Research Article

When The Investor’s Mind Breaks Rationality: Cognitive Biases and Investment Decisions - Evidence from Mongolia Using a PLS-SEM Approach

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Abstract

This study explores how cognitive biases shape investment decision-making by explicitly examining the mediating roles of financial literacy and investor sentiment within an emerging market environment. Drawing on primary survey data from 529 individual investors in Mongolia collected in 2025, the analysis employs Partial Least Squares Structural Equation Modeling (PLS-SEM) to evaluate both direct and indirect behavioral relationships. The findings indicate that cognitive biases do not influence investment decisions in a uniform manner. Anchoring bias and availability bias show no significant direct or mediated effects through financial literacy or investor sentiment, suggesting that these heuristics function mainly as context-dependent judgmental shortcuts. In contrast, mental accounting and representativeness bias exert statistically significant indirect effects on investment decision-making through both cognitive and affective channels. Financial literacy and investor sentiment emerge as key determinants of decision quality, highlighting the importance of knowledge-based capacity and psychological factors in shaping investor behavior. By modeling behavioral transmission mechanisms rather than focusing solely on bias existence, the study offers a more nuanced explanation of how investor rationality is constrained and reinforced. The results provide novel empirical evidence from Mongolia and contribute to behavioral finance research by clarifying the conditions under which cognitive biases become decision-relevant in emerging financial markets.

Keywords

Cognitive Biases; Financial Literacy; Investor Sentiment; Investment Decision-Making; Emerging Markets; Mongolia.

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Introduction

Benjamin Graham famously argued that “the investor’s chief problem, and even his worst enemy, is likely to be himself,” emphasizing that investment performance is often constrained not only by external market conditions but also by predictable limitations in human cognition. This observation underscores a fundamental departure from the assumptions of classical finance, suggesting that investors’ own psychological tendencies may systematically interfere with rational decision making. Consistent with this perspective, behavioral finance demonstrates that cognitive biases, systematic patterns of judgment and decision errors, shape investors’ choices and can undermine optimal portfolio allocation (Tversky & Kahneman, 1974; Kahneman & Tversky, 1979).

In contrast, traditional financial theory conceptualizes markets as rational systems in which asset prices fully and instantaneously reflect available information, as formalized by the Efficient Market Hypothesis (EMH) (Fama, 1970). Under this framework, investors are assumed to process information objectively and make unbiased, utility-maximizing decisions, implying the absence of persistent mispricing or predictable trading patterns. Nonetheless, extensive empirical evidence documents recurring anomalies, including excess volatility, speculative bubbles, and market crashes, that challenge purely rational models and suggest that investment decisions are shaped by factors beyond information and fundamentals.

As Nobel laureate Daniel Kahneman observed, “We are blind to our blindness. We have very little idea of how little we know.” This insight lies at the intellectual core of behavioral finance, a field that integrates psychological principles into financial economics to explain why investors frequently violate the axioms of rational choice. Behavioral finance posits that cognitive biases, systematic errors in perception, judgment, and information processing, play a critical role in shaping investment behavior. Biases such as overconfidence, representativeness, anchoring, availability, and confirmation bias can distort investors’ beliefs, risk assessments, and expectations, leading to suboptimal trading decisions and inefficient portfolio outcomes (Barberis, Shleifer & Vishny, 1998; Tversky & Kahneman, 1974).

Although a substantial body of international research has documented the role of cognitive biases in shaping investment decision making across both developed and emerging markets, empirical evidence from small, frontier, and transition economies remains comparatively scarce. This limitation is particularly evident in the case of Mongolia, where participation in the capital market has expanded rapidly in recent years. The diffusion of digital trading platforms, improvements in financial inclusion, and growing public interest in equities and investment funds have collectively increased retail investor activity. Yet this expansion has occurred within a market environment characterized by relatively low liquidity, concentrated ownership structures, limited analyst coverage, and pronounced information asymmetries, conditions under which behavioral biases are likely to exert a disproportionate influence on investor decisions (Shiller, 2003).

Building on this emerging Mongolia-focused evidence, it becomes clear that while behavioral biases have been empirically identified in the Mongolian capital market, their role in shaping individual investment decision making remains only partially understood. Existing studies provide valuable but segmented insights: market-level analyses document herding behavior using aggregate trading data (Batmunkh et al., 2020), index-based studies reveal short-lived overconfidence effects in price dynamics (Ankhbileg et al., 2024), and survey-based research highlights the coexistence of multiple psychological tendencies such as loss aversion, regret aversion, and optimism among Mongolian investors (Mijiddorj et al., 2025). More recent applications of machine-learning methods further demonstrate that behavioral variables possess predictive power in explaining investment-related outcomes (Bukhsuren, Namsraidorj & Altantsetseg, 2025).

Despite these advances, the current body of Mongolian research remains fragmented in both scope and methodology. Most studies focus either on aggregate market behavior or on isolated psychological traits, offering limited insight into how multiple cognitive biases jointly influence investors' perceptions of risk, asset selection, and trading behavior at the micro level. Moreover, market-based evidence does not directly capture investors' subjective beliefs and decision processes, while survey-based analyses often remain descriptive and weakly connected to concrete investment outcomes. As a result, the behavioral mechanisms underlying observed trading patterns in Mongolia have yet to be examined within a unified empirical framework.

This gap is particularly consequential given the structural characteristics of the Mongolian stock market, low liquidity, concentrated ownership, limited analyst coverage, and persistent information asymmetries, which prior studies suggest may amplify the effects of behavioral distortions (Shiller, 2003). While international behavioral finance literature provides extensive evidence from developed and large emerging markets, its conclusions cannot be readily generalized to frontier markets such as Mongolia without context-specific validation. Consequently, policymakers and regulators currently lack robust micro-level evidence to support the design of effective investor protection measures and financial literacy initiatives tailored to Mongolia's unique market environment.

Accordingly, the present study directly responds to these limitations by providing a comprehensive micro-level analysis of cognitive biases among Mongolian investors and their impact on investment decision making. By integrating multiple cognitive biases within a single empirical framework and explicitly linking them to risk perception, asset selection, and trading behavior, this study extends prior Mongolia-focused research and contributes new evidence from a frontier market perspective. In doing so, it advances the behavioral finance literature while offering policy-relevant insights essential for improving market efficiency, investor welfare, and the sustainable development of Mongolia's capital market.

In doing so, this study responds to Herbert Simon's enduring insight that "a wealth of information creates a poverty of attention." Understanding how Mongolian investors allocate this limited attention, and how cognitive biases shape their decision-making processes, is essential not only for advancing academic knowledge, but also for designing practical policy interventions that enhance market efficiency and investor welfare in emerging financial systems.

Literature Review

Behavioral finance research has progressively shifted attention from aggregate market anomalies toward the cognitive mechanisms through which investors process information and form decisions. Rather than treating biased behavior as a residual deviation from rational benchmarks, contemporary studies emphasize that systematic cognitive biases influence belief formation, attention allocation, and judgment under uncertainty. Among these, confirmation bias, representativeness bias, anchoring, mental accounting, and availability bias have emerged as central explanatory constructs linking individual cognition to observable investment behavior. This section synthesizes the literature on each bias, highlighting their conceptual foundations, empirical regularities, and interconnections.

