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Awareness of Machine Learning for FinTech App Engagement: A Study of User Trust and Perception

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Abstract - The rapid embedding of machine learning (ML) within FinTech applications — powering investment recommendations, copy-trading signals, and automated savings nudges — has outpaced users' recognition of when and how these algorithms operate. Objective: This study measures the level of ML awareness, understanding, and trust among FinTech app users and identifies the demographic and usage-based factors that shape user engagement with ML-powered financial features. Methodology: A descriptive, quantitative research design was adopted. Primary data were collected from 101 FinTech app users through a structured Google Form questionnaire comprising demographic items and nine Likert-scale statements. Data were analysed using Python (pandas, SciPy, scikit-learn) through descriptive statistics, independent-samples t-tests, one-way ANOVA, Pearson correlation, Markov Chain modelling of trust-state transitions, and linear-programming-based prescriptive optimisation. Findings: Average ML Awareness (1.39/5) and ML Trust (1.48/5) were both far below the neutral midpoint, despite a comparatively higher ML Understanding score (3.10/5), revealing a pronounced Awareness-Usage Gap. ML Trust differed significantly by Primary Purpose ($p = 0.00002$) and Education Level ($p = 0.00004$), but not by Gender ($p = 0.582$) or Experience ($p = 0.961$). A moderate positive correlation ($r = 0.533$) linked ML Awareness with perceived Data Security. Markov Chain analysis revealed that both LowTrust (99.7% persistence) and High-Trust (97.1% persistence) states are highly sticky, while the linear-programming model identified content/trainer capacity, rather than budget, as the binding constraint on ML-education outreach. Conclusion: FinTech users actively engage with ML-driven features without recognising or trusting them, and this gap is concentrated among Investing users; targeted, early-stage, purpose-specific education is required to shift entrenched trust patterns.

Keywords: Machine Learning, FinTech, User Awareness, Trust, Markov Chain, Linear Programming, Business Analytics

1. Introduction Financial technology (FinTech) applications have fundamentally reshaped the way individuals invest, transact, save, and plan their finances, and machine learning (ML) now sits at the operational core of many of these transformations. Robo-advisory investment suggestions, automated copytrading signals, fraud-detection alerts, and personalised budgeting nudges are increasingly generated — or heavily shaped — by ML algorithms operating largely out of sight of the end user. As FinTech platforms compete on personalisation, convenience, and speed, the algorithmic layer behind the interface tends to recede into the background: users interact with it constantly, yet rarely register its presence consciously. This creates a meaningful and under-examined divide between usage and awareness. A user may act on an ML-generated investment recommendation, follow a copy-trading suggestion, or accept an automated savings nudge without ever recognising that a machine-learning model, rather than a human advisor or a simple rule-based system, produced that output. This divide matters commercially and ethically, because awareness and understanding are widely regarded as preconditions for informed trust: a user who does not know ML is involved cannot meaningfully evaluate whether to rely on it, question it, or seek clarification when a recommendation appears mistaken. The importance of Business Analytics in this context lies in its capacity to move the conversation from assumption to evidence. Rather than presuming what users know or feel about ML, a well-designed survey combined with descriptive, inferential, and prescriptive statistical techniques can quantify awareness levels, measure trust, isolate the user segments most and least engaged with the ML dimension of their apps, and test whether demographic or behavioural factors are meaningfully associated with these attitudes. The growing relevance of ML within FinTech, and of India's own digital-finance ecosystem, makes this an especially pressing area of enquiry: as regulators and platform designers increasingly emphasise algorithmic transparency as a safeguard against both over-reliance on, and unwarranted distrust of, automated recommendations, empirical measurement of user awareness becomes essential infrastructure for responsible product design. The present study responds to this need directly, applying a structured analytical framework — spanning exploratory data analysis, statistical hypothesis testing, correlation analysis, Markov Chain modelling of trust-state transitions, and linearprogramming-based prescriptive optimisation — to a primary dataset of 101 FinTech app users.

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In doing so, it demonstrates how a compact, well-structured primary survey can be analysed with the same analytical rigour typically reserved for largescale organisational datasets, generating insights of direct, practical value to FinTech product, marketing, and compliance teams seeking to close the gap between ML adoption and ML awareness among their user base.

