Relational Uncertainty and Customer Satisfaction in AI-Enabled Banking: The Moderating Role of Age

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ABSTRACT

Purpose: This study examines customer satisfaction with AI-enabled banking by distinguishing relational evaluations (algorithmic trust and perceived risk) from functional evaluations (perceived usefulness and perceived ease of use), and by examining whether their associations with satisfaction differ across age segments.

Design/methodology/approach: Survey data from 450 Indian customers with recent experience of AI-enabled banking services were analysed using partial least squares structural equation modelling (PLS-SEM). Direct effects were estimated for trust, risk, usefulness and ease of use. Age-based heterogeneity was examined through multi-group analysis comparing respondents aged 18–35 and 36+, after assessment of measurement invariance.

Findings: Algorithmic trust, perceived usefulness and perceived ease of use were positively associated with customer satisfaction, whereas perceived risk was negatively associated with satisfaction. Multi-group results indicated that the trust–satisfaction association was stronger in the 18–35 segment and the risk–satisfaction association was stronger in the 36+ segment. Usefulness and ease-of-use effects did not differ significantly between the two age segments.

Practical implications: Banks can standardize functional design across age groups while adapting relational communication. Trust-building matters more for younger customers; risk-reduction and security communication matter more for older customers.

Originality/value: The study shows that age-related heterogeneity in AI-enabled banking is not uniform across customer evaluations. The observed group differences are concentrated in trust and risk rather than usefulness and ease of use. Socioemotional selectivity theory (SST) is used as an interpretive lens for this pattern; because perceived time horizon was not measured directly, the findings are presented as consistent with SST rather than as a direct test of its motivational mechanism.

Keywords: AI-enabled banking; customer satisfaction; algorithmic trust; perceived risk; socioemotional selectivity theory; age differences

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1. INTRODUCTION

As artificial intelligence becomes more embedded in retail banking, customers increasingly interact with systems whose decisions affect service outcomes but whose internal processes remain difficult to observe. Intelligent banking systems now extend beyond back-office automation to customer-facing applications: chatbots, personalized recommendations, fraud alerts, and predictive support tools (Huang & Rust, 2021; Wirtz et al., 2018; Dwivedi et al., 2021). These systems improve efficiency, convenience, and personalization, but they also alter how customers evaluate service encounters. In many cases, customers see the outcome of an interaction without being able to judge how that outcome was produced or what information shaped it. In banking—where decisions involve financial exposure, privacy concerns, and ongoing reliance on the provider—this lack of visibility fundamentally shapes satisfaction judgments.

Most research on digital service evaluation explains favourable customer responses through instrumental assessments such as usefulness and ease of use (Davis, 1989; Venkatesh et al., 2003; Venkatesh et al., 2012). Those assessments remain important, but they do not fully capture the relational challenge introduced by algorithmic systems. A customer may find an automated service efficient while remaining uncertain about whether the system is reliable, whether it will behave appropriately in future interactions, or whether its use exposes them to unacceptable risk. Prior work on AI and algorithmic decision-making suggests that opacity complicates trust formation and heightens concerns about reliability, fairness, and control (Glikson & Woolley, 2020; Shin, 2021), while also contributing to broader aversion toward automated systems (Jussupow et al., 2021). Satisfaction therefore reflects not only whether the service performs well as a tool, but also whether the customer feels able to rely on it.

This distinction matters in banking because service encounters involve both performance expectations and relationship-based concerns. Customers expect banking services to be useful, easy to use, and capable of helping them complete financial tasks efficiently. At the same time, they must often place trust in systems that process sensitive information and trigger automated interventions without making their underlying logic fully visible. Satisfaction may therefore be shaped by both instrumental assessments of task performance and effort reduction, and trust-based assessments of whether the service can be relied upon and whether its use creates acceptable risk. Rather than treating algorithmic banking simply as another digital channel, this study argues it should also be understood as a service setting where customers may need reassurance about the systems on which they rely.

Age may further shape how these assessments enter into satisfaction, but prior research offers no clear pattern. Some studies suggest younger customers are more receptive to new technologies; others find age differences weaken once customers have actual experience. One reason for this inconsistency may be that age is often treated as a broad moderator without distinguishing between different kinds of evaluation. A customer's assessment of whether a system is useful is not the same as their willingness to rely on that system amid limited transparency. Treating age as a general moderator across all evaluations may obscure a more selective pattern.

To address this, the study draws on Socioemotional Selectivity Theory (SST), which links age to shifts in motivational priorities rather than to declining technological competence (Carstensen, 2006; Charles & Carstensen, 2010; Löckenhoff & Carstensen, 2004). SST suggests younger individuals, with longer time horizons, place greater emphasis on growth and future-oriented gains, while older individuals place greater weight on avoiding negative outcomes. In algorithmic banking, these motivational differences should matter most where customers must manage uncertainty. Trust involves accepting present vulnerability on expectations of future reliability; perceived risk concerns negative outcomes such as financial loss or privacy violations. Instrumental assessments—usefulness and ease of use—should be less sensitive to these age-related differences because both younger and older customers benefit from efficiency and reduced effort.

This analysis brings together relationship marketing and technology acceptance perspectives to explain customer satisfaction. Relationship marketing explains why trust and perceived risk matter when service relationships involve vulnerability, uncertainty, and continued reliance (Morgan & Hunt, 1994; Palmatier et al., 2006; Gefen et al., 2003). Technology acceptance research explains why perceived usefulness and ease of use remain important when customers evaluate automated services as tools (Davis, 1989; Venkatesh et al., 2003). SST provides the basis for expecting age to moderate trust-based pathways more strongly than instrumental ones. The paper examines satisfaction as the outcome of both types of assessment, arguing that age-based heterogeneity is concentrated in trust and risk rather than usefulness and ease of use.

Empirically, the study tests these effects using survey data from 450 Indian banking customers who actively use algorithmic services. India is a useful context because automated banking has expanded rapidly while the customer base remains diverse in age and digital exposure. The findings show both types of assessment shape satisfaction, but age differences are concentrated in trust-based pathways. Trust's positive effect is stronger for younger customers; risk's negative effect is stronger for older customers. Usefulness and ease of use effects do not vary significantly across age groups.

Three contributions emerge from the study. First, it extends research on automated service satisfaction by showing banking satisfaction reflects both instrumental and relationship-related concerns. Second, it refines age's role by showing age differences are concentrated in trust-based assessments rather than distributed uniformly across all dimensions. Third, it offers targeted managerial implications: banks may standardize functional design while adapting trust-building and risk communication more selectively.

The remainder of the paper develops the theoretical framework and hypotheses, presents the methodology and empirical results, and concludes with the discussion, managerial implications, limitations, and future research directions.