Representativeness bias and extrapolative expectations

Representativeness bias arises when investors assess probabilities based on perceived similarity or recent patterns rather than objective statistical properties. In investment contexts, this bias manifests as the extrapolation of recent performance into the future and the misinterpretation of short-term trends as indicators of long-term quality. Seminal models link representativeness-driven expectations to predictable return dynamics, including momentum followed by reversals (Barberis, Shleifer & Vishny, 1998; Daniel, Hirshleifer & Subrahmanyam, 1998).

Empirical evidence confirms that investors systematically overreact to recent earnings surprises and past returns while underweighting base rates, leading to distorted risk assessments (De Bondt & Thaler, 1985; Lakonishok, Shleifer & Vishny, 1994). More recent research demonstrates that diagnostic expectations, an intensified form of representativeness, can amplify credit and asset-price cycles (Bordalo, Gennaioli & Shleifer, 2018). Survey-based evidence further shows that investors' expectations are strongly correlated with recent market performance, consistent with extrapolative belief formation (Greenwood & Shleifer, 2014). Together, these findings highlight representativeness bias as a systematic source of misjudgment in investment decisions.

Anchoring and insufficient adjustment

Anchoring bias affects investment decision making when investors rely excessively on salient reference points, such as historical prices, purchase prices, analyst targets, or round numbers. Once established, these anchors constrain belief revision, leading to insufficient adjustment even when new information becomes available. Empirical studies document anchoring effects in analyst forecasts and consensus estimates, showing that initial values exert a persistent influence on subsequent judgments (Campbell & Sharpe, 2009; Cen, Hilary & Wei, 2013).

Additional evidence indicates that anchoring affects trading behavior and valuation, contributing to price clustering and slow information incorporation (George & Hwang, 2004; Kaustia, Alho & Puttonen, 2008). Experimental and field studies further confirm that anchoring operates even among experienced investors, suggesting that expertise does not fully eliminate this bias (Kaustia, 2010; Dougal et al., 2015). Literature thus establishes anchoring as a robust cognitive constraint that shapes valuation and timing decisions.

Mental accounting and portfolio fragmentation

Mental accounting describes the tendency to evaluate financial outcomes within separate mental categories rather than considering overall portfolio implications. This framing leads investors to treat economically equivalent outcomes differently depending on their mental classification. Foundational work demonstrates that mental accounting produces inconsistent risk preferences and violates portfolio-level optimization (Thaler, 1985; Shefrin & Statman, 2000). Empirical studies show that investors often track gains and losses at the individual asset level, resulting in suboptimal diversification and rigid holding behavior (Barberis & Huang, 2001; Barberis, Huang & Thaler, 2006). Evidence from household portfolios further suggests that mental accounting contributes to under-diversification and inefficient asset allocation (Goetzmann & Kumar, 2008; Odean & Barber, 2013). These findings indicate that mental accounting systematically distorts investment decisions by fragmenting evaluation across mental accounts.

Availability bias and attention-driven decisions

Availability bias influences investment decisions by increasing reliance on information that is vivid, recent, or easily recalled. In financial markets, media coverage, salient events, and social discourse play a central role in shaping attention. Empirical studies show that stocks receiving heightened media attention experience abnormal trading volume and short-term price pressure, consistent with attention-driven buying behavior (Barber & Odean, 2008; Fang & Peress, 2009). Further research demonstrates that investors underreact to less salient but informative signals, while overreacting to attention-grabbing news (P. Tetlock, 2007; Hirshleifer, Lim & Teoh, 2009). Internet search activity and news sentiment measures provide additional evidence that availability-driven attention affects trading and return dynamics (Da, Engelberg & Gao, 2011; Engelberg & Parsons, 2011). Collectively, this literature establishes availability bias as a key mechanism linking limited attention to distorted investment decisions.

Integrating cognitive biases

Although each bias operates through distinct mechanisms, the literature increasingly emphasizes their interaction. Confirmation bias can reinforce representativeness-based beliefs, anchoring can constrain adjustments prompted by new information, and availability determines which signals enter the decision process in the first place. Recent integrative frameworks suggest that investment behavior reflects the joint influence of multiple cognitive biases, rather than isolated effects (Barberis et al., 2018; Bordalo, Gennaioli & Shleifer, 2018). This perspective underscores the importance of modeling cognitive biases simultaneously when analyzing investment decision making.

Hypotheses of Research

Drawing on the behavioral finance literature, this study formulates hypotheses that link cognitive biases to investment decision making. Cognitive biases influence how investors interpret information, update beliefs, and evaluate alternatives under uncertainty. Rather than assuming a single dominant bias, the hypotheses reflect distinct cognitive mechanisms through which decision quality may be systematically affected.

H1. Representativeness bias influences investment decision making.

Representativeness bias is expected to affect investment decision making through pattern-based reasoning rather than statistical inference. When recent performance or salient characteristics are treated as representative of long-term prospects, expectations may be formed on the basis of perceived similarity rather than underlying fundamentals. This cognitive shortcut is therefore expected to influence asset selection and timing decisions.

H2. Anchoring bias influences investment decision making.

Anchoring bias is expected to influence investment decision making by constraining belief adjustment around salient reference points. When initial values or prior expectations serve as cognitive anchors, subsequent information may be insufficiently weighted, leading to persistent valuation rigidity. As a result, anchoring bias is expected to shape investment decisions under conditions of uncertainty.

H3. Mental accounting influences investment decision making.

Mental accounting is expected to influence investment decision making by segmenting financial evaluation into separate mental categories rather than an integrated portfolio framework. Such compartmentalization can alter risk evaluation and allocation logic across assets, suggesting that investment decisions are shaped by framing effects rather than overall optimization.

H4. Availability bias influences investment decision making.

Availability bias is expected to influence investment decision making by increasing reliance on information that is vivid, recent, or cognitively salient. When easily recalled information dominates the decision process, less salient but economically relevant signals may receive insufficient attention, shaping investment choices in a systematic manner.

H5. Financial literacy influences investment decision making.

Financial literacy is expected to influence investment decision making by enhancing investors' ability to interpret financial information, evaluate risk, and apply analytical reasoning. Higher literacy levels are therefore expected to be associated with more structured and informed investment decisions.

H6. Financial literacy mediates the relationship between cognitive biases and investment decision making.

Financial literacy is expected to function as a mediating mechanism through which cognitive biases influence investment decision making. By shaping how information is understood and evaluated, financial literacy may attenuate or transmit the effects of cognitive biases into observable investment choices.

H7. Investor sentiment influences investment decision making.

Investor sentiment is expected to influence investment decision making by shaping perceptions of market conditions and future prospects. Shifts in optimism or pessimism alter perceived risk and expected returns, thereby affecting investment behavior.

H8. Investor sentiment mediates the relationship between cognitive biases and investment decision making.

Investor sentiment is expected to mediate the effects of cognitive biases on investment decision making by translating biased information processing into market-related beliefs and expectations that guide choice behavior.

Research Methodology

This study employs a quantitative research design to investigate how cognitive biases shape individual investment decision making, while accounting for the mediating roles of financial literacy and investor sentiment. Given the psychological nature of the constructs examined, the analysis relies on primary survey data collected directly from individual investors, allowing for a more precise assessment of latent cognitive and behavioral factors than would be possible using market-level indicators alone.

