



AI Adoption and Trading Performance Analysis: Study on Retail Futures and Options Traders of Karnataka

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Abstract

Retail participation in India's Futures and Options (F&O) market has grown rapidly, and AI-based trading tools are now widely available to individual traders, yet regulatory data indicate that most individual derivative traders incur net losses. Existing studies have largely examined why investors adopt AI tools and not whether adoption improves trading outcomes. This study examines the correlation between AI adoption and trading performance among retail F&O traders in six cities of Karnataka, with Trading Decision Quality as the mediating mechanism and Financial Literacy as the moderating condition. Data was gathered using a five-point Likert-scale questionnaire from 401 retail Foreign Exchange (F&O) traders and evaluate using Exploratory Factor Analysis (SPSS) and Partial Least Squares Structural Equation Modelling (SmartPLS, 5,000 bootstrap resamples). AI Adoption was identified as a construct consisting of three factors, namely, Perceived Usefulness and Continued Reliance, Perceived Ease of Use, and Trust in AI Reliability. It can be seen that AI Adoption has a positive impact on both Trading Decision Quality and Trading Performance. Trading Decision Quality acts as a partial mediator in the correlation between AI Adoption and Trading Performance, which means that the use of AI tools leads to favourable results by virtue of facilitating higher quality decisions while trading. Financial Literacy plays a positive moderating role in the influence of

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AI Adoption on Trading Performance, implying that traders with higher levels of financial literacy reap more advantages from AI tools.

Keywords: Artificial Intelligence Adoption, Trading Decision Quality, Financial Literacy, Trading Performance, Retail F&O Traders

Introduction

Artificial Intelligence (AI) is now part of the trading world, for investors. AI shows up in signals, predictive analytics, sentiment tools and AI-driven advice that many online trading sites give. In India more people are joining the Futures and Options market. Official data keep showing that most private derivative traders lose money. As technology grows and overall profit stays weak a real question comes up: do AI tools make retail traders better. Do they just look smart?

Technology adoption in finance has been explained mainly through “the Technology Acceptance Model (TAM) and its extensions (TAM2, TAM3, UTAUT)”(Leykun, 2026) , in which “perceived usefulness and perceived ease of use drive the intention to adopt”(Kafley et al., 2026) (Venkatesh, 2022). These models explain adoption but not performance. A trader can adopt an AI tool and still not improve results if the tool does not improve the decisions made. Behavioural finance treats trading outcomes as the product of information integration, timing, risk assessment and discipline, which motivates Trading Decision Quality (TDQ) as the mechanism linking adoption to performance. The financial literacy literature adds a boundary



condition: the ability to interpret, contextualise and act on information depends on the literacy of the individual, so the same AI tool may benefit traders unequally.

Prior work has mostly examined adoption intention (Sabir et al., 2023) , the technical accuracy of AI models (Cohen, 2022) , or behavioural biases and financial literacy without an AI variable (Divakara Reddy et al., 2025) . No study located in the reviewed literature tests AI Adoption, Trading Decision Quality and Financial Literacy together in the high-risk F&O segment. Karnataka is a suitable setting because Bengaluru combines a financial and technology hub with a large community of retail traders, while Mysuru, Mangaluru, Hubballi-Dharwad, Belagavi and Shivamogga represent Tier-2 centres with varying exposure to AI tools.

This study therefore develops and tests a mediated and moderated model in which AI Adoption affects Trading Performance directly and indirectly through TDQ, and Financial Literacy conditions the strength of the AI–performance relationship. The paper contributes by extending adoption research from intention to performance, by showing when the benefit of AI adoption is stronger, and by offering practical guidance to traders, fintech platforms and financial-literacy educators.

Literature Review

Ten recent studies from national (Indian) and international contexts were reviewed to understand what is known about AI adoption, AI in trading and investor behaviour.