2. THEORETICAL FRAMEWORK AND HYPOTHESIS DEVELOPMENT

2.1 THE NATURE OF ALGORITHMIC BANKING RELATIONSHIPS

AI-enabled banking places automated systems inside customer–bank interactions involving money, personal information and repeated reliance. Customers increasingly encounter chatbots, fraud alerts, personalised recommendations and automated support, often while having limited visibility into how outputs are generated (Huang & Rust, 2021; Dwivedi et al., 2021). Recent banking research likewise shows that trust, security and technology-performance evaluations remain important to customer acceptance and satisfaction with AI-enabled services (Bharti et al., 2023; Alnaser et al., 2023).

For this reason, satisfaction cannot be reduced to convenience alone. Customers evaluate whether an AI-enabled service helps them complete banking tasks, but they also judge whether it is dependable and whether using it exposes them to unacceptable risk. The present study therefore separates functional evaluations (usefulness and ease of use) from relational evaluations (algorithmic trust and perceived risk). This distinction is analytical rather than absolute: both forms of evaluation can operate simultaneously in the same service encounter.

2.2 COMPLEMENTARY THEORETICAL PERSPECTIVES

The model combines two complementary perspectives. Technology-acceptance research explains why perceived usefulness and perceived ease of use influence favourable responses to digital systems (Davis, 1989; Venkatesh et al., 2003; Venkatesh et al., 2012). Relationship-marketing and trust research explain why confidence, vulnerability and perceived risk matter when customers depend on a provider or system under uncertainty (Morgan & Hunt, 1994; Mayer et al., 1995; Gefen et al., 2003).

This combination is particularly relevant to AI-enabled banking. Empirical studies in banking have found that trust, performance-related beliefs and satisfaction are closely connected in AI-enabled or chatbot-mediated services (Bharti et al., 2023; Alnaser et al., 2023; Ikhsan et al., 2025; Kumar et al., 2026). The present model therefore treats usefulness and ease of use as functional evaluations and algorithmic trust and perceived risk as relational evaluations, with customer satisfaction as the outcome.

2.3 RELATIONSHIP MARKETING AND UNCERTAINTY RESOLUTION

Why should trust and perceived risk matter for satisfaction with algorithmic banking? Relationship marketing provides a clear answer. Exchange relationships require customers to remain connected to a provider despite uncertainty, dependence, and the possibility of unfavourable outcomes (Morgan & Hunt, 1994; Palmatier et al., 2006). Banking exemplifies this: customers maintain ongoing relationships involving repeated service use, personal financial information, and decisions affecting their security and well-being. Satisfaction therefore depends not only on efficient service performance, but also on whether the customer feels able to rely on the provider and its systems.

Trust, defined as confidence in an exchange partner's reliability and integrity (Morgan & Hunt, 1994), is central to this logic because it allows exchange to continue when the customer cannot fully verify how the provider or service system will behave. Mayer et al. (1995) describe trust as a willingness to accept vulnerability based on positive expectations about another party's intentions or behaviour. Although these definitions were developed in interpersonal and organisational settings, their logic applies to algorithmic banking. Customers often rely on systems that analyse data, generate recommendations, or trigger service responses without full transparency. Trust reflects a customer's willingness to rely on the automated service despite incomplete visibility. Research in online and AI-mediated environments similarly shows trust becomes especially important when customers face uncertainty about how a system functions, whether it will behave reliably, and whether its outputs can be accepted with confidence (Gefen et al., 2003; Glikson & Woolley, 2020; Shin, 2021).

From a relationship marketing perspective, trust should contribute positively to satisfaction because it reduces the relational burden of relying on the service. When customers believe an algorithmic banking system is dependable, competent, and aligned with their interests, they can engage without continually questioning whether the system will fail, misuse their information, or produce inappropriate outcomes. Trust does not replace functional performance—it complements it. In banking, where the consequences of service failure can be severe and where customers may have limited recourse, this reassurance is particularly consequential. A useful, easy-to-use system may still produce weak satisfaction if customers remain uncertain about whether it can be relied on. When customers feel confident the system will behave appropriately, satisfaction improves because the service relationship becomes easier to sustain.

H1: Algorithmic trust has a positive effect on customer satisfaction.

Perceived risk represents the opposite side of this evaluation. If trust reflects confidence, perceived risk reflects concern that relying on the service may lead to negative outcomes. In consumer settings, perceived risk is the expectation of loss or adverse consequences associated with a purchase or usage decision (Featherman & Pavlou, 2003; Kim et al., 2008). In algorithmic banking, concerns may involve financial loss, privacy breaches, security vulnerabilities, inappropriate recommendations, or harmful automated error. These concerns are particularly relevant because consequences of service failure can be serious and because customers may not always be able to observe the processes through which automated systems reach their outputs.

Perceived risk should undermine satisfaction because it makes the exchange relationship harder to maintain. Customers who believe using an automated service exposes them to significant potential harm are likely to approach the service with caution, discomfort, or resistance. Perceived risk increases the relational cost of using the service. Prior research consistently links perceived risk to lower trust, weaker adoption intentions, and less favourable evaluations of digital service encounters (Featherman & Pavlou, 2003; Kim et al., 2008). In algorithmic banking, satisfaction declines when customers feel relying on the system exposes them to unacceptable uncertainty or potential loss.

H2: Perceived risk has a negative effect on customer satisfaction.

Trust and perceived risk capture the trust-based side of evaluation. They reflect how customers assess the acceptability of relying on automated systems when those systems are partly opaque and service use involves financial and informational vulnerability. These constructs are not intended to replace instrumental assessments. Instead, they capture a different aspect of judgment: whether the customer experiences the service relationship as sufficiently trustworthy and safe to support positive satisfaction. Section 2.4 considers the instrumental side of customer evaluation.

2.4 FUNCTIONAL EVALUATION

Although algorithmic banking introduces relational concerns, satisfaction is also shaped by how well the service performs as a practical banking tool. Technology acceptance research consistently shows favourable evaluations of digital systems depend in part on perceived usefulness and ease of use (Davis, 1989; Venkatesh et al., 2003; Venkatesh et al., 2012). These instrumental assessments remain important because customers use automated services to complete tasks, obtain information, manage accounts, and interact with the bank more efficiently. A customer may value an automated service because it simplifies routine banking, provides faster support, improves decision-making, or reduces transaction effort. Perceived usefulness and ease of use should continue to influence satisfaction even when the service is also evaluated relationally.

