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Cognitive Biases and Financial Decision Making: The Role of Digital Finance and Financial Literacy

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ABSTRACT

Cognitive biases and their influence on investment choices are a key field of research, especially in the context of financial literacy and digital finance. Cognitive biases, which include factors such as emotions, social pressure, and heuristics, lead to deviations from norms or rationality in judgment. This research study aimed to explore the connection between financial literacy, digital finance, cognitive biases, and financial decision-making. Data were collected through structured survey questionnaires from potential investors and banking sector users within Pakistan using a convenience sampling approach—a sample size of 365 potential investors filled out the questionnaire. Suitable econometric techniques, including PSL-SEM and SPSS, were applied to estimate empirical outcomes concerning the impact of cognitive biases, financial literacy, and digital finance on financial decision-making. The findings demonstrate cognitive biases such as heuristics, overconfidence, herding, heuristics, confirmation, and anchoring have a major effect on financial decision-making. This study also uncovered that financial literacy has a strong mediation effect on financial decision-making. This study also revealed digital finance has a moderation effect on financial decision-making. This research aimed to inform investors, financial organizations, and individuals to make more informed choices.

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INTRODUCTION

Cognitive biases play a significant role in financial decision-making, affecting individual investors and institutional actors alike. Deeply rooted in human psychology, these biases lead to systematic deviations from rational behavior, impacting investment choices, risk assessment, and overall financial outcomes (Thaler et al., 1997). Overconfidence, loss aversion, and herding behavior are some of the most prominent biases influencing financial decisions, often resulting in suboptimal investment strategies and market inefficiencies. Financial literacy is a crucial mitigating factor, equipping investors with the knowledge and skills necessary to make informed decisions and navigate the complexities of the financial markets (Lusardi, 2012). The integration of digital finance and FinTech has further complicated the landscape, presenting both opportunities and challenges. While digital technologies provide unprecedented access and convenience, they also necessitate a deeper understanding of how cognitive biases manifest in these new contexts (Gomber et al., 2017). Future research explores the intricate relationships between cognitive biases, financial literacy, and digital finance to develop more effective strategies for enhancing financial decision-making and promoting financial well-being.

Behavioral Finance

Behavioral finance highlights how cognitive biases cause deviations from logical decision-making, influencing investment choices, spending behaviors, and risk management (Mohanty et al., 2023). Cognitive biases, systematic deviations from rationality in judgment, can significantly influence investment choices, often leading to suboptimal outcomes. Prospect Theory, introduced by Thaler et al. (1997), illuminates critical facets of human decision-making amidst risk, underscoring that individuals are more averse to losses than they are incentivized by equivalent gains, shaping their risk tolerance. This theory highlights that individuals exhibit diminishing sensitivity to changes in wealth, framing effects on risk assessment, and a tendency to overestimate the value of possessions, termed the endowment effect. Furthermore, probability weighting leads to assigning greater weight to small probabilities and favoring certainty over uncertain outcomes. At the same time, the isolation effect influences decision-making by directing attention to isolated elements rather than considering the broader context (Thaler et al., 1997). Financial literacy is crucial for making informed financial choices, requiring a solid understanding of financial concepts, products, and strategies. Although digital finance has transformed the financial industry by offering convenience and accessibility, its moderating influence on the relationship between behavioral biases and investment decisions has not been well defined.

Cognitive Biases

Cognitive biases are consistent deviations from norms or rational assessment patterns in which investment decision-makers create their own perception of reality based on emotional feelings (Elessa and Yassin, 2023). This process leads to cognitive Bias, resulting in inaccurate judgments and illogical understandings, commonly termed "irrationality." Overconfidence bias can lead to an overstated sense of one's skills and knowledge, causing irrational financial choices. Loss aversion bias, an emotional trend to avoid losses more than seek gains, is highlighted by behavioral experts. Experiments reveal that overcoming one negative experience requires two positive ones. Investors grappling with this Bias may become excessively conservative, holding onto underperforming stocks while making irrational decisions (Ady, 2018). Financial decision-making, which plays a crucial role in shaping individuals' economic well-being, is a complex procedure that involves evaluating projects, determining their financial profitability, and considering various key objectives and assumptions (Musfidah et al., 2022). The objective of investment evaluation is to achieve efficient outcomes and maximize profits. Investors aim to maximize wealth by making rational decisions based on available information without emotional biases (Junianto et al., 2020).

Digital Finance

Digital finance, which includes online banking, digital wallets, cryptocurrencies, and financial technologies (FinTech), has revolutionized interactions with financial services. These innovations provide unparalleled convenience, lower transaction costs, and greater financial inclusion (Gomber et al., 2017). However, the rapid digital transformation also brings challenges, particularly in understanding how cognitive biases manifest in digital financial contexts. Financial literacy has significantly influenced investment choices across various dimensions, with varying degrees of impact. It is essential to have financial literacy as a mediator to check the impact of biases like herding bias (Khan, 2020). Financial behavior and awareness positively affect investment decisions. However, the role of financial behavior and literacy is not entirely clear according to different studies (Astiti et al., 2019). Risk perception has been identified as a moderating factor, with Hc and Gusaptono (2020) finding that it has a modest influence on the relationship between financial knowledge and investment choices.

Financial Literacy

Financial literacy is crucial in influencing investment decisions by equipping investors with the knowledge and skills necessary to process financial information critically and make rational decisions. Enhanced financial literacy is associated with increased confidence in undertaking and refining investment choices (Lusardi, 2012). It incorporates a variety of competencies, including making financial arrangements, investing, borrowing, and financial planning. Financially literate investors better evaluate risks and returns, leading to more balanced and diversified portfolios (Van et al., 2011). Financial education can reduce susceptibility to cognitive biases by promoting analytical thinking and encouraging a systematic approach to investment decisions (Taffler, 2018). Overconfidence is mitigated by helping investors understand the limits of their knowledge, reducing overestimation of their ability to predict market movements (Barber and Odean, 2001). Anchoring is addressed by encouraging decisions based on comprehensive analysis rather than initial impressions. Confirmation bias is mitigated by training individuals to critically evaluate information from multiple sources. Herding is reduced by fostering independent thinking and confidence in one's analysis. Loss aversion is managed by helping investors understand the long-term nature of investing and the importance of a diversified portfolio (Guiso & Viviano, 2015).

