put the past trends of stocks under your consideration for your investment.	8.80	7.441	.684	.776

ANOVA

		Sum of Squares	df	Mean Square	F	Sig
Between People		1845.108	389	4.743		
Within People	Between Items	52.246	2	26.123	32.583	<.001
	Residual	623.754	778	.802		
	Total	676.000	780	.867		
Total		2521.108	1169	2.157		
Grand Mean = 4.45						

Reliability Statistics

Cronbach's Alpha	N of Items
.849	4

Item Statistics

	Mean	Std. Deviation	N
X21: Other investors' decisions of choosing stock types have impact on your investment decisions.	4.17	1.237	390
X22: Other investors' decisions of the stock volume have impact on your investment decisions.	4.05	1.319	390
X23:Other investors' decisions of buying and selling stocks have impact on your investment decisions.	3.82	1.393	390
X24: You usually react quickly to the changes of other investors' decisions and follow their reactions to the stock market.	3.49	1.439	390

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
X21: Other investors' decisions of choosing stock types have impact on your investment decisions.	11.35	13.309	.578	.852
X22: Other investors' decisions of the stock volume have impact on your investment decisions.	11.48	11.541	.756	.780
X23:Other investors' decisions of buying and selling stocks have impact on your investment decisions.	11.71	11.405	.713	.798
X24: You usually react quickly to the changes of other investors' decisions and follow their reactions to the stock market.	12.03	11.135	.713	.798

ANOVA

		Sum of Squares	df	Mean Square	F	Sig
Between People		1950.323	389	5.014		
Within People	Between Items	103.638	3	34.546	45.716	<.001
	Residual	881.862	1167	.756		
	Total	985.500	1170	.842		
Total		2935.823	1559	1.883		

Grand Mean = 3.88

Reliability Statistics

Cronbach's Alpha	N of Items
.852	3

Item Statistics

	Mean	Std. Deviation	N
Y1: The return rate of your recent stock investment meets your expectation.	3.42	1.359	390
Y2: Your rate of return is equal to or higher than the average return rate of the market.	3.52	1.231	390
Y3: You feel satisfied with your investment decisions in the last year (including selling, buying, choosing stocks, and deciding the stock volumes).	3.54	1.315	390

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Y1: The return rate of your recent stock investment meets your expectation.	7.06	5.641	.666	.850
Y2: Your rate of return is equal to or higher than the average return rate of the market.	6.95	5.504	.826	.700
Y3: You feel satisfied with your investment decisions in the last year (including selling, buying, choosing stocks, and deciding the stock volumes).	6.94	5.734	.686	.827

ANOVA

		Sum of Squares	df	Mean Square	F	Sig
Between People		1528.431	389	3.929		
Within People	Between Items	3.508	2	1.754	3.016	.050
	Residual	452.492	778	.582		
	Total	456.000	780	.585		
Total		1984.431	1169	1.698		

Grand Mean = 3.49

Appendix 4: Structural Equation Modeling for Behavioral Factors and Investment Performance

Notes for Model (Default model)

Computation of degree of freedom (Default model)

Number of distinct sample moments:	78
Number of distinct parameters to be estimated:	27
Degrees of freedom (78 - 27):	51

Result (Default model)

Minimum was achieved
Chi-square = 588.397
Degrees of freedom = 51
Probability level = .000

Regression Weights: (Group number 1 - Default Model)

			Estimate	S.E.	C.R.	P	Label
Investment_Performance	<---	Herding	0.225	0.043	5.233	***	
Investment_Performance	<---	Heuristic	0.38	0.054	7.048	***	
Investment_Performance	<---	Prospect	0.229	0.058	3.935	***	
X24	<---	Herding	1				
X23	<---	Herding	0.943	0.059	16.006	***	
X22	<---	Herding	0.96	0.056	17.038	***	
X21	<---	Herding	0.667	0.054	12.33	***	
X13	<---	Prospect	1				
X11	<---	Prospect	1.887	0.292	6.473	***	
X10	<---	Prospect	0.705	0.095	7.438	***	
X6	<---	Heuristic	1				
X3	<---	Heuristic	1.82	0.257	7.077	***	
Y1	<---	Investment_Performance	1				
Y2	<---	Investment_Performance	1.215	0.076	15.906	***	
Y3	<---	Investment_Performance	1.017	0.07	14.585	***	

Standardized Regression Weights: (Group number 1 – Default model)

			Estimate
Investment_Performance	<---	Herding	0.273
Investment_Performance	<---	Heuristic	0.351
Investment_Performance	<---	Prospect	0.185
X24	<---	Herding	0.806
X23	<---	Herding	0.786
X22	<---	Herding	0.844
X21	<---	Herding	0.625
X13	<---	Prospect	0.594
X11	<---	Prospect	1.027
X10	<---	Prospect	0.39
X6	<---	Heuristic	0.677
X3	<---	Heuristic	1.101
Y1	<---	Investment_Performance	0.714
Y2	<---	Investment_Performance	0.972
Y3	<---	Investment_Performance	0.752

CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default Model	27	588.397	51	.000	11.537
Saturated model	78	.000	0		
Independence model	12	2536.195	66	.000	38.427

RMR, GFI

Model	RMR	GFI	AGFI	PGFI
Default Model	.327	.811	.710	.530
Saturated model	.000	1.000		
Independence model	.599	.412	.305	.348

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default Model	.768	.700	.784	.718	.782

Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default Model	.773	.593	.605
Saturated model	.000	.000	.000
Independence model	1.000	.000	.000

NCP

Model	NCP	LO 90	HI 90
Default Model	537.397	463.032	619.211
Saturated model	.000	.000	.000
Independence model	2470.195	2309.214	2638.508

FMIN

Model	FMIN	F0	LO 90	HI 90
Default Model	1.513	1.381	1.190	1.592
Saturated model	.000	.000	.000	.000
Independence model	6.520	6.350	5.936	6.783

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default Model	.165	.153	.177	.000
Independence model	.310	.300	.321	.000

AIC

Model	AIC	BCC	BIC	CAIC
Default Model	642.397	644.264	749.483	776.483
Saturated model	156.000	161.394	465.359	543.359
Independence model	2560.195	2561.025	2607.789	2619.789

ECVI

Model	ECVI	LO 90	HI 90	MECVI
Default Model	1.651	1.460	1.862	1.656
Saturated model	.401	.401	.401	.415
Independence model	6.581	6.168	7.014	6.584

HOELTER

Model	HOELTER .05	HOELTER .01
Default Model	46	52
Independence model	14	15

Execution time summary

Minimization:	.025
Miscellaneous:	.516
Bootstrap:	.109
Total:	.650

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