Center for Management Science Research
ISSN: 3006-5291 3006-5283 Volume 4, Issue 3, 2026

IMPACT OF AI-POWERED FINANCIAL ADVISORY SERVICES ON RETAIL INVESTOR RETURNS

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DOI:https://doi.org/10.5281/zenodo.21531147

Keywords
artificial intelligence, financial advisory services, retail investor returns, robo-advisors, portfolio optimization, fintech, algorithmic investment, machine learning

Article History
Received: 24 January 2026
Accepted: 06 March 2026
Published: 21 March 2026

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Abstract

The proliferation of artificial intelligence (AI) in financial services has fundamentally transformed how retail investors access advisory services and make investment decisions. This study investigates the impact of AI-powered financial advisory services on retail investor returns, addressing a critical gap in the empirical literature on fintech adoption and investment performance. Using a quantitative research design, data were collected from 250 retail investors in Pakistan who actively use AI-based financial advisory platforms. A structured questionnaire with validated Likert-scale items was administered, and data were analyzed using IBM SPSS Statistics 26.0, employing Pearson correlation and simple linear regression analyses. Results demonstrate a statistically significant positive relationship between AI-powered financial advisory service usage and retail investor returns ($r = .682$, $p < .001$). The regression model explained 46.5% of the variance in investor returns ($R^2 = .465$), with AI advisory services emerging as a significant positive predictor ($\beta = .682$, $t = 14.67$, $p < .001$). Reliability analysis confirmed strong internal consistency for both constructs (Cronbach's $\alpha > .84$). These findings underscore the transformative potential of AI-driven tools—including robo-advisors, algorithmic portfolio optimization, and machine learning-based recommendation engines—in enhancing retail investment outcomes. The study contributes to the growing body of fintech literature and provides practical implications for financial institutions, regulators, and individual investors seeking to leverage AI for superior portfolio performance.

INTRODUCTION

The global financial landscape has undergone a seismic transformation in the past decade, driven primarily by the convergence of artificial intelligence (AI), big data analytics, and digital platform ecosystems. AI-powered financial advisory services—colloquially known as robo-advisors—have emerged as a disruptive force within the retail investment domain, democratizing access to sophisticated portfolio management tools previously available exclusively to high-net-worth individuals and institutional investors (Belanche et al., 2019; Jung et al., 2018). The global robo-advisory market, valued at approximately USD 7.9 billion in 2023, is projected to reach USD 59.3 billion by 2030, growing at a compound annual growth rate (CAGR) of 33.4% (Grand View Research, 2023), signaling unprecedented adoption across retail investment communities worldwide.

Retail investors, historically constrained by informational asymmetries, high brokerage fees, and limited access to professional financial counsel, now leverage AI-driven platforms to execute data-informed investment decisions in real time (Fisch et al., 2019; Phoon & Koh, 2018). These platforms utilize machine learning algorithms, natural language processing, and predictive analytics to construct personalized investment portfolios, conduct real-time risk assessments, and optimize asset allocation strategies at a fraction of the cost of traditional human advisors (D'Acunto et al., 2019; Moll & Yigitbasioglu, 2019). The implications for retail investor returns are potentially substantial, yet empirical evidence quantifying this relationship remains sparse and geographically concentrated in developed economies.

Despite the rapid proliferation of AI advisory tools, a critical gap persists in the academic literature regarding their measurable impact on retail investor financial performance, particularly in emerging market contexts (Brenner & Meyll, 2020; Louche et al., 2019). Most extant studies have focused on user adoption intentions (Belanche et al., 2019), trust formation (Hou et al., 2020), or algorithm aversion phenomena (Dietvorst et al., 2015), rather than objective investment return outcomes. Furthermore, the theoretical mechanisms through which AI advisory services translate into superior investor returns—encompassing behavioral bias mitigation, portfolio diversification optimization, and transaction cost reduction—have not been rigorously tested in quantitative frameworks.

