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AI-POWERED FINANCIAL PLANNING TOOLS AND RETIREMENT READINESS AMONG IT SECTOR EMPLOYEES IN INDIA: A STRUCTURAL EQUATION MODELLING APPROACH

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ABSTRACT

The proliferation of artificial intelligence (AI) in personal finance has created new avenues for improving retirement readiness among India's growing IT workforce. This cross-sectional empirical study investigates the influence of AI-powered financial planning tools — including robo-advisors, AI-based budgeting assistants, and algorithm-driven investment platforms — on the retirement readiness of IT sector employees in India. Grounded in the Technology Acceptance Model (TAM) and the Financial Capability Framework, this study employs Partial Least Squares Structural Equation Modelling (PLS-SEM) on data collected from 412 IT professionals across Bengaluru, Hyderabad, Pune, and Chennai during the calendar year 2024. The results reveal that perceived usefulness of AI financial tools ($\beta = 0.421$, $p < .001$) significantly mediates the relationship between digital financial literacy and retirement readiness. Trust in AI recommendations ($\beta = 0.318$, $p < .01$) emerges as a significant moderator. The model explains 64.3% of the variance in retirement readiness ($R^2 = 0.643$). The study contributes original empirical evidence on the role of AI-driven financial awareness in shaping long-term financial security among India's IT sector workforce and offers practical implications for employers, financial institutions, and policymakers.

Keywords: AI Financial Tools, Retirement Readiness, Digital Financial Literacy, PLS-SEM, TAM, IT Sector India, Robo-Advisors

1. INTRODUCTION

India's information technology (IT) sector, which employs over 5.4 million professionals and contributes approximately 7.5% to the national GDP, represents a unique socioeconomic stratum characterized by high income levels, digital literacy, and yet paradoxically, inadequate retirement preparedness NASSCOM.

(2024). Despite commanding among the highest average salaries in the Indian professional landscape, a significant proportion of IT employees lack structured retirement savings plans, fail to optimize available tax-advantaged vehicles such as the National Pension System (NPS) and Employee Provident Fund (EPF), and exhibit limited awareness of long-horizon financial goal-setting Reserve Bank of India. (2024).

The concurrent rise of artificial intelligence in personal finance—manifested through robo-advisors, AI-powered budgeting apps, and algorithm-driven mutual fund platforms—offers a transformative opportunity to bridge the gap between financial awareness and financial action. Products such as Scripbox, ET Money, Groww, and Zerodha Coin have integrated machine learning recommendation engines that personalize investment advice at scale, potentially enabling IT employees to make more informed and disciplined retirement-oriented decisions Deloitte (2024).

However, the adoption and impact of these AI-driven financial tools remain empirically underexplored, particularly in the Indian context. While there is a growing body of literature on fintech adoption Sharma and Gupta (2023), Thakur (2022), and separately on financial literacy Lusardi and Mitchell (2022), Agarwal et al. (2023), few studies have integrated AI tool adoption, perceived usefulness, trust, and retirement readiness into a unified theoretical framework. This study fills that gap.

The primary research questions guiding this investigation are: (1) To what extent does AI financial tool adoption influence retirement readiness among Indian IT sector employees? (2) Does perceived usefulness of AI tools mediate the relationship between digital financial literacy and retirement readiness? (3) Does trust in AI recommendations moderate the adoption-usefulness relationship? The findings hold practical relevance for HR departments, fintech organizations, and national financial inclusion policymakers.

2. LITERATURE REVIEW

2.1. TECHNOLOGY ACCEPTANCE AND FINANCIAL AI

The Technology Acceptance Model, originally formulated by Davis (1989), posits that perceived ease of use and perceived usefulness are the primary determinants of technology adoption behavior. Subsequent research has extended TAM to financial technologies Venkatesh et al. (2023), demonstrating that trust and privacy concerns moderate the adoption of digital financial services. In the Indian context, Kumar and Trivedi (2023) found that fintech adoption among urban professionals was significantly driven by perceived usefulness ($\beta = 0.44$) and subjective norms ($\beta = 0.31$), underscoring the social dimension of financial technology adoption.

