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Research Article

Predicting Investor Behavior In Online Mutual Fund Investments: A SEM Analytical Framework

Dhara Padia[1], Viral Bhatt[2*]

[1]Research Scholar, Gujarat Technological University, Ahmedabad. padia.dhara@gmail.com,
[2]Karnavati University, Ahmedabad, India. drviralgbhatt@gmail.com

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ABSTRACT

This study investigates the determinants of investor behavior in the context of online mutual fund investments using a Structural Equation Modeling (SEM) framework. The research model integrates demographic variables (age, gender, education, occupation, income, and marital status), performance expectancy, effort expectancy, hedonic motivation, financial knowledge, perceived risk, perceived trust to predict investor behavior in digital mutual fund platforms. Primary data were collected through a structured questionnaire distributed among active online mutual fund investors. SEM analysis was employed to validate the proposed model and examine the relationships between variables. The findings indicate that investment knowledge and risk perception significantly influence online investment behavior, while demographic factors act as moderating variables. The study highlights the growing importance of behavioral and cognitive components in digital investment environments. The insights offer valuable implications for mutual fund providers, fintech platforms, and policymakers aiming to enhance user engagement and build trust in online financial services.

Keywords: Investor behavior, online mutual funds, investment knowledge, risk perception, SEM, digital finance, behavioral finance

1. Introduction:

Efficient mobilization of financial resources is a cornerstone of sustainable economic development, with the financial sector playing a pivotal role in channelling household savings into productive avenues such as the securities market (Kling Christian; Trautmann Stefan T., 2023). The mutual fund industry has emerged as a critical channel for mobilizing household savings into productive investments, especially in developing economies. As global financial markets experience unprecedented digital transformation, understanding the behavioral patterns of investors in online mutual fund platforms has become vital(Kozup Elizabeth; Pagano Michael S., 2008). With increasing internet penetration, the rise of fintech solutions, and the influence of social media, investor behavior has become more dynamic, making traditional investment modeling inadequate. These funds allow investors to benefit from diversification and risk optimization, while also earning returns that are shared with the investors, minus a nominal management fee(D'Arcangelis Giulia, 2021).
Post-COVID-19, retail investors have displayed a notable shift in preferences—from fixed deposits to market-linked instruments like mutual funds. However, despite these favorable conditions, investor participation remains fragmented, and assets under management (AUM) are concentrated among a few investor segments(Kaur, 2018). This highlights the need to explore underlying psychological, technological, and contextual factors that drive or hinder investor behavior in the digital space. The low penetration rate and narrow investor base, reflected in comparatively smaller Assets Under Management (AUM), signal the need for deeper exploration into investor behavior. According to Allied Market Research, the global mutual fund market is projected to grow to approximately $101.2 trillion by 2027, underscoring the vast opportunity and the necessity for targeted marketing strategies(Mishra et al., 2023).
These structural changes have increased financial information transmission and shifted savings from fixed deposits and provident funds to equity-based and mutual fund investments. Equities provide superior long-term returns and wealth creation through compounding, but they need more financial understanding and risk. Actively managed mutual funds are seen as more reliable than direct stock investments or passive index funds by risk-averse investors(Fama Kenneth R., 2010). Understanding investor attitudes and behavioural intentions

is crucial in this changing environment, especially with digital usage accelerating and the post-pandemic investment climate. Thus, research question;
What are the key determinants influencing actual investor behavior in online mutual fund platforms?
This study builds upon and extends existing literature by incorporating contemporary drivers such as digitalization, social influence, risk perception, and psychological variables. Using a Structural Equation Modeling (SEM) framework, we identify and evaluate the key constructs influencing online mutual fund investment behavior, offering a robust analytical lens for marketing strategists and financial service providers.