1.1 Importance of the Study

As ML adoption within FinTech accelerates, the ability to distinguish genuine user understanding from passive, unreflective usage becomes commercially significant. Product and compliance teams that misjudge the depth of user awareness risk either over-investing in redundant education for already-informed segments or under-investing in segments where trust deficits are large enough to depress engagement and retention. By quantifying awareness and trust as distinct, measurable constructs — rather than treating them as proxies for one another — this study equips FinTech organisations with an evidence base for designing targeted, resource-efficient user-education interventions rather than relying on intuition or industry-wide assumptions.

1.2 Scope of the Study

The study is confined to the measurement and statistical analysis of ML awareness, understanding, and trust among a sample of 101 FinTech app users, examined through demographic variables (age, gender, education, FinTech experience) and usage-based variables (primary purpose of app use). The analytical scope extends across descriptive statistics, hypothesis testing (t-test and ANOVA), Pearson correlation, Markov Chain modelling of trust-tier transitions, and linearprogramming-based prescriptive resource allocation. The study does not extend to a longitudinal or experimental design, nor does it evaluate the technical accuracy of the underlying ML models themselves; its focus is squarely on user perception and its statistically observable determinants. 2. Review of Literature The literature bearing on this study spans three streams: the broader FinTech-innovation literature, the technology-trust and acceptance literature, and the methodological literature underpinning Markov Chain and linear-programming techniques used in the analysis. Table 1 summarises the studies most directly relevant to the present enquiry.

Author(s) & Year	**Objective**	**Key Findings**	**Research Gap**
Gomber, Kauffman, Parker & Weber (2018)	Interpret the forces of FinTech innovation and disruption	FinTech reshapes financial services through data-driven personalisation and platform competition	Limited empirical measurement of end-user awareness of underlying algorithms
Gefen, Karahanna & Straub (2003)	Integrate trust and technology-acceptance models in online commerce	Trust and perceived usefulness jointly determine adoption of online systems	Predates ML-specific FinTech contexts; does not address algorithmic opacity
Ashta & Herrmann (2021)	Review opportunities and risks of AI in banking, investment and microfinance	AI improves efficiency and personalisation but introduces new transparency and risk-perception challenges	Conceptual review; lacks primary survey-based validation of user trust
	Examine effects	Explainability significantly improves perceived trust and acceptance of AI-driven systems	Focused on general AI systems rather than FinTech-specific ML features
	of explainability		
Shin (2021)	and causability		

	on trust and		
	acceptance of AI		
	Develop	Markov Chains effectively model persistence and transition in behavioural states over time	Applied traditionally to workforce planning, not consumer trust states
	stochastic		
Bartholomew,	(Markov Chain)		
Forbes &	techniques for		
McClean (1991)	manpower and		
	behavioural		
	planning		
	Apply linear	LP models identify	Applied to HR training rather than FinTech user-

			education contexts
	programming to	capacity, not budget,	
Taylor & Davis	optimise	as the binding	
(2019)	training-budget	constraint in several	
	allocation in HR	resource-allocation	
	analytics	cases	

Collectively, this literature establishes that FinTech innovation is fundamentally data- and algorithm-driven (Gomber et al., 2018), that trust is a necessary precursor to technology adoption (Gefen et al., 2003), and that explainability meaningfully shapes user trust in AI systems generally (Shin, 2021). However, a clear gap persists: little of this literature directly measures ML awareness as a construct distinct from general FinTech usage or adoption, and fewer studies still combine descriptive, inferential, and prescriptive analytics to translate such measurement into an actionable resource-allocation recommendation. The present study addresses this gap directly.

1.1 Research Gap

Existing research on FinTech and AI trust tends to treat awareness, understanding, and trust as a single undifferentiated construct, or examines them only through qualitative or conceptual lenses. Comparatively little empirical work isolates ML awareness as distinct from usage, tests it against demographic and behavioural segments using formal hypothesis testing, and extends the analysis into stochastic (Markov Chain) and prescriptive (linear-programming)

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territory to generate concrete, resource-constrained recommendations. This study addresses that gap using a primary, quantitatively analysed dataset of FinTech app users.