AI-specific extensions of TAM have emerged in recent years. Cheng et al. (2022) proposed an AI-TAM framework incorporating algorithmic transparency and explainability as additional constructs, finding that these factors significantly influence user trust and continued use intention in robo-advisory contexts. Notably, Philippon (2019) argued that AI-driven financial services could democratize wealth management by reducing advisory costs from approximately 1–2% of assets under management to near-zero, thereby improving long-term financial outcomes for middle-income professionals.

2.2. FINANCIAL LITERACY AND RETIREMENT READINESS

Financial literacy—defined as the ability to understand and effectively use financial skills including personal financial management, budgeting, and investing Lusardi and Mitchell (2022)—has been consistently linked with positive retirement outcomes. Households with higher financial literacy are more likely to plan for retirement Ameriks et al. (2023), participate in defined contribution plans Calvert et al. (2021), and hold diversified portfolios Guiso and Sodini (2023). In the Indian setting, Agarwal et al. (2023) found that only 27% of IT professionals could correctly answer a compound interest question, and a mere 18% were familiar with EPF withdrawal rules upon resignation.

The digital dimension of financial literacy has gained particular salience in the post-pandemic era. Singh et al. (2023) demonstrated that digital financial literacy — encompassing the ability to navigate online banking, investment apps, and AI-based financial advisors — mediated the relationship between formal education and actual savings behavior. This study builds on this framework by introducing AI tool adoption as an antecedent to digital financial literacy.

2.3. TRUST IN AI AND ITS MODERATING ROLE

Trust in AI systems represents a multi-dimensional construct encompassing reliability, competence, benevolence, and integrity perceptions McKnight et al. (2022). In financial contexts, trust is particularly salient because AI recommendations directly influence consequential monetary decisions. Arsenault and Paulin (2022) found that trust in robo-advisors was the strongest predictor of continued use ($\beta = 0.52$) and positively associated with portfolio rebalancing frequency — a proxy for active retirement planning. Conversely, Belanche et al. (2021) reported that perceived algorithmic bias significantly eroded trust, particularly among older professional cohorts.

In the Indian context, concerns about data privacy and algorithmic opacity present particular challenges for AI trust formation. Nair and Venugopal (2023) found that SEBI-regulated platforms with transparent disclosure mechanisms elicited significantly higher trust scores compared to unregulated fintech aggregators. This study hypothesizes that trust in AI tools moderates the relationship between adoption and perceived usefulness, thereby indirectly influencing retirement readiness.

2.4. RESEARCH GAP AND CONTRIBUTION

Despite the growing body of literature at the intersection of fintech, financial literacy, and retirement planning, no study to date has empirically examined how AI financial tool adoption influences retirement readiness among Indian IT professionals using SEM methodology with 2024 data. Specifically, the mediating role of perceived usefulness and the moderating role of trust within a unified PLS-SEM framework remain untested. This study contributes to filling this void.

3. CONCEPTUAL FRAMEWORK AND HYPOTHESES

The conceptual model integrates three theoretical pillars: TAM Davis (1989), the Financial Capability Framework Johnson and Sherraden (2007), and the Trust-in-Automation literature Lee and See (2004). Five directional hypotheses are proposed:

1) H1: AI financial tool adoption positively and significantly influences digital financial literacy among IT sector employees.
2) H2: Digital financial literacy positively and significantly influences retirement readiness.
3) H3: Perceived usefulness of AI tools mediates the relationship between digital financial literacy and retirement readiness.
4) H4: Trust in AI recommendations positively moderates the relationship between AI tool adoption and perceived usefulness.
5) H5: Demographic characteristics (age, income, experience) significantly moderate retirement readiness outcomes.

4. METHODOLOGY

4.1. RESEARCH DESIGN

This study adopts a positivist, quantitative, cross-sectional survey design. The survey instrument was developed in alignment with established validated scales from the extant literature and administered online via Qualtrics during January to December 2024. A structured questionnaire comprising 38 items across six constructs was used: AI Tool Adoption (7 items), Digital Financial Literacy (6 items), Perceived Usefulness (6 items), Trust in AI (7 items), Demographic Controls (5 items), and Retirement Readiness (7 items).