Primary data were collected from individual investors through a structured questionnaire administered via Microsoft Forms to analyze the combined effects of financial literacy and cognitive biases on investment decision making. The empirical analysis is based on responses obtained from 519 individual investors actively participating in the capital market. This sample size is adequate for estimating a structural model with multiple latent constructs and mediation paths and exceeds commonly accepted minimum thresholds for Partial Least Squares Structural Equation Modeling (PLS-SEM). The focus on retail investors is particularly appropriate, as cognitive biases are most directly expressed at the individual decision-making level.

To ensure representativeness and reduce selection bias, the study adopts the Equal Probability of Selection Method (EPSEM) as the guiding sampling principle. Under EPSEM, each member of the target population has an equal and non-zero probability of being included in the sample, thereby supporting unbiased parameter estimation and external validity. In practice, EPSEM was implemented through a simple random sampling procedure, with respondents selected without systematic preference based on demographic characteristics, investment experience, or behavioral traits. This approach enhances the credibility of the empirical findings by ensuring that observed relationships are not driven by sampling artifacts but reflect underlying behavioral patterns among individual investors.

Data were collected using a structured questionnaire designed to measure cognitive biases, specifically confirmation bias, representativeness bias, anchoring, mental accounting, and availability bias, as well as financial literacy, investor sentiment, and investment decision making. Measurement items were adapted from well-established scales in the behavioral finance and financial literacy literature and were contextualized to reflect individual investment settings. All constructs were operationalized using Likert-type scales (1-5) to capture variations in perceptions and attitudes consistently across respondents. Prior to full deployment, the questionnaire was pilot-tested to assess clarity, relevance, and content validity. Responses exhibiting incomplete information or inconsistent answering patterns were excluded to preserve data quality, resulting in a final sample of 519 usable observations.

The conceptual framework of this study is grounded in behavioral finance theory, which challenges the assumption of fully rational investors by emphasizing the role of psychological and cognitive factors in financial decision-making. As illustrated in Figure 1, the framework proposes that cognitive biases act as primary behavioral drivers influencing investment decision-making, both directly and indirectly, through key mediating mechanisms. In this framework, cognitive biases, specifically anchoring bias, availability bias, mental accounting, and representativeness bias, are conceptualized as independent latent constructs that shape how investors process information, evaluate risks, and form expectations about financial outcomes. These biases reflect systematic deviations from rational judgment, particularly under conditions of uncertainty and limited information, which are common characteristics of emerging financial markets.

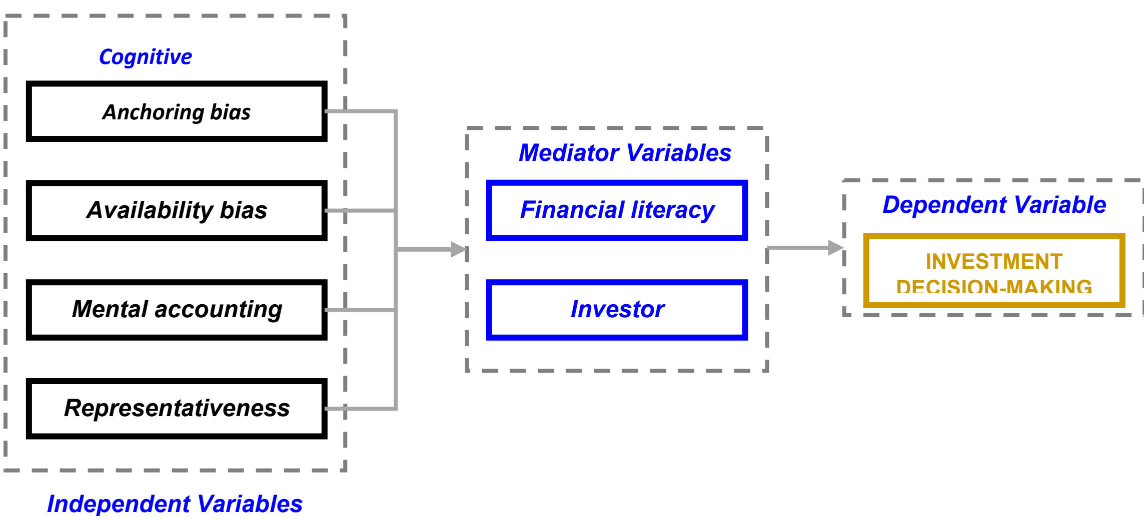

Figure 1. Conceptual Framework
Source: Prepared by the authors

Anchoring bias captures investors' tendency to rely excessively on initial reference points when making investment judgments, even when such anchors are irrelevant or outdated. Availability bias reflects the inclination to overweight information that is more easily recalled or recently observed, leading investors to base decisions on salient rather than comprehensive information. Mental accounting represents the cognitive process through which investors categorize and evaluate financial outcomes separately, often resulting in inconsistent risk preferences across different investment contexts. Representativeness bias refers to the tendency to assess probabilities based on perceived similarities or past patterns, which may cause investors to extrapolate trends without sufficient statistical justification. The framework further incorporates financial literacy and investor sentiment as mediator variables, recognizing that the influence of cognitive biases on investment decision-making is rarely linear or isolated. Financial literacy is expected to shape investors' ability to recognize, interpret, and manage behavioral distortions by enhancing their understanding of financial concepts, risk–return trade-offs, and market dynamics. Higher levels of financial literacy may mitigate the adverse effects of cognitive biases, whereas limited financial knowledge can amplify their impact.

Investor sentiment, on the other hand, captures the affective and psychological state of investors, reflecting optimism, pessimism, or confidence toward market conditions. Cognitive biases are likely to influence sentiment formation, which in turn affects investment decisions by altering risk tolerance, trading intensity, and decision confidence. By modeling investor sentiment as a mediator, the framework acknowledges the emotional channel through which cognitive biases translate into observable investment behavior. The dependent variable, investment decision-making, represents the outcome of these interconnected behavioral processes. It reflects the quality, consistency, and rationality of investors' decisions, encompassing aspects such as risk assessment, timing, and selection of investment instruments.

Within this framework, investment decision-making is not treated as a purely rational outcome but as a behavioral construct shaped by cognitive limitations and psychological influences. The proposed conceptual framework provides an integrated structure for examining how multiple cognitive biases jointly influence investment decision-making through financial literacy and investor sentiment. By employing a PLS-SEM approach, the study is able to simultaneously assess the measurement properties of latent constructs and the structural relationships among them, offering a comprehensive and empirically robust explanation of investor behavior in the Mongolian context.

Results and Discussions

Demographic and Socioeconomic Characteristics

Table 1 presents the demographic and socioeconomic characteristics of the respondents included in this study. The sample consists of 529 individual investors, providing a sufficiently large and diverse dataset for structural equation modeling and behavioral analysis, in line with methodological recommendations for PLS-SEM studies (Hair *et al.*, 2019).