3. Research Objectives

- To preprocess the FinTech-user survey dataset and perform exploratory data analysis of respondents' demographic and behavioural characteristics.
- To measure the current level of ML Awareness, ML Understanding, and ML Trust among FinTech app users using validated Likert-scale items.
- To examine whether ML Trust and ML Understanding differ significantly across demographic and usage- based segments (gender, education, FinTech experience, and primary purpose of app usage).
- To statistically test the relationship between ML Awareness and perceived Data Security.
- To model user movement between Low, Medium, and High ML Trust states using Markov Chain analysis.
- To apply prescriptive analytics (linear programming) to recommend an optimal allocation of a limited ML-education budget across user segments.
- To provide data-driven, practical recommendations to help FinTech companies improve ML awareness, build user trust, and enhance overall app engagement.

4. Research Methodology

This study adopts a descriptive research design with a quantitative approach. Primary data were collected from 101 FinTech app users through a structured Google Form questionnaire administered online between December 2025 and early 2026. The questionnaire captured demographic information (age, gender, education level, FinTech experience) and usage information (primary purpose of app use), together with nine Likert-scale statements (Strongly Disagree to Strongly Agree, mapped to a 1–5 numeric scale) measuring ML Awareness, ML Understanding, ML Difference, ML Trust, Data Security perception, Algorithm Fairness perception, and three concern-related dimensions (financial loss, data security, and automation risk).

The dataset, exported to Microsoft Excel, was found to be fully complete across all 101 respondent records and 16 fields, requiring no imputation. Likert-text responses were mapped to a numeric 1–5 scale, and the Experience and Education columns were treated as ordered categorical variables to preserve meaningful sequencing in visual and statistical comparisons. Custom (non-quantile) bin edges were used to segment respondents into Low, Medium, and High Trust and Awareness tiers, since the underlying distributions were heavily concentrated at the low end of the scale, making standard tercile-based binning infeasible.

All analysis was performed in Python (Jupyter Notebook) using pandas and NumPy for data manipulation, Matplotlib and Seaborn for visualisation, SciPy for independent-samples t-tests, one-way ANOVA, and Pearson correlation ($\alpha = 0.05$ throughout), and scipy.optimize.linprog (HiGHS solver) for the linear-programming prescriptive model. Markov Chain transition probabilities were estimated empirically from the observed distribution of respondents across trust tiers, consistent with established stochastic manpower-planning methodology.

5. Data Analysis and Interpretation

5.1 Demographic Profile of Respondents

The demographic profile of the 101 respondents provides essential context for interpreting the ML-perception results that follow. The sample skews notably young, is fairly balanced by gender, and is dominated by Investing as the primary purpose of FinTech app usage.

Table 2: Age-wise Distribution of Respondents

Age Group	Frequency	Percentage (%)
Below 25	57	56.4
25–34	24	23.8
35–44	18	17.8
18–24 (other coding)	1	1.0
45 and Above	1	1.0

Total	**101**	**100.0**

Table 3: Gender-wise Distribution of Respondents

Gender	Frequency	Percentage (%)
Male	**53**	**52.5**
Female	**48**	**47.5**
Total	**101**	**100.0**

Table 4: Education-wise Distribution of Respondents

Education Level	Frequency	Percentage (%)
Undergraduate	**47**	**46.5**
Working Professional	**32**	**31.7**
Postgraduate	**19**	**18.8**
Other	**3**	**3.0**
Total	**101**	**100.0**

Table 5: Primary Purpose-wise Distribution of Respondents

Primary Purpose	Frequency	Percentage (%)
Investing	**70**	**69.3**
Payments	**13**	**12.9**
Copy-Trading	**12**	**11.9**
Saving/Budgeting	**6**	**5.9**
Total	**101**	**100.0**

Interpretation: Over 80% of respondents fall below the age of 35, and Investing dominates as the primary purpose of app usage (69.3%), far outweighing Payments, Copy-Trading, and Saving/Budgeting combined. This concentration means that findings tied to Primary Purpose are heavily influenced by the behaviour of Investing users, and any ML-education strategy must prioritise this segment to reach the majority of the user base.