2. Theoretical background:

This study investigates the determinants influencing actual investment behavior in online mutual fund platforms by integrating two dominant behavioral theories: the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) and the Theory of Planned Behavior (TPB). This integrated framework enables a more holistic understanding of both the technology adoption and behavioral intention aspects of investment decision-making.
Investor's intention is a measure of the possibility that someone will buy or use a particular product/service/technology (Venkatesh & Davis, 2000). Various studies have been carried out to identify the most important factors influencing the behavior of using new technologies. The development of this model starts from Theory of Reasoned Action (TRA), The Planned Behavior Theory (TPB), The Technology Acceptance Model (TAM) to The Unified Theory of Acceptance and Use of Technology (UTAUT) (Ajzen, 1991; Gefen et al., 2003; Venkatesh, 2000).
The theory of planned behaviour allows for the incorporation of supplementary predictors, provided that their use can demonstrate a significant contribution to explaining the variation in intention or behaviour beyond what is already explained by the hypothesis's developed variables. This adjustment is further supported by (Ajzen Martin, 1974). This study includes variables to assess the investor's intention to invest among prospective mutual fund investors. These variables include financial knowledge, perceived risk, perceived trust. These supplementary constructs are examined in connection with the core constructs of the Theory of Planned Behaviour (TPB).
The rapid proliferation of digital technologies has transformed consumer behavior, particularly in the realms of financial services and digital platforms. Innovations such as cryptocurrencies and digital benchmarking services have disrupted traditional models of value exchange, necessitating new frameworks to understand user adoption. While early technology adoption theories like the Technology Acceptance Model (TAM)(Bailey I. and Mishra A.S. and Mimoun M.S.B., 2017; Gautam et al., 2020) laid the groundwork, recent advancements such as the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) provide a more holistic perspective (Alalwan et al., 2017; Palau-Saumell et al., 2019). Nevertheless, the complexity of consumer behavior in tech-mediated environments calls for hybrid analytical models that can accommodate both linear and non-linear relationships.
Despite increasing interest, gaps remain in understanding the interplay between socio-technical factors and personal behavioral intentions in adopting novel technologies. Moreover, few studies have combined structural equation modeling with artificial intelligence to enhance predictive insights. This research aims to bridge this gap by synthesizing findings from three complementary studies on mutual fund adoption, digital benchmarking, and investor's intention modeling—each employing advanced methods such as PLS-SEM.
The present paper proposes a hybrid analytical framework integrating UTAUT2, PLS-SEM, and TPB to explore the determinants of technology adoption. By doing so, it provides both explanatory depth and predictive precision, offering a new lens for interpreting user engagement with emerging technologies.

2.1 Hypothesis Development:

Performance expectancy (PE) refers to the degree to which an individual believes that using a technology will help achieve gains in job performance or decision-making. Performance Expectancy refers to the belief that using an online mutual fund platform will enhance investment outcomes. Previous studies (Bommer et al., 2022; Kaur, 2018) found PE to be a strong predictor of investment intent in fintech and digital banking contexts. In online mutual fund investment, PE reflects how investors perceive the usefulness of digital platforms in facilitating better investment outcomes. According to (Nur & Ria Panggabean, 2021)performance expectancy is a significant predictor of behavioral intention in digital service usage. Prior studies in fintech adoption have confirmed that perceived usefulness positively influences investors' likelihood to use online mutual fund services (Alalwan Y.K. and Rana N.P., 2017)
H1: Performance expectancy significantly influence investor's intention to mutual fund investment.
Effort expectancy (EE) denotes the ease associated with the use of a system or platform. Effort Expectancy measures how easy it is to use digital investment platforms. As per UTAUT2, ease of use plays a crucial role in driving initial adoption and continued usage behavior (Alalwan, 2020). In financial technology, this translates to how intuitive and user-friendly the investment process is perceived. Studies have found EE to be particularly influential for older or novice users engaging with mutual fund platforms for the first time (Chopdar Justin; Prodanova Jana, 2021). A streamlined interface, automation, and guided onboarding processes can significantly influence digital investment adoption.