FinTech and Digital Finance

FinTech has transformed investment decisions, particularly among students and small-medium enterprises (SMEs), by reducing risks and promoting transparency (Lasmini and Zulvia, 2020; Mutamimah and Hendar, 2020). The use of financial technology by students has been found to influence their investment decisions, while integrated FinTech models have shown potential in reducing risks and promoting transparency in SMEs financing. Lee and Shin (2018) further discuss the ecosystem, business models, and investment types in the FinTech sector, emphasizing the use of real options for investment decisions. These studies collectively underscore the transformative role of FinTech in shaping investment decisions. The evolving digital financial landscape presents new challenges and opportunities in understanding the interplay between digital finance and cognitive biases. Biases have been shown to limit the relevance of new information and the impact of financial education, underscoring the need to explore how digitalization can potentially mitigate them in financial decision-making (Sharma & Sharma, 2023). By leveraging the digital revolution, including Artificial Intelligence (AI), it is possible to mitigate cognitive biases, significantly impacting financial advisors by providing insights into the dynamic relationship between digital finance and cognitive biases (Athota et al., 2023).

Intersection of Technology, Literacy, and Biases

The interplay between FinTech, financial literacy, and cognitive biases is a dynamic area of research. Recent studies have examined the influence of certain cognitive biases, such as recency bias, familiarity, confirmation, and overconfidence, on investors' financial choices, showing the strong influence of these biases on investment decisions (Mohanty et al., 2023). Furthermore, financial literacy moderates cognitive biases, such as the dispositioning effect, mental capability, and herding Bias, providing valuable insights into the complex interaction among financial literacy, digital finance, and cognitive biases (Khan, 2020). The application of investment decisions and behavioral finance is a complex and evolving field. Banerjee (2011) examines how behavioral finance can be applied to investment decisions, emphasizing its importance in understanding the psychological decision-making processes and their systematic financial implications. Jahanzeb (2012) discusses the implications of behavioral biases on investment choices, emphasizing the importance of avoiding irrational decisions and the influence of psychological factors on portfolio selection. Bisen and Pandey (2013) explore the practical utilization of behavioral finance in examining investors' behavior, identifying psychological factors like overconfidence, sentiment, and overreaction as key influencers on investment choices.

Influence of FinTech, Biases, and Financial Literacy

The impact of financial technology (FinTech), financial attitudes, and financial knowledge on financial behavior is significant. FinTech, regarded as a contemporary technological and economic innovation, facilitates financial transactions. Financial attitudes reflect psychological tendencies in evaluating financial management, influencing how individuals agree or disagree with recommended practices. Financial knowledge involves understanding how to organize, manage, and mitigate risks associated with financial resources, which is essential for making informed decisions (Firlianti and Asriany, 2023). Rahayu et al. (2023) highlight how positive financial assertiveness significantly shapes financial management behavior, indicating that stakeholders with positive attitudes tend to make sound financial decisions. The study emphasizes the need to promote financial literacy and positive financial attitudes to support MSMEs as economic powerhouses, suggesting enhancing FinTech awareness to improve financial practices potentially. The continuing digital transformation in the financial industry, commonly referred to as FinTech, is fundamentally altering domains like retail banking, payment services, and investment (Koskelainen et al., 2023). Digital inclusive finance can enhance the performance of individual investors, particularly in regions with less developed traditional finance or strong investor protection. Lu et al. (2024) suggest leveraging digital financial strategies to empower investors and maximize the benefits of digital finance inclusivity, highlighting the intersection of technology and financial services (Al-Smadi, 2023). The digital financial landscape's rapid technological advancements drive smart, sustainable, and inclusive growth, emphasizing the role of information and telecommunications technology in economic progress (Burlacu et al., 2021). The impact of digital finance on students' financial behavior shows that while it offers transactional benefits, it does not necessarily lead to behavioral change. Financial literacy is crucial for making informed financial decisions, which positively affect financial behavior. Additionally, lifestyle choices can significantly affect an individual's financial behavior, with financial literacy and a positive attitude playing key roles in effective financial management (Yulianis and Sulistyowati, 2021).

The significance of this study lies in exploring the factors that influence investment decision-making, particularly cognitive biases, financial literacy, and digital finance. Cognitive biases can result in irrational choices, affecting financial outcomes, while financial literacy equips individuals with the knowledge necessary to make rational decisions (Weixiang et al., 2022). Although digital finance offers convenience, it also introduces new challenges, opportunities, and risks. The research found that financial literacy mediates the relationship between behavioral biases and investment decisions, providing insights for potential interventions and improvements.

LITERATURE REVIEW

Korteling et al. (2023) discussed how cognitive biases impacted decision-making in sustainability issues, highlighting the challenges in addressing global threats like climate change and biodiversity loss. It proposed techniques to mitigate these biases and promote more viable societal choices and behaviors. To foster sustainable decision-making, the paper utilized various intervention techniques, such as incentives and nudges, to mitigate or capitalize on these biases. The paper concluded that cognitive biases significantly influenced decision-making in sustainability issues, hindering effective responses to global challenges. By understanding these biases and implementing appropriate interventions, such as incentives and nudges, promoting more sustainable choices and behaviors was possible, thus addressing threats to the planet and its inhabitants more effectively.

Sorongan (2022) examined the effect of financial behavior, attitudes, and literacy on investment choices among South Jakarta students. Using a quantitative approach and data from 110 respondents via online questionnaires analyzed with Smart-PLS, the findings indicated that financial behavior and attitudes considerably affected investment choices. Financial literacy also played a crucial role in these decisions by improving financial knowledge and management. However, it did not moderate the impact of financial behavior and attitudes on investment choices. Thus, while important, financial literacy did not change the impact of behavior and attitudes on student investment decisions.

Safaie et al. (2024) examined how behavioral biases influenced investors' choices in the Tehran Stock Exchange (TSE). Data from 512 investors were collected via an online survey focusing on personal traits and responses to investment scenarios. Results showed that biases like Loss Aversion, Shifting Risk Preference, Anchoring, Mental Accounting, and Ambiguity Aversion significantly impacted decision-making. Statistical methods, including the Kruskal-Wallis H test, compared biases across demographic groups and investment behaviors. Loss Aversion was the most prevalent, especially among less experienced investors. Shifting Risk Preference was common among older, female, married, and poor-performing investors. Other biases like Anchoring, Mental Accounting, and Ambiguity Aversion were also significant, particularly among older, female, less-experienced, and poor-performing investors. While some biases had minor impacts, they were linked to poor investment performance, highlighting the need for awareness and mitigation strategies.