1.1 Descriptive Statistics of ML-Perception Variables

Table 6: Descriptive Statistics of ML Perception Variables (1–5 Likert Scale)

Variable	Mean	Std. Dev.	Min	Max
ML Awareness	**1.39**	**1.00**	**1**	**5**
ML Understanding	**3.10**	**1.51**	**1**	**5**
ML Difference	**1.35**	**0.92**	**1**	**5**
ML Trust	**1.48**	**1.14**	**1**	**5**
Data Security	1.33	0.85	1	5
Algorithm Fairness	1.51	1.22	1	5
Concern – Financial Loss	1.38	1.05	1	5
Concern – Data Security	1.37	0.95	1	5
Risk – Trust Automation	1.38	1.02	1	5

Interpretation: On a 1–5 scale where 3 represents the neutral midpoint, every ML-perception variable except ML Understanding (mean 3.10) sits well below neutral, in the 1.33–1.51 range. Respondents, on average, actively disagree that they are aware of ML usage, that they can distinguish ML from manual suggestions, and that they trust ML-generated recommendations, while simultaneously reporting a comparatively higher — if still moderate — sense of understanding how the app's features work. The three concern items (financial loss, data security, automation risk) are also low, indicating that the dominant pattern is one of low engagement with the ML dimension of the app rather than active anxiety about it.

5.2 Hypothesis Testing

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Five hypotheses were tested at a 5% level of significance (α = 0.05) to examine whether ML Trust and ML Understanding differ meaningfully across demographic and usage-based segments, and whether ML Awareness is significantly related to perceived Data Security.

Table 7: Summary of Hypothesis Testing Results

#	Hypothesis	Test Used	Statistic	P-value	Result
1	ML Trust vs. Gender	Welch's t-test	t = -0.552	0.582	Not Significant
2	ML Understanding vs. Experience	One-way ANOVA	F = 0.099	0.961	Not Significant
3	ML Trust vs. Primary Purpose	One-way ANOVA	F = 9.215	0.00002	Significant
4	ML Awareness vs. Data Security	Pearson r	r = 0.533	0.00000	Significant
5	ML Trust vs. Education Level	One-way ANOVA	F = 8.700	0.00004	Significant

H1 – ML Trust by Gender: Male respondents (n=53) reported a mean ML Trust of 1.415 against 1.542 for female respondents (n=48). Welch's t-test produced t = -0.552, p = 0.582, indicating no statistically significant gender difference; gender-specific trust-building campaigns are therefore not a priority relative to other segments.

H2 – ML Understanding by Experience: One-way ANOVA across the four FinTech-experience bands produced F = 0.099, p = 0.961 — a flat, non-significant result confirming that longer FinTech tenure alone does not translate into deeper ML understanding; passive exposure is not a substitute for active education.

H3 – ML Trust by Primary Purpose: ANOVA produced F = 9.215, p = 0.00002, a highly significant result. Investing users reported by far the lowest mean ML Trust (1.129), against 2.154 for Payments, 2.167 for Copy-Trading, and 2.667 for Saving/Budgeting users. Because Investing is also the largest segment (70 of 101 respondents), this is the single most actionable finding of the hypothesis-testing chapter.

H4 – ML Awareness and Data Security Correlation: A Pearson correlation of r = 0.533 (p < 0.00001) confirmed a moderate, statistically significant positive relationship between ML Awareness and perceived Data Security, suggesting that awareness-building and security-messaging initiatives are likely to reinforce one another.

H5 – ML Trust by Education Level: ANOVA produced F = 8.700, p = 0.00004, again highly significant, confirming that — alongside Primary Purpose — Education Level is one of the two variables most strongly associated with ML Trust in this sample, rather than Gender or Experience.

1.1 Markov Chain Analysis of ML Trust Transitions

To examine how ML Trust might evolve across successive engagement periods, respondents were segmented into Low, Medium, and High Trust tiers using custom bin edges [0, 2, 3.5, 5], and one-step transition probabilities were estimated empirically from the observed tier distribution.

Table 8: ML Trust Tier Distribution

Trust Tier	Number of Respondents	Percentage (%)
Low_Trust	90	89.1
Medium_Trust	1	1.0
High_Trust	10	9.9

Table 9: ML Trust Tier Transition Probability Matrix

From \ To	Low_Trust	Medium_Trust	High_Trust
Low_Trust	0.9967	0.0033	0.0000
Medium_Trust	0.8710	0.0323	0.0968
High_Trust	0.0000	0.0291	0.9709

Interpretation: The transition matrix reveals a strongly “sticky” structure at both extremes: Low_Trust shows 99.67% one-step persistence, and High_Trust shows 97.09% persistence, while the small Medium_Trust tier is highly unstable, with an 87.10% probability of falling back to Low_Trust against only a 9.68% probability of advancing to High_Trust. This indicates that ML trust, once formed, is difficult to shift through ordinary usage alone; interventions must be front-loaded early in the user journey, before trust perceptions harden into the persistent Low_Trust state.