Perceived usefulness is the extent to which a customer believes using a system improves performance or helps achieve desired outcomes (Davis, 1989). In banking, usefulness is reflected in how automated services help customers complete financial tasks more effectively, obtain relevant information, make better decisions, or manage accounts with greater speed and convenience. This logic is especially relevant in automated contexts because many claimed benefits relate directly to improved responsiveness, personalization, and decision support (Huang & Rust, 2021; Wirtz et al., 2018). If customers believe algorithmic banking helps them solve problems more efficiently, navigate financial tasks more effectively, or receive more relevant support, they should evaluate those services more positively.

H3: Perceived usefulness has a positive effect on customer satisfaction.

Perceived ease of use is the extent to which a customer believes using a system requires little effort (Davis, 1989). In service settings, ease of use matters because customers respond more positively to systems that are straightforward to learn, easy to navigate, and simple to use during routine interactions. Cumbersome interfaces, confusing steps, or difficult interactions create friction even when the underlying service is valuable. Automated services that reduce cognitive effort, simplify problem resolution, and make interactions more intuitive support more favourable evaluations. Prior research consistently links ease of use to positive responses in digital and self-service technologies (Davis, 1989; Venkatesh et al., 2003).

H4: Perceived ease of use has a positive effect on customer satisfaction.

Perceived usefulness and ease of use therefore capture the instrumental dimension of customer evaluation. They reflect whether the service helps the customer accomplish banking tasks efficiently and with manageable effort. These assessments differ from trust and perceived risk, which concern the acceptability of relying on the service amid uncertainty and vulnerability. The distinction matters because automated services can be judged positively on one dimension and less favourably on the other. A system may be useful and easy to use but raise trust or risk concerns, just as a trusted service may fail to deliver sufficient functional value. The study treats satisfaction as the outcome of both instrumental and trust-based assessments. Section 2.5 uses socioemotional selectivity theory to explain why age is expected to shape trust-based pathways more strongly than instrumental ones.

2.5 SOCIOEMOTIONAL SELECTIVITY THEORY

Socioemotional selectivity theory (SST) explains life-span differences in goals primarily through perceived time horizons rather than chronological age itself (Carstensen, 2006; Charles & Carstensen, 2010; Löckenhoff & Carstensen, 2004). More expansive time horizons are associated with exploration and future-oriented goals, whereas more constrained time horizons increase the salience of emotionally meaningful goals and avoidance of negative outcomes. Chronological age is correlated with, but is not equivalent to, these motivational processes.

Accordingly, this study does not treat age as a direct measure of socioemotional selectivity and does not claim to test SST's underlying psychological mechanism. Instead, SST provides an interpretive basis for asking whether age-related differences are more visible in evaluations involving reliance and potential loss than in evaluations of task performance. In AI-enabled banking, trust and perceived risk concern vulnerability and uncertainty, whereas usefulness and ease of use concern practical performance and effort.

The resulting expectation is selective rather than general: age-related heterogeneity should be more apparent in the trust and risk pathways than in usefulness and ease of use. Any observed age-group differences are therefore interpreted as patterns consistent with SST, subject to the limitation that perceived time horizon and motivational priorities were not measured directly.

2.6 AGE AND TRUST-BASED UNCERTAINTY PROCESSING

Age and algorithmic trust

Trust involves willingness to accept vulnerability on the expectation that another party or system will behave reliably (Mayer et al., 1995; Morgan & Hunt, 1994). In AI-enabled banking, trust can reduce uncertainty when customers cannot fully inspect how automated recommendations or service responses are generated. If younger customers place relatively greater weight on future-oriented opportunities, confidence in the system may translate more strongly into satisfaction for this segment. This proposition is consistent with, but does not directly test, SST.

H5: Algorithmic trust exerts a stronger positive effect on customer satisfaction among younger customers than among older customers.

Age and perceived risk

Perceived risk concerns the possibility of financial loss, privacy breaches, security failures or harmful automated error (Featherman & Pavlou, 2003; Kim et al., 2008). If avoidance of negative outcomes becomes relatively more salient with age, perceived risk may have a stronger adverse association with satisfaction among the older segment. Again, the proposed group difference is interpreted through SST rather than treated as evidence that the underlying time-horizon mechanism was directly observed.

H6: Perceived risk exerts a stronger negative effect on customer satisfaction among older customers than among younger customers.

Age and instrumental assessments

Perceived usefulness and ease of use capture practical value and effort reduction. Both are relevant across age groups, and SST offers no strong basis for expecting their effects on satisfaction to differ systematically by age. Accordingly, no directional moderation hypotheses are proposed for these two pathways; their between-group differences are examined as supplementary comparisons.

2.7 RESEARCH MODEL

The conceptual model presented in Figure 1 integrates the theoretical arguments developed in the preceding sections. It distinguishes trust-based assessments (algorithmic trust and perceived risk) from instrumental assessments (perceived usefulness and perceived ease of use), and proposes that age selectively moderates only the trust-based pathways. The model proposes customer satisfaction with algorithmic banking is shaped by two sets of antecedents. The first comprises **trust-based assessments**: algorithmic trust and perceived risk. These capture whether customers feel able to rely on automated services when transparency is limited and potential loss exists. The second comprises **instrumental assessments**: perceived usefulness and ease of use. These capture whether the service helps customers accomplish banking tasks effectively and with manageable effort.

Consistent with the preceding discussion, the model proposes direct effects from all four antecedents to satisfaction. Algorithmic trust is expected to have a positive effect; perceived risk a negative effect. Perceived usefulness and ease of use are both expected to have positive effects. These relationships reflect the argument that satisfaction is shaped by both relationship-related concerns about reliance amid uncertainty and performance-related assessments of the service as a practical banking tool.

Beyond these direct effects, the model proposes that age selectively moderates trust-based pathways. Drawing on SST, the analysis argues age should shape the weight customers place on trust and risk more strongly than the weight they place on usefulness and ease of use. The positive effect of algorithmic trust on satisfaction is expected to be stronger for younger customers; the negative effect of perceived risk stronger for older customers. No formal moderation hypotheses are advanced for usefulness or ease of use.

Six hypotheses are tested in total. **H1–H4** address direct effects. **H5–H6** address age moderation in trust-based pathways. Section 3 describes the research design, measurement approach, and analytical procedures.

