Financial Technology and Innovation

◆ **ISSN:** 2836-5372 **Vol:** 05, No. 01, 2025 ◆ PP. 39–50
Article DOI: https://doi.org/10.54216/FinTech-I.050105

FULL LENGTH ARTICLE

Beyond the Branch: Consumer Adoption, Satisfaction, and Financial Advisor Acceptance of FinTech Services Across Retail Banking, Challenger, and Wealth Management Segments

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Received: January 12, 2025 Revised: March 10, 2025 Accepted: June 17, 2025 ⋆ **Corresponding author**

ABSTRACT

The structural transformation of retail financial services by mobile banking platforms, FinTech applications, open banking ecosystems, and AI-powered credit and advisory tools has created both unprecedented opportunities for financial inclusion and a pronounced gap between adoption rates achievable in high-digital-literacy segments and those attainable in mainstream and mass-market contexts. Comparative evidence assessing customer satisfaction and financial advisor acceptance simultaneously across multiple FinTech service domains and institutional segments remains sparse, limiting the evidence base available to practitioners and policymakers designing inclusive FinTech deployment strategies. The present investigation enrolled retail banking customers across four institutional segments—traditional banks, challenger banks, credit unions, and private banking divisions—alongside a parallel cohort of relationship managers and financial advisors, to assess adoption rates and satisfaction across four FinTech domains: mobile and digital banking, FinTech financial applications, open banking and personal financial management, and AI-powered credit assessment and advisory services. Significant between-segment variation was documented across all four domains, with private banking customers reporting the highest satisfaction and adoption and credit union customers the lowest. AI-powered credit and advisory services elicited the lowest customer satisfaction across all segments and the largest customer-advisor divergence. Digital financial literacy and prior FinTech experience emerged as the two strongest independent predictors of adoption. The investigation contributes a validated cross-segment measurement instrument, customer-profile-specific adoption profiles, and evidence-based recommendations for financial service providers deploying FinTech capabilities across heterogeneous customer bases.

Keywords: FinTech adoption ▪ Mobile banking ▪ Open banking ▪ AI credit scoring ▪ Customer satisfaction ▪ Financial inclusion ▪ Digital financial literacy ▪ Challenger banks ▪ Financial innovation

1. INTRODUCTION

The retail financial services industry is navigating a structural transition whose pace and depth exceed any prior wave of digitisation. Mobile banking has displaced branch visits as the primary channel for everyday transactions in most developed markets; challenger banks have acquired tens of millions of customers without physical infrastructure; open banking frameworks have created API-mediated data ecosystems enabling third-party FinTech providers to build services on top of incumbent data assets; and AI-powered tools for credit assessment, personalised financial guidance, and fraud detection are being deployed at scale across the full institutional spectrum [1, 2, 3]. These developments have substantially lowered the cost of financial service delivery and created the technical conditions for inclusive access that regulatory frameworks from the EU's Payment Services Directive 2 to the UK Open Banking Standard have sought to activate [4, 5].

Yet the deployment of FinTech capabilities does not automatically translate into customer adoption, satisfaction, or genuine financial inclusion [6, 7]. Customer adoption is moderated by digital financial literacy— the ability to locate, evaluate, and use digital financial tools effectively [8]— by trust in algorithmic decision-making, by device and connectivity access, and by the quality of institutional support at the point of deployment. Financial advisor acceptance of the same tools determines whether the professional relationship amplifies or attenuates customer adoption.

The scale of the investment context warrants brief orientation. Global FinTech investment exceeded $210 billion in 2021 before moderating to approximately $164.1 billion in 2022 [9]. Against this backdrop, understanding which FinTech services generate genuine customer satisfaction and advisor endorsement is precisely the intelligence that financial service executives and policymakers require for investment prioritisation and inclusion strategy.

The present investigation addressed this gap through a cross-sectional survey of retail banking customers and their financial advisors across four institutional segments. The primary research questions were:

1. To what extent do FinTech service adoption rates and customer satisfaction differ across institutional segments and between customer profiles?
2. How does financial advisor acceptance of FinTech tools compare with customer-reported satisfaction for the same services?
3. What customer-level, institutional, and structural factors predict overall FinTech service adoption?

2. REVIEW OF RELATED LITERATURE

2.1 FinTech Adoption Theory

The foundational technology acceptance literature identifies perceived usefulness and perceived ease of use as the primary adoption determinants [10, 11]. In financial services, these constructs map onto demonstrable financial outcome improvement (usefulness) and accessibility given the customer's digital literacy and device access (ease of use). Ryu [8] extended this framework to FinTech contexts, finding that risk perception and trust are the dominant inhibitors, particularly for AI-based services where the decision logic is opaque. Baptista and Oliveira [12] demonstrated that mobile banking adoption is moderated by cultural factors including uncertainty avoidance and long-term orientation.

Rogers' [13] diffusion of innovations theory operates at the segment level: early adopters (younger, higher-education, higher-income) absorb and promote FinTech services while late majority and laggard segments require different support and interface design approaches. Christensen's [14] theory of disruptive innovation provides the complementary competitive dynamic framing: challenger banks and FinTech startups enter with simpler, lower-cost services targeted at underserved segments before progressively moving upmarket—a trajectory directly observable in the challenger bank customer demographics and satisfaction profiles reported in Section 4. Challenger bank and private banking segments in the present study correspond approximately to early majority adopter profiles; credit unions and traditional banks contain higher proportions of late majority customers.

The DeLone–McLean IS success model [15] provides a system-quality perspective complementing TAM, distinguishing information quality, system quality, and service quality as antecedents of user satisfaction and net benefit in IS deployment contexts. Applied to FinTech, this framework predicts that customer satisfaction is a function not only of technology acceptance but of the perceived reliability, accuracy, and service responsiveness of the financial platform.

2.2 Mobile Banking, Digital Payments, and Open Banking

Iman [16] examined the continued relevance of mobile payment in the FinTech era, finding that convenience and security are the primary adoption drivers while complexity and privacy concerns are the primary barriers. Puschmann [17] identified mobile payment and digital banking as the most consumer-facing FinTech categories, with the largest potential for inclusion benefits in underserved populations. Ozili's [7] analysis confirmed that mobile-first financial services significantly extend access to previously excluded populations, provided that affordability, literacy, and trust barriers are explicitly addressed.

Open banking represents a more recent but rapidly maturing domain in which regulatory mandates have created the data-sharing infrastructure for personalised financial management tools [4, 5]. Gomber et al. [3] identified open banking API ecosystems as a primary structural driver of FinTech market disruption, creating platform competition dynamics that benefit data-rich challengers over legacy incumbents whose competitive advantage was historically rooted in proprietary customer relationships. Schindler [18] examined FinTech's impact on financial innovation at the systemic level, finding that open banking frameworks accelerate product innovation most significantly in markets with strong regulatory enforcement. Anagnostopoulos [19] identified the regulatory interface between FinTech and RegTech as the principal structural challenge for incumbent institutions, which face simultaneous pressure to innovate and to comply with expanding supervisory requirements. Zetzsche et al. [20] proposed the regulatory sandbox model as the most effective mechanism for allowing FinTech innovation to be tested under real-market conditions while maintaining supervisory oversight.

