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BEHAVIORAL ANTECEDENTS OF INVESTMENT DECISIONS: TESTING THE MODERATING ROLE OF TECHNOLOGY ADOPTION IN PAKISTAN

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Abstract
This study paper investigated how the adoption of technology moderates the relationship between behavioral biases and investment decision-making among the Pakistani investors. In the literature of behavioral finance, cognition biases like overconfidence, confirmation bias, herding and loss aversion have repeatedly been cited as factors that affect investor behavior. However, in developing economies that are undergoing a digital transformation and redefining the nature of investments, there is little understanding of whether these biases can be reduced or enhanced due to the use of technology. A quantitative and cross-sectional design was used to gather data on 380 active investors and brokers in the Pakistan Stock Exchange (PSX). The level of measurement and structure model were evaluated using Structural Equation Modeling (SEM) using Smart PLS 4. Findings show that behavioral biases have significant influence on investment decisions and overconfidence and herding have the most significant impacts. In addition, the use of technology moderates these associations, the detrimental effect of overconfidence and loss aversion, and the beneficial effect of confirmation biases on the quality of decisions. This research adds to the behavioral finance literature by considering technology adoption as a conditioning constraint to the Pakistani setting and providing new information to regulators, brokerage firms, and fin-tech solutions. Implications have identified the necessity of investor education, digital literacy, and regulatory protection to exploit technology as a corrective factor in financial decision-making.
Keywords: Investor decision-making, behavioral biases, technology adoption, Smart PLS 4, Pakistan Stock Exchange.

1. INTRODUCTION

The behavior of investors has always fascinated economists, psychologists, and finance scholars. Traditional finance theories particularly the Efficient Market Hypothesis (EMH) assume that investors are rational actors who process information optimally and make utility-maximizing decisions. Nevertheless, market behavior has impacted this idealized vision throughout decades of evidence. Rationality is a very limited factor in investors' decisions, who then

make systematic errors in judgment and are mainly influenced by emotions and heuristics etc. (Barberis, 2018; Nofsinger, 2017). These cognitive distortions, commonly referred to as behavioral biases, significantly influence investment decision-making.

In case of Pakistan, an upcoming market that is growing rapidly, the stock exchange plays a crucial role in facilitating the flow of capital and generating wealth. However, the volatility of the Pakistan Stock Exchange (PSX) has been associated not only with changes in the overall economy but also with the prevailing mood of the investors. Research has shown that among the various psychological factors that affect the behavior of investors in Pakistan, the most significant ones are overconfidence, herding, and confirmation bias, which often result in the emergence of speculative bubbles and the consequent sharp corrections in the market (Bashir, Javed, Usman, Meer, & Naseem, 2013; Mahmood, Arshad, Khan, Afzal, & Bashir, 2024).

Over the last decade, financial services have undergone through a drastic technological change. The entire process of accessing, interpreting and acting upon market data has now been revolutionized to an extent where the use of online trading platforms, mobile investment applications, robo-advisory, and algorithmic suggestions have become the main streams of the investment market. In Pakistan the Securities and Exchange Commission (SECP) has been a great promoter of digitalization in the brokerage sector. Besides, the fin-tech startups are also creating a new world of investment with their innovative and easy-to-use mobile apps and other platforms (Anttila, 2025). This brings up an important question: Does the usage of technology bring about a reduction in the practice of making wrong decisions by providing high trustable, clear, and reliable data for such decisions or does it grow the prejudices in investors by providing them with the means to do more trading and to be more influenced by the actions of others. Existing research presents inconsistent responses. To begin with, the online platforms might improve the rationality of the investors through providing them with analytical tools, real-time information, and diversification opportunities (Hoang, Nguyen, Dey, & Thi Thu, 2025). On the other hand, those same technologies could also strengthen psychological hazards like too much trading due to overconfidence or panic selling caused by social media whispers (Chen, Gao, Peng, & Yang, 2021). Therefore, the influence of technology adoption as a moderating factor is still an unresolved question especially in a developing country like Pakistan, where the differences in digital literacy and regulatory structures are abruptly high compared to the advanced countries' markets.