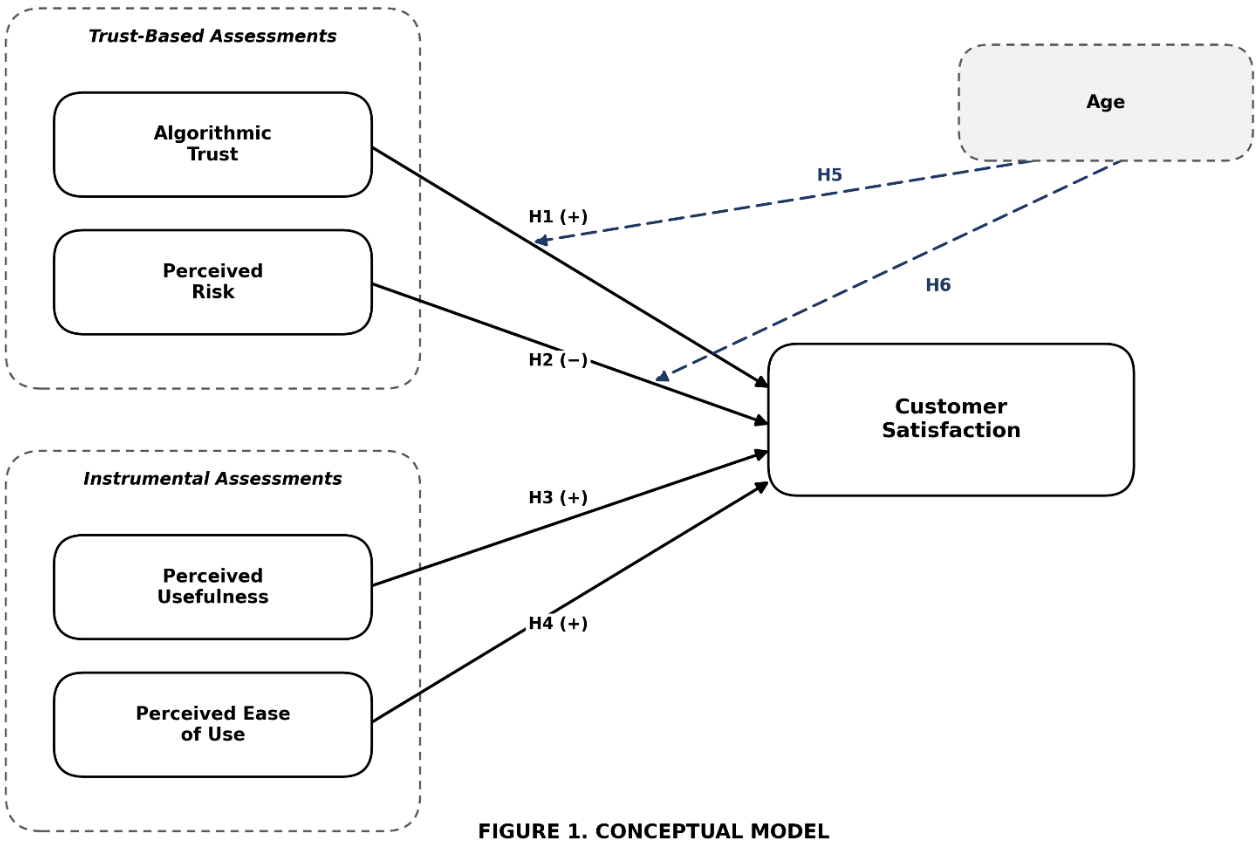

FIGURE 1. CONCEPTUAL MODEL

3. METHODOLOGY

3.1 RESEARCH CONTEXT AND SAMPLE

Retail banking in India provides the empirical context for this study. India provides a relevant setting because digital banking adoption has expanded rapidly and automated services are now common across both public and private sector banks. Customers increasingly encounter AI-mediated features such as chatbots, automated support, personalized recommendations, and fraud alerts as part of routine banking. At the same time, the Indian banking market remains diverse in age, digital exposure, and technology use patterns, making it a useful context for examining whether age moderates evaluations of algorithmic banking.

Eligible respondents were Indian banking customers who had used at least one automated banking service within the three months preceding data collection. Eligible services included AI-powered chatbots, automated customer support, personalized financial recommendation systems, and AI-based fraud detection alerts. Restricting the sample to active users ensured respondents evaluated algorithmic banking on recent experience rather than hypothetical expectations, and aligned the design with the study's theoretical focus on satisfaction, trust, risk, usefulness, and ease of use in actual service encounters.

A non-probability purposive sampling strategy was used because no comprehensive sampling frame of AI-enabled banking users was available. The questionnaire was distributed online through professional networks, banking-focused social-media groups and a market-research recruitment channel. The specific panel provider and the number of respondents obtained from each individual channel were not retained in the study records and are not available for separate reporting. Eligibility required recent use of at least one AI-enabled banking service during the previous three months. Participation was voluntary and anonymous, and respondents were informed of the academic purpose of the study before consent.

The survey was fielded between 15 January 2026 and 2 March 2026 (approximately six and a half weeks). Over this period, 531 responses were received. Screening removed 81 responses that were incomplete, showed straight-line response patterns, or had implausibly short completion times (less than three minutes), leaving 450 usable cases for analysis. The screening criteria were applied as data-quality safeguards before model estimation. Because the exclusions were recorded as an overall screening decision rather than as mutually exclusive categories, the manuscript reports the total number excluded (81) without assigning unsupported counts to individual criteria.

TABLE 1. DEMOGRAPHIC PROFILE OF RESPONDENTS

Characteristic	Category	Frequency (n)	Percentage (%)
Age Group	18–35 years	234	52.0
	36+ years	216	48.0
Gender	Male	261	58.0
	Female	189	42.0
Education	High school or below	72	16.0
	Some college / diploma	99	22.0
	Bachelor's degree	207	46.0
	Master's degree or higher	72	16.0
AI Service Usage Frequency	Daily	189	42.0
	Several times per week	135	30.0
	About once per week	81	18.0
	Less than once per week	45	10.0

Note: Mean age = 37.8 years (SD = 11.4)

Mean respondent age was 37.8 years (SD = 11.4). For multi-group analysis, respondents were divided into an 18–35 segment (n = 234) and a 36+ segment (n = 216). This cut-off is used as a pragmatic analytical segmentation that yields two adequately sized groups; it is not presented as a theoretically universal boundary between “young” and “old” adults. Consequently, the group comparison should be interpreted as evidence of age-segment heterogeneity within this sample rather than as a gerontological classification.

While well suited to the research question, the Indian context sets limits on generalisability. Digital banking infrastructure, mobile payment adoption patterns, and the institutional environment may shape how customers form trust and perceive risk in automated services. These findings should be interpreted as evidence from a rapidly digitising emerging-market banking context rather than automatically generalisable to all banking markets. This issue is revisited in the limitations section.

3.2 MEASUREMENT DEVELOPMENT

All constructs were measured using established multi-item scales adapted to algorithmic banking. Items were phrased to reflect respondents' experiences with automated banking services and measured on five-point Likert-type scales (1 = strongly disagree to 5 = strongly agree). Appendix A reports the full measurement instrument.