Parkash and Parkash (2024) explored how psychological biases like overconfidence, confirmation bias, loss aversion, and herd mentality influenced investor behavior and market dynamics. It used a quantitative research design, analyzing data from 385 respondents through structured questionnaires. The study highlighted that these biases led to irrational and suboptimal investment decisions, affecting asset allocation, portfolio diversification, and risk management. It advocated for integrating behavioral finance with traditional theories, increasing investor education, and developing regulatory frameworks and technological tools to promote rational investment behavior. The study aimed to improve investment practices and market efficiency by addressing these biases.

Haralayya (2024) examined how psychological factors impact personal investment decision-making, involving 68 financial advisors and utilizing IBM SPSS for data analysis. Primary research methods, including an online survey, were employed within a positivist research philosophy and a deductive approach for hypotheses. The findings indicated that psychological, cognitive, emotional, and sociocultural factors significantly influenced investment decisions positively and negatively. Understanding these factors provided investors with a competitive edge for making informed decisions and helped financial advisors reduce financial burdens on individuals. Policymakers and regulators could also intervene to mitigate behavioral biases, potentially leading to more successful investment outcomes.

Shah et al. (2021) identified overconfidence, anchoring Bias, loss aversion, and herding effect as significant factors influencing financial decision-making. The study engaged a qualitative method, developing semi-structured interviews to collect primary data from fifteen participants in the United Arab Emirates. The qualitative research method included structured, semi-structured, and unstructured interviews, focus group interviews, and analysis of documents, scripts, and reports to understand behavioral factors impacting decision-making and the influence of COVID-19 as a mediator. The study found these factors positively impacted decisions in normal situations; during the COVID-19 pandemic, they mostly had a negative impact, except for overconfidence, which remained positive. The pandemic notably altered buying and selling behaviors in the financial sector, highlighting the need to understand and address cognitive biases in decision-making.

Mohanty et al. (2023) inspected the effect of these biases on the investment choices of potential investors during the COVID-19 pandemic, with familiarity and recency bias found to have the greatest significant influence, followed by confirmation bias. A survey of 200 potential investors revealed that familiarity and recency bias significantly influenced investing decisions, surpassing the impact of confirmation bias. Overconfidence bias was found to be negligible. The study filled a gap in the literature by evaluating the effect of cognitive biases during COVID-19 on financial behavior, providing insights for analysts, practitioners, scholars, academicians, policymakers, and firms that trade with stock markets.

Iram et al. (2023) examined the qualitative relationship between heuristic, behavioral biases and investment choices among female entrepreneurs, stressing the role of literacy as a mediator in influencing sensible investment decisions. However, this study showed that the representativeness and anchoring heuristics lacked direct connections to financial literacy or decisions. Availability heuristics directly impacted investment choices but not financial literacy. The findings suggested that enhancing women's financial literacy could effectively incorporate behavioral considerations into decision-making processes.

Sari et al. (2023) focused on the influence of financial attitude, behavior, and knowledge on the profitability of Micro, Small, and Medium Enterprises (MSMEs). It revealed a significant positive correlation between financial attitude, behavior, awareness, and profitability, emphasizing the importance of improving these aspects for increased profitability in individuals or companies. The research employed primary data collection through interviews and questionnaires to gather information from MSMEs. It utilized a causal research design with a quantitative approach, a non-probability sampling technique (purposive sampling), and the multivariate structural equation model for analysis. This study found regular financial literacy training for MSMEs is recommended as it equips them with the essential skills and knowledge to make informed financial decisions, leading to improved profitability and sustainable business growth.

Ranaweera and Kawshala (2022) investigated the effects of overconfidence and herding biases on investment decisions among investors in the Colombo Stock Market, with a focus on the moderating roles of financial literacy and risk attitude. Using data from a survey of 110 individual investors and applying multiple regression analysis, the research found that overconfidence bias significantly influenced investment decisions, while herding Bias did not. Financial literacy significantly moderated the relationship between overconfidence and investment decisions but did not impact the relationship between herding bias and investment decisions. The study concluded that understanding these behavioral biases and the part of financial literacy was crucial for comprehending investor behavior in the Colombo Stock Market.

Suresh (2024) explores how financial literacy and behavioral biases collectively influence investment choices. Data was collected from individual investors through a survey, and structural equation modeling (SEM) was employed for analysis. The findings revealed that heuristics bias was significantly associated with the development of behavioral biases, with a positive association. Furthermore, cognitive illusions, herd mentality, and framing effects showed a negative association with the development of behavioral biases. Particularly, financial literacy was known as a crucial factor in making decisions in the stock markets.

Dureha and Jain (2022) investigated the influence of digital finance, financial literacy, and lifestyle on students' financial behavior, converging on college students in Bandung, Indonesia. Using a quantitative approach, data were collected from 100 respondents through questionnaires. The findings revealed that digital finance alone did not significantly influence financial behavior, while financial literacy and lifestyle had a positive and significant effect. Enhanced financial literacy led to better decision-making, and a high lifestyle often resulted in higher consumption and financial control challenges. The combined influence of these factors was significant, underscoring the need for improved financial literacy and secure digital finance products. Other factors such as investment awareness, risk considerations, and government policies also played crucial roles.

Weixiang et al. (2022) explored the impact of behavioral biases and literacy on investing decisions, especially from the stock market perspective. The study used an experimental technique with a random sampling approach, conducting personal interviews of 450 different investors using a well-designed questionnaire survey to systematically gather and analyze data. The result highlighted a substantial association between heuristic Bias and the advancement of behavioral biases in investment decisions. The herd mentality, cognitive impressions, and the framing effect were recognized as additional factors influencing behavioral biases. Additionally, the study explores how the extent of literacy significantly impacts individual investor's investing decisions.

Rahayu (2023) investigated the impact of literacy, attitudes, and the adoption of (Fintech) on the investing behavior of investors in micro, small and medium enterprises (MSMEs) in DKI Jakarta, Indonesia. This quantitative causality approach was used in this research, as well as a random sampling technique and partial least squares (PLS) for data analysis. Findings revealed that financial literacy and favorable attitude had a conventional influence on management behavior, while the impact of Fintech was restricted due to the operator's deficiency in awareness and comprehension. The research highlighted the imperative to promote literacy, foster optimistic attitudes and enhance Fintech know-how among MSMEs to strengthen their crucial economic function.