5.3 Prescriptive Analytics: Linear Programming for ML-Education Budget Allocation

A linear-programming model was formulated to determine the optimal allocation of a fixed ML-education outreach budget (Rs 50,000) and content/trainer capacity (200 hours, at 4 hours per enrolled user) across the four primary-purpose segments, so as to maximise the total gain in ML Awareness.

Table 10: Decision Variables and Segment Data

Segment	Cost per User (Rs)	Max Eligible Users	Awareness Gain per User
Investing	500	40	0.8
Payments	400	30	0.6
Copy-Trading	450	20	1.0
Saving/Budgeting	350	25	0.7

Objective Function: Maximise $Z = 0.8x_1 + 0.6x_2 + 1.0x_3 + 0.7x_4$, subject to the budget constraint ($500x_1 + 400x_2 + 450x_3 + 350x_4 \leq 50{,}000$), the capacity constraint ($4x_1 + 4x_2 + 4x_3 + 4x_4 \leq 200$), segment eligibility caps, and non-negativity.

Table 11: Optimal Solution (scipy.optimize.linprog, HiGHS solver)

Segment	Optimal Enrolment (Users)
Investing	30
Payments	0
Copy-Trading	20
Saving/Budgeting	0

Interpretation: The optimal solution enrols 30 Investing users and 20 Copy-Trading users, fully exhausting the 200-hour content/trainer capacity while using only Rs 24,000 of the Rs 50,000 budget, for a maximum ML Awareness gain of 44.00 points. Content/trainer capacity, not budget, is therefore the binding constraint on the scale of the ML-education programme, indicating that FinTech firms should prioritise expanding reusable, semi-automated education content over simply requesting a larger budget.

Results and Discussion

Taken together, the descriptive, inferential, stochastic, and prescriptive findings converge on a consistent narrative: FinTech users in this sample are active, engaged app users who nonetheless remain largely unaware that machine learning drives many of the features they interact with daily. This Awareness-Usage Gap is not evenly distributed — it is concentrated among Investing users, the platform's largest and commercially most significant segment, and is statistically unrelated to gender or tenure, meaning that broad, undifferentiated education campaigns are unlikely to be efficient.

These findings align with the technology-acceptance literature's long-standing emphasis on trust as a precondition for adoption (Gefen et al., 2003) and with more recent work linking explainability directly to AI trust and acceptance (Shin, 2021): the low ML Understanding-Trust correlation observed here (moderate, not strong) suggests that comprehension of app features alone is not sufficient to build confidence in the ML mechanism specifically. Where this study extends the literature is in its use of Markov Chain modelling to show that trust states, once established, are strongly self-reinforcing — a finding with direct managerial implications for the timing, not just the content, of ML-education interventions. The linear-programming results further extend the FinTech-analytics literature (cf. Taylor & Davis, 2019) by demonstrating that capacity, rather than budget, is frequently the binding operational constraint in resource-allocation problems of this kind, a nuance easily missed without formal optimisation.

From a Business Analytics and FinTech industry perspective, these results carry clear managerial implications: product and compliance teams should treat ML-awareness measurement as a recurring diagnostic (not a one-time exercise), design interventions around purpose-of-use and education-level segments rather than demographic proxies like gender or age, and prioritise capacity-building in content development over simply expanding education budgets.

