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Understanding Behavioral Biases Among Kazakhstani Investors: Implications for Investment Professionals

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Abstract

Retail investment activity is steadily increasing in Kazakhstan, yet the psychological influences on investor decisions in this emerging market remain underexplored. This study investigates how individual investors in Kazakhstan are affected by behavioral tendencies that may interfere with rational financial reasoning. While traditional finance theory assumes that investors process all available information, behavioral finance suggests that emotions and behavioral biases often guide decision-making.

An online survey was conducted to uncover the behavioral patterns most relevant to this regional context. The questionnaire was built on concepts from behavioral finance literature and included ten items targeting specific biases. A total of 64 valid responses were gathered and analyzed. Statistical validation involved checking internal consistency, principal component analysis, and applying non-parametric tests.

Loss aversion and confirmation bias appear to shape investor choices among the biases measured. Interestingly, the analysis did not reveal strong associations between behavioral tendencies and demographic attributes such as gender, age, or prior investing experience, though a few minor trends were noted. The factor structure also confirmed that these biases function independently, without clustering into broader behavioral types.

The outcomes of this study offer practical guidance for professionals working with retail investors. They can apply these insights to better understand their clients' decision-making process and develop more tailored support tools. More broadly, this study contributes original empirical data to the underexplored field of behavioral finance in Central Asia, offering insights into the psychological dynamics of investors within a developing market context. By identifying the most influential biases across Kazakhstan's investor population, the study helps build a foundation for stronger market participation and supports future research on investor behavior in similar contexts.

Keywords: Behavioral finance, retail investors, investment decision-making, Kazakhstan, loss aversion, overconfidence.

Introduction

Investment market in Kazakhstan

Kazakhstan's investment landscape has seen significant changes since gaining independence in 1991. Key financial institutions, such as the Kazakhstan Stock Exchange (KASE), were introduced to support the development of a capital market within the country's economy, particularly as it moved from a centrally administered system to a market-oriented model (KASE,2023). Despite various government initiatives and financial sector reforms, Kazakhstan's investment market remains underdeveloped by international standards (Satybaldin et al., 2022).

Initial Public Offerings (IPOs) gained popularity in Kazakhstan in the early 2000s as a way for businesses to raise money. The London Stock Exchange (LSE) saw the IPOs of major national firms like KazMunayGas and Halyk Bank, indicating a preference for foreign capital markets over domestic ones (Satybaldin et al., 2022). This pattern demonstrates Kazakhstan's financial market's limited ability to draw significant domestic investment. Furthermore, Kazakhstan's reliance on a narrow range of key sectors, particularly oil and gas, makes it vulnerable to external market fluctuations (Pak, 2015).

The growth and stability of Kazakhstan's investment environment are largely dependent on macroeconomic factors. The country's stock market is very sensitive to changes in exchange rates, oil prices globally, and central bank reserves, according to empirical studies, highlighting its reliance on external economic conditions (Niyazbekova et al., 2016). This dependence on outside factors raises uncertainty, which is a major disincentive for more widespread investor involvement (Pak, 2015). Furthermore, the poor integration of financial markets with the real economy is reflected in the consistently low market capitalization-to-GDP ratio, which further limits market expansion and investment activity (Nurasheva et al., 2020) .Despite ongoing efforts to develop the financial sector, Kazakhstan ranks only 114th out of 144 countries in terms of financial market competitiveness, highlighting persistent problems (Nurasheva et al., 2020). This is exacerbated by a lack of transparency and financial literacy, as firms provide

limited information, which contributes to mistrust on the part of potential investors. Research suggests that in environments characterized by limited information, entrepreneurs frequently rely on personal assumptions and mental shortcuts, which heightens the impact of psychological heuristics and cognitive biases in their investment decisions (Yenikeeva, 2020). Another key factor contributing to low investor activity is the widespread confusion between legitimate stock market investments and fraudulent schemes. This confusion mainly stems from an information gap and inadequate public understanding of how the stock market functions (Amanzholova, 2021). To assess the extent of this problem, a survey was conducted among 84 respondents from different age groups. The results showed that approximately half of the participants did not know that investors in Kazakhstan have open access to the U.S. stock market. In addition, limited trading volumes, a lack of diverse financial instruments, and a narrow investor base continue to hinder market growth, reinforcing overall investor hesitancy (Nurasheva et al., 2020). The predominance of state-owned enterprises and Kazakhstan's heavy reliance on commodity exports also contribute to an investment environment that lacks diversification and stability. This economic structure not only limits the variety of investment opportunities available but also increases market volatility, making the market less attractive to retail investors (Yesdauletov & Dzhakisheva, 2020). As studies indicate, when individuals face heightened uncertainty, they tend to exhibit behavioral distortions such as overconfidence and representativeness bias, which subsequently affect how they formulate investment strategies and assess risks (Rustemkyzy, 2018). In response to these issues, Kazakhstan has launched multiple reforms aimed at enhancing the investment environment, including the creation of the Astana International Financial Center(AIFC), which aims to position the country as a regional financial center offering a legal framework based on English common law to attract foreign investors (KASE, 2023).

In recent years, Kazakhstani banks and financial institutions have expanded efforts to make investing more accessible to the public through mobile apps and digital platforms. Institutions such as Halyk Bank, Jusan Bank, and Bank CenterCredit offer tools for real-time

trading, portfolio management, and investor education. Initiatives like Tabys, backed by the Astana International Exchange and recently supported by Teniz Capital, allow investments starting from $1 and aim to promote financial literacy (Yahoo Finance, 2025). These developments reflect a broader shift toward democratizing capital market access to increase retail investor participation in the years ahead. However, challenges such as low financial literacy, limited transparency, and investor mistrust continue to hinder market expansion (Pak, 2015). Considering all these factors, it can be assumed that investors' hesitation to engage in the stock market could stem not only from external obstacles but also from internal psychological biases that shape their risk perception and decision-making process (Yenikeeva, 2020). Understanding these biases is necessary to address the deeper issues of Kazakhstan's investment landscape. Therefore, this study aims to explore key behavioral biases affecting Kazakh investors and sheds light on the psychological barriers that may hinder broader market engagement.

Research Question and Research Hypotheses

This study seeks to investigate the following key issues:

1. Which behavioral biases are most commonly observed among investors in Kazakhstan?
2. In what ways do these biases shape investment decisions and financial performance?
3. To what extent do demographic factors—such as age, investment experience, and gender —influence the expression of behavioral biases among investors?

To address these questions, the following hypotheses are proposed:

H_{01}: Kazakhstani investors do not demonstrate statistically significant tendencies toward behavioral biases like loss aversion, herding, overconfidence, confirmation bias, the illusion of control,and hindsight bias.

H_{11}: Kazakhstani investors demonstrate statistically significant tendencies toward behavioral biases like loss aversion, herding, overconfidence, confirmation bias, the illusion of control, and hindsight bias.

H_{02}: Behavioral biases among Kazakhstani investors show no significant variation based on age, gender, or investment experience.

H_{12}: Behavioral biases among Kazakhstani investors show significant variation based on age, gender, or investment experience.

Purpose Statement and Significance of the Study

This study was driven by the increasing interest in psychological factors shaping financial behavior, particularly within emerging markets such as Kazakhstan, where rising investor participation is still constrained by mistrust, information asymmetry, and limited financial literacy (Nurasheva et al., 2020; Amanzholova, 2021). Through academic coursework, exposure to behavioral finance literature, and a review of international studies, the authors recognized a disconnect between rational investment models and actual decision-making in Kazakhstan's financial environment. Similar research conducted in countries such as India, Bangladesh, Nepal, Germany, and Finland further supports this observation, revealing that behavioral biases—particularly overconfidence, herding, and loss aversion—consistently influence investor behavior across diverse economic and cultural contexts.