Egamkulovna (2024) delves into the influence of digital technologies on public finance management (PFM), assessing effective gains, transparency improvements, and the hurdles encountered during digital integration. Through a mixed-methods approach, combining quantitative analysis and qualitative perceptions from stakeholder interviews and case studies, the study revealed significant advancements in efficiency and transparency within PFM. Key digital tools like blockchain, AI, and big data analytics were highlighted for their transformative potential. Despite these benefits, challenges such as data safety, privacy concerns, and the digital gap persisted. Looking ahead, the paper underscored the promising future of PFM through continued AI advancements and ongoing digital transformation initiatives.

Kumar et al., (2023) investigated the association among skill, literacy, financial capability, impulsivity, digital finance, financial autonomy, investment decisions and supposed financial well-being in the perspective of Covid-19 and the rise in Fintech. The research used a snowball sampling technique and PLS-SEM. The finding indicated that skills directly influenced investment choices and observed financial stability, with financial digital literacy serving as a mediator. Financial capability and autonomy were identified as crucial mediators, although impulsivity did not mediate investing decision-making. The result had an effect on academia, regulation and management, emphasizing the need for recognizing the relationship among skills, investing decision making and financial stability.

Fauzah (2023) analyzed the influence of Fintech, financial Islamic literacy, herding and overconfidence biases on investing decisions in the Islamic Sharia stock markets. It used a quantitative research methodology with data collected from 190 individuals. The findings indicated that Fintech, literacy of Islamic investment and overconfidence bias exerted significant and major effects on investing choices in the Sharia stock market, although herd bias had no significant effect. The paper provided practical evidence that contributed to the progress of awareness in economic and Islamic business and was useful for academics, investors and researchers.

STRUCTURAL MODEL

The structural model reflects an assessment of the hypothesis in the research framework (See Figure 1). The structural model is used to test whether a hypothesis can be accepted or rejected. The structural model is based on four key components: cognitive biases, digital finance, financial literacy, and investment decision-making. The framework hypothesizes that cognitive biases directly affect financial decision-making, moderated by digital finance and mediated by financial literacy. In the research framework, the structural model reflects the paths hypothesized. The following hypotheses have been tested in this study.

H1: *Cognitive basis has a significant effect on financial decision-making.*
H2: *Financial literacy has a significant effect and mediating role in financial decision-making.*
H3: *Digital Finance has a significant effect and moderator role in financial decision-making.*

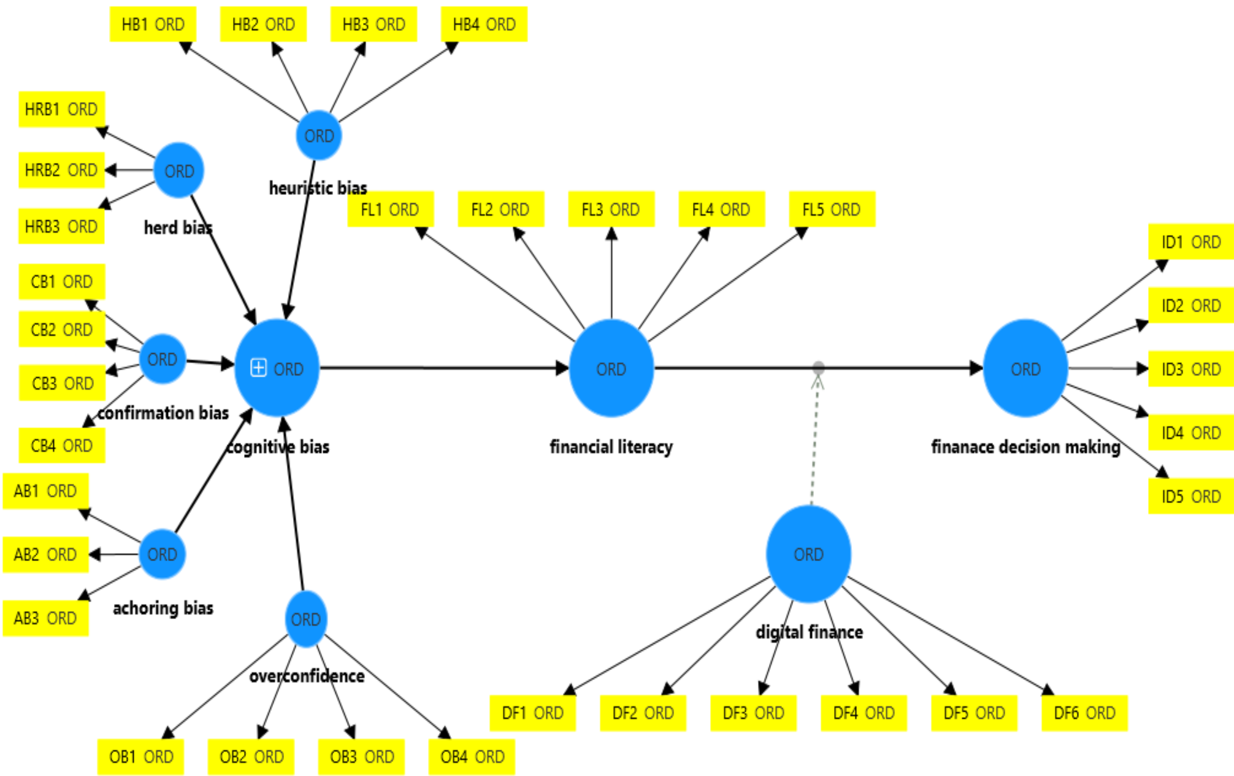

Figure 1: Structural Model

The First Model shows the direct relationship between cognitive biases (herd bias, heuristic Bias, overconfidence, anchoring Bias, and confirmation bias) and financial decision-making, enhancing the decision-making process. The last third model depicts digital finance's moderating role and financial literacy's mediating role in the relationship between cognitive biases and financial decision-making. Digital finance moderates the overall decision-making process.