Drivers and barriers of AI adoption. A multidisciplinary review by 34 experts concluded that AI capability is moving faster than trusted adoption in decision settings, and that trust, explainability, data quality and governance matter as much as technical capability (Dwivedi et al., 2021) . Extending UTAUT to AI, (Venkatesh, 2022) argued that opacity, autonomy and accountability introduce adoption barriers that classical models do not capture, so new trust and transparency constructs are needed. In a survey on AI robo-advisors, trust and perceived usefulness drove adoption while perceived risk reduced it, but the study measured intention and not outcomes (Sabir et al., 2023) . Extending TAM with personality traits and an AI mindset among 1,007 respondents in Germany, (Ibrahim et al., 2024) found that perceived usefulness and a growth AI mindset predicted attitude toward AI and identified four adopter clusters, although the sample was neither Indian nor drawn from finance.

AI in trading: technical effectiveness versus investor outcomes. Technical studies report that AI improves forecasting precision (by 37%) and lowers transaction costs (by 28%) in futures markets, while cautioning about overfitting and the need for regulation. Deep-learning and reinforcement-learning models outperform traditional forecasting but are sensitive to market conditions and data quality (Cohen, 2022) . These studies contain no human decision-makers, so technical gains cannot be assumed to translate into benefits for retail traders. A bibliometric review of 348 articles (2011–2021) found that AI-in-finance research concentrates on prediction accuracy and that decision quality at the investor level remains under-researched (Sabir et al., 2023) .

Indian evidence on trust, attitude and financial literacy. Among 569 Indian retail investors, AI usage was found to build algorithmic trust, and trust predicted sustainable investment behaviour, with human–AI interaction competency moderating the trust–behaviour link (Vijayananth & Saravanabhavan, 2026) . In a South Indian sample of 303 retail investors, perceived usefulness and ease of use influenced adoption intention with technology attitude as a mediator, but financial literacy and actual performance were not included (Sabir et al., 2023). A survey of 151 BSE/NSE investors found that financial literacy (Prajwal et al., 2024) and experience only marginally moderate the effect of behavioural biases, with no AI variable in the model (Divakara Reddy et al., 2025) .

Research gap. Two connected gaps emerge. First, the adoption literature stops at intention or at technical accuracy, and no study tests whether adoption improves trading decisions and, through them, performance. Second, Indian studies of AI adoption ignore financial literacy (Sunkara, 2022) , while studies of financial literacy ignore AI adoption, so it is unknown whether literacy strengthens or weakens the advantage of AI



users. No study has tested a mediated and moderated model of this kind with primary data from retail F&O traders in Karnataka.

Objectives

- To identify the key factors of Artificial Intelligence adoption influencing trading performance among retail Futures and Options traders.
- To examine the relationship between Artificial Intelligence adoption, trading decision quality and trading performance.
- To develop and validate a model of Artificial Intelligence adoption and trading performance by examining the mediating role of trading decision quality and the moderating role of financial literacy.

Method and Methodology

Research design. The study follows a quantitative, cross-sectional design that is descriptive in identifying the underlying factors of AI Adoption and causal in testing direct, mediating and moderating relationships. The approach is deductive, with hypotheses derived from TAM, decision-quality research and the financial literacy literature. The unit of analysis is the individual retail F&O trader in Bengaluru, Mysuru, Mangaluru, Hubballi-Dharwad, Belagavi or Shivamogga. Institutional traders, proprietary desks and professional fund managers are outside the scope.

Instrument and measurement. Primary data were collected with a structured, close-ended questionnaire administered through Google Forms. Items were adapted from validated scales in prior literature (for example, TAM-based usefulness and ease-of-use items and financial literacy scales) and measured on a five-point Likert scale from “Strongly Disagree” to “Strongly Agree”. The questionnaire covered the demographic profile; AI Adoption (items AI 8.1-8.10, with item 8.7 reverse-worded); Trading Decision Quality (TDQ); Financial Literacy (FI); and Trading Performance (TP), which is self-assessed.

Sample Size. The sample size was determined using Cochran’s formula based on the assumptions of a large population size, where $n = Z^2pq/e^2 = (1.96^2 \times 0.50 \times 0.50)/0.05^2 = 384.16$, rounding up to 385 participants (confidence level of 95%, margin of error 5%, $p = 0.50$). Altogether 401 samples were gathered and analysed, which exceeds the minimum requirement.