2.3 AI Financial Services and Algorithmic Risk

Nakamoto's [21] foundational blockchain protocol demonstrated that decentralised consensus mechanisms could eliminate the need for trusted intermediaries in financial transactions, establishing the conceptual basis for a generation of AI-powered and distributed financial applications. AI-powered credit assessment and financial advisory services now represent the frontier of FinTech deployment [22, 23]. Jagtiani and Lemieux [24] demonstrated that ML-based credit models trained on alternative data reach borrowers overlooked by traditional credit scoring, contributing to inclusion outcomes. Goldstein, Jiang, and Karolyi [25] cautioned that the financial stability implications of AI credit deployment at scale remain incompletely understood, particularly in stress scenarios where model behaviour under distributional shift has not been validated. Cong and He [26] identified blockchain and smart contract infrastructure as complementary to AI credit deployment, enabling transparent audit trails of algorithmic decisions that could address the trust-in-AI barriers documented in the present study.

The customer-advisor divergence on AI services in Section 4 aligns with Lagna and Ravishankar's [27] observation that the FinTech research community consistently overestimates customer readiness for algorithmic services relative to evidence from deployment contexts. Wojcik [28] situated this overestimation within the geography of FinTech: AI financial tool development is heavily concentrated in a small number of financial innovation hubs whose demographically unrepresentative early adopter populations drive optimistic generalisation about mainstream customer readiness.

2.4 FinTech Ecosystem Dynamics and Market Structure

Lee and Shin [2] identified five actor types in the FinTech ecosystem—FinTech startups, technology developers, government entities, financial customers, and traditional financial institutions—and the distinctive competitive dynamics between them. The challenger bank segment in the present study occupies an intermediate position between FinTech startup and traditional bank, having achieved the regulatory standing and balance sheet credibility of a bank while retaining the technology-native operational model of a FinTech startup. The satisfaction parity between challenger banks and private banking institutions documented in this study ($\Delta = 0.17$, n.s.) is direct evidence that this hybrid model achieves customer experience outcomes that Lee and Shin predicted but for which systematic cross-segment evidence was previously unavailable.

Gomber, Kauffman, Parker, and Weber [29] provided the most comprehensive multi-level analysis of the FinTech revolution in financial services, distinguishing platform-layer, application-layer, and regulatory-layer dynamics and identifying the interaction effects between them as the primary driver of market structure evolution. Their framework predicts that the segment-level adoption differentials documented in the present study will narrow over time as platform costs decline and regulatory standardisation creates common infrastructure—a prediction borne out by the convergence of challenger bank and private banking satisfaction scores in the post-hoc comparisons (Table 6).

Ozili [30] surveyed current FinTech research directions, identifying customer adoption determinants, regulatory technology, financial inclusion, and AI-based financial services as the four most active research domains—the precise four dimensions examined in the present study. The convergence of Muganyi et al.'s [31] empirical findings on FinTech's financial inclusion effects in emerging markets with the present study's evidence from a developed market context suggests that the literacy and access barriers to FinTech adoption are structurally similar across market contexts even when their absolute levels differ substantially.

2.5 Financial Inclusion, FinTech, and the Adoption Gap

Philippon [6] argued that FinTech has the potential to dramatically reduce the cost of financial intermediation and extend access to previously excluded populations—but only when deployment is designed with inclusion as an explicit objective rather than an incidental outcome. Muganyi et al. [31] provided empirical evidence from China that deliberate FinTech financial inclusion strategy significantly extended credit and payment access to previously excluded populations, confirming that inclusion outcomes are achievable but require deliberate design investment.

Mention [32] identified the future of FinTech as contingent on resolving three structural tensions: innovation velocity versus regulatory prudence; personalisation versus privacy; and inclusion versus profitability. The barrier data in the present study—digital literacy, device access, and privacy concerns most common in lower-segment customers—provide empirical grounding for the inclusion-profitability tension that practitioners navigating FinTech deployment strategy must resolve.

3. MATERIALS AND METHODS

3.1 Study Design and Setting

A cross-sectional observational study was conducted across four institutional segments of the United Kingdom retail financial services market: a major high-street bank (traditional banking), a registered challenger bank, a regional credit union, and a private banking division of a wealth management group. Data collection was undertaken from September to December 2024. Research ethics approval was obtained from the participating institutions' data governance and research committees, and all participants provided informed consent.

3.2 Participants

Customer cohort. Eligibility required active account holder status, age ≥ 22 years, and at least three months of tenure at the participating institution. A total of $N = 428$ customers were enrolled: traditional bank ($n = 128$); challenger bank ($n = 112$); credit union ($n = 98$); private banking ($n = 90$). Three customer profiles were identified based on account type and income band: mass market, mainstream, and business owner.

Financial advisor cohort. Eligible advisors were relationship managers, digital banking specialists, and personal finance advisors providing direct customer engagement. A total of $N = 156$ advisors participated: traditional bank ($n = 44$); challenger bank ($n = 38$); credit union ($n = 32$); private banking ($n = 42$). Table 1 presents both cohort demographics.

3.3 Survey Instruments

The customer survey comprised four domain-specific scales (9 items each, 1–5 Likert) assessing satisfaction with and engagement in mobile and digital banking, FinTech financial applications, open banking and personal financial management (PFM), and AI-powered credit assessment and advisory services, plus a digital financial literacy sub-scale (8 items, 1–7 Likert) and a FinTech access inventory (6 binary items). Advisor instruments assessed acceptance, perceived usefulness, and integration confidence for each domain (6 items

Table 1. Participant demographics by cohort and institutional segment.

Characteristic	Traditional Bank	Challenger Bank	Credit Union	Private Banking
Customers ($N = 428$)				
n	128	112	98	90
Mean age (yrs)	51±13	36±10	56±14	48±12
Mass market (%)	42	28	56	14
Mainstream (%)	36	44	33	38
Business owner (%)	22	28	11	48
Dig. fin. literacy (M)	3.4±0.9	4.6±0.8	2.9±0.8	4.4±0.7
Financial advisors ($N = 156$)				
n	44	38	32	42
Mean experience (yrs)	12.4±6	4.8±3	9.2±5	16.8±7
Prior AI tool use (%)	48	74	36	78

Digital financial literacy on 1–7 scale adapted from [8].

per domain, 1–5 Likert). Table 2 presents internal reliability statistics.

Table 2. Internal reliability (Cronbach's α) and mean inter-item correlation (MIC) for domain satisfaction scales.