RESEARCH METHODOLOGY

This study uses the main data source from a questionnaire, where data collection uses a Likert scale model, according to Siregar (2022). The Likert scale is a scale that can be used to measure a person's attitudes, opinions, and perceptions about an object or phenomenon. The subjects of this research used purposive sampling techniques been used and the target population was potential investors. The secondary data used in the research was used to make questionnaires that are relevant to this research. An adaptive questionnaire is used in this research, as shown in Table 1. The Partial Least Square (PLS-SEM) technique was used for data analysis techniques. It includes the validity and reliability of research instruments and classical assumption tests, shown in the tables below.

Table 1: Constructs, Indicators, Items, and Main References

Constructs	Indicators	Items	Main References
Heuristics	Skills and knowledge of the stock market	4	Lakshmi et al., 2013; Lin, 2011; Ngoc, 2014
Herding Bias	Follow the investment choices of other investors	3	Ngoc, 2014; Lin, 2011
Confirmation bias	Make decisions based on the initial information you obtain.	4	Özen and Ersoy, 2019
Anchoring Bias	Sell a company's shares if a group of investors are selling them.	3	Safaie et al., 2024
Overconfidence Bias	Predict the future price of stocks better than others	4	Safaie et al., 2024; Lin, 2011; Lakshmi et al., 2013; Khan et al. 2017
Financial Decision Making	Informed financial decisions	5	Fisher, 2010; Weber et al. 2013; Khan et al. 2017
Financial literacy	Understanding of basic financial concepts	4	Hassan Al-Tamimi et al., 2009
Digital Finance	How frequently do you use digital platforms for financial transaction	6	Lee et al., 2022
Total Items		33	

Source: Author's Own Calculation

In developing this adaptive questionnaire, the study has drawn extensively from existing literature to ensure the robustness and validity of our measures. The questionnaire items were adapted from various scholarly sources to capture key dimensions of investor behavior and decision-making processes. The study employed a structured questionnaire. The first 18 questions assessed cognitive biases, followed by five questions on financial decision-making. Four questions measured financial literacy, while the final six evaluated digital finance engagement.

Data sourced from questionnaire answers will be processed using the Structural Equation Model (SEM). This second-generation multivariate data analysis method allows researchers to process unobservable variables to be measured by indicators of explanatory variables (Chin, 1998). With the type of Partial Least Square Structural Equation Model (PLS-SEM) analysis in the data process, researchers used SmartPLS software version 4. There are two reasons why this analysis is used. First, this study uses PLS-SEM because the model allows large samples to be analyzed with reflective and formative measurement models. Second, this study determined the amount of data from the questionnaire based on previous studies that have been collected and adjusted to the objectives of this study, which can be seen in Table 1 above. Model evaluation in SmartPLS includes two stages, namely the evaluation of the measurement model or outer model, which includes basic testing of data validity and reliability, and the second stage, which is evaluating the structural or inner model to determine the path coefficient and draw a conclusion.

DATA ANALYSIS

We followed the two-step approach of Anderson and Gerbing (1988) (measurement model and structural model) with partial least square-structure equation modeling using SMART PLS software. In the Measurement model, variables are assessed in terms of their validity and reliability, while in the structural model, path coefficients of the model are evaluated in order to check whether relationships between the variables exist.

Validity and Reliability Test

Validity is a measurement that shows the level of accuracy (validity) of the measure of an instrument against the concept under study (Suharso, 2009). The validity test was carried out with a significance level of r table 5% (0.05). The calculated value is obtained from the correlation of each respondent's answers. The following is a table of the test validity results. According to Mark (1996), reliability is how stable and consistent a measuring instrument Reliability is if a measuring instrument upon and administered again and again yields the same results. Two methods for determining reliability are Cronbach Alpha and Composite Reliability. Cronbach Alpha value ranges from 0.771 to 0.950 (Hair et al., 2017). If the value of composite reliability and Cronbach's alpha is less than 0.6, then there arises an issue in reliability between the latent variables, indicators, or in model (Hair et al., 2017).

In Table 2, the factor loadings for the dependent variables indicate strong relationships between observed variables and cognitive biases, all exceeding 0.8. OFD3 (0.908) is the strongest indicator for overconfidence bias, while HRT1 (0.858) leads to heuristic Bias. Herd bias is best represented by HDB3 (0.898) and confirmation bias by CFB2 (0.870). Anchoring Bias is strongest with AHB2 (0.899), and CGB stands out with a loading of 0.968. For financial decision-making (FDM), FDM5 (0.823) is the strongest indicator, while FDM4 (0.757) is the weakest but still significant. Financial literacy (FNL) is best represented by FNL1 (0.849) and digital finance (DGF) by DGF2 (0.902). Cronbach's alpha values show excellent reliability for Cognitive Bias (0.968) and Digital Finance (0.920), with Financial Literacy (0.886) and Financial Decision Making (0.842) also displaying strong internal consistency. Composite reliability (CR) values reaffirm these findings, with Cognitive Bias (0.969) and Digital Finance (0.928) showing the highest reliability and Financial Decision Making (0.843) being the lowest but still good. Average Variance Extracted (AVE) values demonstrate strong convergent validity, especially for Digital Finance (0.758) and Financial Literacy (0.686). Cognitive Bias (0.650) and Financial Decision Making (0.613) show moderate but acceptable validity. Overall, the measures used exhibit reliability and robustness.

Table 2: Data Reliability and Validity

Items	FL	CA	CR	AVE
CGB		0.968	0.969	0.650
AHB1	0.874			
AHB2	0.899			
AHB3	0.887			
CFB1	0.854			
CFB2	0.870			
CFB3	0.859			
CFB4	0.838			
HDB1	0.847			
HDB2	0.853			
HDB3	0.898			
HRT1	0.858			
HRT2	0.838			
HRT3	0.844			
HRT4	0.813			
OFD1	0.804			
OFD2	0.862			
OFD3	0.908			
OFD4	0.862			
DGF		0.920	0.928	0.758
DGF1	0.869			
DGF2	0.902			
DGF3	0.897			
DGF4	0.827			
DGF5	0.856			
FDM		0.842	0.843	0.613
FDM1	0.775			
FDM2	0.769			
FDM3	0.790			
FDM4	0.757			
FDM5	0.823			
FNL		0.886	0.887	0.686
FNL1	0.849			
FNL2	0.811			
FNL3	0.845			
FNL4	0.817			
FNL5	0.819			

Source: Author's Own Calculation

Multicollinearity/Variance Inflation Factor

VIF indicates a collinearity issue among indicators and depicted in Table 3. If all values are more than 5, then there will be no collinearity issue among indicators. All VIF values are less than 5, meaning there is no collinearity issue among the indicators.