H2: Effort expectancy significantly influence investor's intention to mutual fund investment.
Perceived risk is a TPB-aligned construct and has been a central concern in investment literature. It refers to the investor's belief about the uncertainty and potential negative consequences of an investment decision. Investing inherently involves risk. Perceived financial and operational risks can reduce behavioral intention, especially in online environments where uncertainty is higher (Das & Ali, 2020). Several studies have found that perceived risk negatively impacts behavioral intention, especially among risk-averse investors during uncertain times such as the COVID-19 pandemic (HuuTho et al., 2018). Risk perception is heightened in online environments due to cybersecurity, data privacy, and market volatility concerns.
H3: Perceived risk negatively influence investor's intention to mutual fund investment.
Trust plays a mediating role in online investment behavior. Trust is central in financial decision-making. Research in digital finance has shown that perceived trust in a platform, its management, and regulatory compliance positively correlates with investor confidence (Lee & Lee, 2019; Lin et al., 2020). It encompasses the investor's confidence in the digital platform's reliability, security, and ethical handling of transactions. Trust has been consistently recognized as a strong predictor of both intention and actual usage in fintech settings (Kostovetsky, 2016). In mutual fund investments, trust in fund managers and the platform provider is critical for sustained engagement.
H4: Perceived trust significantly influence investor's intention to mutual fund investment.
Financial knowledge is a critical determinant of investment behavior. It affects how well individuals understand risk-return trade-offs, investment options, and portfolio diversification. Investor literacy and domain-specific knowledge critically affect fund selection and portfolio behavior. High financial knowledge correlates with greater confidence in mutual fund investing (van Rooij et al., 2011). Studies have shown a strong correlation between higher financial knowledge and the likelihood of mutual fund investment (Lusardi Andrea; Yakoboski Paul J., 2020). Well-informed investors are also more confident in using digital platforms for fund selection and monitoring.
H5: Financial knowledge significantly influence investor's intention to mutual fund investment.
Hedonic motivation captures the fun or pleasure derived from using a technology. While traditionally underexplored in financial contexts, recent fintech studies highlight its growing relevance. Hedonic Motivation reflects the enjoyment derived from using digital interfaces and making financial decisions. In fintech applications, emotional gratification from engaging with intuitive platforms enhances usage (Jung E. and H D., 2020). Gamified investment apps and interactive dashboards foster greater user engagement by offering an enjoyable user experience (Venkatesh, 2000). This construct aligns with UTAUT2's expansion of motivation beyond purely utilitarian drivers.
H6: Hedonic motivation significantly influence investor's intention to mutual fund investment.
Actual investment intention refers to the concrete act of investing in mutual funds via online platforms. According to TPB, actual behavior results from behavioral intention, which itself is shaped by attitudes, subjective norms, and perceived behavioral control(Saputri et al., 2024). Integrating UTAUT2 enhances this predictive capability by accounting for technology-related facilitators and motivations(Akhtar & Das, 2019). Hence, actual behavior is a function of not only intent but also technological ease and contextual enablers.
H7: Investment intention significantly influence mutual fund investment.