Two additional, instrumental constructs—**perceived usefulness** and **perceived ease of use**—were adapted from Davis (1989). Perceived usefulness was measured with four items capturing the extent to which algorithmic banking helps customers perform banking tasks more effectively, quickly, and productively. Perceived ease of use was measured with four items capturing the extent to which such services are easy to learn, navigate, and use during banking interactions.

Algorithmic trust was measured with five items adapted from Morgan and Hunt (1994) and Gefen et al. (2003), with wording tailored to algorithmic banking. The items capture respondents' confidence in the reliability, trustworthiness, and dependability of the automated service system. To remain consistent with the theoretical focus, trust items were framed around the automated system rather than the bank as an institution. The intention was to capture trust in the AI-mediated service mechanism rather than broader institutional trust in the bank itself.

Perceived risk was measured with four items adapted from Featherman and Pavlou (2003) and Kim et al. (2008). The items capture customers' concerns about negative outcomes associated with using automated banking services: financial loss, misuse of personal information, system errors, and the overall sense that using the service involves risk. Perceived risk was treated as an overall trust-based assessment reflecting the customer's sense of exposure to potentially harmful outcomes when relying on algorithmic banking.

Customer satisfaction was measured with four items adapted from Oliver (1999) and Anderson and Sullivan (1993). The items capture respondents' overall satisfaction with their experience using automated banking services, including the extent to which the service meets expectations and produces a favourable overall evaluation.

For the primary moderation analysis, age was operationalised using two segments (18–35 and 36+) for multi-group analysis. Exact age in years was also recorded. A continuous-age sensitivity analysis was explored during the original analytical work, but it is not used as confirmatory evidence in this revision; the reported moderation conclusions are based on the fully documented multi-group analysis.

To assess content validity, the survey instrument was reviewed by four academic experts and three banking practitioners familiar with digital and automated service environments. Minor wording adjustments were made to improve clarity and ensure items were understandable in the banking context without altering their substantive meaning.

3.3 COMMON METHOD AND NON-RESPONSE BIAS

Because all focal constructs were collected from the same respondents in a single survey, several procedural and statistical steps were taken to reduce and assess common method bias risk. Procedurally, the questionnaire assured anonymity, explained there were no right or wrong answers, and separated predictor and outcome measures across different survey sections to reduce respondents' tendency to infer focal relationships. Item wording was also reviewed during pre-testing to improve clarity.

Statistically, two reported diagnostics were used to assess common method bias risk. Harman's single-factor test indicated that the first unrotated factor accounted for 29% of total variance. Full-collinearity VIF values ranged from 1.45 to 2.89, below the 3.3 threshold proposed by Kock (2015). These diagnostics are interpreted jointly as checks on common method bias rather than as proof of its absence.

These diagnostics do not indicate that common method variance is the dominant explanation for the observed associations. They do not establish its absence, and the cross-sectional, self-report design remains a limitation.

Non-response bias was assessed by comparing early and late respondents (Armstrong & Overton, 1977). Independent-samples *t*-tests comparing the first 25% and last 25% of responses showed no statistically significant differences in demographics or key study constructs, suggesting non-response bias is unlikely to pose a substantial threat.

3.4 DATA ANALYSIS PROCEDURE

Hypotheses were tested using PLS-SEM in SmartPLS 4 (Ringle et al., 2022). PLS-SEM was appropriate because the model contains multiple antecedents drawn from relational and functional perspectives and requires comparison of structural relationships across age segments. The analysis therefore focused on measurement quality, structural-path estimates, explanatory performance, measurement invariance, and multi-group differences (Hair et al., 2022).

Analysis proceeded through the standard two-stage PLS-SEM procedure. In the first stage, the measurement model was assessed to establish reliability and validity of reflective constructs. Internal consistency reliability was examined using Cronbach's alpha and composite reliability, with values above 0.70 treated as acceptable. Convergent validity was assessed through AVE, with values above 0.50 indicating the construct explains more than half the variance in its indicators. Discriminant validity was evaluated using HTMT (Henseler et al., 2015).

In the second stage, the structural model was evaluated using bootstrapping with 5,000 resamples to estimate path significance. Explanatory performance was assessed using R^2 and predictor effect sizes (f^2). The revised manuscript does not rely on Q^2 or PLSpredict as evidential support because the central hypotheses concern structural relationships and age-segment differences, which are reported directly through the structural model and MGA.

Age moderation was examined using multi-group analysis (MGA) comparing the 18–35 and 36+ segments. Measurement invariance was assessed with the MICOM procedure before group comparisons (Henseler et al., 2016). Configural and compositional invariance were established, which provides partial measurement invariance and permits comparison of standardised path coefficients across the two groups.

Age moderation is evaluated through the multi-group analysis comparing the 18–35 and 36+ segments. A continuous-age sensitivity analysis was explored during the original analytical work, but it is not used as confirmatory evidence in this revision because the manuscript's reported hypothesis tests are based on the fully documented MGA estimates. This avoids giving an ancillary analysis greater evidentiary weight than can be transparently reported in the article.

4. RESULTS

4.1 MEASUREMENT MODEL ASSESSMENT

Prior to estimating structural relationships, the measurement model was first assessed. Table 2 reports internal consistency and convergent validity statistics. Cronbach's alpha values ranged from 0.82 to 0.90, composite reliability from 0.87 to 0.93, and AVE from 0.65 to 0.76. All values exceed recommended thresholds, indicating satisfactory internal consistency and convergent validity.

TABLE 2. RELIABILITY AND CONVERGENT VALIDITY

Construct	Cronbach's α	Composite Reliability	AVE
Perceived Usefulness	0.89	0.92	0.74
Perceived Ease of Use	0.86	0.90	0.68
Algorithmic Trust	0.88	0.91	0.70
Perceived Risk	0.82	0.87	0.65
Customer Satisfaction	0.90	0.93	0.76

Indicator reliability was examined using outer loadings. All indicators loaded above 0.70 on their intended constructs, with loadings from 0.78 to 0.88. The indicators contribute adequately to their latent variables, and no item removal was necessary.

Discriminant validity was assessed using HTMT. As shown in Table 3, all HTMT values were below 0.85, and confidence intervals did not indicate problematic construct overlap. The reliability, convergent validity, and discriminant validity results support measurement model adequacy and provide a satisfactory basis for evaluating the structural model.