Table 3: Multicollinearity/Variance Inflation Factor

Items	VIF
AHB1	3.049
AHB2	4.016
AHB3	3.336
CFB1	3.278
CFB2	3.89
CFB3	4.005
CFB4	4.428
DGF1	2.663
DGF2	3.626
DGF3	3.585
DGF4	2.402
DGF5	2.534
FDM1	1.765
FDM2	1.641
FDM3	1.771
FDM4	1.66
FDM5	2.057
FNL1	2.557
FNL2	2.001
FNL3	2.235
FNL4	2.167
FNL5	2.068
HDB1	3.949
HDB2	3.669
HDB3	3.400
HRT1	3.195
HRT2	3.326
HRT3	3.397
HRT4	4.894
OFD1	3.203
OFD2	5.545
OFD3	4.313
OFD4	3.491

Source: Author's Own Calculation

The Variance Inflation Factors (VIFs) reveal low multicollinearity for variables like FDM1 to FDM5 and FNL1 to FNL5, with VIFs ranging from 1.641 to 2.557, indicating they are relatively independent. Moderate multicollinearity is observed in variables such as AHB1 to AHB3, CFB1 to CFB3, DGF1 to DGF5, HDB1 to HDB3, HRT1 to HRT3, OFD1, OFD3, and OFD4, with VIFs between 2.5 and 4.894. Although these levels suggest some correlation, they generally do not pose significant issues. However, HRT4 (4.894) and OFD2 (5.545) show high multicollinearity, which could affect the reliability of coefficient estimates, requiring careful management to ensure robust statistical results.

Discriminant Validity

Discriminant validity assesses whether concepts or measurements that are not supposed to be related are unrelated. The diagonal elements in the given matrix are missing, indicating that they are likely the square root of the average variance extracted (AVE) for each construct, typically provided to compare against the correlations. For discriminant validity to be recognized, the diagonal elements should be greater than the off-diagonal elements in their respective rows and columns.

Fornell and Lareker Criterion

According to Fornell and Larcker (1981), discriminant validity is developed when the square net of AVE of a construct is greater than its correlation with other constructs and illustrated in Table 4. So, AVE (in Julic and Bold) is greater than its correlation with other constructs, hence its high discriminant validity.

Table 4: Discriminant Validity

	CGB	DGF	FDM	FNL
CGB				
DGF	0.466			
FDM	0.882	0.663		
FNL	0.782	0.841	0.899	

Source: Author's Own Calculation

Discriminant validity assesses whether unrelated concepts remain distinct. In the matrix, diagonal elements (likely the square root of the AVE) should be greater than the off-diagonal correlations to confirm discriminant validity. However, high correlations between constructs CGB and FDM (0.882), CGB and FNL (0.782), DGF and FNL (0.841), and FDM and FNL (0.899) suggest potential issues. The high correlation between FDM and FNL (0.899) indicates they may not be distinct constructs. This raises concerns about discriminant validity, potentially undermining the measurement model's validity.

Model Fit Values

Table 5 infers the model fit values. Evaluation matrices assess key metrics such as P-value (significant if > 0.05) and T-value (significant if < 1.96) to evaluate statistical significance. R-square (R^2) measures the variance explained by exogenous variables, with values of 0.77, 0.50, and 0.25 indicating substantial, moderate, and weak explanatory power, respectively. F-square (f^2) assesses the effect size of removing an endogenous variable, where values > 0.35 are large, > 0.15 are medium, and > 0.02 are small. Q-square (Q^2) evaluates predictive relevance, with values above zero indicating significance (Hair et al., 2017).

Table 5: Model Fit Values

SRMR	0.062
d_ULS	2.160
d_G	2.195
Chi-square	956.744
NFI	0.720

Source: Author's Own Calculation

The model fit shows mixed results. The SRMR value of 0.062 indicates a reasonably good fit (below the 0.08 threshold). However, d_ULS (2.160) and d_G (2.195) suggest moderate discrepancies in the covariance matrices. The chi-square value of 956.744 indicates some misfit, though it must be interpreted with degrees of freedom and sample size in mind. The NFI value of 0.720, below the 0.90 threshold, suggests the model does not fit well overall, leaving room for improvement.

R-Square Values

R-square measures the influence of exogenous variables on endogenous variables, as shown in Table 6. An R-square value below 0.25 indicates a weak association, while values between 0.25 and 0.50 show a moderate association. Values above 0.50 reflect a strong association. The model's strength is assessed through R-square for all structural paths of the endogenous variables. For predictive relevance to be established, the R-square should be equal to or greater than 0.5; thus, an R-square value greater than 0.5 confirms predictive relevance.

Table 6: R-Square Values

	R Square
FDM	0.742
FNL	0.531

Source: Author's Own Calculation

The R-squared values indicate the proportion of variance explained by the model for each dependent variable. For Financial Decision Making (FDM), the R-squared value of 0.742 shows that the model explains 74.2% of its variance, indicating strong explanatory power. For Financial Literacy (FNL), the R-squared value of 0.531 indicates that 53.1% of its variance is explained, reflecting a moderate to strong level of explanatory power. Overall, the model effectively explains a significant portion of the variance for FDM and FNL, with particularly high explanatory power.

PLS- Bootstrapping

Bootstrapping in Smart-PLS is performed to test the significance of the hypothesis in both outer and inner models for producing t-value and p-value. For a hypothesis to be significant in Smart-PLS, bootstrapping is performed. The criteria for p and t values for significant hypothesis is > 0.05 and < 1.95 for H1 in Table 7.

Table 7: Hypothesis 1: Cognitive basis significantly affects investment decision-making.

Hypotheses	Β	SD	T-Statistics	P-Value
CGB -> FDM	0.798	0.046	17.404	0

Source: Author's Own Calculation

Table 7 indicates a strong and statistically significant positive relationship between cognitive biases (CGB) and financial decision-making (FDM). The beta coefficient of 0.798 suggests that increased cognitive biases positively influence financial decision-making. The standard deviation of 0.046 indicates a precise estimate. A T-statistic of 17.404 and a P-value of 0 further confirm the high significance of these results, underscoring the substantial impact of cognitive biases on financial decision-making.

