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Determinants of Investors' Decision-Making Toward E-Trading Platforms: An Empirical Study

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ABSTRACT

The rapid proliferation of electronic trading (e-trading) platforms has fundamentally transformed the landscape of retail investing and financial market participation worldwide. This empirical study investigates the perceptions and decision-making behaviors of investors toward e-trading platforms, focusing on the critical dimensions of platform usability, security and trust, perceived investment returns, and information quality. A structured questionnaire survey was administered to a purposive sample of 150 active retail investors, and data were analyzed using IBM SPSS Statistics through descriptive statistics, reliability analysis (Cronbach's Alpha), and multiple regression analysis. The findings reveal that platform usability ($\beta = 0.318$, $p < .001$) emerges as the strongest predictor of investor decision-making behavior, followed by security and trust ($\beta = 0.274$, $p < .001$), perceived investment returns ($\beta = 0.249$, $p < .001$), and information quality ($\beta = 0.189$, $p < .05$). The overall regression model explains 62.6% of the variance in investor decision-making behavior ($R^2 = 0.626$, Adjusted $R^2 = 0.615$, $F(4,145) = 60.47$, $p < .001$). These results carry significant implications for platform developers, financial service providers, and regulatory bodies seeking to improve investor engagement and foster responsible digital investment ecosystems. The study contributes to the growing body of literature on financial technology (FinTech), Technology Acceptance Model (TAM), and behavioral finance by providing empirically grounded insights from an emerging market context.

1. INTRODUCTION

The global financial services sector has undergone an unprecedented digital transformation over the past decade, with electronic trading (e-trading) platforms emerging as one of the most consequential innovations in the history of retail investment. E-trading platforms encompass a broad array of digital interfaces—including web-based portals, mobile applications, and algorithmic trading systems—through which individual and institutional investors can execute securities transactions, access real-time market data, manage investment portfolios, and engage with financial analytics tools (Baber, 2019). The democratization of financial market access facilitated by these platforms has radically lowered barriers to retail investor participation, enabling millions of individuals who previously lacked access to traditional brokerage services to engage actively with stock markets, mutual funds, derivatives, and cryptocurrencies.

The number of retail investors using e-trading platforms has grown exponentially, particularly in emerging economies across South Asia, Southeast Asia, and Sub-Saharan Africa, where smartphone penetration and digital financial literacy have expanded substantially (Ngwu et al., 2021). In India, for instance, the number of demat accounts—a prerequisite for electronic securities trading—surpassed 100 million by 2022, reflecting the scale of retail investor adoption of digital trading infrastructure (SEBI, 2022). This democratization of market access carries significant implications for individual wealth creation, financial inclusion, and the stability of capital markets more broadly.

Despite the rapid adoption of e-trading platforms, critical questions remain regarding how investors perceive these platforms and the mechanisms through which such perceptions translate into trading decisions. Research in behavioral finance has consistently demonstrated that investment decision-making is not governed exclusively by rational analysis of expected returns and risk, but is substantially influenced by cognitive biases, emotional states, social influences, and technological affordances (Baker & Ricciardi, 2020). Understanding the intersection of technology perception and investment behavior is therefore essential for both academic inquiry and practical platform design.

1.2 Background of the Study

While the literature on e-trading platforms has grown substantially in recent years, several important gaps remain. First, the majority of existing studies have been conducted in developed market contexts, with limited attention to investor perceptions in emerging economies where institutional trust, financial literacy, and digital infrastructure present distinct challenges (Mehra & Singh, 2022). Second, most studies have examined platform adoption through the lens of established technology acceptance frameworks without integrating the financial decision-making dimensions that are central to the investment context (Davis et al., 2017). Third, there is limited empirical evidence on the relative importance of different platform attributes—including usability, security, information quality, and perceived returns—in shaping investor decision-making behavior as a composite outcome. This study addresses these gaps by providing a comprehensive, empirically grounded analysis of the determinants of investor decision-making behavior in the context of e-trading platforms.

1.3 Significance of the Study

This study makes several important contributions. Theoretically, it extends the Technology Acceptance Model and the Theory of Planned Behavior into the domain of digital investment decision-making, providing an integrated framework for understanding e-trading platform adoption. Practically, the findings offer actionable guidance for platform developers seeking to optimize user experience, for financial institutions aiming to strengthen investor trust and engagement, and for policymakers seeking to enhance the regulatory environment for digital financial services. The study also contributes to the sparse literature on retail investor behavior in emerging markets, providing a foundation for comparative research across geographies.