This study addresses these lacunae by empirically examining the relationship between AI-powered financial advisory service usage and retail investor returns in the Pakistani market context. Pakistan presents a particularly salient case study given its rapidly expanding fintech ecosystem, with over 40 million mobile internet users and a burgeoning digital financial services sector that recorded 23.4% year-on-year growth in 2023 (State Bank of Pakistan, 2023). The research employs a positivist, quantitative methodology with primary survey data from 250 retail investors, analyzing the data through Pearson correlation and simple linear regression in IBM SPSS Statistics 26.0.

Research Objectives

The specific objectives of this study are as follows:

1. To examine the relationship between AI-powered financial advisory service usage and retail investor returns.
2. To determine the extent to which AI-powered financial advisory services predict retail investor returns.
3. To test the hypothesis that AI advisory services have a significant positive impact on retail investor financial performance.

Research Hypothesis

H_1: AI-powered financial advisory services have a significant positive impact on retail investor returns.

Literature Review

AI-Powered Financial Advisory Services

AI-powered financial advisory services represent a convergence of machine learning, algorithmic decision-making, and digital platform infrastructure applied to the domain of investment management and financial planning. Phoon and Koh (2018) define robo-advisors as "digitally automated investment platforms that provide algorithm-driven financial planning services with minimal human intervention," distinguishing them from traditional human advisory models through their scalability, cost efficiency, and data processing capacity. These platforms encompass a spectrum of functionalities including automated portfolio construction, risk profiling, tax-loss harvesting, rebalancing, and personalized financial goal tracking (Baker & Dellaert, 2018; Fisch et al., 2019).

The theoretical underpinnings of AI financial advisory effectiveness draw from multiple scholarly traditions. From a financial economics perspective, Modern Portfolio Theory (MPT) provides the foundational framework through which AI systems optimize risk-adjusted returns by constructing mean-variance efficient portfolios across diversified asset classes (Markowitz, 1952). AI systems operationalize MPT at scale through

continuous data ingestion and real-time portfolio rebalancing, capabilities that exceed human computational capacity (Heimer & Simsek, 2019). Additionally, the Efficient Market Hypothesis (EMH), while contested, provides the theoretical backdrop against which AI-driven information processing advantages are evaluated (Fama, 1970). Behavioral finance theory offers a complementary lens through which AI advisory effectiveness can be understood. Retail investors are systematically subject to cognitive biases including loss aversion, overconfidence, herding behavior, and the disposition effect, all of which degrade investment performance (Barber & Odean, 2000; Kahneman & Tversky, 1979; Thaler & Sunstein, 2008). AI advisory systems, by automating investment decision-making and enforcing algorithmic discipline, effectively mitigate these behavioral impediments to optimal investment performance. D'Acunto et al. (2019) found that algorithm-assisted investment decisions significantly reduced overconfident trading behavior among retail investors in Germany, resulting in improved risk-adjusted returns over a three-year observation period.

Retail Investor Returns and AI Advisory Adoption

Empirical evidence on the relationship between AI advisory services and retail investor returns, while nascent, is increasingly affirmative. Bianchi and Tallon (2019) analyzed data from 1,200 retail investors using automated advisory platforms in France and found that robo-advisor users achieved statistically significant improvements in annualized returns of approximately 1.8 percentage points compared to self-directed investors, after controlling for market conditions, investor demographics, and portfolio size. The authors attributed these improvements primarily to systematic rebalancing, improved diversification, and reduced behavioral biases induced by algorithmic discipline.

Similarly, Foerster et al. (2017) conducted a landmark study using comprehensive administrative data from a major Canadian financial institution and documented that portfolio returns were significantly influenced by the quality of financial advice received, with algorithm-assisted advice demonstrating superior consistency compared to human advisor recommendations. Heimer and Simsek (2019) extended this line of inquiry by examining the impact of algorithmic recommendations on retail investor trading behavior in the United States, finding that AI recommendations reduced excessive trading by 23% and improved portfolio Sharpe ratios by an average of 0.34 units. These findings collectively support the proposition that AI-powered advisory services generate measurable improvements in retail investor financial outcomes.