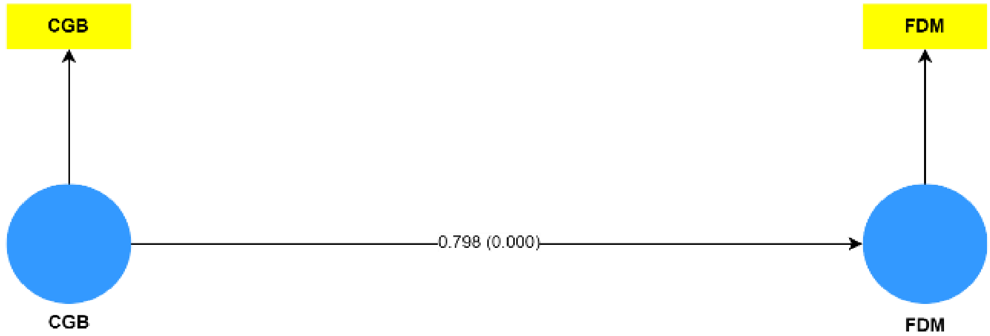

Figure 2: 1st Model

Table 8: Hypothesis 2: Financial literacy has a significant effect and mediating role in investment decision-making

Hypotheses	B	SD	T-Statistics	P-Value
CGB -> FDM	0.491	0.093	5.269	0
CGB ->FNL	0.727	0.05	14.531	0
FNL -> FDM	0.421	0.092	4.576	0

Source: Author's Own Calculation

Table 8 outlines the relationships between cognitive biases (CGB), financial decision-making (FDM), and financial literacy (FNL). The analysis reveals that cognitive biases moderately impact financial decision-making (β = 0.491, T = 5.269, P = 0) and positively affect financial literacy (β = 0.727, T = 14.531, P = 0). Additionally, financial literacy positively influences financial decision-making (β = 0.421, T = 4.576, P = 0). All relationships are statistically significant, highlighting the substantial effects of cognitive biases on both financial literacy and decision-making, with financial literacy also crucial in shaping financial decisions.

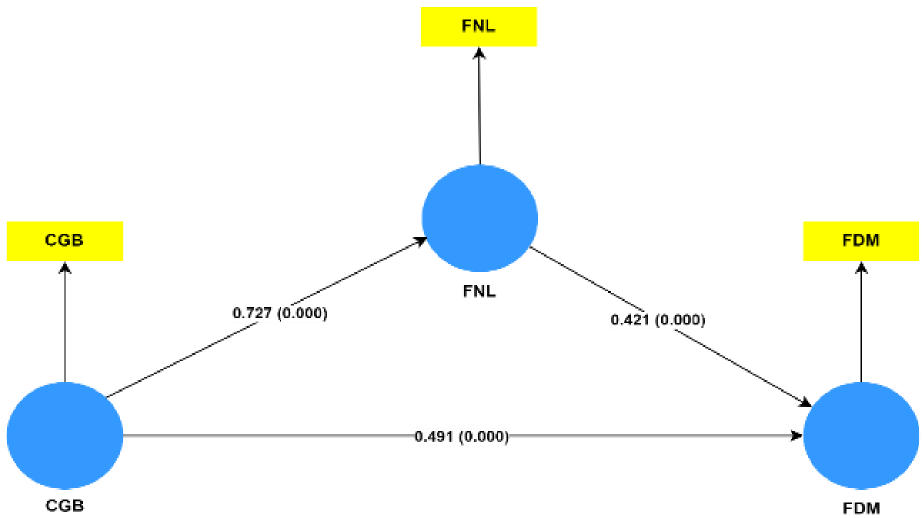

Figure 3: 2nd Model

Table 9: Hypothesis 3: Digital Finance has a significant effect and moderator role in investment decision-making.

Hypotheses	B	SD	T-Statistics	P-Value
CGB -> FDM	0.561	0.090	6.224	0.000
CGB ->FNL	0.727	0.050	14.531	0.000
DGF -> FDM	0.123	0.086	1.423	0.155
FNL-> FDM	0.273	0.116	2.361	0.018

Source: Author's Own Calculation

Table 9 shows that cognitive biases significantly influence both financial literacy (β = 0.727, P = 0.000) and investment decision-making (β = 0.561, P = 0.000), while financial literacy also significantly affects investment decision-making (β = 0.273, P = 0.018). In contrast, digital finance does not significantly affect investment decision-making (β = 0.123, P = 0.155). These findings suggest that cognitive biases and financial literacy are crucial in shaping investment decisions, but digital finance does not significantly impact these decisions, indicating that its hypothesized moderator role is unsupported by the data.

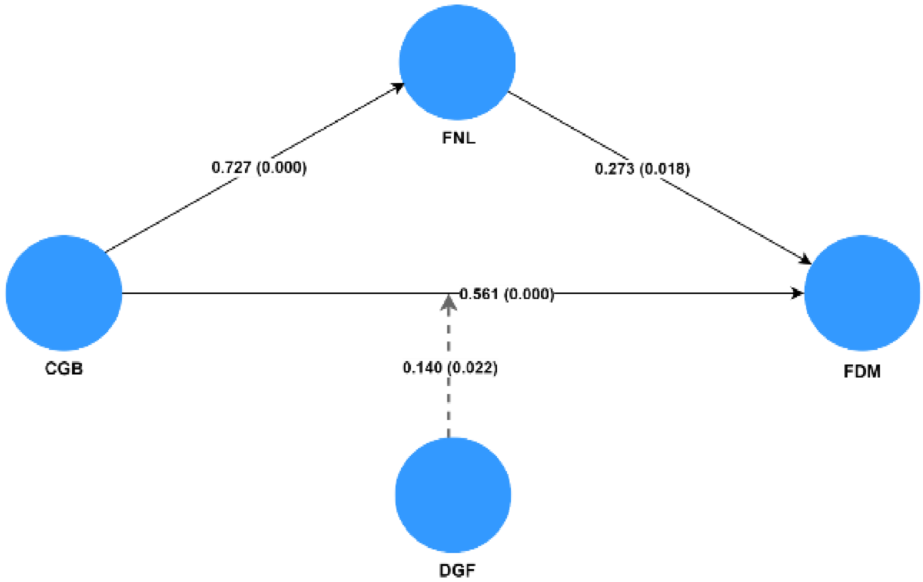

Figure 4: 3rd Model

Mediating and Moderation Path Analysis

Mediating Path Analysis

A mediation analysis is done to evaluate the mediating impact of financial literacy on cognitive biases and financial decision-making, as mentioned in Table 10. The following hypotheses were tested for mediation results.