Analytical tools. Two stages of analysis were used. Exploratory Factor Analysis (EFA) in SPSS established the factor structure of AI Adoption, using the Kaiser–Meyer–Olkin (KMO) measure, Bartlett’s test of sphericity, communalities, Principal Component Analysis with Varimax rotation and Cronbach’s alpha. PLS-SEM in SmartPLS tested the measurement and structural models using outer loadings, composite reliability, Average Variance Extracted (AVE), the Heterotrait-Monotrait ratio and the Fornell–Larcker criterion for validity; path coefficients with bootstrapped t-values, p-values and 95% confidence intervals (5,000 resamples); R^2 , f^2 and Q^2 predict; SRMR and NFI for fit; specific indirect effects and the Variance Accounted For (VAF) for mediation; the product-indicator approach for moderation; and Importance–Performance Map Analysis (IPMA). Thresholds follow (Hair et al., 2017): “loadings and reliability at or above 0.70, AVE at or above 0.50, HTMT below 0.90 and Q^2 predict above zero”.



Conceptual Framework and Hypotheses

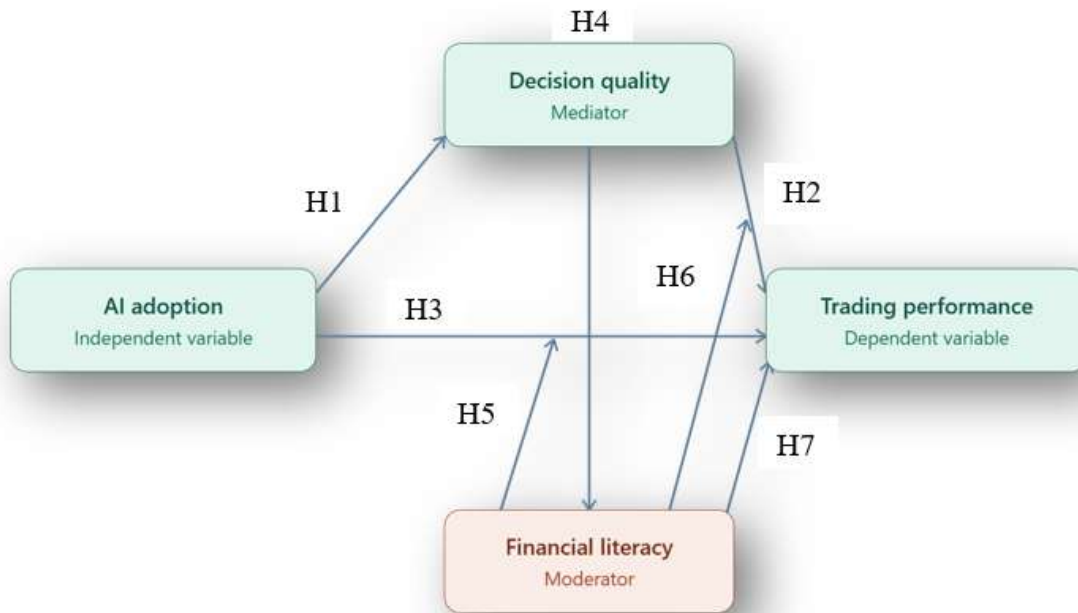


Figure 1: Conceptual framework

AI Adoption (independent variable) captures how useful, easy to use and trustworthy traders find AI tools, and how far they rely on them. Trading Decision Quality (mediator) reflects the perceived quality of decisions made with AI assistance. Financial Literacy (moderator) reflects the ability to interpret and apply financial and AI-generated information, and it is expected to change how much traders gain from AI tools. Trading Performance (dependent variable) reflects self-assessed trading outcomes.

Hypotheses

Hypothesis 1: AI Adoption and Trading Decision Quality. H₁: AI Adoption significantly influences Trading Decision Quality (AI → TDQ).

Hypothesis 2: Trading Decision Quality and Trading Performance. H₁: Trading Decision Quality significantly influences Trading Performance (TDQ → TP).

Hypothesis 3: AI Adoption and Trading Performance. H₁: AI Adoption significantly influences Trading Performance (AI → TP).

Hypothesis 4: Mediation. H₁: Trading Decision Quality mediates the relationship between AI Adoption and Trading Performance (AI → TDQ → TP).

Hypothesis 5: Moderation. H₁: Financial Literacy moderates the relationship between AI Adoption and Trading Performance (FI × AI → TP).