The purpose of this research is to identify the most prevalent behavioral biases among Kazakhstani investors and to examine how these biases are influenced by individual demographic factors such as age, gender, and investment experience. This question is especially relevant given the country's underdeveloped investor education programs and limited trust in domestic financial institutions (Yenikeeva, 2018; Rustemkyzy, 2018). Understanding these behavioral tendencies can help brokers, financial advisors, and fintech platforms adapt their strategies to support more informed investor decisions.

Academically, this research fills a geographic gap in behavioral finance literature by focusing on Central Asia, a region rarely studied in empirical work. Practically, it contributes to improving market engagement in Kazakhstan by highlighting psychological barriers that prevent rational investment behavior (Ricciardi & Simon, 2000; Pompian, 2006).

Literature Review

Traditional finance

Traditional finance theory holds that stock prices take into account all necessary and relevant information, financial markets are efficient, and investors make rational decisions. Fama (1970) introduced the Efficient Market Hypothesis (EMH), an essential principle of traditional finance, according to which financial markets accurately reflect all available information. Under the EMH, financial markets are "informationally efficient," and making excess returns involves, on average, taking higher amounts of risk. Fama has divided into three groups: weak, semi-strong, and strong markets. According to the weak version of the EMH, technical analysis is useless since stock prices cannot be forecast from past price trends. Stock prices quickly react to all information that is available to the public in a semi-strong efficient market, which reduces the ability of fundamental analysis to provide anomalous returns. Going a step further, the strong form of market efficiency contends that stock prices already take insider information into account, making it practically difficult to regularly generate extra profits.

Another key concept in traditional finance is the Modern Portfolio Theory (MPT), introduced by Markowitz (1952). MPT argues the need to diversify and thereby reduce risk with a corresponding improvement in profits. It calls for investors to be risk-averse, suggesting that they prefer lesser risk for the same projected return. Building on previous theories, Sharpe (1964) created the Capital Asset Pricing Model (CAPM). According to the model, the market risk premium, the risk-free rate, and an asset's vulnerability to market movements (beta) all affect its predicted return. This model remains widely used in finance to assess investment risk and determine the cost of capital. Ross (1976) expanded on this with the Arbitrage Pricing Theory (APT), which incorporates multiple factors impacting asset returns. Unlike CAPM, which considers only market risk, APT suggests that returns are influenced by various macroeconomic variables like interest rates, inflation, and economic growth.

Although traditional finance theories assume rational investors and efficient markets

(Fama, 1970; Sharpe, 1964), real-world events frequently show major deviations from these assumptions. For example, the dot-com bubble (1999-2000) and the 2008 global financial crisis demonstrated how investor state of mind and herd behavior may result in asset mispricing. More recently, the GameStop short squeeze in 2021 demonstrated how social media speculation could overpower basic values (Baker, Larcker, & Wang, 2022). These deviations demonstrate the limits of frameworks such as the EMH and the CAPM. As a result, behavioral finance arose to explain such trends by adding psychological variables into financial decisions (Kahneman & Tversky, 1979; Shiller, 2000). This method provides a more practical framework for examining investor behavior in unpredictable situations. Through the creation of prospect theory, Kahneman and Tversky (1979) showed how behavioral biases frequently cause people to make irrational financial decisions, which can lead to market anomalies like asset bubbles and collapses.

Behavioral Finance

As a reaction to the limitations of traditional finance, was creed behavioral finance, which considers that all investors act rationally and efficiently (Fama, 1970; Sharpe, 1964; Markowitz, 1952). However, in practice, financial markets often behave unpredictably, and investor decisions frequently diverge from the predictions of traditional models. To address this gap, behavioral finance integrates concepts from psychology and cognitive science into financial theory (Shefrin, 2000; Ricciardi & Simon, 2000).

At its core, behavioral finance seeks to understand how real people make financial decisions under uncertainty. Unlike traditional models that assume rationality, it recognizes that decisions are influenced by heuristics (mental shortcuts), emotional responses, and social dynamics (Barberis & Thaler, 2003). These influences give rise to behavioral biases—systematic and predictable deviations from rational behavior.

Kahneman and Tversky's prospect theory, which questioned conventional anticipated utility theory by demonstrating that people are loss-averse and evaluate outcomes in relation to a reference point rather than on an absolute scale, was a significant development in

behavioral finance. This shift away from purely rational models introduced a more psychologically realistic approach to understanding financial behavior (Kahneman & Tversky, 1992). Prospect theory also helps explain why investors may become excessively cautious or disproportionately risk-seeking depending on context.

Importantly, behavioral finance does not view these psychological tendencies as random errors. Instead, they are seen as predictable patterns that can explain market phenomena such as bubbles, crashes, and the under- or overreaction to news (Shiller, 2000; Duxbury, 2015). Lo's (2004) adaptive market hypothesis further expands on these ideas, proposing that markets evolve in response to changing participant behavior and environmental conditions, rather than remaining consistently efficient.

Another major contribution to the field is the classification of behavioral biases. Michael Pompian (2006) categorized these into two broad types: cognitive biases, which result from flawed reasoning or information processing, and emotional biases, which stem from affective impulses. While the present study focuses on specific biases influencing Kazakhstani investors, this framework provides valuable context for understanding investor behavior more broadly.

In sum, behavioral finance offers essential tools for analyzing why and how investors deviate from rational decision-making, especially in emerging markets, where differences in education, financial literacy, and access to information can significantly impact behavior. Recognizing these patterns can support the development of more effective advisory services, improve financial education, and foster more stable and inclusive market participation (Belsky & Gilovich, 1999; Sewell, 2007).

Overconfidence, herding behavior, loss aversion, confirmation bias, illusion of control, and hindsight bias are the six main behavioral biases that are the focus of this study. The selection of these specific biases was guided by their frequent occurrence in emerging markets and strong empirical support in prior research (Chen et al., 2007; Zahera & Bansal, 2018; Subash, 2012). These biases have been shown to significantly affect investment

decisions in diverse contexts, including India (Subash, 2012), Bangladesh (Rahman & Hossain, 2021), Nepal (Paudel & Upadhyay, 2021), Finland (Demidova, 2022), and Germany (Pashkevich & Hentschel, 2023). Their recurrence across both emerging and developed markets highlights their universal influence on retail investors. Furthermore, they represent a balanced mix of cognitive and emotional distortions, enabling a comprehensive analysis of irrational investor behavior in the Kazakhstani context.

Overconfidence Bias

Pompian (2006) defines overconfidence as a tendency to exaggerate one's judgment while at the same time downplaying risks, resulting in an illusory feeling of control over market events.This bias arises from the inclination to overrate one’s own understanding and judgment skills. Shefrin (2000) elaborates that overconfidence comes about when people believe they have greater experience or know better than they do, and so are more likely to make riskier financial decisions. Odean (1998) discovered that more active investors in the market earned substantially below the average return of the market, demonstrating the costly financial impact of overconfidence. In a similar investigation, Nofsinger (2001) discovered that investors are most overconfident concerning their stock selections despite their inability to determine profitable investments. This exaggerated confidence in one's ability often results in higher transaction costs, increased vulnerability to market volatility, and ultimately, lower net returns. Gender also affects the overconfidence bias. Barber and Odean (2001) discovered that men, driven by overconfidence, engage in 45% more trading than women, which results in lower annual net returns (-2.5% compared to -1.72%). It implies that excessive trading brought about by overconfidence has negative effects on investment returns.

The frequency of trades is also predominantly utilized as an overconfidence metric in behavioral finance studies because overestimating individuals trade at a high frequency to take advantage of anticipated opportunities. As overconfident investors tend to misjudge their constraints, Barber and Odean (2000, 2001) and Odean (1999) discovered that excessive trading frequently leads to lower portfolio returns. Muhammad et al. (2019) confirmed that

investor overconfidence has a direct influence on risk tolerance to create concentrated and undiversified portfolios and more vulnerability to loss.