In this research, technology adoption is put forth as a moderating mechanism between the effect of behavioral biases and the investment decision-making process. The contributions of this study are three fold. First, it helps to gain better insights into the area of behavioral finance in Pakistan where the local culture, economy, and technology affect the investors' psyche in a different way comparing the western world. Second, the merging of behavioral finance with the technology adoption models such as TAM and UTAUT, where it is suggested that digital platforms are the boundary that influences the decisions made under the influence of biases. Finally, the research briefs information to the regulatory authorities, brokerage companies, and fin-tech providers about the extent to which technology acts as a prohibitive or a reinforcing force in the behaviors of investors.

The rest of the paper is organized as follows: A literature review on behavioral biases, decision making and technology adoption is presented in section 2. Section 3 describes the methodology and data collection techniques. Section 4 reports the results of the measurement and structural model using Smart PLS 4. Section 5 is dedicated to the discussion and implications of the findings. Section 6 wraps up the discussion by mentioning limitations and directions for future research.

2. LITERATURE REVIEW

Behavioral Biases and Investor Decision Making

In classical finance the rational investor was assumed to be disputing the empirical anomalies and psychological insights. To put it in simple terms, behavioral finance accentuates that investors often use heuristics and mental shortcuts. Such thinking are very efficient in daily life but can lead to wrong decisions in financial markets. In fact, such biases are very powerful in emerging markets where the level of financial education is not the same for everybody and the regulations are still in the process of becoming effective (Barberis, 2018; Kahneman & Tversky, 2013). Therefore, the decision-making process in investment cannot be solely attributed to the fundamentals of earnings, interest rates, or macroeconomic indicators. On the other hand, behavioral biases have a large influence on the way investors perceive information, measure risk, and allocate their funds. Overconfidence, for example, is one of the reasons for high trading activity, whereas herding is likely to lead to boom-and-bust cycles (Barber & Odean, 2000; Statman, Thorley, & Vorkink, 2006). Increasingly, researchers are convinced that knowledge of these mental factors is a prerequisite for market forecast in areas like Pakistan, where retail investors are the main players in the stock market (Bashir et al., 2013; Mahmood et al., 2024).

One of the most documented biases in the behavioral finance is overconfidence. It is the unjustified opinion in the correctness of his knowledge, judgment, or predictive power (Glaser & Weber, 2007; Karki, Bhatia, & Sharma, 2024). Overconfident investors are known to underestimate risks, over-estimate returns and trade frequently, thereby

lowering portfolio performance after transaction costs (Singh, Malik, & Jha, 2024; Zhao, Wang, & Cao, 2025). Research conducted in Pakistan has validated that overconfidence is a strong motivating factor of speculative behavior, when the market is seemingly in its bullish phase (Abideen, Ahmed, Qiu, & Zhao, 2023; Jawad, Nazir, & Islam, 2025). Confirmation bias is the act in which investors will selectively seek or interpret information that supports existing beliefs and ignore any information that contradicts them (Khachikian, 2021; Polychronakis, 2023; Shefrin, 2001). This bias may institutionalize ineffective investment policies and postponing the intervention steps such as selling non-performing stocks. Empirical research indicated that confirmation bias is common among investors in emerging markets which tends to support the mispricing and volatility (L. Bogan et al., 2013; Onsomu, 2014; Parashar et al., 2024; Sathya & Gayathiri, 2024).

Herding is the propensity of investors to act in a similar manner as other investors do and often overlook their own information or data (Christie & Huang, 1995; Komalasari, Asri, Purwanto, & Setiyono, 2022). Fear Of Missing Out (FOMO) or feeling secure in numbers may be a cause of herding in financial markets. (Shah, Imran, & Khan, 2024). In Pakistan, there is an indication that herding is more in the case of retail investors that depend on informal recommendations and market speculations. As much as herding may push prices in the short run, it might generally create instability and sudden corrections (Tsuchiya, 2021).