Table 1. Demographic Profile

Socio-Economic Variable		Frequency	Relative Frequency (%)
Gender	**Female**	**273**	**51.6%**
	Male	256	48.4%
Age	24 and below	42	7.9%
	25 – 34	157	29.7%
	35 – 44	**161**	**30.4%**
	45 – 54	103	19.5%
	55 – 64	50	9.5%
	65 and below	16	3.0%
Marital Status	**Married**	**336**	**63.5%**
	Single	150	28.4%
	Widowed	11	2.1%
	Divorced	17	3.2%
	Cohabiting	15	2.8%
Education Level	**Bachelor's degree**	**334**	**63.1%**
	Master's degree or above	153	28.9%
	Completed secondary education	19	3.6%
	Incomplete secondary education	7	1.3%
	Technical and vocational education	14	2.6%
	Technical and vocational education	2	0.4%
Investment experience	**0-3 years**	**290**	**54.8%**
	4-6 years	139	26.3%
	7-9 years	46	8.7%
	10-12 years	23	4.3%
	12-15 years	16	3.0%
	More than 15 years	15	2.8%

Source: Authors' calculations based on the 2025 field survey

In terms of gender composition, the sample is relatively balanced, with female respondents accounting for 51.6 percent (*n=273*) and male respondents representing 48.4 percent (*n=256*). This balanced distribution reduces the likelihood of gender-driven bias in behavioral interpretations and allows for a more representative examination of investment decision-making across genders, which is particularly relevant given prior evidence suggesting that behavioral biases may manifest differently among male and female investors (Barber & Odean, 2001).

The age distribution indicates that the majority of respondents fall within the economically active and investment-relevant age groups. Investors aged between 25 and 44 years constitute the largest share of the sample, accounting for approximately 60 percent of respondents. Specifically, individuals aged 25–34 years represent 29.7 percent, while those aged 35–44 years account for 30.4 percent. This concentration reflects the growing participation of younger and middle-aged individuals in financial markets, a trend commonly observed in emerging economies where digital trading platforms and increased access to financial information have lowered entry barriers (Lusardi & Mitchell, 2014). Older age groups are also represented, with respondents aged 45–54 and 55–64 accounting for 19.5 percent and 9.5 percent, respectively, while investors aged 65 and below constitute a smaller proportion of the sample.

Regarding marital status, the majority of respondents are married (63.5 percent), followed by single individuals who have never married (28.4 percent). Widowed, divorced, and cohabiting respondents collectively represent a relatively small share of the sample. This distribution suggests that most participants are likely to be embedded in household-based financial decision-making contexts, which may influence risk preferences and investment behavior through shared financial responsibilities and long-term planning considerations (Guiso, Sapienza & Zingales, 2018).

The educational profile of the sample reveals a notably high level of formal education. More than 90 percent of respondents hold at least a bachelor's degree, with 63.1 percent possessing a bachelor's degree and an additional 28.9 percent holding a master's degree or higher. This high educational attainment is consistent with prior research indicating that participation in capital markets is positively associated with higher education levels, as education enhances financial awareness, information processing capacity, and engagement with complex financial products (Van Rooij, Lusardi & Alessie, 2011). Respondents with secondary, vocational, or lower levels of education constitute a relatively small fraction of the sample, suggesting that the study primarily captures the behavior of relatively informed market participants.

Investment experience among respondents varies considerably, allowing for meaningful behavioral heterogeneity. A majority of investors (54.8 percent) report having between zero and three years of investment experience, indicating a substantial presence of relatively novice investors in the sample. At the same time, a significant proportion of respondents report moderate levels of experience, with 26.3 percent having four to six years and 8.7 percent having seven to nine years of investment experience. More experienced investors, those with over ten years of market participation, represent a smaller but non-negligible segment of the sample. This distribution is particularly valuable for behavioral analysis, as prior studies suggest that cognitive biases may persist across experience levels but often vary in intensity and expression (Daniel, Hirshleifer & Subrahmanyam, 1998; Kaustia & Knüpfer, 2008).

Collectively, the demographic composition of the sample reflects a diverse group of individual investors in terms of age, marital status, education, and investment experience. Such diversity enhances the external validity of the findings and provides a robust empirical foundation for examining how cognitive biases, financial literacy, and investor sentiment jointly shape investment decision-making in an emerging financial market context.

The descriptive examination of the study variables indicates that the observed indicators display appropriate levels of central tendency, variability, and distributional stability. These preliminary characteristics suggest that respondents engaged meaningfully with the survey items and that the data possess sufficient informational content for multivariate modeling. In light of these properties, the analysis proceeds to a more rigorous evaluation of the measurement structure underlying the latent constructs (see Table 2).

Table 2 reports the descriptive statistics for all observed indicators used to operationalize the latent constructs in the empirical model. The mean values of the indicators range from 2.312 to 4.115, indicating meaningful variation in respondents' evaluations across different behavioral dimensions. The lowest mean value is observed for AV1 (Mean=2.312), suggesting relatively lower agreement with this availability bias–related statement, whereas the highest mean value corresponds to FL5 (Mean=4.115), reflecting strong agreement with a financial literacy item. This spread in mean values suggests that respondents did not uniformly endorse all statements and instead differentiated clearly across constructs and indicators.

Median values further reinforce this pattern. Most indicators exhibit median values of 3 or 4, indicating that responses are concentrated around neutral to agreement categories rather than at the extremes of the scale. For example, items such as AV3, AV5, FL1, FL3, FL4, FL5, IDM1, IDM2, and IS1 all report a median of 4, suggesting that a substantial proportion of respondents expressed agreement with statements related to availability bias, financial literacy, investment decision-making, and investor sentiment. In contrast, indicators with median values of 2, such as AV1, AV2, and AV4, indicate comparatively weaker endorsement of certain availability bias items, highlighting within-construct heterogeneity.

The standard deviation values range between 0.905 and 1.194, reflecting moderate dispersion across all indicators. The lowest dispersion is observed for IDM1 (SD=0.905), suggesting relatively consistent responses regarding this investment decision-making item, whereas higher dispersion is evident for indicators such as MA2 (SD=1.194) and RP2 (SD=1.185), indicating greater variability in respondents' perceptions related to mental accounting and risk preference. This level of variability is desirable for latent variable modeling, as it allows the model to capture individual differences rather than collapsing responses around a narrow range.

An examination of skewness reveals that most indicators exhibit negative skewness, with values generally ranging between −0.095 and −0.954. Stronger negative skewness is observed for indicators such as FL5 (Skewness=−0.954) and RP2 (Skewness=−0.749), indicating that responses are concentrated toward higher scale values, consistent with stronger agreement. Conversely, a small number of indicators, such as AV1 (Skewness=0.372), AV2 (0.324), and AV4 (0.370), display positive skewness, reflecting a tendency toward lower agreement levels for certain availability bias statements. These contrasting skewness patterns further suggest that respondents discriminated meaningfully across different behavioral dimensions.

Excess kurtosis values are predominantly negative and range from −0.773 to 0.212, indicating relatively flat (platykurtic) distributions with no evidence of heavy tails or extreme outliers. Indicators such as AV1 (−0.773) and MA5 (−0.724) exhibit flatter distributions, while values close to zero, such as AV3 (0.212) and FL5 (0.118), suggest distributions approximating normality. The absence of extreme kurtosis values supports the stability of the data and reduces concerns regarding estimation bias or undue influence of extreme observations.