Hypothesis 6: Moderation. H₀: Financial Literacy moderates the relationship between Trading Decision Quality and Trading Performance (FI × TDQ → TP).



Demographics

Demographic Variables	Category	Frequency	%
Age	18–25 years	279	69.6
	26–35 years	71	17.7
	36–45 years	25	6.2
	46–55 years	26	6.5
Gender	Male	228	56.9
	Female	173	43.1
Educational Qualification	Postgraduate	187	46.6
	Undergraduate	168	41.9
	Professional Qualification (CA, CFA, CS, CMA, etc.)	30	7.5
	Doctorate	3	0.7
	Others (B.Sc, LLB, etc.)	13	3.2
Trading Experience	Less than 1 year	243	60.6
	1–3 years	102	25.4
	3–5 years	32	8.0
	More than 5 years	24	6.0
Occupation	Student	180	44.9
	Salaried Employee	154	38.4
	Self-Employed	30	7.5
	Business Owner	29	7.2
	Others (Homemaker, Advocate, Intern, etc.)	8	2.0

Source: Data collected from Questionnaire.

Data Analysis

The analysis uses the 401 responses from retail F&O traders across the six cities and is presented objective-wise, beginning with descriptive statistics.

Descriptive Statistics

Item scores were averaged for each respondent and summarised by construct (Table 1).

Table 1: Descriptive Statistics of the Study Variables

Construct	Mean	Std. Deviation	Minimum	Maximum
AI Adoption	3.313	1.015	1.00	5.00
Trading Decision Quality	3.287	1.028	1.00	5.00
Financial Literacy	3.302	1.039	1.00	5.00
Trading Performance	3.250	1.033	1.00	5.00

Note: Descriptive statistics were computed on the collected data (N = 401).



All four constructs have mean values above 3.00 on the five-point scale, with AI Adoption highest ($M = 3.313$) and Trading Performance lowest ($M = 3.250$). Standard deviations lie between 1.015 and 1.039, showing moderate variation, and responses cover the full 1–5 range. Respondents therefore reported moderately positive levels of AI adoption, financial literacy, decision quality and performance.

Identifying the Factors of AI Adoption (Objective 1)

The EFA was conducted for the ten AI Adoption variables. The result for KMO is 0.967 which shows an adequate sample size, while the sphericity test by Bartlett is also significant with a χ^2 of 3934.081, df of 45, and p-value less than 0.001. All the items had high values for communalities. Three factors emerged after applying PCA with Varimax rotation (83.13%) (Table 2).

Table 2: Factor Structure and Reliability of AI Adoption

Factor	Items	Variance Explained (%)	Cronbach's α
F1: Perceived Usefulness and Continued Reliance	6	33.95	0.948
F2: Perceived Ease of Use	2	25.71	0.875
F3: Trust in AI Reliability	2	23.47	0.813
Total / Overall scale	10	83.13	0.963

Note: KMO = 0.967; Bartlett's $\chi^2 = 3934.081$, $df = 45$, $p < 0.001$.

All three factors exceed the 0.70 reliability threshold, and the overall scale shows excellent internal consistency ($\alpha = 0.963$). Perceived usefulness and behavioural reliance merged into a single factor: traders do not separate “the tool performs well” from “I use it and will keep using it”. Ease of Use and Trust emerged as distinct factors, consistent with their theoretical definitions and with the emphasis on trust in the AI adoption literature (Venkatesh, 2022) (Dwivedi et al., 2021). Item 8.7, a reverse-worded item, was retained at the exploratory stage and excluded from the PLS-SEM measurement model because the two stages apply different item-retention criteria.

Reliability and Validity of the Measurement Model

Reliability and convergent validity were assessed in SmartPLS (Table 3), and indicator loadings are summarised in Table 4.

Table 3: Reliability and Convergent Validity

Construct	Cronbach's α	CR (rho_a)	CR (rho_c)	AVE
AI Adoption	0.960	0.961	0.966	0.759
Trading Decision Quality	0.956	0.958	0.964	0.792
Trading Performance	0.961	0.961	0.968	0.810

Table 4: Indicator Loadings of the Measurement Model

Construct	Indicators retained	Loading range
AI Adoption	9 (AI 8.7 excluded)	0.837 – 0.898
Financial Literacy	7	0.878 – 0.921
Trading Decision Quality	7	0.793 – 0.915
Trading Performance	7	0.878 – 0.928

Source: Author's own analysis using SmartPLS 4.