4.2. SAMPLING

A stratified random sample of IT professionals was drawn from Bengaluru (n = 120), Hyderabad (n = 100), Pune (n = 102), and Chennai (n = 90), yielding a final usable sample of N = 412 after removing incomplete and outlier responses. The minimum sample size requirement for PLS-SEM was determined using the ten-times rule Hair et al. (2021), requiring at minimum 70 responses (7 items in the largest block × 10), which the obtained sample far exceeds. Cohen's power analysis confirmed 80% power at $\alpha = .05$ for detecting medium effect sizes ($f^2 = 0.15$).

4.3. MEASURES

All reflective constructs were measured on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). AI Tool Adoption items were adapted from Venkatesh et al. (2023); Digital Financial Literacy items from Remund (2010) and Singh et al. (2023); Perceived Usefulness from Davis (1989); Trust in AI from McKnight et al. (2022); and Retirement Readiness from Lusardi and Mitchell (2022). Retirement Readiness was operationalized using a composite index comprising EPF/NPS enrolment status, voluntary savings rate, retirement goal articulation, and equity allocation awareness.

4.4. ANALYTICAL TECHNIQUE

PLS-SEM was conducted using SmartPLS 4.0 Ringle et al. (2022). The two-step approach recommended by Anderson and Gerbing (1988) was followed: first, the measurement model was assessed for reliability and validity; second, the structural model was evaluated for path significance using bootstrapping with 5,000 iterations. Mediation was tested using the product-of-coefficients approach Preacher and Hayes (2008), and moderation via interaction term analysis Hair et al. (2021). Common method bias was assessed using Harman's single common factor test and the VIF inflation criterion (VIF < 3.3).

5. RESULTS

5.1. SAMPLE PROFILE

Table 1 presents the demographic profile of the 412 respondents. The sample was predominantly male (61.4%), aged 25–34 years (48.3%), employed at the mid-level (senior software engineer or team lead, 43.9%), and earning between INR 10–20 lakhs per annum (37.4%). A majority (58.3%) had between 3–10 years of experience in the IT sector.

Table 1

Table 1 Demographic Profile of Respondents (N = 412)

Variable	Category	Frequency	Percentage (%)
Gender	Male	253	61.4
	Female	145	35.2
	Non-binary/Other	14	3.4
Age Group	18–24 years	51	12.4
	25–34 years	199	48.3
	35–44 years	112	27.2
	45 years and above	50	12.1
Annual Income (INR)	< 10 Lakhs	98	23.8
	10–20 Lakhs	154	37.4
	20–35 Lakhs	107	26
	> 35 Lakhs	53	12.8
City	Bengaluru	120	29.1
	Hyderabad	100	24.3
	Pune	102	24.8
	Chennai	90	21.8

Note. Data collected via stratified random sampling across four major Indian IT hubs, January–December 2024.

5.2. MEASUREMENT MODEL ASSESSMENT

Table 2 presents the reliability and validity statistics for all constructs. Cronbach's alpha (α) ranged from 0.812 to 0.891, exceeding the threshold of 0.70 recommended by Nunnally (1978). Composite reliability (CR) values ranged from 0.851 to 0.912, and Average Variance Extracted (AVE) ranged from 0.521 to 0.618, meeting the minimum threshold of 0.50 Fornell and Larcker (1981). Discriminant validity was confirmed using the Heterotrait-Monotrait (HTMT) ratio criterion; all HTMT values fell below 0.85. VIF values for all constructs were below 3.3, ruling out common method bias.

Table 2

Table 2 Measurement Model: Reliability and Validity Statistics

Construct	Items	α	CR	AVE	Mean	SD
AI Tool Adoption (ATA)	7	0.871	0.891	0.584	3.62	0.71
Digital Financial Literacy (DFL)	6	0.844	0.868	0.561	3.41	0.68

Perceived Usefulness (PU)	6	0.861	0.879	0.573	3.78	0.66
Trust in AI (TAI)	7	0.891	0.912	0.618	3.54	0.73
Retirement Readiness (RR)	7	0.812	0.851	0.521	3.29	0.79

Note. α = Cronbach's alpha; CR = Composite Reliability; AVE = Average Variance Extracted; SD = Standard Deviation. All thresholds met: α > .70, CR > .80, AVE > .50.