Table 2. Descriptive Statistics

Latent Variables	Mean	Median	Standard deviation	Excess kurtosis	Skewness
AN1	3.301	3.000	1.087	-0.403	-0.309
AN3	3.270	3.000	1.060	-0.348	-0.289
AN4	3.319	3.000	1.167	-0.683	-0.314
AN5	3.234	3.000	1.019	-0.197	-0.267
AV1	2.312	2.000	1.115	-0.773	0.372
AV2	2.448	2.000	1.128	-0.653	0.324
AV3	3.679	4.000	1.012	0.212	-0.642
AV4	2.408	2.000	1.108	-0.545	0.370
AV5	3.529	4.000	1.084	-0.060	-0.589
AV6	3.017	3.000	1.099	-0.551	-0.231
FL1	3.633	4.000	1.156	-0.697	-0.408
FL2	3.389	3.000	1.175	-0.753	-0.252
FL3	3.594	4.000	1.096	-0.586	-0.343
FL4	3.520	4.000	1.160	-0.647	-0.376
FL5	4.115	4.000	1.038	0.118	-0.954
IDM1	3.677	4.000	0.905	-0.096	-0.328
IDM2	3.652	4.000	1.014	-0.140	-0.506
IDM3	3.631	4.000	0.946	-0.158	-0.321
IDM4	3.272	3.000	1.005	-0.308	-0.085
IDM5	3.467	3.000	1.050	-0.234	-0.393
IDM6	3.622	4.000	0.986	-0.037	-0.431
IDM7	3.149	3.000	1.028	-0.312	-0.093
IS1	3.750	4.000	1.097	-0.328	-0.578
IS2	3.382	3.000	1.078	-0.436	-0.242
IS3	3.174	3.000	1.100	-0.467	-0.272
IS4	3.609	4.000	1.008	-0.137	-0.443
MA1	3.533	4.000	1.113	-0.280	-0.504
MA2	3.686	4.000	1.194	-0.382	-0.660
MA3	3.206	3.000	1.169	-0.627	-0.157
MA4	3.004	3.000	1.083	-0.388	-0.025
MA5	3.176	3.000	1.180	-0.724	-0.095
RP1	3.206	3.000	1.083	-0.359	-0.291
RP2	3.743	4.000	1.185	-0.212	-0.749
RP3	2.962	3.000	1.061	-0.434	-0.182
RP4	2.932	3.000	1.179	-0.760	-0.062
RP5	3.459	3.000	1.012	0.092	-0.477

Source: Authors' estimate

Inferential Analysis

Impact of cognitive biases in investment decision-making

The correlation matrix indicates moderate and positive associations among all latent constructs, suggesting meaningful behavioral linkages without evidence of multicollinearity. Anchoring bias is most strongly correlated with availability bias (r=0.547) and representativeness bias (r=0.499), indicating that reference dependence, information salience, and pattern-based reasoning tend to co-occur. Availability bias shows its strongest association with representativeness bias (r=0.566), highlighting the close relationship between salient information processing and heuristic judgment (see Table 3).

Table 3. Correlation Matrix

	AN	AV	FL	IDM	IS	MA	RP
AN	1						
AV	0.547	1					
FL	0.275	0.336	1				
IDM	0.285	0.323	0.550	1			
IS	0.383	0.423	0.559	0.544	1		
MA	0.421	0.487	0.538	0.488	0.541	1	
RP	0.499	0.566	0.495	0.435	0.553	0.614	1

Source: Authors' estimate

Financial literacy exhibits relatively strong correlations with both investment decision-making (r=0.550) and investor sentiment (r=0.559), suggesting that knowledge-related capabilities are closely linked to decision quality and sentiment formation. Investment decision-making is also moderately associated with investor sentiment (r=0.544), underscoring the role of psychological factors in shaping investment outcomes. The strongest correlation in the matrix is observed between mental accounting and representativeness bias (r=0.614), indicating a particularly tight connection between outcome framing and pattern recognition. Importantly, all correlation coefficients remain below 0.70, confirming that multicollinearity is unlikely to affect the subsequent PLS-SEM estimation and supporting the inclusion of all constructs in the structural model.

Discriminant validity refers to the extent to which a latent construct is empirically distinct from other constructs within the model. Its core purpose is to ensure that each construct captures a unique conceptual domain and does not merely reflect another latent variable measured with different indicators. In behavioral and psychological research, where constructs such as cognitive biases, sentiment, and decision-making are theoretically related yet conceptually distinct, establishing discriminant validity is particularly critical. Without adequate discriminant validity, estimated relationships in the structural model may be confounded, leading to inflated path coefficients and ambiguous theoretical interpretations (see Table 4).

Within the PLS-SEM framework, discriminant validity is most robustly assessed using the Heterotrait–Monotrait Ratio (HTMT), which compares the average correlations across constructs to those within the same construct. Unlike traditional criteria, HTMT directly evaluates whether constructs are empirically distinguishable. Values below the commonly accepted thresholds of 0.85 (strict criterion) or 0.90 (liberal criterion) indicate satisfactory discriminant validity (Henseler, Ringle & Sarstedt, 2015).

Table 4 presents the HTMT results for all construct pairs included in the model. All HTMT values remain below the conservative threshold of 0.85, indicating that discriminant validity is well established across the measurement model. The highest HTMT value is observed between Mental Accounting (MA) and Representativeness Bias (RP) (HTMT=0.831), reflecting their close conceptual proximity as cognitive heuristics. However, this value remains within acceptable limits, confirming that the two constructs, while related, capture empirically distinct aspects of investor cognition. Other relatively high HTMT values, such as between Availability Bias (AV) and Representativeness Bias (RP) (HTMT=0.735) and between Investor Sentiment (IS) and Representativeness Bias (RP) (HTMT=0.724), are theoretically consistent with behavioral finance literature and do not threaten construct distinctiveness.

Table 4. Discriminant Validity test - Heterotrait Monotrait Ration (HTMT)

	AN	AV	FL	IDM	IS	MA	RP
AN							
AV	0.736						
FL	0.343	0.315					
IDM	0.368	0.320	0.620				
IS	0.523	0.493	0.653	0.644			
MA	0.579	0.605	0.641	0.577	0.709		
RP	0.686	0.735	0.552	0.522	0.724	0.831	

Source: Authors' estimate

HTMT results provide strong empirical support for the discriminant validity of the measurement model. The findings confirm that anchoring bias, availability bias, financial literacy, mental accounting, representativeness bias, investor sentiment, and investment decision-making represent conceptually and empirically separable constructs. This establishes a reliable measurement foundation for subsequent structural model estimation and hypothesis testing.

Construct reliability and validity assess whether the observed indicators consistently and accurately represent their intended latent constructs. Reliability focuses on the internal consistency of the indicators, while convergent validity evaluates the extent to which a construct explains the variance of its indicators. In the PLS-SEM framework, these properties are commonly examined using Cronbach's alpha, composite reliability (rho_A and rho_C), and average variance extracted (AVE), as they jointly provide a robust evaluation of measurement quality.

Table 5. Construct reliability and validity

Variables	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AN	0.704	0.709	0.819	0.531
AV	0.707	0.733	0.711	0.523
FL	0.874	0.877	0.909	0.666
IDM	0.855	0.877	0.891	0.546
IS	0.784	0.814	0.861	0.612
MA	0.700	0.729	0.801	0.514
RP	0.731	0.747	0.817	0.508

Source: Authors' estimate

As reported in Table 5, Cronbach's alpha values range from 0.700 to 0.874, exceeding the commonly accepted threshold of 0.70 for all constructs. This indicates satisfactory internal consistency across indicators measuring anchoring bias (AN), availability bias (AV), financial literacy (FL), investment decision-making (IDM), investor sentiment (IS), mental accounting (MA), and representativeness bias (RP). The highest internal consistency is observed for financial literacy (α=0.874) and investment decision-making (α=0.855), suggesting particularly stable measurement of these constructs.