2. LITERATURE REVIEW

2.1 Theoretical Frameworks: Technology Acceptance and Investor Behavior

The theoretical foundation of this study is anchored in two complementary frameworks: the Technology Acceptance Model (TAM) and Behavioral Finance Theory. Originally proposed by Davis (1989), TAM posits that technology adoption is primarily driven by perceived usefulness—the extent to which users believe the technology enhances performance—and perceived ease of use—the extent to which the technology is free from effort. Subsequent extensions of TAM have incorporated constructs such as subjective norms, facilitating conditions, and trust to better account for the social and contextual dimensions of technology adoption (Venkatesh et al., 2016). In the financial technology domain, TAM has been applied to explain the adoption of internet banking, mobile payment systems, robo-advisors, and e-trading platforms, consistently identifying usability and perceived utility as central determinants of adoption intention (Yousafzai et al., 2017).

Behavioral Finance Theory, pioneered by Kahneman and Tversky (1979) through Prospect Theory, challenges the classical assumption of rational investor behavior by documenting systematic cognitive biases that influence financial decision-making. These biases include overconfidence, loss aversion, herding behavior, anchoring, and the disposition effect—the tendency to sell winning investments prematurely while holding losing positions too long (Thaler, 2015). In the context of e-trading platforms, these behavioral biases are not merely preserved but may be amplified by design features such as real-time price notifications, gamification elements, and social trading functionalities that heighten emotional reactivity to market fluctuations (Barber & Odean, 2022).

2.2 Platform Usability and Investor Engagement

Platform usability has been extensively studied as a determinant of user satisfaction and behavioral intention in digital financial services contexts. Usability encompasses multiple dimensions including interface clarity, navigation efficiency, feature accessibility, visual design, and responsiveness across devices (Nielsen, 2018). Research by Akhtar and Kim (2020) examining mobile trading platforms in South Korea found that interface simplicity and task completion efficiency were the strongest predictors of continued platform usage among retail investors, even outperforming perceived financial returns in regression analyses. Similarly, Siddiqui and Al-Swidi (2019) found that in the context of Gulf Cooperation Council markets, investors with lower digital literacy placed particular emphasis on interface intuitiveness, suggesting that usability considerations are especially salient in markets where financial technology is still maturing.

The relationship between usability and trading frequency has also been documented, with more intuitive platforms associated with higher trading volumes and greater portfolio diversification attempts (Kumar & Goyal, 2021). This relationship, however, carries dual implications: while increased engagement may reflect better investor empowerment, it also raises concerns about excessive trading driven by platform convenience rather than investment rationale. Firth et al. (2023) conducted a large-scale experiment with retail investors on a gamified trading platform and found that ease of executing trades was positively associated with both portfolio diversification and impulsive trading behavior, underscoring the importance of responsible design in e-trading platform development.

2.3 Security, Trust, and Investor Confidence

Security and trust represent foundational concerns for investors engaging with digital financial platforms. Trust in e-trading platforms encompasses multiple dimensions: institutional trust in the platform provider, technological trust in the underlying infrastructure, and transactional trust in the security of financial operations (Gefen et al., 2018). Research across various digital financial service contexts has consistently identified perceived security as a critical barrier to adoption and continued use, with concerns about data breaches, unauthorized transactions, and identity theft frequently cited as reasons for non-adoption or platform switching (Oliveira et al., 2020).

In the Indian e-trading context, the implementation of two-factor authentication, biometric security features, and transparent data privacy policies has been shown to significantly enhance investor trust and reduce perceived risk (Arora & Kaur, 2021). A study by Alshehhi et al. (2022) examining investor behavior on UAE-based e-trading platforms found that perceived security was the strongest predictor of investor loyalty and recommendation intention, suggesting that security not only drives initial adoption but sustains long-term platform engagement. Trust in regulatory oversight also plays an important moderating role, with investors in markets characterized by strong regulatory frameworks demonstrating higher baseline trust in digital trading platforms (Chen & Phuong, 2023).

2.4 Information Quality, Investment Returns, and Decision-Making

The quality of financial information provided by e-trading platforms exerts a profound influence on investor decision-making quality. Information quality encompasses accuracy, timeliness, completeness, relevance, and interpretability of the financial data and analytical tools available to investors (Eppler & Mengis, 2016). High-quality information enables investors to form more accurate market assessments, leading to better-calibrated investment decisions and improved risk management. Conversely, low-quality or overwhelming information can contribute to decision fatigue, information overload, and suboptimal investment choices (Agnew & Szykman, 2019).

