FACTORS INFLUENCING CUSTOMER TRUST IN AI BASED BANKING SERVICES: A CRITICAL NARRATIVE REVIEW

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Abstract. *This article examines factors influencing customer trust in AI-based banking services through a critical narrative review of selected relevant papers. It compares their methods, findings, and limitations. Accuracy, service quality, privacy, and security emerge as recurring trust factors, while findings on explainability, ethical practices, and perceived risk vary. The article contributes by organizing the evidence, explaining differences between studies, and identifying relationships that need further investigation. It also outlines research priorities for Uzbekistan, where the reviewed papers provide no direct customer evidence.*

Keywords: *artificial intelligence; banking services; customer trust; literature review; privacy and security; service quality, explainability.*

Introduction

AI-based banking services include conversational support, personalized recommendations, financial advisory tools, and automated customer relationship management. Studies of these services associate trust with willingness to adopt or maintain a banking relationship (Fitriani & Basir, 2025; Geetha & Venkatragavan, 2026; Kesharwani et al., 2026, preprint). Yet the term trust does not always refer to the same judgment. Confidence in a chatbot's answer, confidence in a bank's data practices, and willingness to follow financial advice expose customers to different uncertainties. Their determinants cannot be assumed to have identical importance.

For this review, trust means willingness to accept vulnerability in using a particular AI-enabled banking service, informed by favorable expectations about the service and its provider. Mayer et al. (1995) distinguish that willingness from perceived trustworthiness and from risk-taking behavior. McKnight et al. (2002) distinguish trust in a particular party from confidence in protective institutional arrangements. These distinctions are useful when interpreting banking studies that place reliability, security, satisfaction, and intention close to trust. An association between two such measures may have a different meaning when their questionnaire items overlap.

A further difficulty concerns the service being evaluated. Some papers investigate explicitly identified chatbots or financial advisory tools. Others examine mobile banking or self-service channels that include conventional digital technologies. A mobile application or automated teller machine is not evidence of AI exposure by itself. Consequently, a study may illuminate digital service trust without isolating the role of AI. The issue is especially relevant to comparisons between the self-service study of Zungu et al. (2025), the mobile-banking study of Lopes et al. (2025), and the chatbot studies included here.

The review asks three questions: which factors recur in the selected studies, how differences in context and measurement qualify their findings, and which gaps deserve further investigation. Its purpose is to evaluate and organize existing evidence. The analysis also considers what the evidence

can contribute to questions about Uzbekistan, without assuming that results from other populations establish local customer behavior.

Methods

Review design and scope

A critical narrative review was conducted using a purposively assembled collection of fourteen academic papers on AI-related banking and financial services. Twelve are journal publications; the two SSRN manuscripts were examined in their supplied preprint versions and are identified accordingly. Six further sources provide definitions and interpretive guidance on trust, technology acceptance, appropriate reliance, and conceptual research. They are kept separate from the fourteen-paper evidence base. Two other research papers were set aside and not used for this synthesis because of their unresolved publication-date inconsistencies and conflicting sample descriptions.

Papers selected were identified through Google Scholar. The article makes no claim to systematic or exhaustive coverage. Table 1 identifies the included substantive papers. Ashrafuzzaman et al. (2025) was counted as one review article. The studies discussed within it were not included as separate sources in this review.

Appraisal and synthesis

Each paper was examined for service context, research design, reported sample, definition of trust, proposed determinants, outcomes, and limitations. Appraisal considered whether respondents had encountered an identifiable AI service, whether the measures separated trust from its predictors, and whether the conclusions matched the design and results. A journal publication was not taken as sufficient evidence of methodological quality.

The analysis grouped findings by the evaluation they concerned, including performance, protection, explanations, usability, personalization, and support. It then compared agreement, disagreement, and differences in outcomes. The review distinguished direct links between factors from links that work through other factors. Customers' stated preferences and recommendations for banks were also considered separately. Results from studies using different methods were not combined or used to rank the factors. When a paper's numerical results were unclear, it was used for background discussion rather than exact comparisons. Findings from preprints were treated as preliminary.

Table 1. Included papers and their analytical contributions

Paper	Reported design and sample	Contribution to this synthesis
Kumar (2025)	Bank comparison; survey reported as 150	Context on speed, accuracy, security, and satisfaction.
Zungu et al. (2025)	Ghana; survey 422; PLS-SEM	Experience links personalization and convenience with trust.
Ashrafuzzaman et al. (2025)	Review reporting 111 included studies	Secondary context on personalization, privacy, and control.