Loss Aversion

Through the creation of prospect theory, Kahneman and Tversky (1979) established loss aversion as a fundamental idea in behavioral finance, emphasizing that people typically feel the pain of losses more keenly than the joy of comparable gains. So, people take more risks to avoid losses but play safe to have a gain. In order to explain a number of behavioral discrepancies, such as the endowment effect (Thaler, 1980), the equity premium puzzle (Benartzi & Thaler, 1995), and the status quo bias (Samuelson & Zeckhauser, 1988), loss aversion has been widely used in economics and finance. Empirical studies confirmed that loss aversion affects decision-making in investment choices, such as holding losing stocks too long (Wakker & Tversky, 1993); consumer behavior, including reluctance to switch service providers or brands (Schmidt & Traub, 2002); and insurance decisions, where people prefer more comprehensive coverage to avoid potential financial losses.

Herding Behavior

Herding behavior in financial markets occurs when investors copy the behaviors instead of making their judgments and decisions based on (Shiller, 2000; Kahneman and Tversky, 1979). Investors herd because they perceive collective judgments as more reliable than their own. As a result, herding behavior can cause variations in asset prices from their intrinsic values, contributing to market inefficiencies. Factors like unequal access to information, uncertainty, and concerns about reputation could cause herd behavior. Compared to other market systems, herding behavior is comparatively less prevalent in financial markets, where prices are impacted by order flows, according to Avery and Zemsky (1998), Lee (1998), Cipriani and Guarino (2008), and Park and Sabourian (2010). However, rational traders may still herd because of numerous sources of uncertainty or because their trading is impacted by non-informational factors such as liquidity requirements or hedging.

Herding is more noticeable during times of market stress or significant returns. Christie and Huang (1995) discovered decreased return volatility during periods of severe

market swings, confirming the theory that investors herd in reaction to abrupt price changes.

Similarly, Hwang and Salmon (2004) and Wang and Canela (2006) investigated herding behavior in developing and established markets, concluding that emerging markets had greater levels of herding, most likely due to poorer market regulation and lower financial literacy. During financial crises, herding may intensify as investors fear and follow the pack. Economou, Kostakis, and Philippas (2010) analyzed the stock markets in Greece, Italy, Portugal, and Spain, finding evidence of asymmetric herding behavior—more pronounced during rising markets and more restrained during declines. Herd behavior distorts market efficiency, leading to price bubbles, excessive volatility, and crashes. It prevents prices from accurately reflecting basic values, resulting in speculative booms followed by severe declines.

Confirmation bias

The tendency to ignore contradicting facts in favor of information that confirms one's preconceived notions is known as confirmation bias. Festinger's (1957) concept of cognitive dissonance, which holds that people feel emotionally uneasy when they are presented with competing viewpoints, is the source of this bias. People selectively look for evidence that supports their preconceived notions and reject or undervalue contradicting facts to quell this uneasiness. Because of this, individuals might consider contradicting information, even when it is well-supported, to be false. "More and more often, people search the Web to support their opinion formation," according to Schwind et al. (2012), implying that people increasingly actively seek out and stay in forums that support their beliefs.

In financial markets, confirmation bias can distort decision-making and lead to inefficient markets due to mispriced assets. Cipriano and Gruca (2014) studied this effect by experimenting with closed and open markets. They found that market prices failed to reflect new information in closed markets, where all traders were required to submit their forecasts and justifications before trading, provoking confirmation bias. However, in open markets, where some traders were not subject to this requirement, prices more efficiently incorporated available data.

The study by Duong et al. (2014) reflects how confirmation bias prevents investors from realizing actual value. It explores how value investors, those who favor undervalued stocks, and glamour investors, those who focus on overvalued stocks, react to conflicting financial news. Value investors expect bad news and ignore the good news, while glamour investors react the opposite. Such a selective reaction prevents investors from adapting their views objectively and realizing gains.

Schwind et al. (2012) recommend exposing individuals to preference-inconsistent recommendations—information that challenges their beliefs to mitigate confirmation bias. In financial markets, brokers could apply this approach by presenting clients with high-quality but conflicting financial analyses, encouraging clients to consider both perspectives, and resulting in balanced investment decisions. This strategy may be useful since investors' cognitive flexibility—" the ability to adapt the cognitive processing strategies to face new and unexpected conditions in the environment"—is a result of informational diversity (Cañas et al. 2006).

Hindsight bias

Investors rely on two key tools to predict future stock values: experience and data (Hussain et al., 2013). A successful investor recalls and learns from past mistakes, applying those lessons to future decisions. However, hindsight bias often prevents this process by distorting how past events are remembered. Originally called “creeping determinism” by Fischhoff (1982), hindsight bias occurs when people distort their past judgments after learning the actual outcome, convincing themselves they “knew it all along.” This bias is prevalent in the stock market.

Tavor (2013) illustrates this with a clear example: Suppose an investor hesitates to buy a stock due to doubts. Later, when the stock price rises, they forget their initial uncertainty and believe they could have predicted the increase. This false sense of accurate prediction can lead to riskier investment decisions later on.

Hindsight bias challenges Bayesian Updating, which assumes that people adjust their

prior knowledge based on new information to yield a more accurate perception.Hindsight-biased investors misremember their past expectations, making them less likely to incorporate fresh data accurately.

The most damaging effect of hindsight bias is that it prevents investors from learning from their mistakes (Biais & Weber, 2009). A study of investment bankers in Frankfurt and London showed that even highly experienced professionals exhibited hindsight bias. Bankers with the highest performance displayed the lowest sign of hindsight bias. Another study by Monti & Legrenzi (2009) found that both students and financial advisors exhibited hindsight bias, demonstrating that these bias influences information processing and decision-making at all levels.

To counter hindsight bias, Hussain et al. (2013) emphasize continuous education. Investors should rely on fundamental and technical analysis rather than personal assumptions. In extreme cases, financial advisors or brokers may need to remind investors of past misjudgments to help them avoid repeating the same mistakes. By expanding their knowledge and enhancing cognitive abilities, investors can reduce bias and improve their ability to make well-informed choices.

Illusion of control bias

Ellen J. Langer initially identified the cognitive bias known as the illusion of control in 1975. She defined it as being "inappropriately confident" in circumstances when chance or outside causes predominate. It is the feeling that one can beat the odds, since otherwise, having no control over an event can feel incapacitating. According to Langer, factors such as skill, competition, and familiarity can stimulate this bias.

Fellner’s experiment (2009) found that the illusion of control affects individual investment decisions, often leading to poorly diversified portfolios. Investors believe they can control stock performance and company outcomes, so they tend to select too few stocks, thinking that a smaller portfolio is easier to manage and influence. To reduce this bias, Matute et al. (2015) suggest taking a step back emotionally, especially in high-stakes

situations. While this might seem counterproductive, the reality is that the more involved an investor is, the more they tend to act—and falsely believe their actions caused the outcome, when in fact it may have occurred purely by chance. Additionally, Matute recommends encouraging skepticism of one's intuitions by seeking input from objective third parties, which can help introduce diverse perspectives.

Methodology

Research Design

The survey was administered online using Google Forms and was designed to be completed in approximately 3–5 minutes. It was offered in three language options—Kazakh, Russian, and English—to ensure accessibility for a wider audience of Kazakhstani investors.

The questionnaire included three parts: (1) an informed consent form, (2) demographic questions covering age, gender, and investment experience, and (3) six behavioral bias items. Each bias was assessed using a Likert scale of one to five statements, where 1 is strongly disagree, while 5 is strongly agree. An exception was made for overconfidence, which was evaluated through a ranking task in which participants prioritized various sources of investment judgment (e.g., themselves, brokers, friends, media, experts) (see Appendix A).

Each of six items was formulated to target a specific behavioral bias, based on definitions and prior literature in behavioral finance. In developing the questionnaire, items addressing overconfidence, herding behavior, loss aversion, confirmation, and hindsight bias were adapted from Subash's (2012) study on behavioral biases among Indian investors. One of the questionnaire items used to assess the illusion of control bias was adapted from Demidova's (2022) study on Finnish investors. While the core constructs were retained, the items were modified to present contextually relevant scenarios tailored to the Kazakhstani investment environment.