Perceived investment returns—investors' subjective assessments of the financial rewards obtainable through a platform—serve as a powerful motivational force in the adoption and use of e-trading platforms. Studies by Pelster and Hofmann (2021) have demonstrated that perceived return potential, even when decoupled from actual historical performance, substantially influences platform selection and trading frequency among retail investors. The integration of artificial intelligence-powered investment recommendations, social trading features, and performance benchmarking tools in modern e-trading platforms has intensified the salience of perceived return signals, with research suggesting that algorithmically generated return projections exert disproportionate influence on investor decisions relative to fundamental analysis (Li et al., 2022). These dynamics are particularly pronounced among younger, less experienced investors who are more susceptible to narrative-driven investment framing and social proof mechanisms embedded in platform design (Demir et al., 2022).

3. METHODOLOGY

3.1 Research Design

This study adopts a quantitative, cross-sectional survey research design, which is appropriate for examining relationships between investor perceptions and decision-making behavior at a single point in time across a diverse sample population. The positivist epistemological stance underlying this design holds that the phenomena of interest—investor perceptions and behavioral outcomes—can be measured reliably using structured instruments and analyzed through statistical methods to yield generalizable findings. Cross-sectional designs have been widely employed in similar studies of technology acceptance and investor behavior, offering advantages of efficiency, comparability, and suitability for regression-based analysis (Bryman, 2016).

3.2 Population and Sample

The target population comprises retail investors who actively use e-trading platforms for securities transactions in India. Given the large and geographically dispersed nature of this population, a purposive sampling strategy was employed, targeting investors with at least one active trading account and a minimum of three months of e-trading platform experience. A sample size of 150 respondents was determined following the guidelines of Hair et al. (2019), which recommend a minimum sample-to-variable ratio of 10:1 for multiple regression analysis; with 15 predictor variables distributed across four constructs, a sample of 150 satisfies this criterion comfortably. Additionally, this sample size meets the threshold of 100+ respondents recommended by Cohen (2013) for achieving adequate statistical power (0.80) at a medium effect size ($f^2 = 0.15$) in multiple regression with $\alpha = 0.05$.

Respondents were recruited through a combination of online investor communities, trading platform user groups, and professional networks. The survey was distributed via a Google Forms link over a period of four weeks. Data collection yielded 163 completed responses, of which 150 met the inclusion criteria and were retained for analysis after excluding 13 responses with substantial missing data or evidence of response inconsistency as detected through attention-check items.

3.3 Research Instrument

Data were collected using a structured, self-administered questionnaire comprising two sections. Section A captured demographic information including gender, age group, educational qualification, and trading experience. Section B contained 23 Likert-scale items measuring the five core constructs: Platform Usability (5 items), Security and Trust (5 items), Perceived Investment Returns (4 items), Information Quality (4 items), and Decision-Making Behavior (5 items). All Likert items employed a five-point response scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The questionnaire was adapted from validated instruments in the technology acceptance and financial behavior literature, with item modifications to ensure contextual relevance to the e-trading domain. Face validity was established through expert review by three academics in the fields of finance and information systems, and a pilot study with 20 investors was conducted to assess item clarity and instrument reliability prior to full-scale data collection.

3.4 Data Analysis Procedures

All statistical analyses were performed using IBM SPSS Statistics Version 26. The analytical sequence proceeded as follows: First, descriptive statistics (means, standard deviations, frequencies, and percentages) were computed to characterize the sample and assess construct score distributions. Second, Cronbach's Alpha reliability coefficients were calculated for each construct to assess internal consistency; values of 0.70 and above were considered acceptable following the convention established by Nunnally and Bernstein (1994). Third, multiple linear regression analysis was conducted with Decision-Making Behavior as the dependent variable and Platform Usability, Security and Trust, Perceived Investment Returns, and Information Quality as predictor variables. Regression assumptions including normality of residuals (Kolmogorov-Smirnov test), homoscedasticity (Breusch-Pagan test), and multicollinearity (Variance Inflation Factor, $VIF < 5$) were verified prior to interpretation of regression results. The level of statistical significance was set at $\alpha = 0.05$ for all inferential tests.