All reliability coefficients are above 0.70, AVE scores are greater than 0.50, and all indicators have a load higher than 0.70, which proves the reliability and convergent validity of the analysis. Discriminant validity is illustrated in Table 5, as the HTMT scores are below 0.90 and the AVE score square roots are larger than their correlation with other constructs.



Table 5: Discriminant Validity (HTMT and Fornell–Larcker)

Constructs	HTMT	Correlation ($\sqrt{\text{AVE}}$ of both constructs)
AI Adoption $\leftrightarrow$ TDQ	0.753	0.723 (0.871 and 0.890)
AI Adoption $\leftrightarrow$ TP	0.766	0.737 (0.871 and 0.900)
TDQ $\leftrightarrow$ TP	0.723	0.695 (0.890 and 0.900)

Source: Author's own analysis using SmartPLS 4.

Structural Model and Mediation (Objective 2)

A PLS-SEM model with AI Adoption, TDQ and TP was estimated first (Table 6). AI Adoption has a strong positive effect on TDQ ($\beta = 0.723$, $t = 26.138$, $p < 0.001$), a moderate direct effect on TP ($\beta = 0.492$, $p < 0.001$), and TDQ has a moderate effect on TP ($\beta = 0.339$, $p < 0.001$). The model explains 52.2% of the variance in TDQ and 59.8% of the variance in TP. The f^2 of 1.093 shows that the largest structural effect of AI Adoption is on decision quality.

Table 6: Structural Model Results (Mediation Model)

Path	β	Std. Dev.	t-value	p-value	f^2
AI Adoption $\rightarrow$ TDQ	0.723	0.028	26.138	< 0.001	1.093
AI Adoption $\rightarrow$ TP (direct)	0.492	0.051	9.616	< 0.001	0.288
TDQ $\rightarrow$ TP	0.339	0.053	6.444	< 0.001	0.137

Note: $R^2 = 0.522$ (TDQ) and 0.598 (TP). Bootstrapping with 5,000 resamples.

The mediation results are decomposed in Table 7. The indirect effect through TDQ is 0.245 ($t = 6.362$, $p < 0.001$) and the direct effect remains significant, so the mediation is partial. The VAF is $0.245/0.737 \approx 33.2\%$, within the 20–80% range that indicates partial mediation. About one-third of the total effect of AI Adoption on performance therefore operates through better decisions, and the remaining two-thirds is either direct or runs through channels not measured in this model. Candidate channels such as execution speed or reduced emotional influence were not tested here. H1, H2, H3 and H4 are supported.

Table 7: Analysis of the Effect of AI Adoption on Trading Performance

Effect	β	t-value	p-value	Share of total effect
Direct (AI $\rightarrow$ TP)	0.492	9.616	< 0.001	66.8%
Indirect (AI $\rightarrow$ TDQ $\rightarrow$ TP)	0.245	6.362	< 0.001	33.2% (VAF)
Total (AI $\rightarrow$ TP)	0.737	28.433	< 0.001	100%

Note: Shares are computed as each effect divided by the total effect ($0.492/0.737$ and $0.245/0.737$).

Moderated-Mediation Model (Objective 3)

The full model adds Financial Literacy and its interaction with AI Adoption. In the estimated model, TDQ also carried a path to Financial Literacy, and a second interaction term ($\text{FI} \times \text{TDQ}$) was included (Table 8, Figure 2).