While previous studies from India and Finland have used multiple items per behavioral bias (Subash, 2012; Demidova, 2022), this study employed a one-question-per-bias approach. The decision was driven by both participant feedback during the pilot phase and concerns about response fatigue. Fass-Holmes (2022) emphasizes that repeated or lengthy surveys often result in lower participation and poorer data quality due to what is referred to as "survey fatigue." Though the phenomenon is difficult to define uniformly, it is broadly understood as a form of respondent burden caused by excessive length or frequency of survey exposure. Subash (2012) also noted the importance of keeping behavioral finance

questionnaires “compact and focused” to retain participant engagement. The bias-question mapping was as follows:

Overconfidence bias: *"Whose judgment analysis do you trust most while making investments?"*

Herding bias: *"You notice that many of your colleagues and competitors are buying Company X’s stock. How likely are you to invest in it as well?"*

Loss aversion bias: *"If my stock investment is losing value, I would prefer to hold rather than sell."*

Confirmation bias: *"You are considering buying a certain stock because your analysis is positive. You then check expert reports, but some are against the purchase, while others are in favor. Would you be likely to proceed with the purchase?"*

Hindsight bias: *"Looking at AirKZ's price drop, you realize it was clear this was going to happen. You believe that if you had paid more attention earlier, you could have predicted the change. How much do you agree with this opinion?"*

Illusion of control bias: *"When I play cards (or a similar game), I feel more optimistic and confident when I deal the cards myself."*

An attention check question— *“What is 3 + 5?”* with multiple-choice options 7, 8, and 9—was placed near the middle of the survey. Participants who failed to select the correct answer (8) or selected *“I do not wish to participate”* were excluded during the data cleaning process.

The inclusion of the attention check was implemented following a recommendation from an assistant professor of the ISE Scientific Research to guarantee the integrity and reliability of the data that was collected.

Population and Sample

As seen in Figure 1, among the valid responses, 80.95% completed the survey in Russian, 11.11% in English, and 7.94% in Kazakh, reflecting the dominant language preference among the participants.

Figure 1.

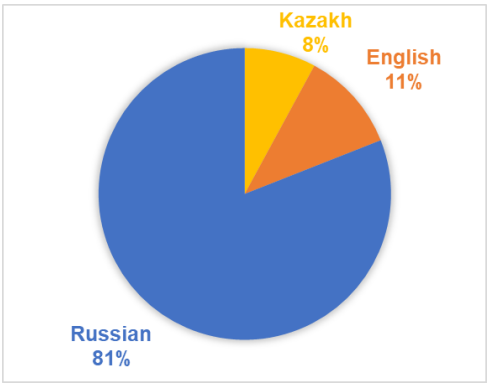
Language Distribution of Survey Participants

The final sample consisted of 37 male (58.7%) and 26 female (41.3%) participants (see Figure 2). The mean age of respondents was approximately 27.4 years, with a range from 18 to 46 years and a median of 29.

In terms of investment experience, the majority (87.3%) had less than five years of experience, while the remaining 12.7% reported five to ten years of experience.

Figure 2.

Gender Distribution of Survey Participants



Data Collection

A total of 69 survey responses were initially collected. Participants were recruited through two primary channels:

1. Investment influencers and retail investors on platforms such as Instagram and LinkedIn.

2. Investment professionals and portfolio managers via direct messages on LinkedIn.

The survey was distributed electronically to both students and faculty members at Maqsut Narikbayev University via email. To improve the response rate, a follow-up reminder was also sent.

To ensure data quality, responses were screened for attention. Three participants were removed for failing the attention check. One respondent selected the opt-out response ("I do not want to participate in this study") and was excluded, and one test response (the author'sown) was also removed. After cleaning, the final dataset included 64 valid responses, which formed the basis for all subsequent analysis.

Two observations were excluded from analyses involving age and gender: one respondent selected "Prefer not to say" for age, and another did so for gender. These responses could not be numerically encoded and were therefore omitted to avoid introducing ambiguity into the statistical analyses.

Pilot Testing

To verify the clarity, neutrality, and overall suitability of the questionnaire before full-scale distribution, a pilot study was conducted with 9 faculty members from Maqsut Narikbayev University. The majority of these participants were affiliated with the Research Department, providing expert-level feedback on the logical structure and psychological framing of the questions.

The pilot test aimed to assess whether the survey items effectively captured intuitive behavioral tendencies without making the underlying biases too obvious. Respondents noted that several of the original questions prompted overly direct reflection on one's own behavioral biases, potentially triggering socially desirable answers or deliberate rationalization. This type of self-awareness was inconsistent with the study's goal of capturing automatic, unconscious decision-making patterns.

Based on this feedback, the questions were reformulated into scenario-based formats. Instead of asking respondents whether they agreed with abstract statements, each item was rewritten to describe a realistic investment situation and prompt participants to indicate how they would likely behave. This

subtle framing was intended to elicit natural, intuitive responses without signaling the specific bias being measured.

Reliability

Cronbach's alpha was employed to examine the scale's internal reliability, as it measures the degree of interrelatedness among items and reflects their consistency as a single unified construct (Tavakol & Dennick, 2011, p. 53). As noted by DeVellis (2016), internal consistency is a key requirement when using scale-based data in analyses such as correlation, factor analysis, and regression. Values of Cronbach's alpha range from 0 to 1, with greater values signifying a higher degree of internal coherence across the scale items (Chauhan & Patel, 2023, p. 7).

During the initial reliability check, Cronbach's alpha was computed using all questionnaire items. The resulting coefficient was relatively low ($\alpha = 0.210$), as shown in Table 1. However, the item corresponding to overconfidence bias was subsequently excluded from the reliability analysis due to its distinct response format, which differed from the Likert scale used for the other items. According to Taber (2018), the accurate calculation of Cronbach's alpha requires that all items in the scale have the same type of response options and measure data on a consistent scale (e.g., a Likert scale). Failing to meet this criterion can result in distorted reliability estimates and misinterpretation of internal consistency (Taber,2018).

After excluding the inconsistent item, Cronbach's alpha rose to 0.423, indicating weak internal consistency. While this value remains low, it is considered acceptable in this context, as each item in the scale was intentionally constructed to reflect a distinct behavioral bias (see Table 1). Tavakol and Dennick (2011) state that Cronbach's Alpha works well with unidimensional scales and that low results can occur whena questionnaire evaluates several constructs. This perspective is supported by the UCLA Statistical Consulting Group (n.d.), which emphasizes that internal consistency tends to be lower when the items in a scale address different underlying concept.

Table 1.

Cronbach's Alpha scores from the reliability test

Bias type	Number of Items	Cronbach's Alpha if Deleted
Confirmation bias	1	0.16
Hindsight bias	1	0.04
Illusion of control bias	1	0.06
Herding bias	1	0.09
Loss aversion bias	1	0.26
Overconfidence bias	1	0.42
Overall Cronbach's Alpha	6	0.21

Data Analysis and Findings

All statistical procedures were performed using both IBM SPSS Statistics (for reliability test and inferential statistics) and Python (via Jupyter Notebook) for tasks such as descriptive statistics, dimensionality reduction (Principal Component Analysis), and diagnostic tests (e.g., KMO, Bartlett's, and Shapiro–Wilk). Each software platform was selected based on its strengths in executing specific types of analysis and visualization.

Descriptive Statistics

The original dataset was compiled in Microsoft Excel and included responses in three languages: Kazakh, Russian, and English. To ensure consistency in data processing and analysis, all responses were translated into English. As part of the data cleaning procedure, any respondent who failed the attention check question was removed to ensure the inclusion of only attentive participants in the final dataset. The cleaned and standardized dataset was then exported for statistical processing in Python.

