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STRATEGIES TO INTEGRATE ARTIFICIAL INTELLIGENCE TOOL USAGE AMONG CLIENTS: AN EMPIRICAL STUDY IN FINANCIAL SERVICES

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Abstract- This study examines the determinants influencing AI tool adoption among clients of a full-service regional brokerage firm in India. Using primary data collected from active investors, the study analyses the impact of awareness, trust, social influence, ease of use, and technical literacy on perceived usefulness of AI tools. Statistical techniques, including correlation, ANOVA, chi-square, and regression analysis, were employed. Results indicate that the combined behavioural and technological factors significantly predict perceived usefulness, explaining 54.8% of the variance ($R^2 = 0.548$, $p < 0.001$). Client tenure shows a strong positive relationship with prior AI exposure ($r = 0.705$, $p < 0.001$), while demographic variables such as age, gender, and occupation show no significant influence. The study concludes that AI integration in financial services is primarily a behavioural and trust-driven challenge, and recommends hybrid human-AI advisory models, phased rollouts, and client education initiatives as key strategies for sustainable adoption.

Keywords: *Artificial Intelligence, Client Adoption, Financial Services, Perceived Usefulness, Technology Acceptance, Brokerage Industry*

1. INTRODUCTION:

Artificial Intelligence (AI) is rapidly transforming financial services in India, enabling automated trading, robo-advisory systems, personalised investment support, and real-time risk management. While technology-first discount brokers have accelerated digital adoption among retail investors, traditional full-service brokerage firms, particularly those operating in semi-urban and rural markets, face a more complex challenge: integrating AI tools without disrupting the trust-based, relationship-driven service models their clients depend on.

Despite growing AI capabilities, client-side adoption remains uneven. Industry evidence suggests most firms have applied AI only to back-office functions, while the full potential of client-facing AI remains unrealised. Behavioural factors such as awareness, trust, ease of use, social influence, and technical literacy, as established in Davis's (1989) Technology Acceptance Model, are widely recognised as key determinants of technology adoption. However, empirical evidence examining these factors among retail brokerage clients in semi-urban Indian markets remains limited.

This study investigates these determinants among clients of a full-service brokerage firm serving over 50,000 retail clients across 150+ branches in South India. The findings aim to provide strategic direction for brokerage firms seeking to implement hybrid AI adoption models that balance automation with human advisory oversight.

2. OBJECTIVES OF THE STUDY:

1. To analyze and suggest strategies to integrate AI tools among the client base of the brokerage firm.
2. To examine the impact of Awareness of AI, Trust in AI, Social Influence, Ease of Use, and Technical Literacy on perceived usefulness of AI tools in investment decision making.
3. To evaluate the tenure of investors in trading and their duration as a client of the brokerage firm.
4. To examine the relationship between demographic variables and AI tool usage among investors.

3. SCOPE OF THE STUDY:

The study focuses on client-facing AI adoption within the Indian stock broking industry, examining behavioral and technological determinants among retail investors of a regional brokerage firm in Tamil Nadu. It reflects the current phase of AI integration within the Indian regulatory framework.

4. LIMITATIONS OF THE STUDY:

The study is limited to clients of a single regional brokerage firm in Tamil Nadu, which may restrict generalizability.

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Convenience sampling and self-reported data introduce potential bias. Rapidly evolving regulatory and technological conditions may affect the continued relevance of findings.

5. REVIEW OF LITERATURE:

1. AI in Customer Relationship Management Chatterjee et al. (2021), reviewing 138 studies in the *Journal of Business and Industrial Marketing*, found that AI–CRM integration fails when clients lack trust in automated decisions and when data privacy concerns are neglected, directly supporting this study's emphasis on trust as a primary adoption barrier in financial advisory contexts.
2. User Acceptance of AI Applications Zhang et al. (2024), in *Behavioral Sciences* (MDPI), identified perceived usefulness and ease of use — the core constructs of Davis's (1989) Technology Acceptance Model, as the strongest predictors of AI adoption across 80 studies, validating the present study's selection of perceived usefulness as the dependent variable.
3. Strategic Integration of AI for Sustainable Businesses Jovanović et al. (2023), in *MDPI Sustainability*, found that firms adopting AI gradually through strategy-driven processes achieve significantly better outcomes than those pursuing sudden technological upgrades, reinforcing this study's recommendation for phased implementation.
4. AI Readiness and Adoption Framework Issa, Jabbouri & Palmer (2022), in *Technological Forecasting and Social Change*, identified digital skills, management literacy, and organizational support as preconditions for AI adoption, directly paralleling the technical literacy and ease-of-use constructs examined here.
5. Effect of AI-Based CRM on Organizational Performance Chatterjee et al. (2021), in *Industrial Marketing Management*, demonstrated across 307 firms that AI delivers performance gains only when users actively trust and understand the system, confirming that behavioral readiness outweighs technological capability in determining adoption success.

6. THEORETICAL BACKGROUND:

This study is grounded in Davis's (1989) Technology Acceptance Model (TAM), which identifies perceived usefulness and ease of use as the primary drivers of technology adoption. As shown in Figure No 1, five independent variables , Awareness of AI Tools, Trust in AI, Social Influence, Ease of Use, and Technical Literacy, are hypothesized to predict Perceived Usefulness, which subsequently influences AI Tool Usage Among Clients.