3. Research methodology:

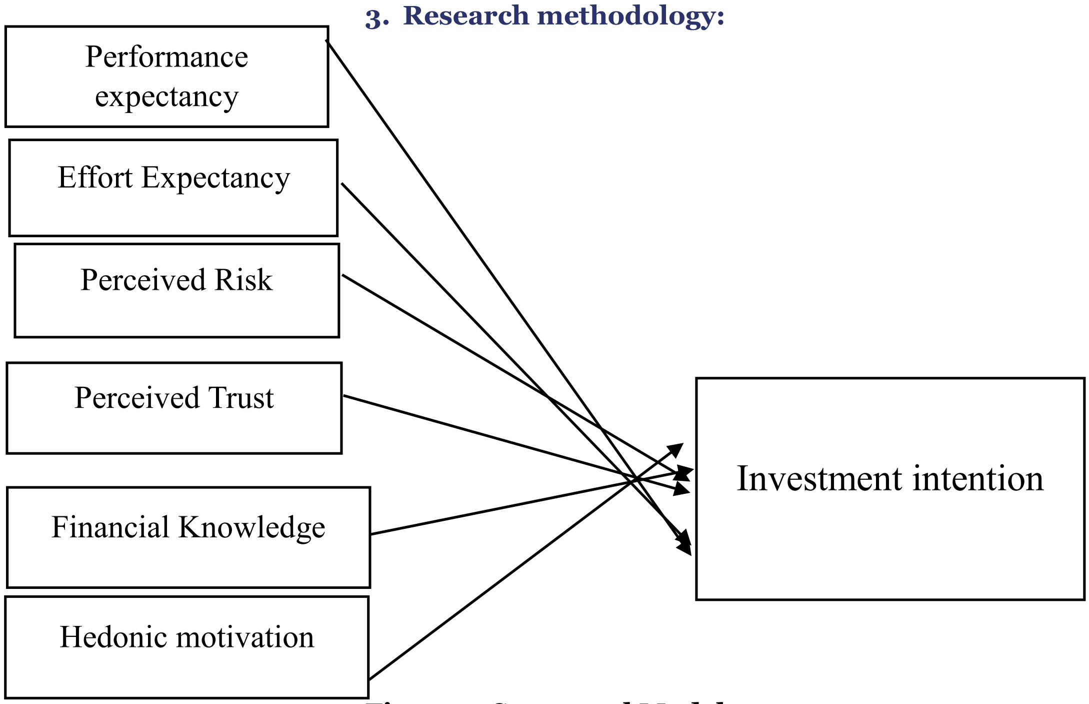

Figure 1: Structural Model

3.1 Demographic characteristics and Measurements:

A total of 779 respondents participated in the study. The majority were aged between 20 to 30 years (48.1%), followed by those aged 30 to 40 (31.2%), and above 40 (20.7%). Most respondents had low investment experience (62.4%), while 37.6% had high experience. In terms of marital status, 54.2% were married and 45.8% were unmarried. Regarding income, the largest group belonged to the lower middle class (37.7%), followed by upper class (22.6%), upper middle class (22.1%), and middle class (17.6%). Educationally, 42% held a postgraduate degree, 21.3% were graduates, 19.9% were professionals, and 16.7% had undergraduate qualifications, with only one respondent identified as a researcher (0.1%).(Demographic profile attached as Appendix 1).

3.2 Measurement of Variables:

The study employed a detailed set of measurement scales to assess multiple factors. A total of 38 items were used to capture responses across nine key constructs. These constructs were measured using established scales, which were adapted and modified from prior research (see Appendix Table 2). The study presents the measurement sources and item scales for the study variables. Performance expectancy and effort expectancy were adopted and modified from (Sung et al., 2015) and (Palau-Saumell et al., 2019), respectively, each measured using 4 items. Perceived risk was measured using a 3-item scale from (Kim et al., 2008), while perceived trust was assessed with 4 items from (Grabner-Kräuter & Kaluscha, 2003). Financial knowledge used a 4-item scale adapted from (van Rooij et al., 2011), and hedonic motivation was measured with 4 items from (Gefen E. and Straub D.W., 2003). Finally, investment intention was assessed using a 5-item scale from (Bhatt, 2021). All measurement items were adapted to fit the context of the current study. The assessment consisted of two sections: the first employed a seven-point Likert scale to measure various factors, and the second collected demographic information to profile the investors. Variables such as age, and income were measured using nominal scales with two to four categories, while education was classified into five distinct levels.

3.3 Pre and pilot testing:

A systematic questionnaire was created using a validated scale and a conceptual framework based on earlier research. This questions was designed to investor profiles and mutual fund investment habits. Three experienced financial professionals gave the standardised questionnaires to verify clarity, dependability, and relevance. Participants assessed item criteria validity to ensure comprehension and accurate responses. A panel of subject-matter experts modified the questionnaire's structure, phrasing, and sequence to ensure face and content validity. Industry experts conducted internal practice trials to familiarise themselves with the framework and implement expert panel comments before data collection. This pilot study included 70 mutual fund investors from Ahmedabad's cohesive community. The structured questionnaire was tested for internal consistency and category validity during pilot testing. SPSS 26 was used for preliminary data analysis. The Cronbach's alpha coefficient exceeded 0.70, validating the data's reliability and the nine pre-defined latent constructs' internal consistency, per Chou and Bentler (1995).

3.4 Target Population and Sampling Design:

This study aimed to help mutual fund investors understand their choices' consequences. The respondents to the survey included tech-savvy savers who invest online or offline. Respondents include mobile investment app users and non-users. All of the investors were experienced and skilled at handling market volatility and other unpredictability. Business-friendly policies and strong economies draw investors to Maharashtra and Gujarat, where the research was conducted. The sample size was difficult to determine, so non-probability judgemental sampling was utilised. This method works when sample parameters are known.

3.5 Data Collection Process:

The trial lasted four months, December-March 2024. Major investor-friendly cities provided data. The study found a 23-minute mean reaction time. The study's objective and goals were explained to participants, and their replies were protected.

A cohort of investors provided 779 full responses, matching SEM analysis standards (Myers et al., 2011). Researchers found that the sample size exceeded the benchmark value by ten times the structured questionnaire's assertions (Anderson et al., 1988). The G Power 3.1.2 software also determined sample size for a specific study.