6 key cognitive biases were evaluated: overconfidence, herding, loss aversion, confirmation, hindsight, and illusion of control. For each variable, key descriptive metrics such as the mean, median, and standard deviation were computed to summarize the data. Given the use of a 5-point Likert scale, these descriptive measures were considered appropriate for interpreting central tendencies and dispersion across responses. All calculations were performed using Python 3.13, with the *pandas*

library used for data manipulation and summary statistics.

Table 2

Descriptive Statistics measures for Behavioral Biases

	Mean	Median	Standard Deviation
Overconfidence bias	3.39	2.5	1.52
Herding bias	2.79	3	0.94
Loss aversion bias	3.87	4	0.97
Confirmation bias	3.71	4	0.82
Hindsight bias	2.90	3	1.10
Illusion of control bias	2.37	2	1.22

As shown in Table 2, loss aversion bias had the highest mean score *(M* = 3.871), indicating strong agreement with statements reflecting reluctance to realize losses. Confirmation bias (*M* = 3.710) and overconfidence bias (*M* = 3.387) also showed relatively elevated means, suggesting frequent reliance on selective information or self-assured judgment in investment decision-making.

In contrast, the lowest mean was observed in the illusion of control bias (*M* = 2.371), indicating a lower overall endorsement of beliefs related to perceived control over outcomes. Additionally, the standard deviation was highest for overconfidence (*SD* = 1.519) and illusion of control (*SD* = 1.218), suggesting greater variability in how respondents perceive and express these biases.These findings highlight individual differences in the expression of behavioral biases, with stronger central tendencies observed in loss aversion and greater dispersion in confidence-related dimensions.

Normality Testing

Because the sample size was relatively small, the Shapiro–Wilk test, recognized for its effectiveness with samples under 2000, was employed to test the normality of the behavioral bias variables (Razali & Wah, 2011). The 6 bias dimensions evaluated included: overconfidence, herding, loss aversion, confirmation, hindsight, and illusion of control.

All tests were conducted in Python 3.13 using the *scipy.stats.shapiro()* function. While data transformations are sometimes used to improve normality, the extremely low *p*-values observed

suggest that such transformations would not meaningfully resolve the distributional issues. Because the Likert-scale data was ordinal and the minimal likelihood of achieving normality through transformation, it was determined that no transformations would be applied. Instead, the study proceeded with non-parametric methods and dimension-reduction techniques that do not assume normality.

Table 3 summarizes the outcomes of the Shapiro–Wilk test conducted across all 6 behavioral bias variables. The results revealed that all *p*-values were significantly below the 0.05 threshold, suggesting strong evidence of non-normal distributions for each variable assessed.

Table 3

Normality Assessment using the Shapiro–Wilk Test

Bias	Shapiro-Wilk p-value
Overconfidence Bias	0.0000
Herding Bias	0.0001
Loss Aversion Bias	0.0000
Confirmation Bias	0.0000
Hindsight Bias	0.0002
Illusion of Control	0.0000

These findings confirm that the behavioral bias data are non-normally distributed, supporting the use of non-parametric or dimension reduction methods such as Principal Component Analysis (PCA) in subsequent analysis.

Factorability Test (KMO & Bartlett's)

To evaluate the dataset's suitability for Exploratory Factor Analysis (EFA), two widely used statistical tests were applied: the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy and Bartlett's Test of Sphericity. These analyses were conducted using Python 3.13 with the *factor_analyzer* and *scipy* libraries (see Appendix B).

The Kaiser–Meyer–Olkin (KMO) test is used to evaluate whether the variance among observed variables may be attributed to underlying common factors, with values closer to 1 indicating greater adequacy for factor analysis. In contrast, Bartlett's Test of Sphericity determines whether the variables

are significantly correlated by testing if the correlation matrix differs from an identity matrix.

In this study, the KMO result was 0.5084, which is below the commonly accepted threshold of 0.6, suggesting that the sample may not be suitable for reliable factor extraction through EFA. Nevertheless, Bartlett's test was significant ($p < 0.001$), providing evidence of meaningful intercorrelations among the six behavioral bias variables.

Table 4 presents the results of both tests, along with their statistical outputs and implications for proceeding with Exploratory Factor Analysis:

Table 4

KMO and Bartlett's Test Results for Factorability

Test	Result	Interpretation
Kaiser-Meyer-Olkin (KMO)	0.5084	Below threshold; unsuitable for EFA
Bartlett's Test (p-value)	0.0000	Significant correlations exist

Although Bartlett's test confirmed the presence of statistically significant correlations among variables, the relatively low KMO score suggested insufficient shared variance to support Exploratory Factor Analysis (EFA). Instead, the study employed Principal Component Analysis (PCA) as a more appropriate method for dimensionality reduction in this context.

Principal Component Analysis (PCA)

Given the low KMO value of 0.5084, the dataset was considered unsuitable for Exploratory Factor Analysis (EFA). As an alternative, Principal Component Analysis (PCA) was employed to examine the underlying structure of the six behavioral biases and reduce data dimensionality.

Before conducting PCA, all variables were standardized using the *StandardScaler* function to ensure equal variance across components. The analysis was implemented in Python 3.13, utilizing the PCA module from the *scikit-learn* library.

Component selection was guided by the cumulative explained variance, which was also visualized through a cumulative variance plot. As indicated in Table 5, the first four principal

components explained 79.07% of the total variance, demonstrating a substantial reduction in dimensionality while preserving the majority of the dataset's informational content. (see Appendices C and D)

Table 5

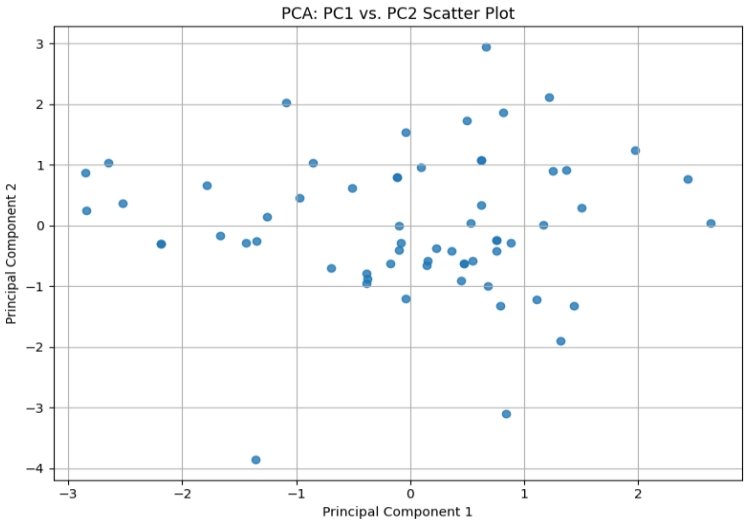
Variance Explained by Principal Components

Component	Variance Explained	Cumulative Variance
PC1	25.55%	25.55%
PC2	21.84%	47.39%
PC3	18.99%	66.38%
PC4	12.69%	79.07%

Components beyond PC4 contributed only marginally to the overall variance and were not retained for further interpretation. To illustrate how participants differed in their behavioral tendencies, a scatter plot was produced based on their positions along the primary axes of variation in the PCA output (commonly referred to as PC1 and PC2). As shown in Figure 3, the plot revealed a wide dispersion of scores across both dimensions.

Figure 3.

PCA scatter plot of Participant Scores on PC1 and PC2



This widespread indicates substantial individual variation in how behavioral biases manifest in the sample. No tight clustering or grouping patterns were observed, suggesting that the expression of behavioral biases is multi-dimensional and does not conform to a single dominant profile. The visual separation of points in the PCA space complements the numerical findings, supporting the

interpretation that biases are expressed independently across respondents.

Inferential Statistics

To determine whether gender influenced behavioral bias responses, the Mann–Whitney U test was applied to the two most salient biases—loss aversion and confirmation bias. Since the normality assumption was not met by the data and was measured on an ordinal scale (5-point Likert), this non-parametric method was deemed suitable (Nachar, 2008).