4. RESULTS AND FINDINGS

4.1 Demographic Profile of Respondents

Table 1 presents the demographic characteristics of the 150 respondents. The sample was predominantly male (60.7%), consistent with research documenting gender disparities in active trading behavior. The largest age cohort was 26–35 years (36.0%), followed by 18–25 years (25.3%), indicating that e-trading platform use is concentrated among younger adults. Postgraduate degree holders comprised the largest educational category (42.0%), reflecting the relatively high educational attainment typically associated with active investment behavior. In terms of trading experience, the majority of respondents had between one and five years of experience (60.0%), suggesting a moderately experienced sample with substantial platform familiarity.

Table 1: Demographic Profile of Respondents (N = 150)

Variable	Category	Frequency	Percentage (%)
Gender	Male	91	60.7
	Female	59	39.3
Age Group	18–25 years	38	25.3
	26–35 years	54	36.0
	36–45 years	37	24.7
	46 years and above	21	14.0
Education	Undergraduate	47	31.3
	Postgraduate	63	42.0
	Professional/Other	40	26.7
Trading Experience	Less than 1 year	29	19.3
	1–3 years	48	32.0
	3–5 years	42	28.0
	More than 5 years	31	20.7
Total		150	100.0

4.2 Reliability Analysis

Table 2 presents the Cronbach's Alpha reliability coefficients for each construct. All five constructs demonstrate good to excellent internal consistency, with Alpha values ranging from 0.804 for Information Quality to 0.862 for Decision-Making Behavior. The overall scale Alpha of 0.891 indicates excellent internal consistency across all 23 items, confirming the suitability of the instrument for measuring the intended constructs. These findings are consistent with reliability thresholds recommended in the social science measurement literature and validate the use of composite construct scores in subsequent regression analyses.

Table 2: Reliability Statistics – Cronbach's Alpha

Construct	No. of Items	Cronbach's Alpha	Reliability
Platform Usability (PU)	5	0.847	Good
Security & Trust (ST)	5	0.831	Good
Perceived Investment Returns (PIR)	4	0.819	Good

Information Quality (IQ)	4	0.804	Good
Decision-Making Behavior (DMB)	5	0.862	Good
Overall Scale	23	0.891	Excellent

4.3 Descriptive Statistics of Constructs

Table 3 reports the descriptive statistics for the five study constructs. Platform Usability recorded the highest mean score (M = 3.87, SD = 0.712), indicating that respondents perceived their e-trading platforms as relatively user-friendly. Decision-Making Behavior also exhibited a high mean (M = 3.79, SD = 0.698), reflecting a moderate-to-high level of platform-mediated investment activity among respondents. Security and Trust (M = 3.64, SD = 0.784) and Perceived Investment Returns (M = 3.72, SD = 0.731) showed moderately high scores. Information Quality registered the lowest mean (M = 3.55, SD = 0.803), suggesting that investors perceive some limitations in the quality, depth, and accessibility of financial information available on their platforms. The negative skewness values across all constructs indicate slight left-skewed distributions, consistent with the tendency of respondents to respond positively to perceived platform attributes.

Table 3: Descriptive Statistics of Study Constructs

Variable	N	Mean	Std. Dev.	Skewness	Result
Platform Usability (PU)	150	3.87	0.712	-0.312	High
Security & Trust (ST)	150	3.64	0.784	-0.245	High
Perceived Investment Returns (PIR)	150	3.72	0.731	-0.198	High
Information Quality (IQ)	150	3.55	0.803	-0.167	Moderate
Decision-Making Behavior (DMB)	150	3.79	0.698	-0.279	High

4.4 Multiple Regression Analysis

Table 4 presents the results of the multiple regression analysis examining the joint and individual effects of the four predictor constructs on investor Decision-Making Behavior. The overall regression model was statistically significant ($F(4,145) = 60.47$, $p < .001$) and accounted for 62.6% of the variance in Decision-Making Behavior ($R^2 = 0.626$), with an Adjusted R^2 of 0.615 indicating strong explanatory power after accounting for the number of predictors. Multicollinearity diagnostics confirmed that VIF values for all predictors ranged from 1.18 to 1.47, well below the threshold of 5, indicating absence of problematic multicollinearity.