TABLE 3. HTMT DISCRIMINANT VALIDITY

Pair	HTMT	95% CI Lower	95% CI Upper
PEOU ↔ PU	0.51	0.42	0.60
Trust ↔ PU	0.58	0.49	0.67
Trust ↔ PEOU	0.49	0.40	0.58
Risk ↔ PU	0.42	0.33	0.51
Risk ↔ PEOU	0.38	0.29	0.47
Risk ↔ Trust	0.55	0.46	0.64
SAT ↔ PU	0.67	0.59	0.75
SAT ↔ PEOU	0.61	0.52	0.70
SAT ↔ Trust	0.74	0.66	0.82
SAT ↔ Risk	0.52	0.43	0.61

Note: PU = Perceived Usefulness; PEOU = Perceived Ease of Use; Trust = Algorithmic Trust; Risk = Perceived Risk; SAT = Customer Satisfaction

4.2 STRUCTURAL MODEL RESULTS

Table 4 reports structural path estimates for direct effects. All four hypothesised direct relationships were statistically significant and in expected directions. Algorithmic trust positively affected satisfaction ($\beta = 0.31$, $p < 0.001$), supporting **H1**. Perceived risk negatively affected satisfaction ($\beta = -0.19$, $p < 0.001$), supporting **H2**. Perceived usefulness ($\beta = 0.28$, $p < 0.001$) and ease of use ($\beta = 0.22$, $p < 0.001$) positively affected satisfaction, supporting **H3** and **H4**.

TABLE 4. STRUCTURAL PATH COEFFICIENTS (DIRECT EFFECTS)

Hypothesis	Path	β	t-value	p-value	f^2	Supported
H1	Trust → SAT	0.31	7.82	<0.001	0.21	Yes
H2	Risk → SAT	-0.19	4.91	<0.001	0.06	Yes
H3	PU → SAT	0.28	6.45	<0.001	0.13	Yes
H4	PEOU → SAT	0.22	5.12	<0.001	0.09	Yes

Effect size estimates suggest the four antecedents do not contribute equally. Algorithmic trust showed the largest contribution ($f^2 = 0.21$), followed by usefulness ($f^2 = 0.13$), ease of use ($f^2 = 0.09$), and risk ($f^2 = 0.06$). Both trust-based and instrumental assessments are important, with algorithmic trust and usefulness emerging as the strongest direct predictors.

The model accounted for 57% of the variance in customer satisfaction ($R^2 = 0.57$), indicating substantial in-sample explanatory performance for the present data. The revised manuscript does not use Q^2 or PLSpredict as evidence for the hypotheses and confines its predictive interpretation to the reported R^2 and effect-size results.

Overall, the structural results support the argument that satisfaction reflects both instrumental assessments and trust-based assessments linked to reliance amid uncertainty. Section 4.3 examines whether relationship strength differs across age groups.

4.3 AGE MODERATION RESULTS

Age moderation was evaluated through multi-group comparisons of the 18–35 and 36+ segments. The MGA is treated as the primary moderation analysis because it directly corresponds to H5 and H6 and is fully reported through group-specific coefficients, between-group differences, confidence intervals, and p values.

MGA results are reported in Table 5. The positive effect of algorithmic trust on satisfaction was significantly stronger for younger customers than older customers, supporting **H5**. The path from algorithmic trust to satisfaction remained positive in both groups, but its magnitude was higher among younger respondents ($\beta = 0.38$ vs. 0.22), indicating trust plays a more influential role for this group. The negative effect of perceived risk on satisfaction was significantly stronger for older customers than younger customers, supporting **H6**. Perceived risk reduced satisfaction in both groups, but the negative effect was greater among older respondents ($\beta = -0.25$ vs. -0.14), consistent with older customers placing greater weight on risk.

TABLE 5. MULTI-GROUP ANALYSIS RESULTS (TRUST-BASED PATHWAYS)

Hypothesis	Path	Younger (18–35) β	Older (36+) β	Δβ	95% CI	p-value	Supported
H5	Trust → SAT	0.38	0.22	0.16	[0.04, 0.28]	0.008	Yes
H6	Risk → SAT	-0.14	-0.25	-0.11	[-0.21, -0.01]	0.021	Yes

Instrumental pathway comparisons showed a different pattern. Usefulness and ease of use effects on satisfaction were positive in both age groups, but group differences were not statistically significant ($\beta = 0.29$ vs. 0.26 for usefulness; $\beta = 0.23$ vs. 0.21 for ease of use). Younger and older customers did not differ meaningfully in how usefulness and ease of use shaped satisfaction judgments. This finding aligns with the expectation that age-based heterogeneity is concentrated in trust-based rather than instrumental pathways.

TABLE 6. MULTI-GROUP ANALYSIS RESULTS (INSTRUMENTAL PATHWAYS)

Path	Younger (18–35) β	Older (36+) β	Δβ	95% CI	p-value
PU → SAT	0.29	0.26	0.03	[-0.07, 0.13]	0.52
PEOU → SAT	0.23	0.21	0.02	[-0.08, 0.12]	0.63

The moderation conclusions are based on the documented MGA results in Tables 5 and 6. The continuous-age sensitivity analysis is not used as confirmatory evidence in the revised manuscript. H5 and H6 are therefore evaluated solely from the reported between-group path differences, while the limitations section explicitly recognises the constraints of dichotomising chronological age.

The documented MGA indicates selective age-segment heterogeneity: the trust–satisfaction path is stronger in the 18–35 group and the risk–satisfaction path is stronger in the 36+ group, while usefulness and ease-of-use differences are not statistically significant. These results support H5 and H6 within the specified segmentation, but they should not be interpreted as demonstrating a universal life-span threshold or the unmeasured motivational mechanism proposed by SST.

4.4 DESCRIPTIVE STATISTICS AND CORRELATIONS

Table 7 reports descriptive statistics and correlations. Mean scores indicate generally favourable evaluations, with usefulness, ease of use, algorithmic trust, and satisfaction above the scale midpoint. Perceived risk was lower than positive evaluation constructs, suggesting respondents did not, on average, view algorithmic banking as highly risky.

TABLE 7. DESCRIPTIVE STATISTICS AND CORRELATIONS

Construct	Mean	SD	1	2	3	4	5
1. Perceived Usefulness	3.82	0.89	(0.86)				
2. Perceived Ease of Use	3.75	0.92	0.44	(0.82)			
3. Algorithmic Trust	3.68	0.95	0.52	0.41	(0.84)		
4. Perceived Risk	2.91	1.08	-0.35	-0.31	-0.48	(0.81)	
5. Customer Satisfaction	3.79	0.94	0.59	0.52	0.66	-0.46	(0.87)

Note: Diagonal values (in parentheses) are square root of AVE. All correlations significant at $p < 0.01$.

Correlations align closely with the proposed model. Satisfaction was positively associated with usefulness, ease of use, and algorithmic trust, and negatively associated with risk. The strongest bivariate association with satisfaction was algorithmic trust, followed by usefulness and ease of use. Risk was negatively correlated with satisfaction and with other positive evaluation constructs. These associations align with structural results while remaining below levels suggesting problematic construct overlap.