Table 6 indicates that gender-based comparisons yielded no statistically significant variation in responses:

- Loss aversion ($U = 409.000$, $p = 0.287$)
- Confirmation bias ($U = 426.000$, $p = 0.380$)

As both *p*-values exceeded the 0.05 threshold, the findings suggest that gender is not a significant determinant in the manifestation of these behavioral biases.

The Mann–Whitney U test was also used to examine variation in responses based on investment experience, dividing participants into two categories: less than five years and five years or more. As reported in the Table 6, this analysis also showed no statistically significant differences:

- Loss aversion ($U = 203.000$, $p = 0.950$)
- Confirmation bias ($U = 195.500$, $p = 0.933$)

Both *p*-values far exceeded the significance threshold, indicating that investment experience does not significantly influence the expression of these biases.

Table 6

Mann–Whitney U Test Summary for Independent Samples

Behavioral Bias	Grouping Variable	U Statistic	Z Score	p-value
Loss Aversion	Gender	409.00	–1.06	0.29
Confirmation Bias	Gender	426.00	–0.88	0.38
Loss Aversion	Investment Experience	203.00	+0.08	0.95
Confirmation Bias	Investment Experience	195.50	–0.098	0.93

Since age is a continuous variable, it was not appropriate to compare groups using the Mann–Whitney U test, which is only appropriate for analyzing distinctions between two unrelated samples when the data are ordinal or non-normally distributed (Kaliyadan & Kulkarni, 2022).

Instead, a Spearman's rank-order correlation analysis was used to assess how age relates to the two principal behavioral biases—loss aversion and confirmation bias. As shown in Table 7, the observed relationships were weakly negative and failed to reach statistical significance:

- Age and loss aversion: Spearman's rho = –0.159, $p = 0.213$
- Age and confirmation bias: Spearman's rho = –0.083, $p = 0.519$

In both cases, the p-values were above 0.05, indicating no significant relationship between age and the strength of behavioral biases.

Table 7

Spearman's Rank-Order Correlations Between Behavioral Biases and Age

	Loss Aversion	Confirmation Bias	Age
Loss Aversion	1.00	–0.09 $p = 0.47$	–0.16 $p = 0.21$
Confirmation Bias	–0.09 $p = 0.47$	1.00	–0.08 $p = 0.52$
Age	–0.16 $p = 0.21$	–0.08 $p = 0.52$	1.00
N	63	63	63

To further examine whether key behavioral biases tend to co-occur, a Spearman rank-order correlation was also performed between loss aversion and confirmation bias. This step aimed to determine whether individuals who exhibit one bias are also likely to display the other.

The analysis revealed a very weak and statistically non-significant negative correlation between the two variables:

- $\rho = –0.092$, $p = 0.470$ (see Table 8)

Table 8

Spearman's Rank-Order Correlation Between Behavioral Biases

	Loss Aversion	Confirmation Bias
Loss Aversion	1.00	–0.09 p = 0.47
Confirmation Bias	–0.09 p = 0.47	1.00
N	64	64

Multiple Regression Analysis

To explore how demographic factors, affect behavioral biases, multiple linear regression was run using loss aversion and confirmation bias as the dependent variables. The goal was to determine whether characteristics such as age, gender, and investment experience could explain individual differences in these biases.

The survey's 5-point Likert scale items were used to measure the dependent variables, confirmation bias and loss aversion, which were handled as continuous variables. Age, gender, and prior investment experience were the independent variables. One continuous variable that was used was age. Gender and experience, being categorical, were label-encoded using Python's *LabelEncoder* function. Gender was encoded as a binary variable (Male = 1, Female = 0), and investment experience was encoded as 0 for "Less than 5 years" and 1 for "5–10 years".

To explore whether the impact of gender on bias differed based on experience level, an interaction term was included in the regression model. This term was constructed by multiplying the encoded values of gender and experience, allowing the model to capture any combined effects between these two variables. Thus, the model for each dependent variable included age, gender, experience, and the interaction between gender and experience.

Using the *statsmodels* module, the Ordinary Least Squares (OLS) method in Python was used to do the regression analysis. To capture the model intercept, a constant term was added to the independent variables before estimation. In order to evaluate the outcomes, the study concentrated on looking at each predictor's coefficients, standard errors, and p-values. The F-statistic and R-squared

values were also reviewed to evaluate the overall explanatory power of the models.

For both loss aversion and confirmation bias, additional model variations were tested to explore nonlinear relationships and alternative specifications. In the case of loss aversion, a squared age term was included to test for a potential U-shaped relationship, but the coefficient was not statistically significant. Age categories were also introduced (18–24, 25–34, and 35+), but this model did not improve explanatory power.

For confirmation bias, neither the main effects nor the interaction term showed significance, and the overall model fit remained low. Model diagnostics such as the Durbin–Watson statistic and tests for the normality of residuals (Omnibus and Jarque–Bera) were used to verify the assumptions of linear regression. The Durbin–Watson values were around 2, suggesting there was no autocorrelation. However, the errors in the confirmation bias model showed slight non-normality. Finally, multicollinearity was checked when polynomial terms were added to the model, particularly during testing of the squared age variable.

Overall, the regression methodology allowed for testing not only the individual contributions of age, gender, and experience, but also their combined effects through interaction terms. While the results for confirmation bias did not indicate significant predictors, the interaction term in the loss aversion model showed marginal significance, suggesting that gender differences in loss aversion may depend on experience level (see Tables 9 and 10).

Loss Aversion Results

The multiple linear regression model for loss aversion included age, gender, investment experience, and an interaction term between gender and experience. With an R-squared of 0.117 and an adjusted R-squared of 0.055, the model demonstrated considerable explanatory power despite not being statistically significant at the 5% level (F-statistic $p = 0.126$). Table 9 displays these findings.

Among the predictors, the interaction term had a coefficient of 1.557 ($p = 0.074$), indicating a marginally significant effect. This suggests that the impact of gender on loss aversion may depend on

the investor's level of experience. Specifically, the results imply that more experienced male investors used to be less loss-averse than female investors, especially among those with less experience, gender differences are minimal.

A minor but detectable trend for older investors that demonstrated relatively lower levels of loss aversion was indicated by the regression coefficient for age, which was negative (–0.028) with a p-value of 0.087. However, this relationship was not statistically significant. Gender alone had a coefficient of –0.983 (p = 0.226), and experience alone had a coefficient of –1.234 (p = 0.090), both of which were also statistically insignificant.

Residual diagnostics showed no evidence of autocorrelation (Durbin–Watson = 1.988), and the distribution of residuals did not violate the normality assumption.

Table 9

Multiple Regression Results for Loss Aversion (N = 62)

Predictor	B	SE	t	*p*	95% CI (LL, UL)
Intercept	5.52	0.89	6.22	0	[3.75, 7.30]
Age	-0.03	0.02	-1.74	0.09	[-0.06, 0.00]
Gender (1 = Male)	-0.98	0.80	-1.22	0.23	[-2.60, 0.63]
Experience (1 = 5–10 yrs)	-1.23	0.72	-1.73	0.09	[-2.67, 0.20]
Gender × Experience	1.56	0.85	-1.82	0.07	[-0.15, 3.27]

Confirmation Bias Results

The regression model for confirmation bias included the same independent variables: age, gender, investment experience, and the interaction between gender and experience. With an R-squared of 0.052 and an adjusted R-squared of -0.013, this model's explanatory power was extremely low, suggesting poor performance. None of the individual predictors or the interaction term exhibited significant correlations with confirmation bias, and the overall model was not statistically significant (F-statistic p = 0.528). Full results are shown in Table 10.

The interaction term had a coefficient of 0.853 with a p-value of 0.254, indicating no

statistically meaningful interaction. Similarly, age (p = 0.576), gender (p = 0.500), and experience (p = 0.362) were all far from significance.