Based on Prospect Theory (Kahneman & Tversky, 2013), the loss aversion has a tendency of the investors who tend to experience losses more than similar gains. Therefore, investors can also retain losing stocks longer than would be predicted by rational models a phenomenon referred to as the disposition effect. Loss aversion is therefore capable of compromising the quality of the decisions and portfolio performance with time (Wesslen, Karduni, Markant, & Dou, 2021).

Technology Adoption and Financial Decision-Making

The high pace of digitalization in financial services has changed how investors can access markets, how they can consider information and the manner in which they can trade. Currently, there are a number of AI-based robo-advisors and mobile trading applications available to investors. Technology has created possibilities as well as some risks. Regarding technology acceptance and usage several frameworks are proposed by researchers. Prominent of such models include the Technology Acceptance Model (TAM) (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh, Morris, Davis, & Davis, 2003). Both these emphasized perceived usefulness and ease of use as primary determinants of technology adoption.

Technology adoption can have two functions in the context of investment. It involves real-time information, analytical systems, and algorithmic advice that may minimize the impact of behavioral biases. (Hoang et al., 2025). For instance, risk dashboards and automated alerts may temper overconfidence or counteract confirmation tendencies by presenting disconfirming evidence. On the other hand, excessive reliance on digital platforms may amplify biases. Overconfident investors, for instance, may overtrade when armed with faster execution tools, while social trading apps may intensify herding effects (Loang, 2025).

Behavioral Biases, Technology Adoption and Investor's Decision-Making

Although the effects of behavioral biases have been widely studied, no study has been carried out on the moderating effect of technology adoption in this particular context. There is some evidence in the developed markets that digital platforms contribute to rationality through increased transparency and diversification choice (Chen et al., 2021). However, in emerging markets, the results can be varied by the fact that there is the lower level of digital literacy, less protection of investors, and more speculative trading. The moderating effect of technology is an aspect that should be considered closely in the context of fin-tech use in Pakistan, which is a country where fin-tech adoption is gaining momentum. Technology can be a constraint on the behavioral finance model by influencing the way biases are turned into decisions. In particular, technology can mitigate the adverse impacts of overconfidence by giving feedback. It can mitigate the influence of loss aversion by providing stop-loss products and portfolio rebalancing services. On the other hand, technology could reinforce herding and confirmation bias by enhancing the influence of the social network with trading communities and recommendation algorithms.

On the basis of above discussions, the following hypotheses are posed:

H1: Investor's overconfidence is positively associated with their decision-making.
H2: Confirmation bias is positively associated with investor's decision-making.
H3: There is correlation between herding bias and the investor's decision-making.
H4: There is a relationship between loss aversion and investor's decision-making.
H5: Technology adoption moderates the association between overconfidence bias and investor's decision-making.
H6: Technology adoption moderates the association between confirmation bias and investor's decision-making.
H7: Technology adoption moderates the association between herding bias and investor's decision-making.
H8: Technology adoption moderates the association between loss aversion and investor's decision-making.

The conceptual framework incorporated behavioral biases as independent variables, the investor's decision-making as a dependent variable, and the technology adoption as a moderating variable.