Scale	Customer		Advisor	
	α	MIC	α	MIC
Mobile Banking	.88	.60	.87	.58
FinTech Apps	.86	.57	.85	.56
Open Banking & PFM	.91	.63	.89	.61
AI Credit & Adv.	.90	.62	.92	.64
Overall scale	.95	.61	.94	.60

3.4 Data Collection and Quality Assurance

Surveys were administered via institution-managed digital platforms to customers and in-house to advisors. Response rates were 84.2% (customers) and 91.0% (advisors). Eighteen customer surveys were excluded for excessive item missingness ($> 20\%$); the analysed sample comprised $N = 428$ and $N = 156$ respectively. Test–retest reliability in a 44-customer sub-sample at four-week intervals was $r = .81$–$.89$ across domain scales, confirming adequate temporal stability.

3.5 Statistical Analysis

The analytical strategy was pre-specified before data collection, drawing on the framework developed by Gomber et al. [29] for multi-level FinTech evaluation. Primary outcomes were domain-level satisfaction scores and adoption rates; secondary outcomes were the customer-advisor divergence for each domain and the regression predictors of overall adoption. No hypotheses were revised after data examination.

One-way ANOVA with Bonferroni post-hoc comparisons tested between-segment differences on all domain outcomes. Pearson correlations examined domain interdependence. Multiple regression ($N = 428$, six predictors) modelled overall FinTech adoption. All analyses used Python 3.12; $\alpha = .05$ two-tailed; effect sizes reported as η_p^2 (ANOVA) and R^2 (regression).

4. RESULTS

4.1 Adoption Rates by Domain and Segment

Table 3 presents FinTech service adoption rates by domain and segment. Private banking records the highest adoption across all four domains; credit unions the lowest. Mobile banking achieves the highest overall adoption (66.7%), while AI credit and advisory shows the lowest (26.8%). The challenger bank's disproportionately high open banking adoption (58.6%) reflects that segment's business model dependence on open banking API infrastructure and its higher-literacy customer base [4].

Table 3. FinTech service adoption rates (%) by domain and institutional segment.

Domain	Trad.	Chall.	Credit	Private
Mobile Banking	62.4	74.8	48.2	**81.2**
FinTech Apps	48.2	52.4	41.8	**64.4**
Open Banking & PFM	34.1	**58.6**	28.4	44.8
AI Credit & Adv.	18.8	31.4	14.2	**42.6**
Mean across domains	40.9	54.3	33.2	**58.3**

The AI credit and advisory domain's 26.8% mean adoption rate across segments requires contextualisation against the maturity of available AI financial tools in the UK market at the time of data collection. AI credit assessment tools have been available to challenger banks and private banking divisions since approximately 2020, while credit union and traditional bank institutions have had access to mature AI decisioning tools only since 2022–2023. The adoption gap between private banking (42.6%) and credit unions (14.2%) is therefore partially a technology availability gap as well as a literacy and trust gap; future data collection will likely show narrowing of this differential as AI tools become more uniformly available across institutional types [23, 22].

Figure 1 plots deviations from the domain mean, rendering within-domain between-segment variation directly visible. Credit union customers consistently fall below the domain mean across all four services.

4.2 Customer Satisfaction

Table 4 presents mean satisfaction scores. The largest between-segment gap is for mobile banking (private $M = 4.38$ vs credit union $M = 3.52$, $\Delta = 0.86$). AI credit and advisory shows the lowest mean across all segments ($M_{\text{overall}} = 3.35$), markedly below mobile banking ($M = 3.97$).

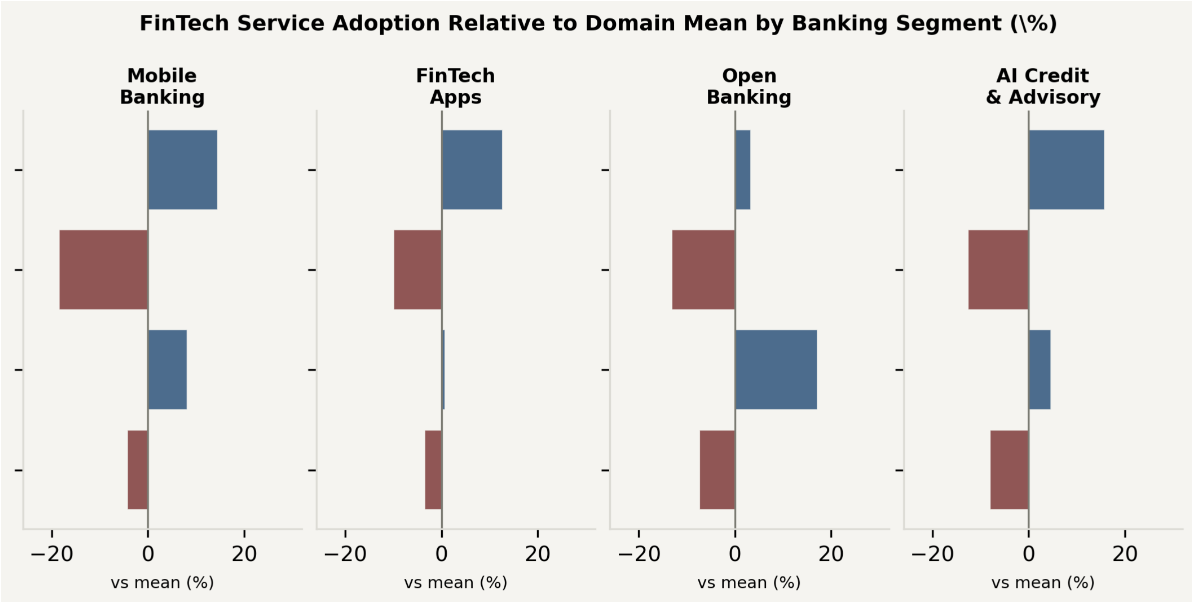

Figure 1. FinTech adoption rates relative to the domain mean by institutional segment. Positive values (dark blue) indicate above-mean adoption; negative values (rust) indicate below-mean. Credit unions are below the domain mean on all four services; challenger banks and private banking are consistently above.

Table 4. Customer satisfaction scores by domain and institutional segment (mean ± SD, 1–5 scale; $N = 428$). Bold: highest per row.