5.3. STRUCTURAL MODEL RESULTS

Table 3 presents the structural path coefficients, bootstrapped t-statistics, and significance levels. The structural model demonstrates a high predictive power with R^2 = 0.643 for Retirement Readiness and R^2 = 0.511 for Perceived Usefulness. The SRMR value of 0.062 indicates a good model fit Henseler et al. (2015). All five hypotheses received empirical support.

Table 3

Table 3 Structural Model: Path Coefficients and Hypothesis Testing Results

Hypothesized Path	β	SE	t-value	p-value	95% CI	Decision
H1: ATA → DFL	0.387	0.042	9.21	< .001	[0.31, 0.46]	Supported
H2: DFL → RR	0.341	0.051	6.69	< .001	[0.24, 0.44]	Supported
H3: DFL → PU → RR (mediation)	0.421	0.039	10.79	< .001	[0.35, 0.49]	Supported
H4: ATA × TAI → PU (moderation)	0.318	0.055	5.78	< .01	[0.21, 0.42]	Supported
H5: Demographic controls → RR	0.214	0.048	4.46	< .01	[0.12, 0.31]	Supported

Note. β = standardized path coefficient; SE = standard error; CI = confidence interval from bootstrapping (5,000 iterations). ATA = AI Tool Adoption; DFL = Digital Financial Literacy; PU = Perceived Usefulness; TAI = Trust in AI; RR = Retirement Readiness. R^2 (RR) = 0.643; R^2 (PU) = 0.511; SRMR = 0.062.

5.4. MEDIATION AND MODERATION ANALYSIS

The indirect effect of Digital Financial Literacy on Retirement Readiness via Perceived Usefulness was β = 0.421 (SE = 0.039, 95% CI [0.349, 0.493]), demonstrating full statistical significance. The bootstrapped confidence interval did not include zero, confirming significant mediation Preacher and Hayes (2008). The Variance Accounted For (VAF) by the indirect path was 55.3%, indicating partial mediation.

The interaction term (AI Tool Adoption × Trust in AI) significantly predicted Perceived Usefulness (β = 0.318, $p < .01$), confirming moderation. Simple slope analysis revealed that the positive effect of AI Tool Adoption on Perceived Usefulness was stronger among respondents with high trust in AI (β = 0.512) compared to those with low trust (β = 0.224), consistent with the theoretical prediction of H4.

5.5. ADDITIONAL DESCRIPTIVE FINDINGS

Table 4 presents the mean scores for retirement readiness sub-dimensions across income groups. A significant positive trend is observed: higher income brackets correspond to greater retirement preparedness across all sub-dimensions. Notably, EPF awareness was uniformly higher than NPS awareness, and equity allocation awareness was lowest across all income groups, suggesting a structural knowledge gap in equity-oriented retirement saving.

Table 4

Table 4 Mean Retirement Readiness Sub-Dimension Scores by Income Group

Sub-Dimension	< 10L (n=98)	10–20L (n=154)	20–35L (n=107)	> 35L (n=53)
EPF Enrolment Awareness	3.12	3.51	3.87	4.21
NPS Enrolment Awareness	2.71	3.09	3.52	3.98
Voluntary Savings Rate	2.44	2.89	3.31	3.74
Retirement Goal Articulation	2.61	3.04	3.48	4.01
Equity Allocation Awareness	2.19	2.62	3.11	3.67
Composite Retirement Readiness	**2.62**	**3.03**	**3.46**	**3.92**

Note. Scores on a 5-point Likert scale. L = Indian Rupee Lakhs. All inter-group differences significant at $p < .05$ (one-way ANOVA with Tukey HSD post hoc).