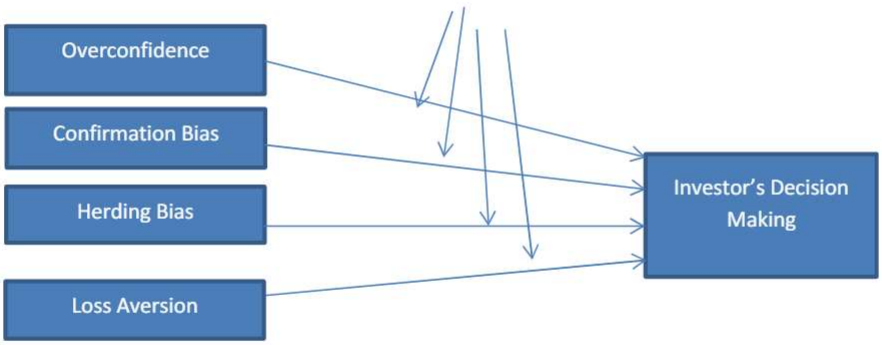

FIGURE 1 Conceptual Model

3. METHODOLOGY

In this study, the researchers deployed quantitative, cross-sectional research design to examine the moderating effect of technology adoption in the association between behavioral biases and investment decision making in Pakistan. It was considered suitable to use survey strategy due to the perceptual and subjective nature of behavioral constructs. (Creswell & Creswell, 2017). Partial Least Squares (PLS) operated on the structural equation modeling (SEM) model is suitable in exploratory studies, complex-based studies, and data which are not normally distributed. (Hair, 2014). The population to be targeted was individual investors and licensed brokers of the Pakistan Stock Exchange (PSX). Pakistan is an appropriate research subject because it offers an ideal investors base, a high number of retail investors, and the quick uptake of the digital trading platform.

The researchers made use of a purposive sampling technique specifically considering investors who were actively trading in the last 12 months. This policy was applied so that such individuals are approached who were sufficiently exposed to both the behavioral biases and the technological advancements in investing. The three largest financial centers in Pakistan— Karachi, Lahore, and Islamabad— were the places where the data was collected from investors. Following Comrey and Lee (2013) rule of thumb for factor analysis, a sample size of 200–300 is regarded as acceptable, 300–500 as good, and samples larger than 500 as excellent. A total of 420 questionnaires were distributed, out of which 392 were returned (response rate = 93%). After the elimination of missing values and straight-lining, 380 valid responses were considered for the analysis. The process of data collection took place from March to July 2024 mixing online and in-person surveys. The distribution of questionnaires was done through brokerage firm portals, investor WhatsApp groups, and email invitations. Apart from this, some hard copies were distributed at PSX regional offices and investment seminars. The confidentiality and anonymity of respondents were assured to reduce social desirability bias. The researchers' affiliated university's Institutional Review Board granted ethical clearance.

Measurement of Variables

All constructs were operationalized using established scales from prior studies. Responses were recorded on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). Further details of each measure are depicted in table 1.

Table 1. Variable Measures

Variable Name	Measurement and Reference
Overconfidence Bias (OC)	Six items adopted from (Barber & Odean, 2000; Glaser & Weber, 2007)
Confirmation Bias (CB)	Five items based on (L. Bogan et al., 2013; Shefrin, 2001)
Herding Bias (HB)	Five items adopted from (Christie & Huang, 1995; Sabir, Javed, Hameed, & Yousaf, 2020)
Loss Aversion (LA)	Four items from (Frazzini, 2006)
Technology Adoption (TA)	Five items derived from the Technology Acceptance Model (Davis, 1989) and UTAUT (Venkatesh et al., 2003)
Investment Decision-Making (IDM)	Six items adopted from (Bashir et al., 2013)

PLS-SEM was selected instead of Covariance-based SEM for a number of reasons. It can process sophisticated models with several constructs and moderating effects. It is ideal for non-normal data distributions, commonly found in behavioral finance studies. Furthermore, PLS-SEM focuses more on prediction and exploratory modeling, which is in accordance with this study's goals. Smart PLS 4.0 was utilized for measurement model, structural model, and bootstrapping evaluation.