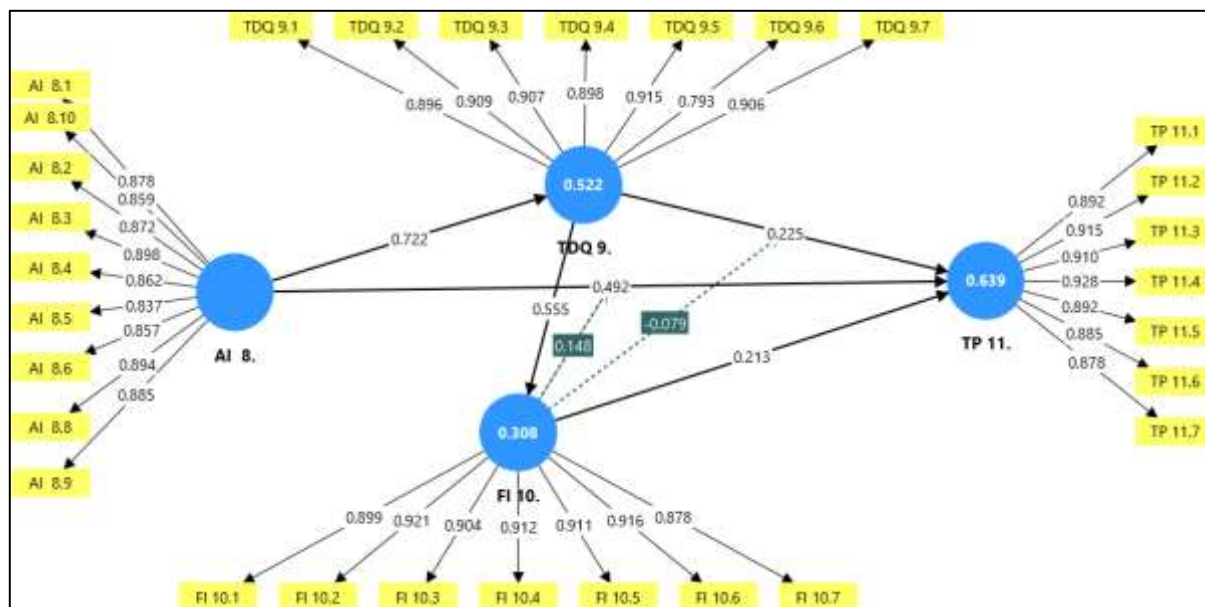


Figure 2: Estimated structural model (selected paths; all estimated paths are in Table 8)

Table 8: Structural Model Results (Full Moderated-Mediation Model)

Path	β	t-value	p-value	95% CI	f^2
AI Adoption $\rightarrow$ TDQ	0.722	26.068	< 0.001	[0.666, 0.774]	1.091
AI Adoption $\rightarrow$ TP	0.492	10.224	< 0.001	[0.398, 0.588]	0.316
TDQ $\rightarrow$ TP	0.225	4.114	< 0.001	[0.116, 0.332]	0.052
FI $\rightarrow$ TP	0.213	5.191	< 0.001	[0.130, 0.291]	0.086
FI $\times$ AI $\rightarrow$ TP	0.148	3.256	0.001	[0.056, 0.239]	0.033
FI $\times$ TDQ $\rightarrow$ TP	-0.079	1.761	0.078	[-0.167, 0.010]	0.009
TDQ $\rightarrow$ FI	0.555	13.930	< 0.001	[0.475, 0.632]	0.444

Note: $R^2 = 0.308$ (FI), 0.522 (TDQ) and 0.639 (TP; adjusted 0.635). Bootstrapping with 5,000 resamples.

Moderation by Financial Literacy. The interaction between Financial Literacy and AI Adoption on Trading Performance is positive and significant ($\beta = 0.148$, $t = 3.256$, $p = 0.001$). The confidence interval does not include zero. Financial Literacy therefore makes the effect of AI Adoption on Trading Performance stronger. Hypothesis 5 is supported. The effect size is small ($f^2 = 0.033$). The strength of the moderation should not be overestimated. Adding Financial Literacy. The interaction terms increased the R squared of Trading Performance from 0.598 to 0.639 an increase of about four percentage points. The interaction between Financial Literacy and Trading Decision Quality is not significant ($\beta = -0.079$, $p = 0.078$ CI -0.167 to 0.010). There is no evidence that Financial Literacy affects the relationship, between decision quality and performance.

Conditional effects. Because latent variable scores in SmartPLS are standardised, the AI $\rightarrow$ TP coefficient of 0.492 is the effect at average Financial Literacy, and the interaction coefficient shifts it by 0.148 for each standard deviation of Financial Literacy. Table 9 and Figure 3 show the resulting conditional effects.