The calculation utilised the subsequent parameters: an average effect size of 0.15, a target margin of variation of 0.05, and an impact size of r = 0.50. While 315 was deemed an adequate sample size for the study, the actual participant count exceeds the recommended threshold based on simulated samples. The sample of 779 individuals is adequate for SEM research, since it exceeds 10 times the number of synaptic weights in the current model. The second step of the SEM methodology entailed utilising seven principal external components and a mediating variable (779 > 50*8=400) to predict continuous investment intention behaviour.

4. Assessing CMB (Common Method Bias) and Non-Response Bias:

Cross-sectional studies examining human behaviour are inherently susceptible to common method bias (CMB) to some extent (Jordan & Troth, 2020). The collection of data on relevant endogenous and exogenous variables using established scale items may lead to the occurrence of common method bias (CMB). Our research employed both qualitative and quantitative testing methods to ensure that the dataset was devoid of any issues related to CMB (Leong et al., 2019). No "correct" answers were present in any of the questions, and participants were fully informed of this in advance. Furthermore, the confidentiality of their data was maintained.
Harman's single factor test recovered variance below the 50% statistical threshold. The study found that CMB is under-represented in the dataset (Podsakoff et al., 2003). The CMB was validated using more thorough approaches to overcome Harman's single-factor approach's shortcomings (Harman, 1976). CMB was initially assessed using block and collinearity test VIF results (Bhatt, 2020; Bhatt et al., 2021; Kock & Lynn, 2012). Each construct's VIF value was below 3.3 in both the independent block and whole collinearity test. VIF was calculated for each scale and variable (Patel et al., 2024). The dataset's scale items' VIF values are always below 5, indicating no multicollinearity (Thomas et al., 2024). The discussed procedural and statistical data show that Common Method Bias (CMB) is absent from the datasets.

4.1 Multivariate Assumption:

Before final structural modelling, empirical tests were undertaken to understand data assumptions. Multivariate analysis began with data normality assessment. Statistical methods include the Shapiro-Wilk test and QQ plots. The test results emphasise behavioural intention and sustained involvement. Figure 2 shows that the QQ plots for these two variables illustrate the non-normality of the current data distribution.
The test diverges from linearity and uses all latent components to assess data linearity. All significant values are less than 0.05, indicating a linear relationship between investors' intentions and Independent variables.

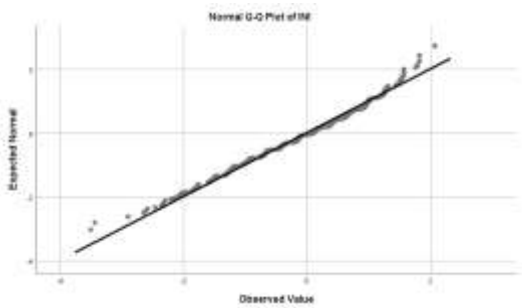

Figure :2

Numerous regressions have been performed. Standardise residuals and data to assess homoscedasticity and outliers. Figure 2 shows a dispersed point distribution without a linear trend. The study confirmed homoscedasticity. The statistical conclusions above demonstrate the data's non-normality and linearity. We also tested homogeneity variance with Levens' test [Appendix Table: 03]. Investment intention has a significant score of 0.747, which is greater than 0.05 and shows that the variance group has equal variance and did not break the homogeneity variance assumption. The statistical results above indicate that structural equation model testing should be used.

4.2 Assessing Measurement Of The Model:

Considering validity and reliability (Hair Jeffrey J.; Sarstedt Marko; Ringle Christian M., 2019) allows for the evaluation of the effectiveness of the reflective measurement paradigm. The AVE importance must exceed 0.5, while the minimum acceptable values for outer loading and CR should be greater than 0.7 (Hair C.M. and Sarstedt M., 2011). Table 1 presents the results of the calculations for average variance extracted (AVE), convergent reliability (CR), and outer loading. Table 1 presents the study's findings on outer loading and composite reliability, indicating that all values exceed the 0.70 threshold. The AVE values exceed 0.5 in magnitude.
According to (Henseler et al., 2015), the HTMT ratio serves as a measure for evaluating the attainment of discriminant validity. The acceptable limit for the HTMT ratio is below 1.00. Findings of the HTMT ratio are presented in Tables 2 and 3. All estimated ratios for each component pair were found to be below the 1.00 threshold, as indicated by the analysis. The study's conclusions demonstrated the concurrent and discriminant validity of the reflecting measurement scale.