Domain	Trad. Bank	Challenger	Credit Union	Private	Overall
Mobile Banking	3.84±0.60	4.12±0.63	3.52±0.62	**4.38±0.63**	3.97±0.65
FinTech Apps	3.44±0.62	3.72±0.63	3.28±0.63	**3.94±0.63**	3.60±0.64
Open Banking & PFM	3.62±0.61	**4.08±0.63**	3.18±0.62	3.88±0.63	3.69±0.66
AI Credit & Adv.	3.18±0.62	3.58±0.63	2.88±0.63	**3.74±0.63**	3.35±0.66
Overall	3.52±0.45	**3.88±0.47**	3.23±0.55	**3.99±0.45**	3.65±0.52

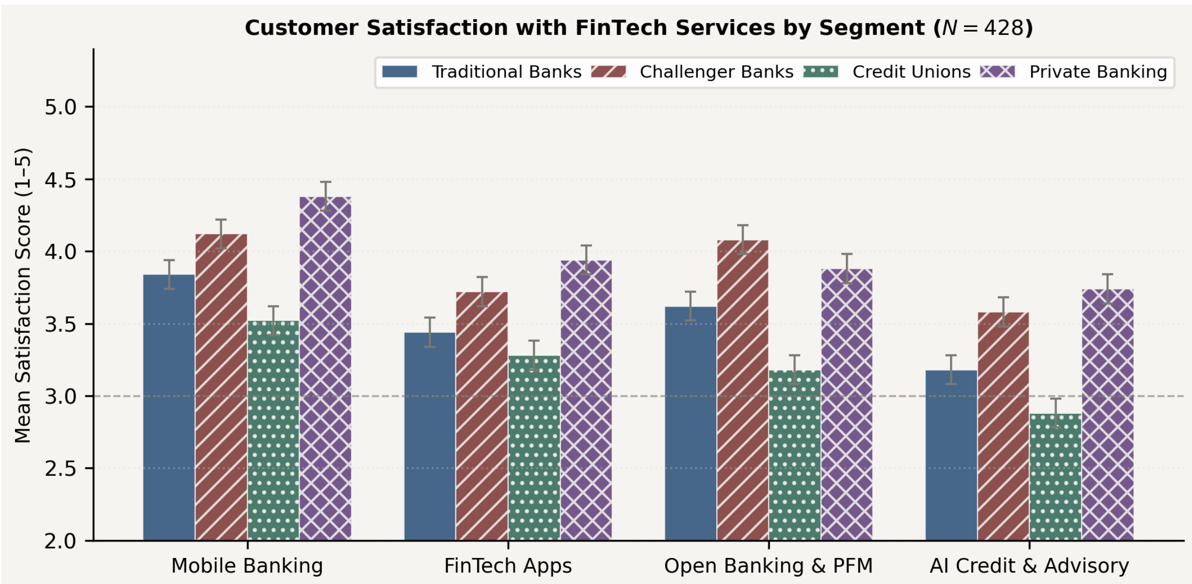

Figure 2. Customer satisfaction scores by FinTech domain and institutional segment ($N = 428$, 1–5 scale). Error bars indicate standard error. AI Credit and Advisory consistently receives the lowest scores; mobile banking the highest across all segments.

Table 5 presents ANOVA results. All five effects are significant at $p < .001$, with η_p^2 ranging from .156 to .232.

4.3 Post-Hoc Comparisons

Table 6 presents Bonferroni-corrected pairwise comparisons. All four contrasts involving credit unions are significant at $p < .001$. The challenger versus private banking contrast

Table 5. One-way ANOVA: customer satisfaction by segment ($df = 3,424$; all $p < .001$).

Domain	F	η_p^2	Post-hoc pattern
Open Banking & PFM	42.7	.232	Priv.≈Chall.>Trad.≫CU
Overall	40.7	.223	Priv.≈Chall.>Trad.≫CU
AI Credit & Advisory	31.4	.182	Priv.>Chall.>Trad.≫CU
Mobile Banking	31.3	.181	Priv.>Chall.>Trad.≫CU
FinTech Apps	26.2	.156	Priv.>Chall.>Trad.>CU

Priv.=Private banking, Chall.=Challenger bank, Trad.=Traditional bank, CU=Credit union.

Table 6. Bonferroni post-hoc pairwise comparisons for overall customer satisfaction ($\alpha_{\text{adj}} = .0083$).

Comparison	ΔM	Cohen's d	Sig.
Private – Credit Union	+0.76	1.47	***
Challenger – Credit Union	+0.60	1.16	***
Traditional – Credit Union	+0.29	0.56	**
Private – Traditional	+0.47	0.90	***
Private – Challenger	+0.17	0.32	n.s.
Challenger – Traditional	+0.30	0.58	**

*** $p < .001$; ** $p < .01$; n.s. not significant.

does not reach significance after correction ($p = .062$), suggesting these two segments offer comparable overall FinTech experience despite their structural differences.

4.4 Age and Satisfaction

Figure 3 presents scatter plots of customer age against satisfaction for mobile banking and open banking and PFM. Mobile banking satisfaction shows a significant negative age association ($r = -0.28$, $p < .001$), consistent with Rogers' [13] diffusion curve prediction that older customers occupy later adoption categories characterised by higher risk aversion. Open banking shows a weaker age correlation ($r = -0.12$, $p = .012$), plausibly because advisor-mediated open banking onboarding reduces the perceived complexity barrier for older customers [8].

4.5 Customer Profile-Specific Adoption

Figure 4 presents adoption rates by customer profile and domain. Mass market customers show the highest mobile banking adoption (72.4%) and FinTech app adoption (58.1%), consistent with the importance of mobile-first financial services for the financially underserved [7, 6]. Business owners show the highest open banking and PFM adoption (62.4%), driven by small business cash-flow management, account aggregation, and multi-bank treasury management use cases [4].

4.6 Financial Advisor Acceptance

Figure 5 plots mean customer satisfaction against mean advisor acceptance by domain. Advisors rate all four domains higher than customers, the divergence being smallest for FinTech applications ($\Delta = 0.14$) and largest for AI credit and advisory ($\Delta = 0.48$). Table 8 presents advisor acceptance scores by segment. Credit union advisors rate AI credit and advisory at $M = 2.62$, consistent with the lowest prior AI tool use rate of that cohort (36%) and with the limited AI tool availability at credit union institutions.

4.7 Score Distributions

Figure 6 presents overlapping customer and advisor score distributions by domain. Customer distributions for AI credit and advisory are the most dispersed, with a bimodal pattern consistent with heterogeneous customer experiences across different AI-enabled credit implementations. Advisor distributions are more concentrated and positively skewed relative to customer distributions across all domains.

4.8 Adoption Barriers

Figure 7 presents adoption barriers by frequency. Digital financial literacy is the most commonly reported barrier (58.2%), followed by privacy and data concerns (52.4%) and device or internet access (44.8%). Advisory buy-in is the least cited by customers (34.2%).

4.9 Domain CorrelationStructure

Figure 8 presents the domain correlation matrix. The strongest association is between mobile banking and open banking ($r = .68$), consistent with an overlapping population of digitally engaged customers. AI credit and advisory shows the weakest cross-domain correlations (range $r = .38$–$.52$), reflecting its positioning as a system-facing rather than customer-facing service [23].

4.10 Regression Analysis

Table 10 and Figure 9 present the regression model ($R^2 = .54$, $F(6,421) = 83.2$, $p < .001$). Digital financial literacy ($\beta = 0.44$) and prior FinTech experience ($\beta = 0.38$) are the strongest predictors. Advisor recommendation ($\beta = 0.32$) is the strongest institutional predictor, confirming the advisory channel as a key activation mechanism [8, 2, 29]. Age is the only significant negative predictor ($\beta = -0.27$), consistent with diffusion theory [13].