Table 9: Conditional Effect of AI Adoption on Trading Performance by Financial Literacy

Level of Financial Literacy	Calculation	Conditional effect of AI $\rightarrow$ TP
Low (-1 SD)	0.492 - 0.148	0.344
Average (mean)	0.492	0.492
High (+1 SD)	0.492 + 0.148	0.640

Note: Computed from the coefficients in Table 8, holding other paths constant. Formal significance tests of the conditional slopes were not conducted.

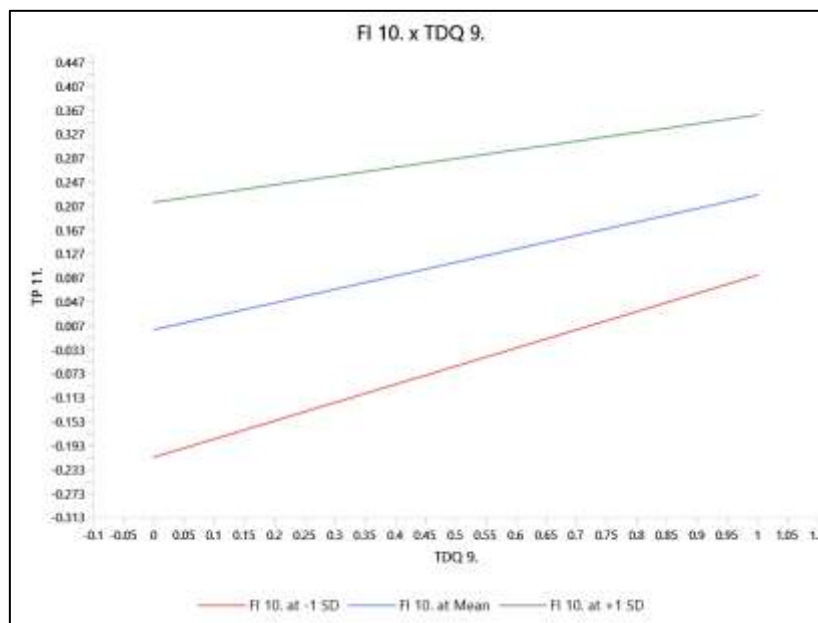


Figure 3: Effect of AI Adoption on Trading Performance at low and high Financial Literacy

The conditional effect of AI Adoption is about 86% larger for traders with high Financial Literacy (0.640) than for those with low Financial Literacy (0.344). Traders at all observed levels of literacy benefit from AI Adoption, but the gain is steeper for the more financially literate.

Indirect effects. In the full model the indirect effect of AI Adoption on Trading Performance through TDQ is 0.162 ($t = 4.072$, $p < 0.001$), smaller than the 0.245 in the mediation model because the additional paths involving Financial Literacy absorb part of the effect. Other significant specific indirect effects are $TDQ \rightarrow FI \rightarrow TP$ (0.118), $AI \rightarrow TDQ \rightarrow FI \rightarrow TP$ (0.085) and $AI \rightarrow TDQ \rightarrow FI$ (0.401), all with $p < 0.001$.

Model Fit, Predictive Relevance and IPMA

Table 10: Model Fit and Predictive Relevance

Indicator	Value	Assessment
SRMR (estimated model)	0.034	Good fit (below 0.08)
NFI (estimated model)	0.935	Good comparative fit
Q^2 predict – TDQ	0.519	Large predictive relevance
Q^2 predict – Financial Literacy	0.181	Moderate predictive relevance
Q^2 predict – Trading Performance	0.542	Large predictive relevance

Source: Author's own analysis using SmartPLS 4.

The SRMR of 0.034 indicates a small discrepancy between observed and model-implied correlations, and the NFI of 0.935 indicates good comparative fit. All Q^2 predict values are positive, so the model has predictive relevance for every endogenous construct.

Table 11: IPMA for the Target Construct Trading Performance

Construct	Importance (Total Effect)	Performance (0–100)
AI Adoption	0.740	57.850
Trading Decision Quality	0.343	57.276
Financial Literacy	0.213	57.582

Source: Author's own analysis using SmartPLS 4.