RELIABILITY AND CONVERGENT VALIDITY (TABLE-1)

Construct	Factor Loading (Min-Max.)	Cronbach's Alpha(A)	Dijkstra-Henseler's Rho_A	Joreskog's Rho_C	The Average Variance Extracted (Ave)	VIF Range
INI	0.6963-0.5205	0.7761	0.7811	0.7748	0.4101	2.349-2.495
PEX	0.7295-0.6225	0.7464	0.7499	0.7441	0.4228	2.370-2.425
EEX	0.8549-0.5335	0.8413	0.8590	0.8386	0.5719	2.346-2.749
HEM	0.8514-0.6247	0.8584	0.8668	0.8568	0.6024	2.386-2.454
FIK	0.7068-0.5781	0.7514	0.7554	0.7512	0.4316	1.271-3.701
PRS	0.9900-0.8709	0.9431	0.9472	0.9432	0.8474	1.813-1.709
PTS	0.7191-0.5430	0.7434	0.7491	0.7422	0.4209	1.700-3.352

(N= 779, INI= Investor's intention, PEX= Performance expectancy, EEX= Effort expectancy, HEM= Hedonic motivation, FIK, Financial knowledge, PRS= Perceived risk, PTS= Perceived trust)

DISCRIMINANT VALIDITY: HTMT RATIO OF CORRELATIONS (TABLE-2)

Construct	INI	PEX	EEX	HEM	FIK	PRS	PTS
INI							
PEX	0.6543						
EEX	0.3776	0.2431					
HEM	0.4568	0.3740	0.0952				
FIK	0.4811	0.2999	0.0779	0.4446			
PRS	0.2789	0.1201	0.0295	0.1400	0.1775		
PTS	0.6008	0.3681	0.3178	0.2573	0.2501	0.0418	

(N= 779, INI= Investor's intention, PEX= Performance expectancy, EEX= Effort expectancy, HEM= Hedonic motivation, FIK, Financial knowledge, PRS= Perceived risk, PTS= Perceived trust)

FORNELL-LARCKER CRITERION VALIDITY (TABLE-3)

Construct	INI	PEX	EEX	HEM	FIK	PRS	PTS
INI	0.4101						
PEX	0.4312	0.4228					
EEX	0.1470	0.0596	0.5719				
HEM	0.2137	0.1408	0.0101	0.6024			
FIK	0.2380	0.0896	0.0073	0.1959	0.4316		
PRS	0.0768	0.0149	0.0014	0.0194	0.0298	0.8474	
PTS	0.3701	0.1351	0.1029	0.0700	0.0640	0.0019	0.4209

(N= 779, INI= Investor's intention, PEX= Performance expectancy, EEX= Effort expectancy, HEM= Hedonic motivation, FIK, Financial knowledge, PRS= Perceived risk, PTS= Perceived trust)

5. Statistical result:

5.1 Structural model:

The collected data is analysed using the PLS-SEM technique facilitated by Smart PLS 4.0 software. This research examined all assumptions in the structural model using the PLS-SEM approach, as described by (Hair M. and Pieper T.M. and Ringle C.M., 2012). To evaluate the hypothesis without modifying the sign, 5000 bootstrap samples were conducted (Henseler G. and Ray P.A., 2016). (Hair C.M. and Sarstedt M., 2011) identify this as one of the most sophisticated and robust methods for addressing linear and non-normal distributions. Path analysis indicates that six factors significantly influence an investor's intention to invest. The bootstrapping results indicate that all hypothesized direct effects on innovation initiatives (INI) are statistically supported. Perceived external pressure (PEX → INI, $\beta = 0.3769$, $p < 0.001$), environmental expectations (EEX → INI, $\beta = 0.1498$, $p < 0.001$), hedonic motivation (HEM → INI, $\beta = 0.1047$, $p = 0.0115$), familiarity with innovation knowledge (FIK → INI, $\beta = 0.2032$, $p < 0.001$), and perceived technological support (PTS → INI, $\beta = 0.3356$, $p < 0.001$) all show significant positive effects. In contrast, perceived risk (PRS → INI, $\beta = -0.1612$, p < 0.001) has a significant negative effect. Since none of the confidence intervals cross zero and all p-values are below the 0.05 threshold, each hypothesis is supported.