5. DISCUSSION

5.1 SUMMARY OF FINDINGS

The results support a two-part account of satisfaction with AI-enabled banking. Trust, usefulness and ease of use are positively associated with satisfaction, whereas perceived risk is negatively associated with it. Trust has the largest reported direct effect, but functional evaluations also remain important. This pattern is consistent with recent empirical work showing that customer responses to AI-enabled banking depend on both technology-performance beliefs and trust-related evaluations (Bharti et al., 2023; Alnaser et al., 2023; Ikhsan et al., 2025; Kumar et al., 2026).

The age comparison is more selective. The trust–satisfaction association is stronger in the 18–35 segment, while the adverse risk–satisfaction association is stronger in the 36+ segment. Differences in usefulness and ease of use are not significant. The contribution is therefore not that age changes every element of technology evaluation, but that heterogeneity appears concentrated in trust and risk within this sample.

5.2 DISCUSSION OF DIRECT EFFECTS

Algorithmic trust shows the largest direct association with satisfaction ($\beta = 0.31$), followed by perceived usefulness ($\beta = 0.28$), ease of use ($\beta = 0.22$) and perceived risk ($\beta = -0.19$). The results suggest that customers judge AI-enabled banking both as a functional service and as a system on which they must rely. This interpretation is compatible with relationship-marketing theory, which places trust at the centre of exchanges involving vulnerability and uncertainty, and with technology-acceptance research, which emphasises usefulness and ease of use.

The negative risk effect is also substantively relevant. Banking involves financial and informational exposure, so concerns about loss, privacy, security and automated error can reduce satisfaction even when a service is convenient. Conversely, usefulness and ease of use remain significant, indicating that relational reassurance does not replace functional service quality. The findings therefore favour a complementary rather than competing interpretation of relational and functional evaluations.

5.3 DISCUSSION OF AGE MODERATION

The age-segment comparison should be interpreted cautiously. Trust has a stronger positive association with satisfaction among respondents aged 18–35 ($\beta = 0.38$) than among those aged 36+ ($\beta = 0.22$), whereas perceived risk has a stronger negative association among the 36+ segment ($\beta = -0.25$ versus -0.14). Usefulness and ease-of-use differences are not statistically significant.

This pattern is consistent with the SST-based expectation that evaluations involving vulnerability and avoidance of negative outcomes may vary more with age than straightforward performance evaluations. However, the study measured chronological age rather than perceived time horizon, emotional goals or motivational priorities. SST therefore helps interpret the pattern; it is not directly demonstrated by these data. The 18–35/36+ split is also a pragmatic segmentation rather than a universal developmental boundary.

The absence of significant group differences for usefulness and ease of use is theoretically useful because it narrows the age claim. Both segments appear to value functional performance similarly, while the documented heterogeneity is concentrated in trust and risk. Future work should test this interpretation with continuous age, directly measured future-time perspective and more finely grained age cohorts.

5.4 THEORETICAL IMPLICATIONS

The study makes three bounded theoretical contributions. First, it shows that satisfaction with AI-enabled banking can be modelled through both functional evaluations and relational evaluations. This extends a purely technology-acceptance account without displacing it.

Second, the findings suggest that demographic heterogeneity may be pathway-specific rather than global. In this sample, age-segment differences occur in trust and risk paths but not in usefulness and ease of use. This distinction provides a more precise basis for future age research than treating age as a moderator of every technology-evaluation relationship.

Third, SST is positioned as an interpretive bridge between age and uncertainty-related evaluations, not as a directly tested mechanism. Establishing the mechanism itself would require measures of perceived time horizon, goal priorities or related motivational constructs. This qualification narrows the theoretical claim while preserving the observed pattern that motivated it.

5.5 MANAGERIAL IMPLICATIONS

For banks seeking to expand or refine automated service delivery, several implications follow. Satisfaction depends on both functional service quality and relational reassurance. Banks need to think about automated service design in two layers. The first is instrumental: whether the service is useful, easy to use, and capable of helping customers complete banking tasks efficiently. The second is trust-based: whether customers feel able to trust the service and whether risks are manageable. Automated banking initiatives are unlikely to produce strong satisfaction if either layer is neglected.

First, banks should continue to prioritise instrumental fundamentals. Usefulness and ease of use contributed positively to satisfaction, and their effects did not differ significantly across age groups. The practical value of algorithmic banking remains central for all customers. Banks should ensure automated services solve real customer problems, reduce friction, provide timely support, and remain easy to navigate. Chatbots, recommendation tools, fraud alerts, and other automated interfaces should be designed to minimise effort, improve task completion, and provide clear service value regardless of age.

Second, banks should treat trust-building and risk-reduction as distinct priorities rather than assuming a functionally efficient automated service will automatically be accepted. The strong role of algorithmic trust suggests customers need confidence in dependability and appropriateness. The negative effect of perceived risk indicates concerns about loss, privacy, security, and automated error can materially reduce satisfaction. Banks should support automated service deployment with clear communication about what the system does, how it supports the customer, what safeguards are in place, and what recourse is available. Trust is unlikely to be built by performance alone; it also depends on transparency, reassurance, and visible accountability.

The age-segment results suggest that reassurance strategies can be tested for differential effectiveness rather than assumed to work identically for every customer. For the 18–35 segment, the stronger trust association indicates potential value in communications that demonstrate reliability, competence and accountability. For the 36+ segment, the stronger risk association indicates potential value in clear security, privacy, fraud-prevention and human-recourse information. These recommendations are segment-level implications from the present sample, not prescriptions based on a universal age threshold.

Finally, banks should avoid interpreting AI adoption purely as feature rollout or digital functionality. Satisfaction with algorithmic banking is partly a matter of relationship management. Successful AI deployment requires more than adding automated capabilities to existing service channels. It also requires designing service experiences where customers understand the value of the automated system, feel able to rely on it, and know how the bank will respond if problems arise. Algorithmic banking should be managed as both a technology implementation challenge and a customer-relationship challenge shaped by trust, perceived risk, and different concerns of different customer groups.

6. LIMITATIONS AND FUTURE RESEARCH

Several limitations should be acknowledged.

First, the study relies on cross-sectional survey data from a single source. Although procedural remedies and diagnostic checks suggested common method bias is unlikely to be the dominant explanation, the design does not allow strong causal claims about how satisfaction develops over time. Observed relationships should be interpreted as theoretically informed associations rather than definitive causal evidence. Future research could strengthen causal inference using longitudinal designs, field experiments, or repeated-measure studies tracking how trust, risk, and satisfaction evolve as customers gain experience with algorithmic banking.