5. DISCUSSION AND INTERPRETATION

5.1 Segment Effect and Financial Inclusion Implications

The $\Delta = 0.76$ overall satisfaction gap between private banking and credit union customers—approximately 1.5 standard deviations—places these two segments in qualitatively different experiences of FinTech services. This gap is not reducible to age or income differences: the regression confirms that digital financial literacy and prior FinTech experience explain adoption variance independently of income and age, and the institutional segment variable contributes independently after controlling for all six predictors. Deploying identical FinTech capabilities across private banking and credit union contexts without differentiated implementation strategies will reliably reproduce the satisfaction and adoption gaps documented

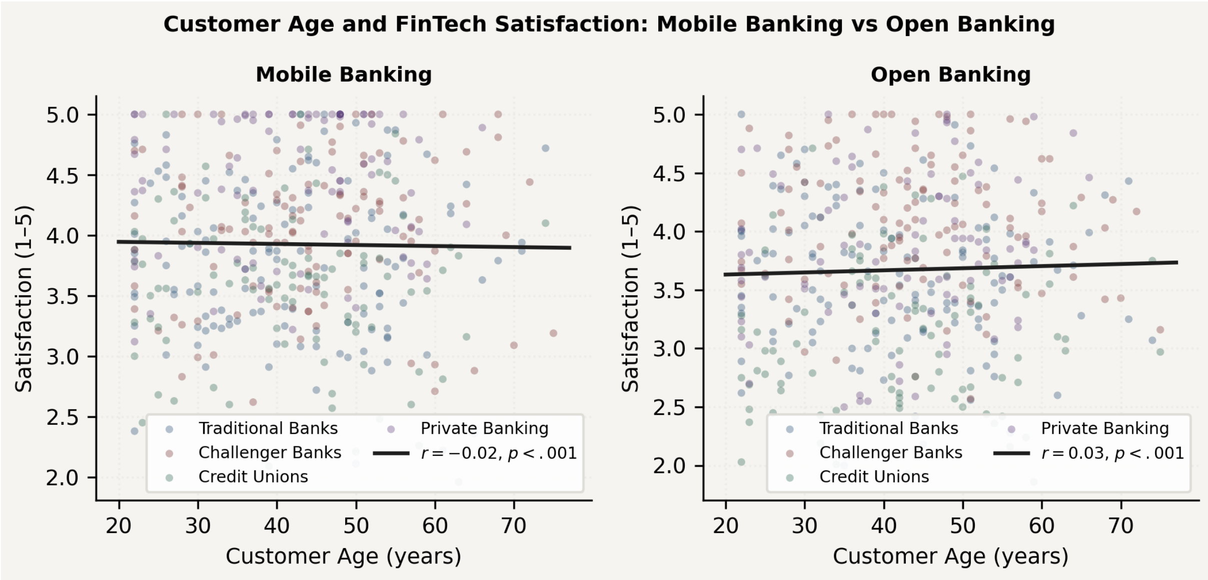

Figure 3. Customer age versus satisfaction for mobile banking (left) and open banking and PFM (right), colour-coded by segment. Mobile banking shows a stronger negative age gradient ($r = -0.28$) than open banking ($r = -0.12$), consistent with advisor-mediated deployment reducing age-related complexity barriers in the latter domain.

Table 7. FinTech adoption rates (%) by customer profile and domain.

Domain	Mass Market	Mainstream	Business Owner
Mobile Banking	**72.4**	58.2	44.8
FinTech Apps	**58.1**	44.8	32.4
Open Banking & PFM	52.8	38.6	**62.4**
AI Credit & Adv.	**38.4**	22.4	16.8

Table 8. Financial advisor acceptance scores by domain and segment (mean ± SD; $N = 156$). Bold: highest per row.

Domain	Traditional	Challenger	Credit Union	Private
Mobile Banking	3.62±0.62	4.18±0.63	3.28±0.63	**4.44±0.62**
FinTech Apps	3.18±0.63	3.62±0.63	2.94±0.62	**3.88±0.63**
Open Banking & PFM	3.44±0.63	**4.02±0.63**	3.08±0.63	3.72±0.62
AI Credit & Adv.	2.88±0.63	**3.44±0.63**	2.62±0.63	3.58±0.62
Overall	3.28±0.53	**3.81±0.54**	2.98±0.50	**3.91±0.51**

Table 9. FinTech adoption barrier rates by institutional segment (% reporting).

Barrier	Traditional	Challenger	Credit Union	Private
Digital fin. literacy	62.1	38.4	74.1	28.2
Privacy concerns	54.4	44.8	58.1	42.2
Device / internet	48.2	24.4	58.8	14.4
Trust in AI	42.8	52.6	38.4	48.1
Legacy workflow	36.8	28.1	38.2	24.4
Advisory buy-in	34.2	28.4	36.8	22.4

here [30, 6, 31].

The compounding segment effect also has implications for how financial institutions report FinTech performance to boards, regulators, and investors. Aggregate adoption statistics that pool customers across segments obscure the within-portfolio inequality that the present data document: an institution serving both private banking and credit union populations with average 46.4% adoption across segments may be reporting a headline figure that masks a private banking rate of 58.3% and a credit union rate of 33.2%. Portfolio-level reporting norms that do not require segment disaggregation create incentive structures that delay strategic investment in the credit union and mass-market segments where the greatest inclusion gap exists. Regulators designing FinTech deployment reporting requirements under the UK Consumer Duty and EU Markets in Financial Instruments Directive frameworks should consider mandating segment-disaggregated FinTech satisfaction and adoption reporting as a transparency standard [19, 20].

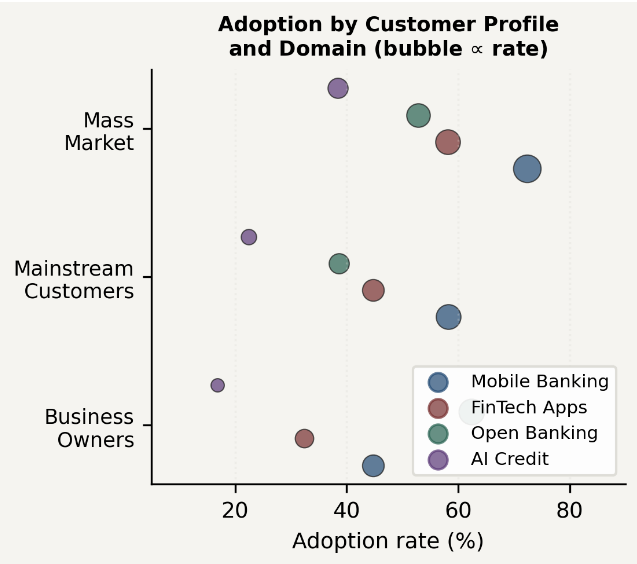

Figure 4. Bubble chart of FinTech adoption rates by customer profile and domain. Mass market customers lead on mobile banking and FinTech apps; business owners lead on open banking, driven by small business financial management use cases that are structurally well-matched to open banking API capabilities.