4. DATA ANALYSES AND RESULTS

The analyses were carried out in two phases: the first one included the measurement model assessment that provided details of reliability and validity, while the second portion dealt with the structural model evaluation aimed at verifying the hypothesized relationships among variables including the impact of technology adoption as a moderator. All the analyses techniques were done through Smart PLS 4.0 employing 5,000 bootstrap resamples. To measure convergent validity, factor loadings, Cronbach's alpha, Composite Reliability (CR), and Average Variance Extracted (AVE) were assessed. Every loading was more than 0.70, all of the Cronbach's alphas were >0.80, CR values surpassed 0.90, and AVE values were higher than the 0.50 cutoff (Hair, 2014). Thus, the mentioned validity is confirmed (Table 2). For the purpose of discriminant validity, the Fornell–Larcker criterion along with HTMT ratios was used (Table 2). Diagonal values (square root of AVE) were higher than inter-construct correlations, confirming discriminant validity. All HTMT ratios were below the recommended threshold of 0.85 (Henseler, Ringle, & Sarstedt, 2015), confirming discriminant validity (Table 3).

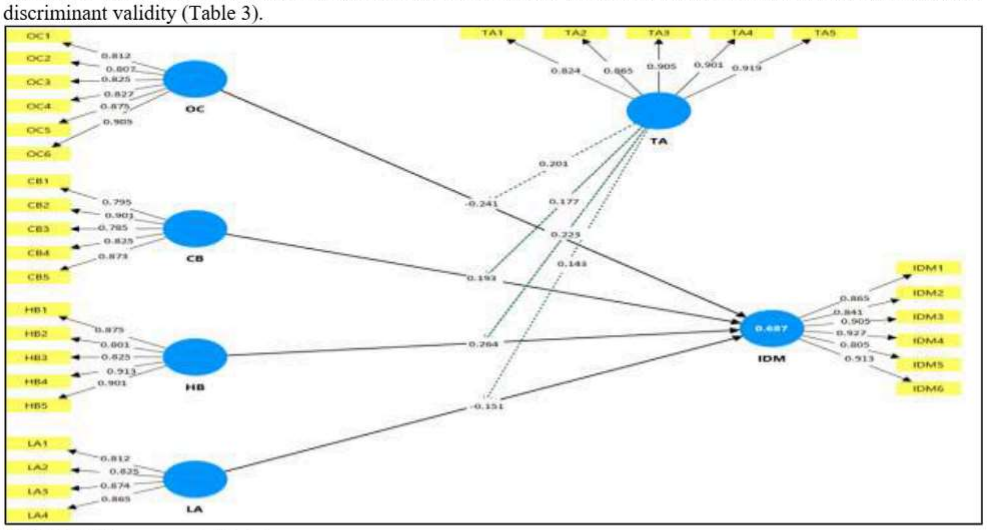

FIGURE 2Measurement Model

Table 2. Convergent Validity, Reliability, and AVE

Construct	Indicators	Loadings	Cronbach's Alpha	CR	AVE
Overconfidence (OC)	OC1–OC6	0.812–0.925	0.911	0.939	0.684
Confirmation Bias (CB)	CB1–CB5	0.785–0.902	0.886	0.924	0.708
Herding Bias (HB)	HB1–HB5	0.801–0.913	0.903	0.935	0.744
Loss Aversion (LA)	LA1–LA4	0.812–0.874	0.853	0.902	0.698
Technology Adoption (TA)	TA1–TA5	0.824–0.919	0.918	0.943	0.767
Investment Decision-Making (IDM)	IDM1–IDM6	0.841–0.927	0.928	0.951	0.764

Table 3. Fornell–Larcker Criterion

Construct	OC	CB	HB	LA	TA	IDM
OC	0.827					
CB	0.452	0.842				
HB	0.416	0.503	0.863			
LA	0.398	0.367	0.431	0.836		
TA	0.471	0.488	0.512	0.446	0.876	
IDM	0.529	0.541	0.564	0.483	0.601	0.874

Table 4. HTMT Ratios

Construct Pair	HTMT Value
OC – CB	0.515
OC – HB	0.498
OC – LA	0.442
CB – HB	0.566
CB – LA	0.421
HB – LA	0.463
TA – IDM	0.612

Structural Model Assessment

The structural model was evaluated through R^2, f^2, and Q^2 statistics. R^2 for Investment Decision-Making = 0.672 → substantial explanatory power (Chin, 1998). Q^2 = 0.421 → predictive relevance confirmed. Effect sizes (f^2): Overconfidence (0.15, medium), Confirmation Bias (0.12, small-medium), Herding (0.17, medium), Loss Aversion (0.10, small), and Technology Adoption (0.22, medium-large).