The composite reliability measures further confirm these results. Values of rho_A range between 0.709 and 0.877, while rho_C ranges from 0.711 to 0.909, all exceeding the recommended minimum of 0.70. Notably, financial literacy (rho_C=0.909) and investment decision-making (rho_C=0.891) demonstrate strong composite reliability, indicating that their indicators jointly provide a highly consistent representation of the underlying constructs. Constructs related to cognitive biases, such as anchoring bias and mental accounting, also exhibit acceptable reliability levels, supporting their inclusion in the model.

Convergent validity is assessed using AVE. All constructs report AVE values above the threshold of 0.50, ranging from 0.508 to 0.666. This indicates that each construct explains more than half of the variance of its indicators. Financial literacy shows the highest convergent validity (AVE=0.666), followed by investor sentiment (AVE=0.612), while constructs such as representativeness bias (AVE=0.508) and mental accounting (AVE=0.514) remain slightly above the minimum acceptable level, suggesting adequate but more modest convergence.

Taken in their empirical context, these results provide strong evidence that the measurement model exhibits satisfactory reliability and convergent validity across all latent constructs. The indicators consistently measure their intended concepts, and the constructs capture a substantial proportion of indicator variance. This confirms that the measurement model is well specified and provides a sound foundation for subsequent structural model estimation and hypothesis testing.

Model fit indices provide an overall assessment of how well the proposed structural model reproduces the observed data. In the context of PLS-SEM, model fit is evaluated using a set of approximate fit measures rather than strict covariance-based criteria, as the primary objective is prediction-oriented modeling. Among these indices, the Standardized Root Mean Square Residual (SRMR) serves as a key indicator of the average discrepancy between observed and model-implied correlations, while d_ULS and d_G capture the discrepancy between empirical and model-implied covariance matrices. The Normed Fit Index (NFI) provides a relative measure of model fit compared to a null model, and the chi-square statistic is reported for completeness, although it is known to be sensitive to sample size in SEM applications.

Table 6 reports the overall fit statistics for both the saturated and estimated models. The SRMR values of 0.077 for the saturated model and 0.071 for the estimated model fall below the recommended threshold of 0.08, indicating an acceptable approximation of the observed correlation structure. The slightly lower SRMR for the estimated model suggests an improvement in model fit after specifying the structural relationships.

Table 6. Results of Model Fit

	Saturated model	**Estimated model**
SRMR	0.077	0.071
d_ULS	5.048	5.497
d_G	0.964	0.999
Chi-square	2943.901	2981.838
NFI	0.863	0.857

Source: Authors' estimate

Discrepancy measures d_ULS and d_G remain stable across model specifications, with values of 5.048 and 0.964 for the saturated model and 5.497 and 0.999 for the estimated model, respectively. This stability indicates that the introduction of structural constraints does not materially distort the model's ability to reproduce the empirical data. Normed Fit Index (NFI) values of 0.863 for the saturated model and 0.857 for the estimated model indicate a satisfactory level of relative fit, particularly within a PLS-SEM framework. The marginal decline in NFI reflects increased model parsimony rather than a substantive reduction in explanatory adequacy. Despite the increase in the chi-square statistic from 2943.901 to 2981.838, the model demonstrates satisfactory overall fit, as supported by the SRMR and NFI values, confirming that the estimated structural specification adequately represents the observed data. Taken as a whole, the reported fit indices support the adequacy of the estimated structural model, providing a sound basis for subsequent hypothesis testing and interpretation of structural relationships.

Empirical Analysis of PLS-SEM

Building on the proposed conceptual framework and the results of the structural model estimation, the following section discusses the direct effects hypothesized among the latent constructs. Each hypothesis is evaluated based on its statistical significance, direction, and magnitude, and the findings are interpreted in light of existing international empirical evidence (see Table 7).

Table 7. Testing of Hypothesis (Direct Effect)

Hypothesis	beta	SE	t statistics	p − value	Decision
AN -> FL	-0.026	0.056	0.450	0.652	Rejected
AN -> IS	0.072	0.050	1.437	0.151	Rejected
AV -> FL	0.026	0.080	0.188	0.851	Rejected
AV -> IS	0.080	0.047	1.585	0.113	Rejected
FL -> IDM	0.358	0.048	7.479	0.000	Accepted
IS -> IDM	0.346	0.050	6.934	0.000	Accepted
MA -> FL	0.376	0.052	7.236	0.000	Accepted
MA -> IS	0.290	0.055	5.321	0.000	Accepted
RP -> FL	0.267	0.058	4.596	0.000	Accepted
RP -> IS	0.298	0.060	4.902	0.000	Accepted

Source: Authors' estimate

Hypothesis H1: Anchoring Bias → Financial Literacy (Rejected)

Turning to Hypothesis H1, the direct effect of anchoring bias on financial literacy is negative and statistically insignificant ($\beta=-0.026$, $p=0.652$), leading to the rejection of the hypothesis. This result indicates that anchoring bias does not meaningfully influence investors' levels of financial knowledge. From a theoretical perspective, anchoring is widely understood as a cognitive shortcut that affects judgment and estimation rather than the acquisition of objective financial competence. Empirical studies consistently show that anchoring persists even among well-educated and financially sophisticated individuals, suggesting that knowledge does not eliminate reliance on reference points (Tversky & Kahneman, 1974; Northcraft & Neale, 1987; Campbell *et al.*, 2011; Furnham & Boo, 2011; Pompian, 2012; Kudryavtsev, Cohen & Hon-Snir, 2013). The present finding is therefore consistent with international evidence and supports the view that anchoring operates independently of financial literacy.

Hypothesis H2: Anchoring Bias → Investor Sentiment (Rejected)

With respect to Hypothesis H2, anchoring bias does not exhibit a statistically significant effect on investor sentiment ($\beta=0.072$, $p=0.151$). This finding suggests that anchoring alone is insufficient to shape investors' emotional or affective responses toward market conditions. Prior literature indicates that sentiment is more strongly driven by market-wide signals, news intensity, and social interaction than by individual reference-point dependence (Baker & Wurgler, 2007; Barberis *et al.*, 2018). While anchoring influences valuation judgments, its emotional impact appears weaker unless reinforced by salient market narratives (Shiller, 2015; De Bondt et al., 2008). Similar empirical results are reported by Schmeling (2009), Statman et al. (2008), and Kaplanski et al. (2015), who emphasize that sentiment formation reflects broader psychological and informational environments rather than isolated heuristics. Accordingly, the rejection of H2 aligns with existing behavioral finance evidence.

Hypothesis H3: Availability Bias → Financial Literacy (Rejected)

Regarding Hypothesis H3, the estimated path from availability bias to financial literacy is statistically insignificant (β=0.026, p=0.851). This result implies that reliance on salient or easily recalled information does not systematically influence investors' financial knowledge. Conceptually, availability bias affects information weighting rather than knowledge accumulation, meaning that investors may selectively attend to vivid information regardless of their literacy level (Tversky & Kahneman, 1974). Empirical studies confirm that even financially literate investors are prone to availability-driven distortions, particularly during periods of intense media coverage or market shocks (Barber & Odean, 2008; Hirshleifer, Lim & Teoh, 2009; Kliger & Kudryavtsev, 2010; Da, Engelberg & Gao, 2011; Engelberg & Parsons, 2011). The absence of a significant relationship in this study is therefore consistent with international findings.