AI Adoption has the highest importance for Trading Performance (0.740), followed by TDQ (0.343) and Financial Literacy (0.213). Performance scores are almost identical across the three constructs (about 57–58 out of 100), so improving AI Adoption offers the largest potential gain in Trading Performance.



Summary of Hypothesis Testing

Table 12: Summary of Hypothesis Testing

Hypothesis	Relationship Tested	β	p-value	Decision
H1	AI Adoption $\rightarrow$ TDQ	0.723	< 0.001	Supported
H2	TDQ $\rightarrow$ Trading Performance	0.339	< 0.001	Supported
H3	AI Adoption $\rightarrow$ Trading Performance	0.492	< 0.001	Supported
H4	AI $\rightarrow$ TDQ $\rightarrow$ TP (indirect)	0.245	< 0.001	Supported (partial mediation)
H5	FI $\times$ AI $\rightarrow$ Trading Performance	0.148	0.001	Supported
H6	FI $\times$ TDQ $\rightarrow$ TP	-0.079	0.078	Not supported

Note: H1–H4 are from the mediation model; H5–H6 is from the full model.

Discussion

The results show that AI Adoption is associated with better trading performance mainly through two routes: a direct association and an indirect one through better decisions. The strong AI $\rightarrow$ TDQ path ($\beta = 0.723$) suggests that traders who find AI tools useful, easy to use and trustworthy also report better decision-making, which is the behavioural step that adoption studies built on intention alone do not capture (Sabir et al., 2023). The finding that adoption is linked to performance, and not only to intention, addresses the concern in the technical literature that gains in forecasting accuracy do not automatically reach retail traders (Fan, 2025) (Cohen, 2022).

The partial mediation ($VAF \approx 33.2\%$) means decision quality is an important but incomplete explanation. The moderation result indicates that the benefit of AI is not uniform: traders with higher financial literacy gain more from the same level of adoption. This is in line with the evidence that human competency conditions the behavioural value of AI tools (Vijayananth & Saravanabhavan, 2026), and with the view that financial literacy alone has limited power to offset behavioural errors (Divakara Reddy et al., 2025) while it can still change how effectively other resources are used. At the same time, the moderation effect is small ($f^2 = 0.033$) and the conditional slopes in Table 9 were not formally tested, so the conclusion should be treated as a modest, not a dominant, effect. Because the data are cross-sectional and self-reported, all relationships are associations and not proof of causation.

Conclusion

This study asked whether AI adoption improves the trading performance of retail F&O traders in Karnataka or only adds technological sophistication. Among 401 responses, AI Adoption is significantly and positively associated with Trading Performance, both directly and through Trading Decision Quality, which partially mediates the relationship ($VAF \approx 33.2\%$). The influence of AI Adoption on Trading Performance is greatly enhanced by Financial Literacy, although the impact is relatively small and implies that the benefit from using AI technology varies among traders. AI Adoption has the greatest importance among all variables influencing Trading Performance within IPMA, while the model has acceptable goodness of fit and predictive relevance. Having access to AI technologies alone is not enough; better decisions and financial knowledge make the difference.

Theoretical implications. The study extends TAM-based adoption research from the intention stage to the performance stage through Trading Decision Quality, and it shows that financial literacy is a boundary condition for the performance benefit of AI adoption.

Practical implications. Retail traders can expect AI tools to be worthwhile, and more so when their financial knowledge is stronger. Fintech platforms should design AI tools to improve decision quality and not only engagement. Policymakers and educators should provide financial literacy programmes alongside access to AI-based trading technology, particularly in the Tier-2 cities of Karnataka.



Limitations and Future Scope

The findings should be read with the following limitations. The study is cross-sectional and covers six cities of Karnataka, so results reflect one time period and one region. Trading Performance and the other constructs were self-reported, which raises the possibility of common-method bias, and the associations should not be read as proof of causation. Only four constructs were modelled, and market volatility, broker execution quality and psychological biases were not controlled.

Further research may include (i) extending the sample to other Indian states and even semi-professional investors, (ii) including variables such as risk perception, trading experience and AI trust, and (iii) analysing different cities using multi-group analysis provided that there is enough sample size for each city. Objective measures such as broker statements would improve Trading Performance measure.

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