The residuals showed signs of non-normality, with skewness = –1.056 and kurtosis = 5.021, as confirmed by a significant Jarque–Bera test (p < 0.01). These results suggest that confirmation bias in this dataset may not be adequately explained by the linear model.

Table 10

Multiple Regression Results for Confirmation Bias (N = 62)

Predictor	B	SE	t	*p*	95% CI (LL, UL)
Intercept	4.29	0.77	5.55	0.00	[2.74, 5.84]
Age	-0.01	0.01	-0.56	0.58	[-0.04, 0.02]
Gender	-0.47	0.70	-0.68	0.50	[-1.86, 0.92]
Experience	-0.57	0.62	-0.92	0.36	[-1.82, 0.67]
Gender × Experience	0.85	0.74	1.15	0.25	[-0.63, 2.34]

Ethical considerations

All study participants remained anonymous and participated voluntarily. Before starting the survey, a comprehensive welcome document explaining the nature of the questions, the research's goal, and the participants' rights was given to each respondent.

The ability to exit the survey at any time by shutting down their browser was made clear to participants. No personally identifiable data was gathered. Additionally, they had the option to email the main researcher to request that their data be removed within a week after finishing the questionnaire or before the study's conclusion on June 3, 2025.

The information was safely kept on a password-protected device that only the research team could access. The ISE Committee for Scientific Research of Maqsut Narikbayev University examined and approved the paper.

Assumptions and Limitations

This study is based on several key assumptions. It is assumed that respondents provided honest answers and that the questions were understandable in each of the three language versions (English, Russian, and Kazakh). It is further assumed that the Likert-scale responses offer a reasonable reflection of participants' actual behavioral tendencies during investment decision-making. Additionally, it presumes that the six selected behavioral biases—overconfidence, loss aversion, herding, hindsight bias, confirmation bias, and illusion of control—are sufficiently representative of the most impactful behavioral factors relevant to Kazakhstani retail investors. One important limitation is the narrow scope of behavioral biases examined. Although numerous biases have been documented in behavioral finance research, such as mental accounting, disposition effect, framing, and representativeness bias, this study focused on six of the most frequently referenced and empirically supported biases, as highlighted in the systematic review by Sahu and Singh (2022). Future research should consider a wider set of biases and more nuanced constructs to grasp a deeper understanding of investor psychology.

Another observed limitation was participants' hesitation to access the online questionnaire. Several potential respondents expressed concern that the Google Forms link might be fraudulent or unsafe. This distrust may have reduced the response rate and reflects a broader issue of digital skepticism. Such hesitancy may itself be a form of behavioral barrier to engagement with formal financial services and research.

Finally, the study's sample size (n = 63) limits generalizability. Only a single second in time's worth of investor behavior is shown by the cross-sectional design. Mixed-methods or longitudinal studies may be better able to document how these biases change over time or in response to changes in the economy.

Results

In the course of the research aimed at identifying the most common behavioral biases among investors in Kazakhstan and establishing the influence of demographic characteristics on their expression, the results obtained allow us to draw several valid conclusions. Following the initial research question - “What are the most common behavioral biases among Kazakhstani investors?” - the analysis showed that the highest median value was observed for such biases as loss avoidance (median = 4.0) and confirmation bias (median = 4.0), indicating investors' pronounced propensity to retain unprofitable assets and seek confirmation of earlier decisions. These results support the alternative hypothesis H_{11}, according to which investors in Kazakhstan do have the key behavioral biases identified in behavioral economics. In contrast, the lowest median was recorded for illusion of control (median = 2.0), indicating respondents' low confidence in their ability to influence market events.

The Shapiro-Wilk test evaluation of the data distribution revealed statistically significant non-normality of all variables ($p < 0.001$), which supported the adoption of non-parametric analysis techniques and the median as the primary measure of central tendency. To find out the structure of relationships between biases, the principal component analysis (PCA) method was applied, which showed that four of the components explained 79.07% of the variance; however, the distribution graph of the components showed no pronounced clusters, indicating the independent nature of the manifestation of different behavioral biases.

Regarding the second and third research questions, “How do behavioral biases affect investment decisions?” and “Are demographic characteristics associated with the expression of biases?” - as a function of gender, age, and investment experience, the inferential analysis's findings showed no statistically significant differences in the degree of confirmation bias and loss aversion expression ($p > 0.05$ in all cases). The second null hypothesis (H_{02}), which proposed that there was no statistically significant correlation between the manifestation of behavioral biases and demographic factors (age, gender, and investment experience), is supported by these data.

Nevertheless, multiple linear regression revealed a borderline significant interaction between gender and experience ($p = 0.074$) in explaining loss aversion bias, indicating a possible behavioral specificity among men with more than 5 years of investment experience, expressed as a lower sensitivity to losses compared to other groups.

Discussion and Conclusion

The purpose of this study is to investigate if behavioral biases exist among Kazakhstani individual investors and what demographic factors influence them. The results demonstrated the importance of psychological factors influencing investment decisions, including confirmation bias, loss aversion, and, to a lesser degree, overconfidence. These findings offer compelling empirical evidence in favor of Hypothesis H_{01}, confirming that Kazakhstani retail investors are vulnerable to the emotional and cognitive distortions that have been extensively reported in behavioral finance literature.

Loss aversion's substantial prevalence is consistent with Prospect Theory (Kahneman & Tversky, 1979), which postulates that people fear losses more than they fear gains of the same magnitude. These results are consistent with similar studies in emerging markets of Bangladesh (Yasmin & Ferdaous, 2023) and India (Sowmya & Muralidhar, 2024), where loss aversion and confirmation bias have been shown to shape irrational financial behavior. The cross-cultural persistence of these two biases supports their classification as universal tendencies in investor psychology (Zahera & Bansal, 2018).

In contrast, biases such as herding, illusion of control, and anchoring were not strongly expressed among the respondents. This contrasts with studies conducted in other Asian markets, such as Pakistan and India (Asad, 2018; Chhapra et al., 2018), where collective behavior and belief in one's predictive control play a larger role. One possible explanation is the increasing individualization of financial decision-making in Kazakhstan, supported by digital financial tools, independent trading platforms, and a growing culture of personal financial responsibility.

Crucially, behavioral biases and demographic characteristics like age, gender, or investment experience did not show a statistically significant association. As a result, the null hypothesis (H_{02}) was not rejected. These findings deviate from earlier research that linked gender to overconfidence or age to risk tolerance (Mishra, 2015; James & Ilaboya, 2019), but may be attributed to the relative homogeneity of the sample, especially in terms of digital fluency and financial awareness.

Moreover, Principal Component Analysis (PCA) demonstrated that behavioral biases operate as independent psychological constructs, rather than as interrelated elements of broader investor profiles. This reinforces the growing argument in the literature (e.g., Chira & Adams, 2008) that effective interventions should target specific biases directly, rather than being based on generalized demographic segmentation.

In conclusion, this research confirms the psychological complexity of investment behavior among Kazakhstani retail investors. By providing one of the earliest empirical studies from Central Asia, it adds to the body of knowledge in behavioral finance by demonstrating that important behavioral biases are still applicable across cultural and economic divides.

Behavioral biases were manifested as separate and independent phenomena rather than as part of complex behavioral types. This underscores the need for individualized approaches in investment advice and education initiatives that focus not on segmentation by gender or age, but on correcting specific cognitive and emotional distortions in investor behavior. The results have meaningful implications for the design of financial advisory tools, investor education programs, and digital financial platforms. As Kazakhstan’s retail investment market continues to develop, recognizing and addressing psychological biases will be critical to improving investor outcomes and promoting financial stability.