Hypothesis H4: Availability Bias → Investor Sentiment (Rejected)

Turning to Hypothesis H4, availability bias does not exert a statistically significant direct effect on investor sentiment (β=0.080, p=0.113). Although availability bias shapes attention and recall, sentiment formation often requires emotional amplification through collective narratives and social contagion. Prior research shows that sentiment responds more strongly to aggregated news tone, macroeconomic uncertainty, and market-wide events than to individual-level availability heuristics (Baker & Wurgler, 2007; P. C. Tetlock, 2007; Shiller, 2015). Studies by Schmeling (2009), García (2013), Kaplanski et al. (2015), and Barberis et al. (2018) similarly suggest that availability alone is insufficient to generate persistent sentiment shifts. The rejection of H4 is therefore theoretically and empirically well supported.

Hypothesis H5: Financial Literacy → Investment Decision-Making (Accepted)

Turning to Hypothesis H5, financial literacy has a positive and highly significant effect on investment decision-making (β=0.358, $p < 0.001$), supporting the hypothesis. This result indicates that financially knowledgeable investors tend to make more informed and structured investment decisions. Extensive international evidence confirms that financial literacy improves portfolio diversification, risk assessment, and long-term investment performance (Van Rooij, Lusardi & Alessie, 2011; Fernandes, Lynch & Netemeyer, 2014; Lusardi & Mitchell, 2014; Calcagno & Monticone, 2015; OECD, 2020). The finding strongly aligns with prior research and reinforces the central role of financial education in enhancing investment decision quality.

Hypothesis H6: Investor Sentiment → Investment Decision-Making (Accepted)

With respect to Hypothesis H6, investor sentiment exhibits a positive and statistically significant effect on investment decision-making (β=0.346, $p < 0.001$). This result highlights the influential role of emotional and psychological states in shaping investment behavior. Behavioral finance literature consistently documents that sentiment affects trading intensity, risk-taking, and asset allocation decisions (De Long *et al.*, 1990; Baker & Wurgler, 2006; Statman, Fisher & Anginer, 2008; Schmeling, 2009; Shiller, 2015;

Barberis *et al.*, 2018). The present finding is fully consistent with these international results and confirms sentiment as a key behavioral driver of investment decisions.

Hypothesis H7: Mental Accounting → Financial Literacy (Accepted)

Regarding Hypothesis H7, mental accounting shows a strong and statistically significant positive effect on financial literacy (β=0.376, $p < 0.001$). This suggests that investors who actively categorize and track financial outcomes tend to develop higher levels of financial understanding. Prior studies indicate that budgeting, categorization, and record-keeping behaviors are closely linked to improved financial awareness and learning (Gneezy et al., 2014; Hastings & Mitchell, 2020; Heath & Soll, 1996; Lusardi et al., 2017; De bond Shefrin, 2008; Thaler, 1999). The result aligns well with international evidence and highlights the constructive dimension of mental accounting.

Hypothesis H8: Mental Accounting → Investor Sentiment (Accepted)

Turning to Hypothesis H8, mental accounting has a significant positive effect on investor sentiment (β=0.290, $p < 0.001$). This finding indicates that structured financial categorization influences investors' emotional responses to gains and losses. Prior research demonstrates that mental accounting shapes how investors emotionally frame outcomes, thereby affecting confidence and sentiment (Shefrin & Statman, 1985; Thaler, 1999; Barberis and Huang, 2001; Kaustia, 2010; Barberis and Xiong, 2012; Gneezy, Imas & Madarász, 2014). The result is consistent with international behavioral finance evidence.

Hypothesis H9: Representativeness Bias → Financial Literacy (Accepted)

With respect to Hypothesis H9, representativeness bias exerts a positive and statistically significant effect on financial literacy (β=0.267, $p < 0.001$). This suggests that investors who rely on pattern recognition and heuristics may actively seek financial information to justify their beliefs. Empirical studies show that representativeness often coexists with information acquisition rather than ignorance (Tversky & Kahneman, 1974; De Bondt, 1993; Barberis, Shleifer & Vishny, 1998; Bloomfield, O'hara & Saar, 2009; Pompian, 2012; Kudryavtsev, Cohen & Hon-Snir, 2013). The finding is therefore consistent with prior international research.

Hypothesis H10: Representativeness Bias → Investor Sentiment (Accepted)

Finally, turning to Hypothesis H10, representativeness bias has a strong positive effect on investor sentiment (β=0.298, $p < 0.001$). This indicates that pattern-based reasoning significantly shapes emotional expectations and market optimism or pessimism. International studies consistently document that representativeness drives extrapolative beliefs and sentiment cycles in financial markets (De Bondt & Thaler, 1985; Barberis, Shleifer & Vishny, 1998; Hirshleifer, 2001; Bordalo, Gennaioli & Shleifer, 2012; Shiller, 2015; Barberis *et al.*, 2018). The result aligns closely with established behavioral finance theory.

Building on the structural relationships identified in the direct effects analysis, the present study proceeds to examine the indirect pathways through which cognitive biases influence investment decision-making. From a behavioral finance perspective, such mediation analysis is essential for uncovering the underlying cognitive and affective transmission mechanisms, as behavioral biases rarely affect final investment outcomes in a purely direct manner. Instead, their influence is often conveyed through intermediate processes such as financial literacy and investor sentiment.

Examined within this analytical framework, the results indicate that anchoring bias and availability bias do not generate statistically significant indirect effects on investment decision-making through either financial literacy or investor sentiment. Specifically, the indirect paths linking anchoring bias and availability bias to investment decision-making via financial literacy and investor sentiment fail to reach statistical significance. This empirical pattern suggests that these two biases primarily operate as context-dependent judgmental heuristics, exerting influence at the point of decision rather than through sustained changes in investors' knowledge structures or emotional dispositions. In this sense, anchoring and availability biases appear to affect how information is processed in specific situations, without translating into stable learning or sentiment-driven behavioral channels (see Table 8).

Table 8. Testing of Hypothesis (Indirect Effect)

Hypothesis	beta	Stdev	t statistics	p − value	Decision
AN -> FL -> IDM	-0.010	0.020	0.444	0.657	rejected
AV -> FL -> IDM	0.010	0.029	0.185	0.853	rejected
MA -> IS -> IDM	0.101	0.025	4.063	0.000	accepted
RP -> IS -> IDM	0.103	0.026	3.924	0.000	accepted
MA -> FL -> IDM	0.135	0.028	4.893	0.000	accepted
RP -> FL -> IDM	0.095	0.024	4.028	0.000	accepted
AN -> IS -> IDM	0.025	0.018	1.389	0.165	rejected
AV -> IS -> IDM	0.028	0.017	1.529	0.126	rejected

Source: Authors' estimate

By contrast, a markedly different transmission pattern emerges for mental accounting and representativeness bias. Viewed through an integrated empirical lens, both biases demonstrate statistically significant indirect effects on investment decision-making, operating through financial literacy and investor sentiment. The indirect effects transmitted via investor sentiment indicate that structured outcome framing and pattern-based reasoning shape investors' emotional responses to market information, which in turn influence decision quality. This finding underscores investor sentiment as a critical affective conduit through which certain cognitive biases materialize into observable investment behavior.