Bootstrapping Direct Effects (Table 4):

BOOTSTRAPPING DIRECT EFFECTS							
EFFECTS		**STANDARD BOOTSTRAP RESULTS**					
	ORIGINAL COEFFICIENT	MEAN VALUE	2.5%	T VALUE	P VALUES	97.5%	FINAL RESULT
PEX > NI	0.3769	0.3770	0.2810	7.6829	0.0000	0.4709	Supported
EEX > NI	0.1498	0.1489	0.0842	4.4169	0.0000	0.2155	Supported
HEM >INI	0.1047	0.1040	0.0236	2.5291	0.0115	0.1873	Supported
FIK > INI	0.2032	0.2051	0.1008	3.8844	0.0001	0.3075	Supported
PRS > INI	-0.1612	-0.1604	-.2199	-5.3707	0.0000	-.1016	Supported
PTS > INI	0.3356	0.3364	0.2444	7.2227	0.0000	0.4290	Supported

R^2 and Adjusted R^2 values (Table 5):

Construct	Coefficient of determination (R^2)	Adjusted R^2
INI	0.7013	0.6990

The structural model explains a substantial portion of the variance in innovation initiatives (INI), with an R^2 value of 0.7013 and an adjusted R^2 of 0.6990. This indicates that approximately 70% of the variability in INI is accounted for by the six predictor variables. All hypothesized paths to INI are statistically supported. Perceived external pressure (PEX), environmental expectations (EEX), hedonic motivation (HEM), familiarity with innovation knowledge (FIK), and perceived technological support (PTS) each have significant positive effects on INI. Among them, PEX and PTS show the strongest influence. In contrast, perceived risk (PRS) has a significant negative effect, indicating that higher perceived risk discourages innovation initiatives. All paths meet the threshold for significance ($p < 0.05$), and none of the confidence intervals cross zero. These results confirm the robustness of the model in explaining the key factors driving innovation initiatives.

Discussion

The findings of this study reveal that among the considered variables, investment knowledge and risk perception significantly influence investor behavior in online mutual fund investments. This supports the view that informed investors are more confident and proactive in making online investment decisions. Risk perception, acting as a psychological determinant, also demonstrates a strong role in shaping investment behavior, indicating that even in digital platforms, investors are influenced by their subjective assessment of financial risk.

Interestingly, demographic variables such as age, gender, and income show moderate effects, suggesting that while individual characteristics shape preferences, behavioral and cognitive factors play a more decisive role in the digital context. This aligns with contemporary research emphasizing the psychological underpinnings of financial decision-making over purely economic rationality. The adoption of Structural Equation Modeling (SEM) allowed for a comprehensive examination of both direct and indirect effects, reinforcing the robustness of the proposed framework.

Theoretical Contribution

This research contributes to the growing body of behavioral finance literature by extending traditional investment behavior models to the context of online mutual fund platforms. By integrating investment knowledge and risk perception into a Structural Equation Modeling (SEM) framework, the study presents a holistic understanding of how psychological and demographic factors jointly influence investor decisions in the digital age.

Unlike earlier models focused primarily on offline or general investment behavior, this study provides empirical evidence specific to the online investment environment, addressing a gap in existing literature. Moreover, the model establishes investment knowledge as a critical enabler in navigating digital platforms, and risk perception as a key psychological barrier, contributing to a nuanced understanding of investor psychology in fintech-driven contexts. The validated framework may serve as a basis for future studies exploring investor behavior in other digital financial instruments.

Limitations and Future Scope

While this study offers valuable insights into the factors influencing investor behavior in online mutual fund investments, it has certain limitations. First, the research is geographically constrained, with data collected from a specific region, which may limit the generalizability of the findings across diverse investor populations. Second, the study relies on self-reported data through structured questionnaires, which may be subject to response bias or social desirability bias. Third, only a select number of variables—namely demographic factors, investment knowledge, and risk perception—were considered, potentially overlooking other influential psychological or technological variables such as trust in digital platforms, user experience, or perceived ease of use.

Future research can extend this framework by incorporating a larger and more geographically diverse sample to enhance generalizability. Additionally, integrating technology-related constructs such as perceived usefulness, digital literacy, and platform trust can provide a more comprehensive understanding of online investor behavior. Longitudinal studies could also be conducted to observe behavioral patterns over time and assess the impact of market dynamics. Moreover, cross-country comparative studies may help uncover cultural and regulatory influences on digital investment behavior. Finally, the proposed SEM model could be tested across different fintech products beyond mutual funds, such as ETFs, robo-advisory services, and cryptocurrency platforms.

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