Table 10: Mediating Path Analysis

Hypotheses	B	SD	T-Statistics	P-Value
CGB -> FNL -> FDM	0.199	0.087	2.283	0.022

Source: Author's Own Calculation

The mediating path analysis reveals that financial literacy significantly mediates the relationship between cognitive biases and financial decision-making. The indirect effect ($\beta = 0.199$) is statistically significant (T-statistic = 2.283, P = 0.022), indicating that cognitive biases impact financial decision-making through financial literacy. This underscores the essential role of financial literacy in this process.

Moderating Path Analysis

Moderating path analysis examines whether the relationship between an independent variable (predictor) and a dependent variable (outcome) is influenced by a third variable (moderator) and mentioned in Table 11.

Table 11: Moderating Path Analysis

Hypotheses	B	SD	T-Statistics	P-Value
DGF x CGB -> FDM	0.140	0.061	2.287	0.022

Source: Author's Own Calculation

The moderating path analysis indicates that the interaction between Digital Finance (DGF) and Cognitive Biases (CGB) significantly impacts Financial Decision-Making (FDM). The coefficient (B = 0.140) suggests that a one-unit increase in the interaction term leads to a 0.140-unit increase in FDM. With a T-statistic of 2.287 and a p-value of 0.022, this effect is statistically significant, demonstrating that the DGF-CGB interaction meaningfully influences FDM, with only a 2.2% chance that the effect is due to random variation.

Moderating Path Analysis Graph

Figure 5 depicts the interaction effect of Cognitive Biases (CGB) and Digital Finance (DGF) on Financial Decision Making (FDM). The x-axis represents cognitive bias levels (low and high), while the y-axis measures FDM scores from 1 to 5. The solid line indicates low DGF, and the dashed line shows high DGF. As cognitive biases increase, FDM scores rise for both groups, suggesting that individuals with higher cognitive biases make more confident financial decisions. Specifically, FDM scores for those with low DGF rise from approximately 2.5 to 3.5, while those with high DGF increase from around 3 to 4. This indicates that digital finance enhances the positive impact of cognitive biases on financial decision-making, with individuals possessing higher digital finance resources showing a greater increase in FDM scores. Thus, digital finance significantly strengthens the influence of cognitive biases on financial decision-making.

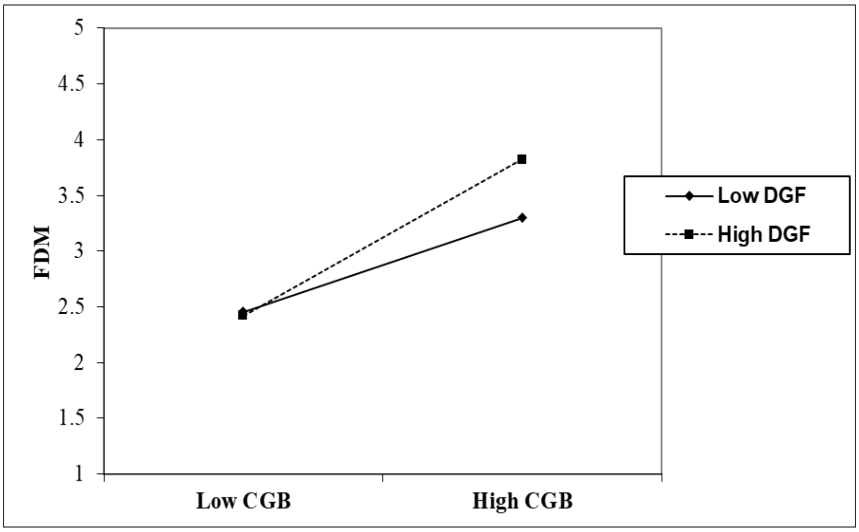

Figure 5: Moderating Path Analysis

CONCLUSION

The research provides a foundation for developing strategies to enhance investor outcomes and financial well-being, as the evolution of digital finance necessitates adaptive approaches to understanding and mitigating cognitive biases. Embracing the interplay between technology, education, and psychology will lead to a more informed and resilient financial ecosystem. Despite its limitations, this study significantly contributes to understanding cognitive biases in financial decision-making and the roles of digital finance and financial literacy.

This research emphasizes the significant impact of cognitive biases on financial decision-making, highlighting the essential roles of digital finance and financial literacy. The findings call for a multi-faceted approach involving policymakers, financial institutions, and individual investors to tackle the challenges posed by cognitive biases. By addressing these biases, stakeholders can foster a more rational and efficient financial system. Comprehensive financial education, responsible digital finance practices, and ongoing research are vital for improving investor outcomes and promoting financial well-being in a digital landscape. Identified limitations offer valuable directions for future research, underscoring the complexity of financial behavior today. Continued exploration of these areas is crucial for developing effective strategies to improve financial decision-making and promote overall financial well-being.

RECOMMENDATIONS

Public awareness campaigns are essential to educate individuals about common cognitive biases and their effects on financial decision-making. Financial institutions must design products encouraging long-term investment strategies and providing comprehensive educational resources to enhance financial literacy. Transparency in communication about risks is crucial for informed decision-making. Individuals should engage in continuous learning, develop self-awareness about their cognitive biases, and seek professional financial advice to navigate complex financial decisions effectively. Policymakers should integrate financial education into school curricula from an early age and promote lifelong learning opportunities, particularly for vulnerable groups. Regulations should ensure that digital finance platforms promote responsible trading through clear risk disclosures and resources to help users manage cognitive biases.

Future research should investigate the interaction between cognitive biases, digital finance, and financial literacy through longitudinal studies to assess how these elements evolve over time. Examining cultural influences on cognitive biases across regions can inform tailored financial literacy programs. The potential of emerging technologies like AI and machine learning should be explored to identify and mitigate cognitive biases in real-time. Additionally, evaluating the effectiveness of financial literacy programs and regulatory interventions will help identify best practices and guide policies to enhance investor protection and education.

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