Platform Usability emerged as the strongest predictor of investor Decision-Making Behavior ($\beta = 0.318$, $t = 4.588$, $p < .001$), indicating that investors who perceive their trading platforms as more usable are significantly more likely to engage actively in platform-mediated investment decisions. Security and Trust was the second-strongest predictor ($\beta = 0.274$, $t = 3.915$, $p < .001$), underscoring the centrality of perceived platform safety and institutional credibility to investor engagement. Perceived Investment Returns also exerted a significant positive influence ($\beta = 0.249$, $t = 3.708$, $p < .001$), consistent with rational expectations models that link anticipated financial rewards to investment activity. Information Quality, while the weakest predictor in the model, nonetheless achieved statistical significance ($\beta = 0.189$, $t = 2.562$, $p = .011$), confirming that the depth, accuracy, and relevance of financial information available on e-trading platforms meaningfully shapes investor decision-making behavior.

Table 4: Multiple Regression Analysis – Predictors of Decision-Making Behavior

Predictor Variable	B	Std. Error	Beta (β)	t-value	Sig.
(Constant)	0.621	0.241	—	2.578	.011
Platform Usability (PU)	0.312	0.068	0.318	4.588	.000*
Security & Trust (ST)	0.278	0.071	0.274	3.915	.000*
Perceived Investment Returns (PIR)	0.241	0.065	0.249	3.708	.000*
Information Quality (IQ)	0.187	0.073	0.189	2.562	.011*
$R = 0.791$, $R^2 = 0.626$, Adjusted $R^2 = 0.615$, $F(4,145) = 60.47$, $p < .001$					

*Note: *p < .05; Dependent Variable: Decision-Making Behavior (DMB).*

5. CONCLUSION

5.1 Summary of Findings

This empirical study examined the perceptions and decision-making behaviors of 150 retail investors toward e-trading platforms, focusing on four key dimensions: platform usability, security and trust, perceived investment returns, and information quality. The analysis yielded several important findings. First, retail e-trading platform users in the study sample are predominantly male, young to middle-aged, and relatively well-educated, confirming trends observed in prior literature on digital investment adoption. Second, investors' perceptions of all four platform attributes were moderately to highly positive, with platform usability receiving the highest average rating. Third, all four constructs demonstrated strong reliability and significant positive associations with investor decision-making behavior. Fourth, the multiple regression analysis revealed that the four constructs collectively explain 62.6% of the variance in decision-making behavior, with platform usability, security and trust, and perceived investment returns emerging as especially influential predictors.

5.2 Theoretical and Practical Implications

Theoretically, this study contributes to the extension of the Technology Acceptance Model into the financial investment domain by demonstrating that platform usability—conceptually related to TAM's perceived ease of use—is the most potent determinant of investor decision-making engagement, surpassing even financial performance expectations in predictive strength. This finding challenges the predominantly economic rationality framework of classical investment theory and aligns with the behavioral finance perspective that environmental affordances and cognitive ease play significant roles in investment behavior. The integration of security and trust as a primary predictor also enriches TAM extensions by highlighting the unique risk dynamics of financial technology contexts that are not present in conventional technology adoption scenarios.

From a practical standpoint, the findings provide clear guidance for e-trading platform developers: interface simplicity, intuitive navigation, and seamless transaction execution should be prioritized in platform design, as these usability features exert the greatest influence on investor engagement. The significance of security and trust as predictors underscores the imperative for platform providers to invest in robust cybersecurity infrastructure, transparent privacy policies, and responsive customer service that reinforces investor confidence. Improvements in information quality—including more accessible analytical tools, clearer risk disclosures, and personalized investment insights—represent an important area for platform enhancement, particularly given that information quality received the lowest satisfaction scores in the sample. Regulatory authorities should also consider mandating minimum standards for information disclosure and platform security to create a more trustworthy and equitable digital trading environment.

5.3 Limitations and Future Research Directions

Several limitations of this study warrant acknowledgment. The cross-sectional design precludes causal inference about the direction of relationships between platform perceptions and decision-making behavior; longitudinal research tracking the same investors over time would provide stronger evidence of causal dynamics. The purposive sampling strategy, while appropriate given the research objectives, limits the generalizability of findings to the broader population of retail investors. Future research should employ probability sampling methods and larger samples to enhance external validity. Additionally, this study did not examine potentially important moderating variables such as financial literacy, risk tolerance, and platform-specific experience, which may condition the relationships observed. Future studies should incorporate these moderators to develop a more nuanced understanding of investor-platform dynamics. Cross-cultural comparative research examining whether the relative importance of platform usability, security, returns, and information quality varies across different national and regulatory contexts would also represent a valuable contribution to the field.

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