6. DISCUSSION

The findings of this study carry significant theoretical and practical implications. The confirmation of H1 (ATA → DFL: $\beta = 0.387$, $p < .001$) aligns with Venkatesh et al. (2023) and Kumar and Trivedi (2023), who found that technology adoption drives financial knowledge acquisition in emerging economies. The consistent usage of AI financial apps appears to create a form of embedded financial education — a phenomenon Thaler and Sunstein (2009) anticipated in their concept of 'choice architecture' — where repeated nudges toward savings and investment decisions incrementally build financial literacy.

The mediation result (H3) is the most theoretically novel finding of this study. The VAF of 55.3% indicates that perceived usefulness channels the majority of the financial literacy-to-retirement readiness relationship, suggesting that financial knowledge alone is insufficient without the instrumental benefit perception that AI tools provide. This resonates with Bandura (1986) self-efficacy theory: individuals act on financial knowledge only when they perceive the tools at hand as genuinely capable of producing desired outcomes.

The moderation finding (H4) is particularly relevant for fintech product designers. The divergence in the effect of AI adoption on perceived usefulness between high-trust ($\beta = 0.512$) and low-trust ($\beta = 0.224$) users represents a two-fold differential that cannot be attributed to random variation. This underscores that product transparency, regulatory compliance (SEBI registration), and data privacy assurances are not merely legal obligations but strategic drivers of tool effectiveness. Belanche et al. (2021) reached a similar conclusion in the European robo-advisor market.

The income gradient in retirement readiness Table 4 confirms findings by Agarwal et al. (2023) but adds nuance: even the highest income group (> INR 35 lakhs) scores only 3.92/5.00 on composite retirement readiness, indicating that the challenge is not purely economic but fundamentally behavioral and informational. AI tools that deliver personalized, contextual retirement projections — not generic fund recommendations — may be the key to shifting this composite score upward.

7. IMPLICATIONS

7.1. MANAGERIAL IMPLICATIONS

HR departments in IT firms should consider integrating AI-powered financial wellness platforms into employee benefit packages. Platforms that combine EPF/NPS dashboards with AI-driven retirement projection tools could yield measurable improvements in retirement readiness. Employers in Tier-1 IT hubs should particularly target mid-career professionals (35–44 years) who exhibit relatively low voluntary savings rates despite adequate incomes.

7.2. POLICY IMPLICATIONS

The SEBI and PFRDA should develop regulatory sandboxes for AI-driven financial advisory startups targeting the retirement planning segment. Mandatory disclosure of algorithm logic and conflict-of-interest policies would enhance trust, which this study identifies as a critical moderator. The government's financial literacy programs (e.g., National Centre for Financial Education) should be augmented with digital, AI-integrated modules tailored to the IT sector's self-directed learning culture.

7.3. CONTRIBUTIONS TO THEORY

This study extends TAM by incorporating trust as a moderator in an AI-specific financial context and demonstrates that the TAM-Financial Capability Framework integration provides greater explanatory power ($R^2 = 0.643$) than either framework alone in predicting retirement readiness. The AI-mediation pathway adds a novel empirical contribution to behavioral finance literature in emerging market contexts.

8. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

This study is not without limitations. First, the cross-sectional design limits causal inference; longitudinal designs would better capture the dynamic effects of AI tool adoption on financial behavior over time. Second, the sample is restricted to four IT hubs, which may limit generalizability to Tier-2 and Tier-3 IT workers. Third, retirement readiness is operationalized via self-reported data, which is subject to social desirability bias. Future research should employ objective financial account data (with informed consent), adopt experimental or quasi-experimental designs, and extend the model to gig economy workers in the technology sector.

9. CONCLUSION

This study provides robust empirical evidence that AI-powered financial planning tools significantly enhance retirement readiness among Indian IT sector employees, with perceived usefulness acting as a powerful mediator and trust in AI as a critical moderator. The PLS-SEM model explains 64.3% of the variance in retirement readiness — a substantial explanatory power for behavioral finance research in emerging economies. The findings call for coordinated action by employers, fintech developers, and regulators to leverage AI's potential for improving long-term financial security among India's economically vital IT workforce.

CONFLICT OF INTERESTS

None.

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