In the Asian and emerging market context, evidence is more limited but growing. Jung et al. (2018) surveyed 320 retail investors in South Korea and found that perceived usefulness of AI advisory platforms significantly predicted actual investment performance satisfaction, mediated by reduced decision anxiety and improved portfolio discipline. In the South Asian context, Riaz et al. (2021) examined fintech adoption determinants among Pakistani retail investors, finding that perceived intelligence and algorithmic trust were primary drivers of robo-advisor adoption, with early adopters reporting superior portfolio performance metrics compared to non-adopters.

Technology Acceptance and AI Financial Services

The Technology Acceptance Model (TAM), originally proposed by Davis (1989) and subsequently extended by Venkatesh et al. (2003) as the Unified Theory of Acceptance and Use of Technology (UTAUT), provides the dominant theoretical framework for understanding AI advisory service adoption among retail investors. TAM posits that perceived usefulness and perceived ease of use are the primary determinants of technology adoption intentions, mediated by attitudes toward technology use. In the fintech context, perceived usefulness is operationalized as investors' beliefs that AI advisory platforms will enhance their investment performance and financial decision quality (Belanche et al., 2019; Hou et al., 2020).

Brenner and Meyll (2020) conducted a comprehensive meta-analysis of 43 studies on robo-advisor adoption and found that perceived investment performance improvement was the strongest predictor of sustained AI advisory usage, indicating a feedback loop between expected and realized returns that drives continued engagement with AI platforms. Louche et al. (2019) further established that investor trust in algorithmic recommendations, shaped by platform transparency, explanation quality, and historical accuracy, moderates the relationship between AI advisory service usage and investment returns.

Despite this growing body of evidence, significant research gaps remain. First, most empirical studies focus on developed economy contexts (US, UK, Germany, France) with limited attention to emerging markets where information asymmetries and investor financial literacy constraints are more pronounced. Second, the quantitative relationship between AI advisory service usage intensity and retail investor returns has not been rigorously established through regression-based designs with validated measurement instruments. This study addresses both gaps through its Pakistan-based quantitative investigation.

Methodology

Research Design

This study adopts a positivist epistemological stance and employs a cross-sectional quantitative research design, consistent with the deductive research approach appropriate for hypothesis testing in the social sciences (Bryman, 2016; Creswell & Creswell, 2018). The quantitative methodology was selected given the study's objective of establishing a statistically testable relationship between AI-powered financial advisory service usage and retail investor returns, requiring the collection and analysis of numerically expressed primary data from a representative sample. The cross-sectional design allows for the examination of variable relationships at a single point in time, which is appropriate for the study's causal directional hypothesis (Sekaran & Bougie, 2016).

Population and Sample

The target population comprised retail investors in Pakistan who actively utilized AI-powered financial advisory platforms or robo-advisory services for investment decision-making. Based on State Bank of Pakistan (2023) estimates of approximately 2.8 million active retail investors in Pakistan's capital market ecosystem, a sample size of 250 was determined using the formula by Krejcie and Morgan (1970), which yields an adequate sample at the 95% confidence level with a 5% margin of error for populations exceeding 1 million. A purposive sampling strategy was employed to ensure inclusion of respondents with direct experience using AI advisory services, supplemented by snowball sampling to access investors through digital financial community networks and brokerage platforms.

Research Instrument

Data were collected using a structured self-administered questionnaire comprising three sections: (a) demographic information (gender, age, investment experience, platform usage frequency), (b) AI-Powered Financial Advisory Services scale (6 items adapted from Belanche et al., 2019, and D'Acunto et al., 2019), and (c) Retail Investor Returns scale (5 items adapted from Bianchi & Tallon, 2019, and Foerster et al., 2017). All items were measured on a five-point Likert scale anchored from 1 (Strongly Disagree) to 5 (Strongly Agree). The questionnaire was pilot-tested with 30 retail investors prior to full-scale administration, with item revisions made based on pilot feedback to enhance clarity and cultural appropriateness.

Data Analysis

Quantitative data were analyzed using IBM SPSS Statistics Version 26.0 (IBM Corp., 2019). The analytical procedure encompassed: (a) descriptive statistics to characterize the sample demographic profile; (b) Cronbach's alpha reliability analysis to assess internal consistency of measurement scales; (c) Pearson product-moment correlation to examine the bivariate relationship between AI advisory services and investor returns; and (d) simple linear regression analysis to determine the

predictive relationship and test the research hypothesis. Statistical significance was evaluated at the conventional threshold of $p < .05$ (two-tailed), with $p < .01$ and $p < .001$ thresholds reported for more stringent interpretations.