Recommendations

In consideration of the results, the following suggestions are put forth:

The results of the study allow for the proposal of a number of scholarly and practical recommendations. First, behavioral finance elements that include both technical and psychological aspects of investment should be included in financial literacy programs in Kazakhstan. Helping people identify and lessen biases like confirmation bias and loss aversion, which were found to be particularly prevalent, should receive special attention. Second, financial institutions and investment advisors are encouraged to implement behavioral profiling methods, such as those developed by Pompian (2006), to better understand individual investor tendencies and provide tailored guidance. Third, the small number of demographic factors used in the analysis may be the reason for the regression models' very low explanatory power. While the study considered age, gender, and investment experience, it did not account for other potentially influential variables such as educational attainment, risk tolerance, income level, or financial literacy. The absence of these factors may have reduced the models' ability to capture the full variability in behavioral bias expression, highlighting the need for more comprehensive demographic profiling in future research. Finally, future academic research should widen the range of studied biases, utilize multi-item measurement tools for greater reliability, and include larger, more diverse samples. Longitudinal studies and comparative analyses across regions could also offer valuable insight into how behavioral patterns shift over time and under different economic conditions.

Financial literacy programs in Kazakhstan should address the psychological aspects of investing, not just technical skills. Workshops should include content on recognizing and mitigating behavioral biases. Financial institutions and advisors should consider integrating behavioral profiling tools, as suggested by Pompian (2006), to identify common investor tendencies and adjust recommendations accordingly.

Future studies should expand the range of biases examined, include multi-item scales for better reliability, and increase the sample size to improve generalizability. Longitudinal studies could also explore how biases evolve over time or in response to macroeconomic shocks.

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Appendices

Appendix A

Survey Questions

1) Age: ☐

2) Gender:

☐ Male ☐ Female ☐ Prefer not to say

3) Investment Experience:

☐ Less than 5 years ☐ 5 - 10 years ☐ More than 10 years

1) Whose judgment analysis do you trust most while making investments?

☐ Self ☐ Broker ☐ Friends ☐ Media ☐ Expert opinios ☐ Other

2) You notice that many of your colleagues and competitors are buying Company X's stock. How likely are you to invest in it as well?

	1	2	3	4	5	
Very unlikely	○	○	○	○	○	Very likely

3) If my stock investment is losing value, I would prefer to hold rather than sell.

	1	2	3	4	5	
Strongly disagree	○	○	○	○	○	Strongly agree

4) You are considering buying a certain stock because your analysis is positive. You then check expert reports, but some are against the purchase, while others are in favor. Would you be likely to proceed with the purchase?

	1	2	3	4	5	
Very unlikely	○	○	○	○	○	Very likely

5) Looking at AirKZ's price drop, you realize it was clear this was going to happen. You believe that if you had paid more attention earlier, you could have

predicted the change. How much do you agree with this opinion?

	1	2	3	4	5	
Strongly disagree	○	○	○	○	○	Strongly agree

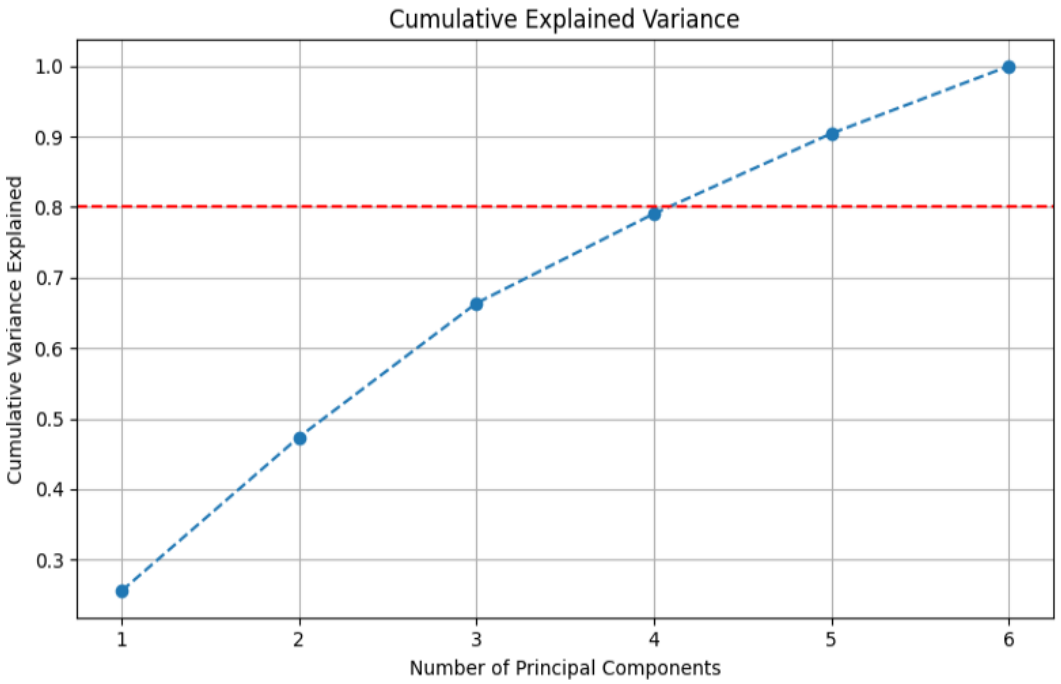
6) When I play cards (or similar game), I feel more optimistic and confident when I deal the cards myself.

	1	2	3	4	5	
Strongly disagree	○	○	○	○	○	Strongly agree

Appendix B. Python code for Factor Analysis and p-values

```
C:\Users\USER>cd "C:\Users\USER\Documents\descriptive stats"

C:\Users\USER\Documents\descriptive stats>python normality_test.py
Normality Test (Shapiro-Wilk):
overconfidence bias: p-value = 0.0000
herding bias: p-value = 0.0001
loss aversion bias: p-value = 0.0000
confirmation bias: p-value = 0.0000
hindsight bias: p-value = 0.0002
Illusion of control bias: p-value = 0.0000

C:\Users\USER\Documents\descriptive stats>

C:\Users\USER\Documents\descriptive stats>cd "C:\Users\USER\Documents\descriptive stats"

C:\Users\USER\Documents\descriptive stats>python normality_test.py
Normality Test (Shapiro-Wilk):
overconfidence bias: p-value = 0.0000
herding bias: p-value = 0.0001
loss aversion bias: p-value = 0.0000
confirmation bias: p-value = 0.0000
hindsight bias: p-value = 0.0002
Illusion of control bias: p-value = 0.0000

C:\Users\USER\Documents\descriptive stats>cd "C:\Users\USER\Documents\descriptive stats"

C:\Users\USER\Documents\descriptive stats>python factorability_test.py
KMO Score: 0.5084
Bartlett's Test p-value: 0.0000

C:\Users\USER\Documents\descriptive stats>cd "C:\Users\USER\Documents\descriptive stats"

C:\Users\USER\Documents\descriptive stats>python pca_analysis.py
Explained Variance per Component:
PC1: 0.2555 (Cumulative: 0.2555)
PC2: 0.2184 (Cumulative: 0.4739)
PC3: 0.1899 (Cumulative: 0.6638)
PC4: 0.1269 (Cumulative: 0.7907)
PC5: 0.1137 (Cumulative: 0.9044)
PC6: 0.0956 (Cumulative: 1.0000)

C:\Users\USER\Documents\descriptive stats>
C:\Users\USER\Documents\descriptive stats>python pca_scatter.py

C:\Users\USER\Documents\descriptive stats>
```

Appendix C. Cumulative Explained Variance



Appendix D. Explained Variance per Component

```
C:\Users\USER\Documents\descriptive stats>cd "C:\Users\USER\Documents\descriptive stats"

C:\Users\USER\Documents\descriptive stats>python pca_analysis.py
Explained Variance per Component:
PC1: 0.2555 (Cumulative: 0.2555)
PC2: 0.2184 (Cumulative: 0.4739)
PC3: 0.1899 (Cumulative: 0.6638)
PC4: 0.1269 (Cumulative: 0.7907)
PC5: 0.1137 (Cumulative: 0.9044)
PC6: 0.0956 (Cumulative: 1.0000)
```