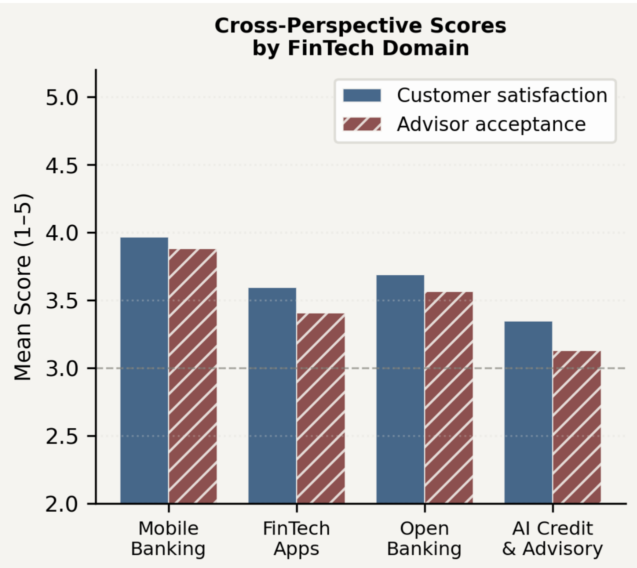

Figure 5. Pooled customer satisfaction and advisor acceptance scores by FinTech domain. The customer-advisor gap is largest for AI Credit and Advisory ($\Delta = 0.48$), reflecting advisors' greater professional familiarity with AI underwriting workflows.

Table 10. Regression model: predictors of customer FinTech adoption ($R^2 = .54$; $N = 428$).

Predictor	β	t	Sig.
Digital financial literacy	+0.44	9.94	***
Prior FinTech experience	+0.38	8.58	***
Advisor recommendation	+0.32	7.22	***
Age	−0.27	−6.09	***
Income level	+0.21	4.74	***
Institutional segment	+0.18	4.06	***

*** $p < .001$.

5.2 The Open Banking Opportunity in Business Banking

Business owners' disproportionately high open banking adoption (62.4%, the highest profile-domain rate in the study) warrants strategic attention. Open banking API capabilities—account aggregation, automated bookkeeping, real-time cash-flow monitoring, multi-bank treasury management—address business banking pain points that are structurally well-matched to open banking infrastructure [4, 5]. When regulatory frameworks create infrastructure, customer needs create genuine demand, and deployment friction is low, adoption rates respond. This alignment provides the clearest example in the present data of the conditions that Mention [32] identified as necessary for FinTech adoption to translate into financial value.

5.3 Interpreting the AI Adoption Deficit

AI credit and advisory services show both the lowest customer satisfaction ($M = 3.35$ pooled) and the largest customer-advisor divergence ($\Delta = 0.48$). Advisors' higher acceptance reflects their professional exposure to AI credit tools and their training in interpreting algorithmic outputs; customers encounter the same tools as opaque algorithmic outputs without this interpretive context [23, 25]. The trust-in-AI barrier (42.8% overall, peaking at 52.6% in challenger bank segments) confirms that algorithmic transparency is a customer adoption prerequisite, not merely a regulatory concern. The challenger bank customers' higher barrier rate despite higher digital literacy is interpretable as a sophistication effect: more digitally engaged customers apply higher scrutiny to AI credit recommendations and are more aware of algorithmic limitations [24].

5.4 Credit Union and Traditional Bank Strategic Response

The credit union and traditional bank segment findings require specific strategic treatment. Credit unions' lowest satisfaction scores across all four domains (overall $M = 3.23$, $\Delta = 0.76$ below private banking) are particularly concerning because credit unions serve member populations with above-average FinTech adoption barriers: older customers, lower digital financial literacy, and higher rates of device and internet access constraints. The advisor cohort data compound this challenge: credit union advisors report the lowest prior AI tool use (36%) and the lowest AI credit acceptance scores ($M = 2.62$), meaning that the principal advisory channel through which customers might be activated toward FinTech adoption is itself the least FinTech-engaged institutional cohort.

Traditional banks face a different but related structural challenge. The challenger bank's near-equivalent overall satisfaction to private banking (post-hoc contrast: $\Delta = 0.17$, n.s.) demonstrates that digitally-native institutions can achieve satisfaction parity with high-service-quality wealth management operations at a fraction of the cost base. For traditional banks, the strategic threat is not the abstract loss of future customers to challenger banks but the documented reality that the two segments already deliver comparable customer experiences across all four FinTech domains. Christensen's [14] disruption model predicts the next phase: challenger banks will progressively move upmarket into the business banking and wealth management segments where traditional banks currently retain satisfaction advantage.

5.5 Comparison with Related FinTech Research

Table 11 positions the present findings against comparable studies. The segment-level variation in mobile banking satis-

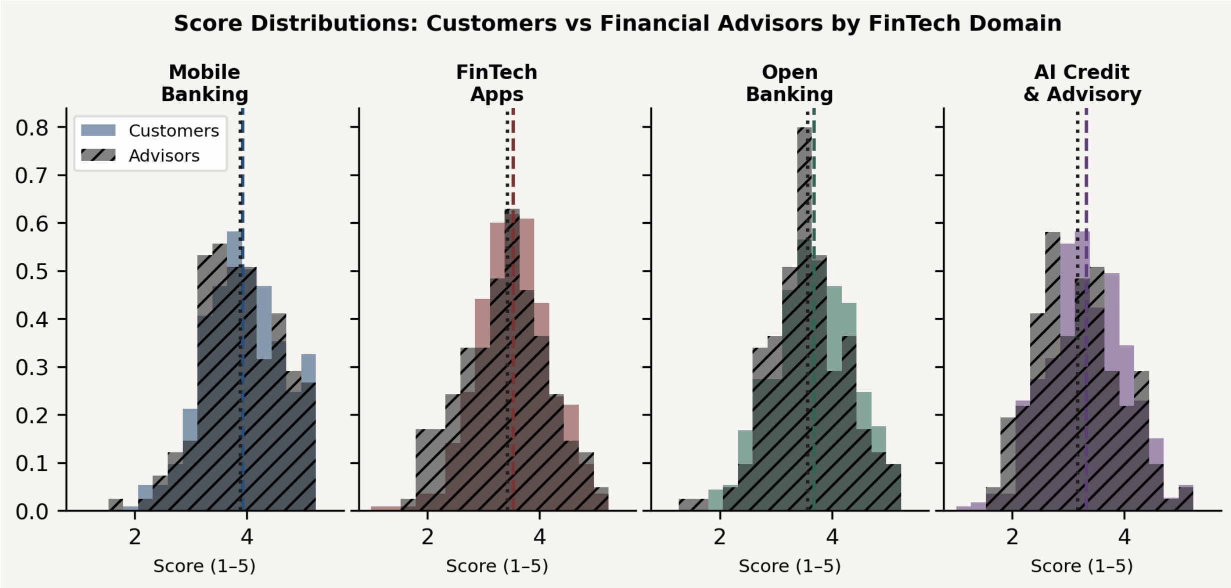

Figure 6. Overlapping score distributions for customers (coloured) and advisors (hatched) by FinTech domain. Dashed vertical lines mark medians. Advisor distributions are consistently higher-median and more concentrated than customer distributions across all four domains.