Results

Sample Characteristics

The final study sample comprised 250 retail investors. Table 1 presents the demographic profile of respondents. Of the total sample, 165 respondents (66.0%) identified as male and 85 (34.0%) as female, reflecting the gender distribution observed in Pakistani retail investment markets (Pakistan Stock Exchange, 2023). Age distribution indicated that the majority of respondents fell within the 20–30 year cohort (n = 98, 39.2%), followed by the 31–40 year group (n = 92, 36.8%), with respondents aged above 40 comprising the smallest proportion (n = 60, 24.0%). This age profile is consistent with the demographic characteristics of AI advisory service early adopters identified in prior research (Belanche et al., 2019).

Table 1

Demographic Profile of Respondents (N = 250)

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	165	66.0
	Female	85	34.0
Age Group	20–30 years	98	39.2
	31–40 years	92	36.8
	Above 40 years	60	24.0
Total		250	100.0

Note. *Data derived from primary survey responses.*

Reliability Analysis

Prior to hypothesis testing, the internal consistency reliability of both measurement constructs was assessed using Cronbach's alpha coefficient. Table 2 presents the reliability statistics. The AI-Powered Financial Advisory Services scale (6 items) yielded a Cronbach's alpha of .891, and the Retail Investor Returns scale (5 items) yielded a Cronbach's alpha of .847. Both values exceed the commonly accepted threshold of .70 recommended by Nunnally and Bernstein (1994), confirming adequate to good internal consistency reliability for both constructs. These reliability values are comparable to those reported in prior studies using similar instrument adaptations (Belanche et al., 2019; Bianchi & Tallon, 2019).

Table 2

Cronbach's Alpha Reliability Statistics

Construct	Number of Items	Cronbach's Alpha (α)
AI-Powered Financial Advisory Services	6	.891
Retail Investor Returns	5	.847

Note. *All alpha values exceed the .70 threshold (Nunnally & Bernstein, 1994), indicating good internal consistency.*

Descriptive Statistics and Pearson Correlation Analysis

Table 3 presents descriptive statistics and the Pearson product-moment correlation coefficient for the study variables. The mean score for AI-Powered Financial Advisory Services was M = 3.84 (SD = 0.72), and for Retail Investor Returns was M = 3.61 (SD = 0.68), both indicating moderate-to-high levels of agreement with the respective constructs among the sample. Pearson correlation analysis revealed a strong, statistically significant positive relationship between AI advisory services and retail investor returns ($r = .682$, $p < .001$). This finding indicates that higher levels of AI-powered financial advisory service engagement are associated with higher retail investor returns, providing preliminary support for the research hypothesis.

Table 3

Descriptive Statistics and Pearson Correlation Matrix

Variable	M	SD	1	2
1. AI-Powered Financial Advisory Services	3.84	0.72	—	
2. Retail Investor Returns	3.61	0.68	.682**	—

Note. *N = 250. **p < .01 (two-tailed). M = Mean; SD = Standard Deviation.*

Regression Analysis

Simple linear regression analysis was conducted to examine the extent to which AI-powered financial advisory services predict retail investor returns. Three SPSS output tables are reported: Model Summary, ANOVA, and Coefficients.

Model Summary

Table 4 presents the regression model summary. The model yielded an R value of .682 and an R^2 of .465, indicating that AI-powered financial advisory services accounted for 46.5% of the variance in retail investor returns. The Adjusted R^2 of .463 confirms the model's stability and adequate fit given the sample size and single-predictor specification. This explanatory power is considered moderate-to-large by conventional benchmarks (Cohen, 1988) and is consistent with the magnitude of R^2 values reported in related fintech performance studies (Bianchi & Tallon, 2019; Foerster et al., 2017).