Hypothesis Testing (Direct Effects)

Table 5. Structural Model Direct Effects

Hypothesis	Path	β (Beta)	t-value	p-value	Decision
H1	OC → IDM	-0.241	3.12	0.002	Supported (negative)
H2	CB → IDM	0.193	2.89	0.004	Supported
H3	HB → IDM	0.264	4.01	0.000	Supported
H4	LA → IDM	-0.151	2.27	0.024	Supported (negative)
H5	TA → IDM	0.342	4.85	0.000	Supported

Moderating Effects of Technology Adoption

Interaction terms were generated in Smart-PLS, and moderation was tested via bootstrapping. The details are drawn in table 6.

Behavioral biases significantly influenced investment decision-making. Overconfidence and loss aversion negatively impacted decision quality, while confirmation and herding had positive effects on decision engagement. Technology adoption directly improved investment decision-making and significantly moderated all bias-decision paths. It weakened negative effects (OC, LA) and strengthened positive effects (CB, HB). The model explained 67% of variance in investment decision-making, demonstrating substantial predictive power.

Table 6. Moderating Effects

Hypothesis	Interaction Path	β (Beta)	t-value	p-value	Decision
H6	OC × TA → IDM	0.201	2.61	0.009	Supported
H7	CB × TA → IDM	0.177	2.44	0.015	Supported
H8	HB × TA → IDM	0.223	3.15	0.002	Supported
H9	LA × TA → IDM	0.148	2.02	0.044	Supported

5. Findings

The results indicate that overconfidence has a negative impact on decision quality ($\beta = -0.241$, $p < 0.01$). This is in line with the work of (Barber & Odean, 2000) showing that overconfident investors overtrade, leading to lower returns after transaction costs. This implies that people with greater degrees of overconfidence make less accurate and efficient decisions, which may be caused by an exaggerated assumption in the accuracy of their judgments and underestimation of the associated risks. This cognitive bias can make decision-makers put too much trust in their own judgment and forget about the important information or objective evaluation criteria.

Likewise, confirmation bias influenced positively investment decision-making ($\beta = 0.193$, $p < 0.01$). Even though this seems paradoxical—because confirmation bias is so frequently associated with bad decision-making (Sabir et al., 2020; Shefrin, 2001). Our result suggests that in the Pakistani context, seeking information that validates prior beliefs may increase investor confidence, reducing indecision. However, this also raises a caution: the short-term "confidence boost" may not translate into long-term rationality.

Herding behavior showed a positive relationship to investment decision-making ($\beta = 0.264$, $p < 0.001$). This is in line with research conducted earlier which showed herd behavior to be a common phenomenon in Pakistan. However, it is noteworthy that herding is usually considered as irrational behavior, yet in areas where financial literacy is poor and the analytical infrastructure is weak the investor may use the crowd as a heuristic shortcut to get a better decision. This highlights the two faces of herding. On one hand, it is a short-run stabilizer while on other hand, it is a bubble-forming destabilizer.

The loss aversion revealed a negative influence on investment decision-making ($\beta = -0.151$, $p < 0.05$), which is in accordance with the tenets of prospect theory (Kahneman & Tversky, 2013). Investors were concerned about the fear of loss primarily to an impressive degree and at times they held on to the losing shares much longer than would be obtained by rational models. This finding (similar to Frazzini, 2006) is evident on the disposition effect, reinforcing that loss aversion hampers rational reallocation of capital.