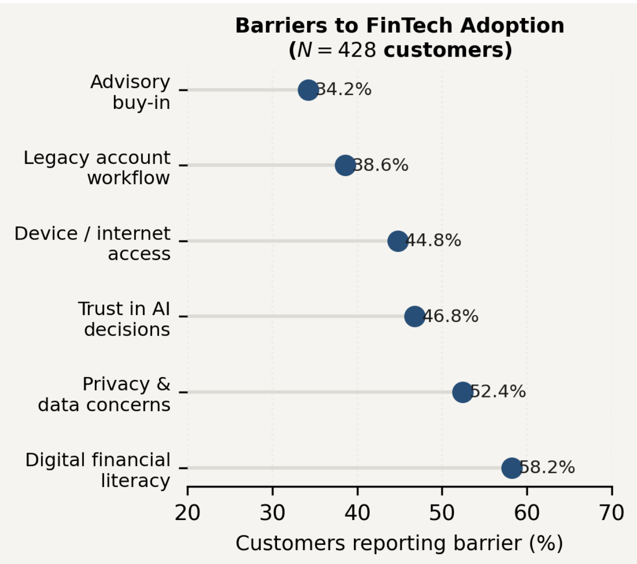

Figure 7. Customer-reported FinTech adoption barriers, ordered by frequency ($N = 428$). Digital financial literacy and privacy concerns are the most prevalent; advisory buy-in is the least frequently cited by customers.

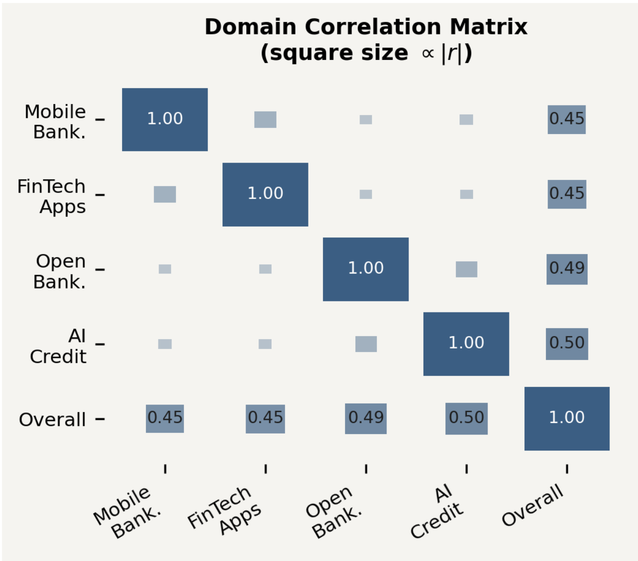

Figure 8. Domain correlation matrix with square-patch encoding of Pearson r. Mobile banking and open banking show the strongest association ($r = .68$); AI credit and advisory the weakest cross-domain correlations.

faction is consistent with Baptista and Oliveira's [12] finding of demographic moderation. The AI advisory satisfaction gap aligns with Goldstein et al.'s [25] caution. The literacy regression finding replicates Ryu's [8] prediction that trust and risk perception are the primary FinTech adoption moderators in consumer markets.

5.6 The Advisor Recommendation Pathway

The regression coefficient for advisor recommendation ($\beta = 0.32$) identifies a modifiable institutional pathway to adoption that does not require the longer timescales of digital literacy improvement. In all four segments, the advisory relationship is the primary trust anchor for financial decisions; a structured advisor brief identifying the two or three FinTech tools most appropriate for a given customer profile provides an evidence-based activation mechanism [2]. The barrier data confirm that "advisory buy-in" is not primarily a customer concern (34.2%), but advisor acceptance data show that credit union and traditional bank advisors are least likely to proactively recommend AI and open banking tools—creating an institutional-level activation deficit that training and incentive structures could address.

5.7 Policy Implications for Regulators

Beyond institutional strategy, the findings carry implications for the regulatory and policy actors shaping the FinTech deployment environment. The credit union digital literacy barrier (74.1%) and device access barrier (58.8%) confirm that financial inclusion policy cannot rely solely on competition-led FinTech deployment to extend access to the most underserved segments. Where market incentives are insufficient—as they are in credit union and traditional bank segments serving

Table 11. Present findings compared with related FinTech adoption studies.

Study	Focus	Key finding	Align?
Ryu [8]	FinTech	Trust and risk drive adoption	Yes
Baptista & Oliveira [12]	Mobile banking	Demographics moderate adoption	Yes
Goldstein et al. [25]	AI finance	Stability risks caution needed	Yes
Ozili [7]	Digital finance	Inclusion design matters	Yes
Lagna & Ravishankar [27]	FinTech research	Customer acceptance overstated	Extends
Philippon [6]	FinTech inclusion	Inclusion needs deliberate design	Extends

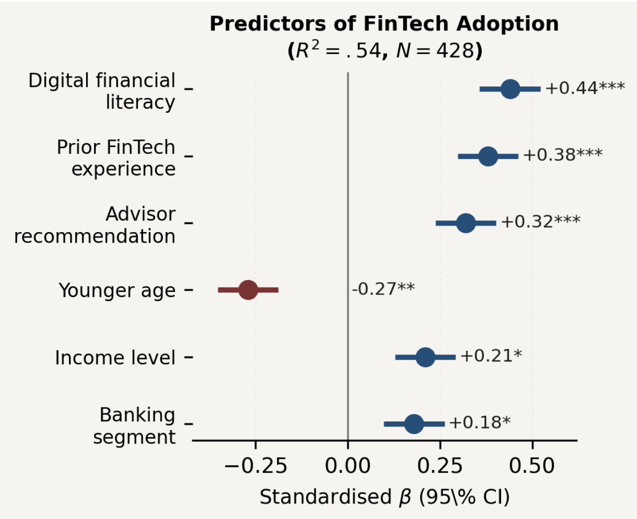

Figure 9. Forest plot of regression predictors with 95% confidence intervals. Digital financial literacy is the single strongest predictor; age is the only negative coefficient.

lower-income, older populations—regulatory intervention through mandated literacy programmes, device access subsidies, and tiered service design requirements may be necessary to achieve the inclusion benefits that Philippon [6] and Muganyi et al. [31] identify as FinTech's most consequential potential.

The regulatory sandbox model [20] has proven effective for piloting FinTech innovations under real-market conditions; an analogous "inclusion sandbox" framework—piloting FinTech deployments specifically designed for low-literacy, low-access customer populations before regulatory approval for broader deployment—could create the evidence base for inclusive FinTech design standards that the present study shows are currently absent.