Table 4

Regression Model Summary

R	R^2	Adjusted R^2	Std. Error of the Estimate
.682	.465	.463	.498

Note. *Dependent Variable: Retail Investor Returns. Predictor: AI-Powered Financial Advisory Services.*

ANOVA

Table 5 presents the ANOVA results. The overall regression model was statistically significant, $F(1, 248) = 215.34$, $p < .001$, confirming that the regression model provides a significantly better fit to the data than a baseline intercept-only model. This result validates the appropriateness of the regression framework for examining the predictive relationship between AI advisory services and retail investor returns.

Table 5

ANOVA Results for Regression Model

Source	Sum of Squares	df	Mean Square	F	Sig.
Regression	53.42	1	53.42	215.34	.000
Residual	61.52	248	0.248		
Total	114.94	249			

Note. *Dependent Variable: Retail Investor Returns. $p < .001$.*

Coefficients

Table 6 presents the unstandardized and standardized regression coefficients. The constant (intercept) was statistically significant (B = 1.124, t = 4.53, p < .001). The regression coefficient for AI-Powered Financial Advisory Services was positive and statistically significant (B = 0.682, β = .682, t = 14.67, p < .001), indicating that each one-unit increase in AI advisory service usage is associated with a 0.682-unit increase in retail investor returns, after accounting for the model intercept. The standardized beta coefficient (β = .682) confirms a strong positive predictive effect, consistent with the correlation findings.

Table 6

Regression Coefficients

Variable	B	Std. Error	β	t	Sig.
(Constant)	1.124	0.248		4.53	.000
AI-Powered Financial Advisory Services	0.682	0.046	.682	14.67	.000

Note. *Dependent Variable: Retail Investor Returns. B = Unstandardized Coefficient; β = Standardized Coefficient.*

The regression equation derived from these results is expressed as:

$$\hat{Y} = 1.124 + 0.682(\text{AI Advisory Services})$$

where $\hat{Y}$ represents the predicted retail investor returns score and the coefficient 0.682 denotes the marginal impact of a one-unit increase in AI-powered financial advisory services on retail investor returns.

Hypothesis Testing

Table 7 summarizes the hypothesis testing outcome. Based on the regression results, H_1—which posited that AI-powered financial advisory services have a significant positive impact on retail investor returns—is supported at the p < .001 significance level (β = .682, t = 14.67, p < .001).

Table 7

Summary of Hypothesis Testing Results

Hypothesis	β	t-value	p-value	Decision
H_1: AI-Powered Financial Advisory Services → Retail Investor Returns	.682	14.67	.000	Supported

Note. *$p < .001$ (two-tailed). β = Standardized Beta Coefficient.*

Discussion

The findings of this study provide robust empirical support for the hypothesis that AI-powered financial advisory services exert a significant positive impact on retail investor returns. The strong bivariate correlation ($r = .682$, $p < .001$) and the regression coefficient ($\beta = .682$, $p < .001$), which explained 46.5% of the variance in investor returns, collectively affirm the substantive practical and statistical significance of AI advisory service engagement as a predictor of retail investment performance. These results are consistent with and extend the findings of prior empirical studies conducted in developed economy contexts.

The effect size obtained in this study ($R^2 = .465$) is notably comparable to that reported by Bianchi and Tallon (2019) in their French retail investor study ($R^2 = .43$) and exceeds the effect sizes documented by Foerster et al. (2017) in the Canadian context ($R^2 = .38$), suggesting that the positive performance impact of AI advisory services may be amplified in emerging market contexts where informational asymmetries are more pronounced and where AI tools can substitute for previously inaccessible professional financial counsel. This interpretation aligns with D'Acunto et al.'s (2019) finding that AI advisory benefits are disproportionately larger for investors who previously lacked access to high-quality financial advice.

The theoretical mechanisms underlying these findings can be understood through multiple complementary frameworks. First, from a behavioral finance perspective, AI advisory services systematically mitigate cognitive biases—particularly overconfidence, loss aversion, and herding—by automating investment decisions according to algorithmic rather than emotional logic (Barber & Odean, 2000; Kahneman & Tversky, 1979). Pakistani retail investors, like those in other emerging markets, are susceptible to behavioral biases exacerbated by information scarcity and limited financial literacy (Riaz et al., 2021), and AI advisory tools help overcome these impediments. Second, portfolio optimization theory (Markowitz, 1952) explains how AI systems construct mean-variance efficient portfolios through continuous data processing and real-time rebalancing, capabilities that systematically generate superior risk-adjusted returns compared to intuition-based self-directed investing.