Findings

- The survey dataset was fully complete across all 101 respondents and 16 fields, with a young (56.4% below 25), Investing-dominated (69.3%) respondent base, 59.4% of whom have less than one year of FinTech experience.
- Average ML Awareness (1.39/5) and ML Trust (1.48/5) are both far below the neutral midpoint, while ML Understanding (3.10/5) is comparatively higher, revealing an internally inconsistent Awareness-Usage Gap.
- Gender and FinTech tenure/experience are not statistically significant drivers of ML Trust or Understanding ($p = 0.582$ and $p = 0.961$ respectively).
- Primary Purpose and Education Level are both statistically significant drivers of ML Trust ($p = 0.00002$ and $p = 0.00004$ respectively), with Investing users reporting the lowest trust (mean 1.129) of any segment.
- ML Awareness and perceived Data Security are moderately, significantly, and positively correlated ($r= 0.533$, $p < 0.00001$).
- Markov Chain analysis shows 89.1% of respondents in the Low_Trust tier, with both Low_Trust (99.67%) and High_Trust (97.09%) states highly persistent, while the Medium_Trust tier is unstable and prone to regressing to Low_Trust.
- The linear-programming prescriptive model identifies content/trainer-hour capacity, not budget, as the binding constraint on ML-education programme scale, with an optimal enrolment of 30 Investing and 20 Copy-Trading users yielding a maximum awareness gain of 44.00 points.
- Concern about financial loss, data security, and automation risk remain low (~1.37–1.38) across all age groups, indicating low engagement rather than active anxiety as the dominant issue.

Recommendations

- Prioritise Investing users for ML-education campaigns, as they represent both the largest user segment and the segment with the lowest ML Trust.
- Introduce in-app ML-transparency cues (e.g., a simple "Powered by ML" label or short explainer tooltip) to directly close the identified awareness gap.
- Design education content around Primary Purpose and Education Level segments rather than gender or age, given the statistically significant and non-significant relationships identified respectively.
- Invest in expanding content-development and trainer capacity ahead of requesting additional budget, since capacity — not budget — is the binding constraint identified by the LP model.
- Intervene early in the user journey, before trust perceptions harden, given the strong persistence of both Low- and High-Trust states identified by the Markov Chain analysis.
- Bundle ML-awareness messaging with data-security communication, given the significant positive correlation between the two constructs.
- Track ML Awareness and Trust Tier metrics on a recurring basis (e.g., quarterly in-app micro-surveys) to monitor the effectiveness of interventions over time.
- Use plain-language, non-technical explainer content rather than assuming technical literacy alone drives trust, since Understanding and Trust are only moderately correlated.

Limitations of the Study

The statistical tests employed are correlational rather than causal; the significant association between ML Awareness and Data Security, for instance, cannot confirm that raising awareness will causally improve perceived security without a controlled before/after intervention design. The sample of 101 respondents, drawn predominantly from young, Investing-focused users, may not generalise to FinTech user populations with a materially different demographic or usage composition. The Markov Chain transition probabilities are estimated from a single cross-sectional snapshot rather than genuine longitudinal panel data, and should therefore be interpreted as an illustrative rather than a definitively validated behavioural model.

Future Scope

Future research could extend this study through a longitudinal panel design that tracks the same respondents' ML Trust and Awareness scores across multiple periods, allowing the Markov Chain transition probabilities to be empirically validated rather than estimated from a cross-section. Comparative studies across different FinTech platforms, geographies, or age cohorts would help establish the generalisability of the Investing-segment trust deficit identified here. Future work could also incorporate experimental (A/B-tested) ML-education interventions to establish causal, rather than correlational, evidence of their effect on awareness and trust.

Conclusion

This study set out to measure and analyse the level of Machine Learning awareness, understanding, and trust among FinTech app users, and to identify the factors shaping user engagement with ML-powered financial recommendations. The analysis reveals a striking Awareness-Usage Gap: users actively and routinely engage with ML-driven FinTech features while remaining largely unaware of, and distrustful toward, the underlying technology. This gap is statistically unrelated to gender or tenure but is strongly and significantly associated with Primary Purpose and Education Level, with Investing users — the platform's largest segment — showing the weakest trust of any group.

Markov Chain analysis adds an important temporal dimension, showing that ML trust, once formed in either direction, is highly persistent and unlikely to shift through ordinary continued usage alone. Prescriptive optimisation translates these findings into a concrete, resource-constrained recommendation: given a fixed education budget and content-development capacity, FinTech firms should prioritise Investing and Copy-Trading users, since capacity rather than budget is the true limiting factor on programme scale.

In conclusion, closing the gap between ML adoption and ML awareness in FinTech applications requires deliberate, early-stage, segment-specific intervention rather than reliance on passive, tenure-based exposure. With targeted transparency measures, purpose-specific education, and combined awareness-security messaging, FinTech platforms can convert passive ML usage into informed, confident, and sustained user engagement.

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