Second, the study is situated in the Indian retail banking context. This setting is substantively important because automated banking has expanded rapidly in India, but it limits generalisation. Customer expectations, digital-service habits, regulatory conditions, and institutional environments may differ across banking markets, shaping how trust and risk enter into satisfaction. Replication across other national settings would help establish boundary conditions.

Third, the study operationalises algorithmic trust and perceived risk as broad trust-based assessments rather than finely differentiated constructs. This is appropriate for the current model but leaves important distinctions unresolved. Trust may reflect a combination of trust in the algorithmic system itself, trust in the bank, and trust in the broader service process. Perceived risk may include privacy, security, financial, and performance dimensions that may not influence satisfaction in the same way. Future research could disentangle these dimensions and examine whether different forms of trust and risk have distinct effects.

Fourth, age is examined through a pragmatic 18–35 versus 36+ segmentation. The cut-off is not a universal developmental boundary, and chronological age is only a proxy for the motivational processes discussed by SST. The moderation inference in this article is therefore based on the reported MGA and should be interpreted as age-segment heterogeneity within this sample rather than as a universal life-stage effect. Future research should model age continuously and directly measure the motivational mechanisms proposed by SST.

Finally, the study focuses on satisfaction as the principal outcome. Satisfaction captures customers' overall response but is unlikely to be the only consequential outcome. Future research could examine whether the same pattern of trust-based and instrumental assessments extends to continued use, advocacy, loyalty, complaint behaviour, resistance to automated channels, or willingness to accept higher automation in financial decision-making. Such work would clarify whether the selective age effects observed are specific to satisfaction or reflect a broader pattern.

These limitations define the appropriate scope of the conclusions. The study provides evidence that satisfaction is associated with both relational and functional evaluations and that the strength of trust and risk associations differs across the two age segments examined. Replication using continuous-age modelling, alternative age operationalisations, and direct measures of SST mechanisms would help establish the generalisability of these patterns.

7. CONCLUSION

This study finds that satisfaction with AI-enabled banking reflects both what the service enables customers to do and how comfortable they are relying on it. Algorithmic trust, perceived usefulness and ease of use are positively associated with satisfaction, while perceived risk is negatively associated with it. The age-segment comparison adds a narrower result: trust is more strongly associated with satisfaction in the 18–35 group, whereas risk is more strongly associated with satisfaction in the 36+ group; usefulness and ease-of-use associations do not differ significantly.

The theoretical implication is deliberately bounded. The observed pattern is consistent with an SST-informed interpretation of age-related differences in responses to uncertainty, but the study does not directly measure SST's motivational mechanism, and the age split is not a universal developmental threshold. For banks, the results support maintaining strong functional design for all customers while testing whether trust-building and risk-reduction communications need to be adapted across customer segments.

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APPENDIX A: MEASUREMENT INSTRUMENT

All items measured on a five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree).

PERCEIVED USEFULNESS (ADAPTED FROM DAVIS, 1989)

PU1: Using AI-enabled banking services improves my banking efficiency.

PU2: AI-enabled banking services help me accomplish my banking tasks more quickly.

PU3: AI-enabled banking services increase my banking productivity.

PU4: I find AI-enabled banking services useful for my banking needs.

PERCEIVED EASE OF USE (ADAPTED FROM DAVIS, 1989)

PEOU1: Learning to use AI-enabled banking services is easy for me.

PEOU2: I find it easy to get AI-enabled banking services to do what I want.

PEOU3: My interaction with AI-enabled banking services is clear and understandable.

PEOU4: I find AI-enabled banking services easy to use.

ALGORITHMIC TRUST (ADAPTED FROM MORGAN & HUNT, 1994; GEFEN ET AL., 2003)

Trust1: The AI system in my bank is reliable.

Trust2: The AI system in my bank has my best interests in mind.

Trust3: I trust the AI system to handle my banking transactions accurately.

Trust4: The AI system in my bank is trustworthy.

Trust5: I feel confident relying on the AI system for banking services.

PERCEIVED RISK (ADAPTED FROM FEATHERMAN & PAVLOU, 2003; KIM ET AL., 2008)

Risk1: Using AI-enabled banking services could expose me to financial loss.

Risk2: There is a risk that my personal information could be misused by the AI system.

Risk3: The AI system might make errors that affect my finances.

Risk4: Overall, using AI-enabled banking services involves significant risk.

CUSTOMER SATISFACTION (ADAPTED FROM OLIVER, 1999; ANDERSON & SULLIVAN, 1993)

SAT1: I am satisfied with my experience using AI-enabled banking services.

SAT2: AI-enabled banking services meet my expectations.

SAT3: My choice to use AI-enabled banking services was a wise one.

SAT4: Overall, I am happy with AI-enabled banking services.

APPENDIX B: MICOM RESULTS FOR AGE GROUPS

Construct	Original Correlation (c)	5% Quantile	Compositional Invariance?
Perceived Usefulness	0.998	0.995	Yes
Perceived Ease of Use	0.997	0.994	Yes
Algorithmic Trust	0.996	0.993	Yes
Perceived Risk	0.997	0.994	Yes
Customer Satisfaction	0.998	0.995	Yes

Measurement invariance of composites (MICOM) was assessed following Henseler et al. (2016). The procedure is reported using the standard three-step terminology.

Step 1 - Configural invariance: The same measurement model, indicators, data treatment and algorithm settings were used for both age segments; configural invariance was therefore established by design.

Step 2 - Compositional invariance: The permutation-based compositional correlations reported in the retained output exceed the corresponding 5% quantiles for all five constructs (see table above). Compositional invariance is therefore supported for each construct.

Step 3 - Equality of composite means and variances: Equality of composite means and variances constitutes the third MICOM step. The revised manuscript does not use equality of means and variances as a prerequisite for the structural comparisons reported here. Following Henseler et al. (2016), establishment of Steps 1 and 2 provides partial measurement invariance, which is sufficient for comparing standardised structural relationships across groups. The manuscript therefore makes the more conservative claim of partial, rather than full, measurement invariance.

MICOM conclusion: Partial measurement invariance is established across the 18–35 and 36+ segments. The MGA comparisons are therefore interpreted as comparisons of standardised path coefficients, without claiming equality of all composite means and variances.

Declaration on the use of generative artificial intelligence: Generative AI tools were used during manuscript preparation to assist with language refinement, organisation and editorial revision. The author critically reviewed and revised all AI-assisted material and assumes full responsibility for the intellectual content, theoretical arguments, interpretation of results, references and final text. *Generative AI was not used to create or fabricate respondents, research data, statistical results or empirical findings.*

Data availability: Respondents were assured of anonymity and confidentiality as a condition of participating in this online survey. Consistent with this assurance, the respondent-level dataset has not been deposited in a public repository and is not available for external sharing. The author remains responsible for the accuracy of the analyses and results reported in the article.

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