The primary goal of the research was to assess that adoption of technology has a moderating effect on the relationship between psychological biases and making investment decisions. Initially, technology diminished the negative effect of overconfidence ($OC \times TA \rightarrow IDM$: $\beta = 0.201$, $p < 0.01$). This indicates that digital platforms with features such as automated performance tracking and risk dashboards are supplying corrective feedback which calms overconfidence. This aligns with Kuppan, Acharya, and Divya (2024), who argued that fin-tech tools improve decision accuracy by offering objective insights.

Furthermore, technology increased the confirmation bias's positive effect ($CB \times TA \rightarrow IDM$: $\beta = 0.177$, $p < 0.05$). The traditional view of confirmation bias is that it stops the application of reason, but in case of the technology, it might help each investor by letting him/her to instantly confirm his/her assumption with data and thus reducing the burden of thinking. Nevertheless, this is a very delicate situation: personalization driven by algorithms (like news feeds or app recommendations) could also make echo chambers stronger, which in turn might lead to the biased digital signals being relied upon in the long run (Tsekhmeistruk, 2024).

Additionally, technology strengthened the effect of herding ($HB \times TA \rightarrow IDM$: $\beta = 0.223$, $p < 0.01$). Features such as social trading platforms and discussion forums likely enhance investors' tendency to follow peer behavior. While this may increase participation and engagement, it also risks exacerbating volatility when collective moves lack fundamental justification.

Finally, technology softened the negative effect of loss aversion ($LA \times TA \rightarrow IDM$: $\beta = 0.148$, $p < 0.05$). Tools like stop-loss orders, portfolio rebalancing, and AI-driven alerts are helpful for investors to cut losses earlier, counteracting the tendency to hold on declining assets. This finding contributes to the behavioral finance literature by showing how technological mechanisms can recalibrate cognitive distortions.

6. CONCLUSION

The research aimed to analyze the role of behavioral biases in the investment decision-making of Pakistani investors and the moderating role of technology adoption in the relationships between behavioral biases and investment decisions. The four biases i.e. overconfidence, confirmation, herding, and loss aversion were found to have a significant impact on investor behavior. The introduction of technology adoption into the process acted as a strong moderator, reducing the adverse effects of overconfidence and loss aversion, while supporting confirmation and herding in decision-making.

From theoretical perspective, the results contribute to behavioral finance by asserting that the condition of adoption of the technology is the boundary that determines the outcome of cognitive biases. Contrary to classical view that cognitive biases are only negatives, the present study affirmed that in certain cases, they could portray the good side of the engagement process when digital tools are the intermediaries. This sophisticated perspective contributes to redefine the rationality and bounded behavior in emerging markets. From practical perspective, the results imply that

the regulators, fin-tech developers, and the operators of brokerage houses should not consider technology as a silver bullet but rather as a double-edged sword. Hence, the policy recommendations must comprise of digital literacy policies, investor protection regulations, and technology-driven designs to ensure that the technology should not deteriorate the quality of decisions rather facilitate the process. The study was cross-sectional, like many others, and thus may not provide the basis for the causal relationship; nonetheless it is a timely illustration of the interplay between consumer psychology and technology in the financial sector.

Like any good research, this study also carries few limitations. First, the cross-sectional design undertaken in current research does not allow effective causal impacts; longitudinal research may be involved in determining the influence of technology adoption on decision-making in the long run. Second, although this paper concentrated on four biases, there are additional heuristics including mental accounting or anchoring that can also act as mediator between technology adoption. Third, the sample size was restricted to urban PSX investors; any future attempt should be extended to rural and diaspora investors who might adopt digitization differently. It is also possible to compare various digital platforms (e.g., mobile application and desktop platforms) in future researches to determine whether the bias effects are moderated by interface design. Moreover, cross-country comparison in South Asia might indicate whether the moderating effect of technology adoption is culture specific or it is generalizable to the emerging economies.

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