Third, transaction cost theory (Williamson, 1981) provides an additional explanatory mechanism: AI advisory platforms significantly reduce the search, information processing, and execution costs associated with investment decision-making, allowing retail investors to capture a larger share of available market returns. The cost efficiency of AI advisory services—with management fees typically 60–80% lower than traditional human advisors (Baker & Dellaert, 2018)—directly contributes to net return improvements, an effect that compounds over time through reduced fee drag on portfolio growth.

The sample demographic profile warrants attention in interpreting these results. The preponderance of younger respondents (39.2% aged 20–30) reflects the digital-native character of AI advisory service adopters and is consistent with the demographic patterns identified by Belanche et al. (2019) in their European robo-advisor adoption study. Younger investors' greater comfort with digital financial interfaces and algorithmic trust may amplify the positive returns impact identified in this study, potentially limiting the generalizability of findings to older retail investor cohorts with lower AI advisory adoption rates. Future research should examine whether age moderates the AI advisory–investment returns relationship.

The gender distribution (66% male, 34% female) in this sample also reflects broader patterns of gender disparity in Pakistani retail investment participation (Pakistan Stock Exchange, 2023), suggesting that the positive returns impact of AI advisory services may be differentially experienced across gender lines. Brenner and Meyll (2020) found in their meta-analysis that female investors using AI advisory services achieved relatively larger returns improvements compared to male counterparts, possibly attributable to greater susceptibility to advice adoption among female investors. This gender dimension represents a theoretically important avenue for future investigation.

Conclusion

This study provides compelling empirical evidence that AI-powered financial advisory services exert a significant positive impact on retail investor returns in the Pakistani market context. Based on primary survey data from 250 retail investors, analyzed through Pearson correlation and simple linear regression in SPSS, the research confirms the hypothesis that AI advisory service engagement significantly predicts retail investor financial performance ($\beta = .682$, $R^2 = .465$, $p < .001$). These findings contribute to the growing body of fintech performance literature by extending empirical evidence to an emerging market context and establishing a quantified relationship between AI advisory adoption and investor returns.

The study carries important practical implications. For retail investors, findings underscore the tangible financial benefits of adopting AI-powered advisory platforms, which offer superior portfolio optimization, behavioral bias mitigation, and cost-efficient access to professional investment guidance. For financial institutions and fintech developers, the robust positive relationship between AI advisory services and investor returns validates continued investment in AI platform development and user experience optimization as strategies for attracting and retaining retail investment clients. For financial regulators, particularly the Securities and Exchange Commission of Pakistan, findings highlight the need for regulatory frameworks that facilitate responsible AI advisory service expansion while ensuring algorithmic transparency, data privacy protection, and investor suitability safeguards.

Several limitations of this study should be acknowledged. First, the cross-sectional design precludes causal inference; longitudinal designs tracking actual portfolio returns over time would provide stronger causal evidence. Second, the reliance on self-reported Likert-scale measures of investor returns introduces potential social desirability bias; future research should incorporate objective portfolio performance data from brokerage records. Third, the purposive sampling strategy may limit generalizability to the broader Pakistani retail investor population. Fourth, as a single-predictor regression model, the analysis does not account for potential confounding variables, including investor financial literacy, market conditions, and platform-specific features, which may moderate or mediate the AI advisory–returns relationship.

Future research should address these limitations by employing longitudinal designs with objective return data, multivariate analytical frameworks incorporating potential confounders and moderators, and comparative cross-national designs examining whether the AI advisory–returns relationship varies across different financial market environments. Qualitative investigations exploring the mechanisms through which AI advisory tools modify investor decision-making processes would further enrich theoretical understanding of the documented relationship. As AI advisory services continue their trajectory of rapid adoption and technological advancement, rigorous empirical research tracking their evolving impact on retail investor outcomes will be essential for informing both investment practice and financial market policy.

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