In addition, the mediation results reveal that financial literacy serves as an important cognitive transmission channel for mental accounting and representativeness bias. The significant indirect effects through financial literacy suggest that these biases may coexist with, or even stimulate, greater engagement with financial information and learning processes. Rather than uniformly impairing decision-making, mental accounting and representativeness bias appear to interact with investors' cognitive development, indirectly enhancing investment decision-making through improved financial understanding.

Synthesizing the empirical evidence, the mediation analysis reveals a selective and asymmetric pattern of indirect effects. While anchoring bias and availability bias do not transmit their influence through financial literacy or investor sentiment, mental accounting and representativeness bias exert meaningful indirect effects through both cognitive and affective mechanisms. This asymmetry highlights the importance of distinguishing among different types of cognitive biases when modeling investor behavior and demonstrates that not all behavioral distortions operate through identical pathways. The findings provide a nuanced understanding of how cognitive biases shape investment decision-making in an emerging market context and offer strong empirical support for incorporating mediating variables into behavioral finance models.

Conclusion

The importance of this study is underscored by its ability to empirically demonstrate how cognitive biases translate into investment decision-making through specific behavioral transmission channels within an emerging financial market context. The results reveal that investor behavior in Mongolia cannot be adequately explained by direct bias effects alone; rather, decision outcomes emerge from a structured interaction between cognitive heuristics, financial literacy, and investor sentiment. This finding directly addresses a longstanding limitation in the behavioral finance literature, which has predominantly focused on identifying bias presence without systematically modeling the mechanisms through which such biases become behaviorally consequential, particularly outside developed market settings.

Our study provides a mechanism-based explanation of investment decision-making in Mongolia by linking cognitive biases, financial literacy, and investor sentiment within a unified PLS-SEM framework. The hypothesis testing results demonstrate that behavioral effects are neither homogeneous nor purely direct. Instead, investment decisions emerge from selective transmission mechanisms that differentiate between situational heuristics and structurally relevant cognitive biases.

Empirical evidence shows that anchoring bias and availability bias do not exert statistically significant direct or indirect effects on investment decision-making through financial literacy or investor sentiment. These rejected hypotheses indicate that such heuristics operate primarily as context-specific judgmental shortcuts rather than as stable drivers of learning or sentiment formation. This finding refines behavioral finance theory by challenging the implicit assumption that all cognitive biases systematically undermine decision quality.

In contrast, mental accounting and representativeness bias display statistically significant indirect effects on investment decision-making through both financial literacy and investor sentiment, confirming the acceptance of the corresponding mediation hypotheses. These results indicate that certain biases interact with information processing and belief formation, thereby influencing decisions through structured cognitive and affective channels. Financial literacy and investor sentiment also exhibit strong and significant direct effects on investment decision-making, confirming their role as proximate determinants of decision quality.

The robustness of these conclusions is supported by data collected from 529 active individual investors through a targeted 2025 field survey. The sample size and heterogeneity across demographic and investment experience categories provide sufficient statistical power and external validity for PLS-SEM estimation. By jointly testing multiple biases and explicitly modeling mediation mechanisms, this study closes a key research gap by moving beyond bias identification toward explaining how and why specific behavioral pathways influence investment outcomes in an emerging market context.

Policy Implications and Future Research

Policy relevance of this study emerges directly from the empirically identified behavioral transmission mechanisms shaping investment decision-making in Mongolia. Evidence shows that decision quality is not uniformly distorted by all cognitive biases; rather, influence materializes selectively through financial literacy and investor sentiment. This finding implies that effective investor policy must move beyond generalized assumptions of irrationality and instead focus on strengthening the specific channels through which behavior is empirically shown to operate.

Strong direct and mediating effects associated with financial literacy indicate that knowledge-based capacity remains a central determinant of sound investment behavior. Enhancing financial literacy should therefore extend beyond basic awareness toward the development of analytical competencies related to risk evaluation, portfolio diversification, and long-term planning. Mediation results further indicate that financial literacy functions not only as an independent driver of decision quality but also as a mechanism through which certain cognitive biases, particularly mental accounting and representativeness bias, translate into observable investment outcomes. It implies policies that promote financial literacy can reduce the behavioral impact of such biases by embedding them into a more structured and informed decision-making process.

Investor sentiment also plays a decisive role in shaping investment decisions, highlighting the importance of affective and expectation-driven dynamics in an emerging market environment. Empirical results demonstrate that sentiment operates as a key transmission channel linking representativeness-based beliefs and mental framing to final decisions. These results underscore that effective regulatory communication and disclosure frameworks are essential for reducing information asymmetry, stabilizing investor expectations, and constraining excessive swings in optimism or pessimism during volatile market conditions. Transparent and timely dissemination of market information can therefore serve as an indirect behavioral stabilizer by influencing sentiment formation rather than attempting to suppress heuristics directly.

Absence of statistically significant direct or indirect effects associated with anchoring bias and availability bias carries equally important policy implications. These findings suggest that such heuristics function primarily as situational judgment shortcuts rather than as persistent drivers of learning or sentiment. As a result, broad debiasing initiatives targeting anchoring or information salience are unlikely to generate sustained improvements in investment decision-making. Greater effectiveness is likely to be achieved by concentrating policy resources on biases that exhibit stable transmission through empirically supported cognitive and affective channels.

Future research directions follow naturally from these findings. Longitudinal data would allow examination of how cognitive biases, financial literacy, and investor sentiment evolve over time and interact across different market conditions, thereby strengthening causal inference and capturing dynamic behavioral adjustments. Incorporating objective behavioral indicators, such as transaction records or portfolio performance measures, would further validate the mechanisms identified in survey-based analysis and reduce potential self-reporting biases. Comparative studies involving other emerging or frontier markets would help determine whether the selective mediation patterns observed in Mongolia reflect broader institutional conditions or market-specific characteristics. Expanding the framework to include additional psychological or institutional variables, such as overconfidence, risk tolerance, trust in financial institutions, or regulatory credibility, would also deepen understanding of investor behavior and refine the explanatory power of behavioral finance models.

Alignment of investor policy with empirically validated behavioral mechanisms and continued extension of research toward dynamic and comparative perspectives offer a credible pathway for improving both academic insight and practical outcomes in emerging financial markets such as Mongolia.

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Appendices

Appendix 1. Result of VIF test

	AN	AV	FL	IDM	IS	MA	RP
AN			1.557		1.557		
AV			1.753		1.753		
FL				1.455			
IDM							
IS				1.455			
MA			1.698		1.698		
RP			1.971		1.971		

Appendix 2. Outer loadings matrix

	AN	AV	FL	IDM	IS	MA	RP
AN1	0.726						
AN3	0.786						
AN4	0.856						
AN5	0.732						
AV1		0.741					
AV2		0.822					
AV3		0.845					
AV4		0.383					
AV5		0.743					
AV6		0.712					
FL1			0.813				
FL2			0.829				
FL3			0.872				
FL4			0.809				
FL5			0.754				
IDM1				0.801			
IDM2				0.818			
IDM3				0.831			
IDM4				0.503			
IDM5				0.703			
IDM6				0.816			
IDM7				0.734			
IS1					0.821		
IS2					0.829		
IS3					0.707		
IS4					0.854		
MA1						0.780	
MA2						0.803	
MA3						0.746	
MA4						0.829	
MA5						0.711	
RP1							0.726
RP2							0.704
RP3							0.805
RP4							0.772
RP5							0.757