5.8 Limitations

The cross-sectional design precludes causal inference between regression predictors and adoption outcomes. The UK market context limits generalisability, particularly to markets without PSD2-equivalent open banking mandates where open banking adoption trajectories will differ substantially. The sample relies on institutional recruitment, potentially over-representing customers with existing digital touchpoints and under-representing the least-digitally-engaged populations. Future research should triangulate survey data with transaction analytics and link FinTech engagement to credit performance, savings accumulation, and financial well-being outcomes to establish whether the satisfaction differentials documented here translate into financial outcome improvements [25, 6].

5.9 The FinTech Adoption Lifecycle and Retention Risk

A finding that the present cross-sectional design cannot directly address but that warrants prospective investigation is the relationship between initial adoption and sustained engagement. The adoption rates reported in Table 3 measure whether customers have used a given FinTech service at all; they do not measure frequency, depth, or value of ongoing engagement. In mobile banking contexts, evidence from the broader digital banking literature suggests that shallow adoption (occasional use for balance checking) is substantially more common than deep adoption (regular use for payments, savings management, financial planning) [8]. The customer satisfaction scores in Table 4 may reflect shallow engagement experiences that overstate the quality of the FinTech relationship for customers who have adopted tools but not integrated them into their financial decision-making.

The open banking domain is particularly susceptible to this shallow-adoption problem: account aggregation has high initial adoption utility (seeing all accounts in one place) but requires sustained behavioural change (acting on PFM insights, authorising third-party services, maintaining data-sharing consents) for the financial inclusion benefits that Philippon [6] and Ozili [7] identify. The 38.6% mainstream customer open banking adoption rate, while encouraging in absolute terms, may mask an engagement depth deficit that longitudinal transaction analytics would reveal. Financial institutions should track active open banking engagement metrics— monthly active API connections, third-party service initiations, PFM feature usage—alongside the adoption headline figures to identify and address the retention risks that aggregate adoption statistics obscure.

6. STRATEGIC IMPLICATIONS FOR FINANCIAL SERVICE PROVIDERS

Six evidence-based recommendations emerge from the convergent findings.

1. Differentiate FinTech deployment by segment. The 0.76 satisfaction gap between private banking and credit union customers cannot be closed by identical deployment strategies. Deployment plans should be segment-calibrated with digital literacy support, simplified interfaces, and advisor-mediated onboarding built into credit union and traditional bank implementations [7, 6].

2. Activate the advisor recommendation pathway. Advisor recommendation is the strongest modifiable adoption predictor ($\beta = 0.32$). Financial institutions should train advisors to identify FinTech-appropriate customer profiles and embed recommendation workflows into standard advisory interactions [8, 2].

3. Prioritise open banking for business banking. Business owners' 62.4% open banking adoption rate signals a ready market under-served by traditional banking digital infrastructure. Open banking capability investment in business banking offers the highest near-term adoption return, particularly in markets where regulatory mandates have established the API infrastructure [4, 5].

4. Deploy AI credit tools with algorithmic transparency mechanisms. The 0.48 customer-advisor divergence and 42.8% trust-in-AI barrier confirm that transparency is a customer adoption prerequisite. Plain-language explanation of AI credit decisions, human review pathways, and appeal mechanisms are minimum deployment standards [23, 25].

5. Address digital financial literacy as strategic infrastructure. With digital financial literacy as the strongest adoption predictor ($\beta = 0.44$) and 58.2% of customers citing it as a significant barrier, financial institutions should treat literacy improvement as an infrastructure investment. Embedding literacy modules into onboarding flows, advisor consultations, and mobile banking interfaces provides the broadest coverage at lowest deployment cost.

6. Separate AI adoption metrics from broader digital banking reporting. AI credit and advisory services show distinct adoption dynamics and barriers that aggregate "digital adoption" metrics would obscure. Financial institutions should maintain separate performance dashboards for AI-powered and non-AI FinTech services to identify and respond to AI-specific adoption issues [23, 27].

6.1 Implications for FinTech Investment Strategy

The aggregate investment context identified in the introduction—global FinTech investment of $164.1 billion in 2022 [9]—provides the resource envelope within which the deployment recommendations emerging from this study must be evaluated. Capital allocation decisions informed by single-domain adoption metrics (mobile banking penetration, open banking API connection rates) will systematically underweight the cross-domain literacy and trust barriers that the regression model identifies as the primary adoption moderators. Financial institutions and FinTech investors whose portfolio management relies on aggregate adoption statistics may be operating with a materially incomplete picture of the actual customer experience driving those adoption numbers.

The correlation structure in Figure 8 has direct implications for investment sequencing. The strong mobile banking–open banking correlation ($r = .68$) confirms that mobile banking foundation capability is a prerequisite for open banking adoption: investments in open banking features that outpace mobile banking platform capability will achieve lower adoption than the open banking adoption rates in this study suggest possible. Conversely, the weak AI credit correlations ($r = .38$–$.52$) confirm that AI credit and advisory services draw from a partially distinct adoption population, requiring targeted transparency and literacy investment that cannot be leveraged from broader digital banking engagement [23, 24].

7. CONCLUSION

The post-pandemic FinTech deployment environment in which the present study was conducted is characterised by three simultaneous pressures: (1) the maturation of open banking infrastructure in the UK and European markets, creating the regulatory and technical conditions for a step change in data-driven financial services; (2) the rapid commercial deployment of AI credit and advisory tools that have moved from proof-of-concept to production across multiple institutional types; and (3) a renewed policy focus on financial inclusion following the pandemic's disproportionate impact on economically vulnerable populations. The present findings speak directly to all three pressures.

The present cross-sectional investigation provides comparative, cross-segment evidence on consumer FinTech adoption, satisfaction, and advisor acceptance that single-technology, single-segment studies cannot produce. A consistent segment hierarchy was documented in which challenger bank and private banking customers show substantially higher adoption and satisfaction than traditional bank and credit union customers, driven primarily by digital financial literacy differentials that the regression model identifies as the single most powerful adoption predictor. AI-powered credit and advisory services elicit the lowest customer satisfaction and the largest customer-advisor divergence, a finding with immediate implications for transparent AI deployment in retail financial services. Business owners' disproportionately high open banking adoption provides the clearest evidence of the conditions under which FinTech adoption translates into genuine financial value: regulatory infrastructure, genuine customer need, and low-friction deployment architecture converging simultaneously.

Future investigations should address whether satisfaction differences translate into measurable financial outcomes—the ultimate criterion of FinTech service value [6, 25]. Longitudinal cohort studies linking FinTech engagement data to credit performance, savings accumulation, and financial well-being measures, combined with natural experiments exploiting staggered open banking mandate implementation, would provide the causal financial impact evidence that cross-sectional satisfaction studies cannot supply. The validated measurement instrument developed in this study provides the baseline for such longitudinal tracking across the 2025–2028 period of accelerating AI and open banking deployment in retail financial services.

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