Conceptual Model:

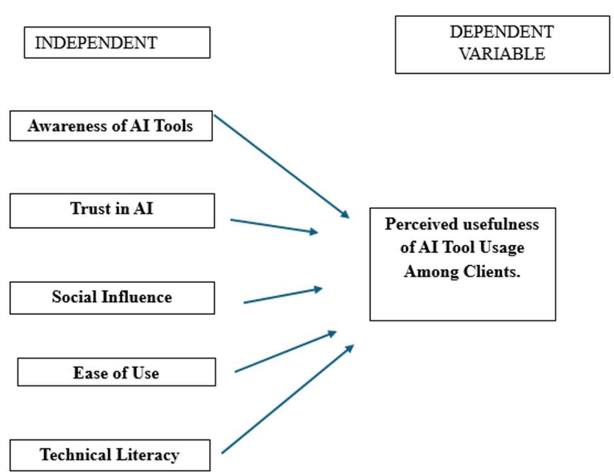

Figure No: 1

7. RESEARCH DESIGN:

A descriptive research design is employed to systematically document and analyse client perceptions, attitudes, and usage patterns related to AI tools at south Indian stockbroker firm. This design enables accurate measurement of existing behaviours and factors without manipulating any variables.

8. DATA ANALYSIS:

The Table Represent the Demographic Variable

Variables	Category	Frequency	Percent
Age	Below 25	9	7.6
	25 – 35	21	17.6
	36 – 45	53	44.5
	Above 45	36	30.3
	Total	119	100.0
Gender	Male	79	66.4
	Female	40	33.6
	Total	119	100.0
Occupation	Salaried	22	18.5
	Self–employed	65	54.6
	Student	9	7.6
	Others	23	19.3
	Total	119	100.0
Prior experience using AI tools	Yes	62	52.1
	No	56	47.1
	Total	119	100.0

Table No: 1

MULTIPLE REGRESSION FOR THE DEMOGRAPHIC VARIABLE (Perceived Usefulness) AND INDEPENDENT VARIABLE (Awareness of AI Tools, Trust in AI, Social Influence, Ease of Use, Technical Literacy)

HYPOTHESIS:

- Null Hypothesis (H0): The combined effect of awareness of AI tools, trust in AI, social influence, ease of use, technical literacy does not significantly predict perceived usefulness.
- Alternative Hypothesis (H1): The combined variables significantly predict perceived usefulness.

Model Summary

The following table presents the regression model summary, indicating the strength of the relationship between the combined predictor variables and perceived usefulness.

Table No:2

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.740ᵃ	.548	.544	.4218	.548	141.953	1	117	.000

a. Predictors: (Constant), Combined mean

INTERPRETATION:

The multiple regression model summary demonstrates exceptionally strong predictive performance. The correlation coefficient (R = 0.740) indicates a strong linear relationship between the combined mean of all variables and perceived usefulness.

Anova

The ANOVA table examines the overall statistical significance of the regression model, determining whether the combined predictor variables significantly explain the variance in perceived usefulness.

Table No: 3

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	25.255	1	25.255	141.953	.000ᵇ
	Residual	20.815	117	.178		
	Total	46.070	118			

Coefficients

The coefficients table presents the specific contribution of the combined predictor variable in explaining perceived usefulness of AI tools among clients.

Table No: 4

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	.191	.170		1.126	.262	-.145	.527
	Combined mean	.130	.011	.740	11.914	.000	.108	.151

a. Dependent Variable: Perceived Usefulness Mean

INTERPRETATION:

The ANOVA table confirms the overall statistical significance of the regression model. The F-statistic = 141.953 with $p < 0.001$ provides strong evidence against the null hypothesis that all regression coefficients equal zero.

a. Predictors: (Constant), Combined mean

INTERPRETATION:

The combined mean significantly predicts perceived usefulness ($\beta = 0.740$, $t = 11.914$, $p < 0.001$), confirming that the combined effect of all five behavioral factors strongly drives perceived usefulness of AI tools.

9. MANAGERIAL IMPLICATIONS:

The regression result ($R^2 = 0.548$, $p < 0.001$) confirms that AI adoption is primarily a behavioral challenge, not a technological one. Firms must therefore prioritize client education and trust-building alongside any platform deployment. Low awareness and technical literacy scores (means ranging 1.91–2.30) indicate that tiered onboarding programs, vernacular-language tutorials, and branch-level demonstrations are essential, particularly for semi-urban clients.

Since trust scores (2.11–2.35) reveal clients prefer AI as a support tool rather than an autonomous decision-maker, a hybrid human-AI advisory model where Relationship Managers validate AI recommendations before client delivery is strongly recommended. The strong tenure–AI experience correlation ($r = 0.705$) further suggests that long-tenure clients should be prioritized as early adopters in any phased rollout.

Finally, since age, gender, and occupation show no significant differences in AI experience, adoption interventions should be designed universally across all client segments rather than targeted demographically.

10. CONCLUSION:

This study confirms that AI adoption in financial services is fundamentally a behavioral challenge rather than a technological one. The regression model ($R^2 = 0.548$, $p < 0.001$) demonstrates that awareness, trust, ease of use, social influence, and technical literacy collectively predict perceived usefulness, explaining over half its variance. Trust remains the most critical barrier, while the strong tenure–AI experience correlation ($r = 0.705$, $p < 0.001$) confirms that familiarity drives readiness more than any demographic factor. The absence of significant differences across age, gender, and occupation further signals that adoption interventions must be universal rather than demographically targeted. Successful AI integration ultimately demands a phased, client-centric approach combining explainable AI outputs, vernacular interfaces, and hybrid human-AI advisory models.

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