Paper	Reported design and sample	Contribution to this synthesis
Basri and Almutairi (2023)	Saudi banking; 150 employees and 200 customers	Transparency, AI trust, and financial self-efficacy.
Cheng and Trinidad (2026)	China; survey 402; sequential regression	Security and institutional assurance; conflicting risk result.
Ehsan et al. (2026)	China; banking and e-commerce; survey 1450	Transparency, bias mitigation, and perceived ethical culture.
Sharma and Agarwal (2026)	Banking chatbots; survey 120	Descriptive trust priorities; usefulness and risk linked to intention.
Kumar and Sen Gupta (2023)	Delhi; survey 187	Context on support, data management, privacy, and relationships.
Ni (2024)	Banking; survey 169; ordered probit	Perceived accuracy and reliability associated with trust.
Fitriani and Basir (2025)	Financial advisory; survey 412; PLS-SEM	Cognitive and emotional trust; satisfaction and risk pathways.
Geetha and Venkatragavan (2026)	Private sector banks; survey 361; PLS-SEM	Ethical governance, sustainable trust, and reported retention.
Kesharwani et al. (2026)	India; survey 342; SEM; preprint	Chatbot features, facilitating conditions, trust, and reliability.
Lopes et al. (2025)	Portugal; survey 452; regression	Service quality and security linked to mobile-banking trust.
Salazar-Altamirano et al. (2026)	Survey 274; CB-SEM; preprint	Ethics linked with trust and well-being as parallel pathways.

Sample sizes and designs follow the original papers. The two preprints are identified explicitly. The papers were included because they were relevant to the topic. Their strengths and limitations are discussed when interpreting their findings.

Theoretical sources help interpret the categories without being counted as empirical confirmation. Davis (1989) explains the relevance of usefulness and ease of use to acceptance. Glikson and Woolley (2020) inform the distinction between cognitive evaluations and emotional responses to AI. Lee and See (2004) provide a criterion for interpreting practical implications: trust should support reliance that matches actual system capability and limitations.

Results

Characteristics of the reviewed evidence

The collection contains banking chatbot, financial advisory, mobile-banking, self-service, and ethical-governance studies, together with a review of personalization. Cross-sectional questionnaires predominate among the original studies, and several use convenience, purposive, or snowball recruitment. The studies measured customer trust, satisfaction, plans to use the service, self-reported use, and willingness to remain a customer. These differences prevent treating all papers as tests of the same trust model. The evidence below is organized thematically, with nine domains summarized in Table 2.

Performance accuracy and service quality

Perceived performance recurs as a reason for trusting banking technology. Ni (2024), analyzing 169 valid responses, reports positive associations of perceived accuracy and system reliability with trust. In Sharma and Agarwal's (2026) sample of 120 customers, accuracy and reliability were the most frequently selected trust consideration. That descriptive ranking concerns one sample and does not estimate an independent causal effect. It is also based partly on expectations: only a minority of respondents reported prior chatbot use. Neither study verifies system accuracy through observed task performance.

Lopes et al. (2025) find positive associations of service quality and security with mobile-banking trust among 452 Portuguese respondents. Their study extends the performance theme beyond individual answers to broader service delivery, although it does not isolate a specific AI effect. Kumar's (2025) comparison of SBI and ICICI adds context on convenience, accuracy, and customer perceptions. Its reporting does not support attributing differences in bank profitability to AI. Across these papers, performance has recurring relevance, but the evidence concerns what customers believe the service can do more than what independent performance tests establish.

Privacy and security

Security concerns protection against unauthorized access, fraud, and interference; privacy is about the acceptability of collecting, using, and sharing information. Cheng and Trinidad (2026) report a positive adjusted association between perceived security and trust. Lopes et al. (2025) relate security to both trust and intention to use mobile banking. Sharma and Agarwal (2026) also identify data privacy and security as a frequently chosen trust consideration. These findings justify treating protection as a recurring theme, while their different measures and outcomes prevent a common effect ranking.

The distinction between protection and trust is not always secure in the measurement. A trust item in Lopes et al. (2025) refers to financial information being protected, bringing it close to the security construct. This overlap may contribute to the observed association. Geetha and Venkatragavan (2026) include data security and privacy within their governance model, but reporting ambiguities limit numerical interpretation. Kumar and Sen Gupta (2023) discuss privacy and data management in customer relationships; inconsistencies in their regression reporting restrict the weight given to estimates. The reviewed evidence concerns perceived safeguards, not independently audited cybersecurity or data governance.

Transparency, explainability and fair treatment

Transparency makes AI use and relevant practices visible, whereas explainability deals with whether an output and its basis are understandable. Ehsan et al. (2026) report positive associations of transparency and bias mitigation with trust in 1,450 respondents across Chinese banking and e-

commerce. Perceived organizational ethical culture strengthens the reported relationships. Because the sample combines sectors and relies on customer perceptions, the study does not establish a banking-only causal effect or independently verified bias reduction.

Cheng and Trinidad (2026) provide a less straightforward pattern. Transparency and competence have positive associations with trust in their attributes-only regression, but are nonsignificant after broader evaluations enter the model. The paper also reports substantial overlap between constructs. The result therefore cannot establish that explanations cease to matter; their contribution may be difficult to separate from correlated judgments. Ni (2024) foregrounds explainable AI in the title, yet the displayed trust model does not offer a direct test of an explanation variable. Its accuracy and reliability results should not be counted as independent confirmation of an explanation effect.

Geetha and Venkatragavan (2026) distinguish concrete governance practices from broad normative ethical alignment. The latter is nonsignificant in displayed retention and indirect-effect results. However, estimates in the tables labeled direct and indirect effects are duplicated, limiting precise comparisons. Fair treatment, accountability, and general ethical approval also differ conceptually. The combined evidence supports closer examination of particular practices; it does not show that every ethical dimension has an independent effect or that a general ethical label increases trust.

Usefulness, ease of use and customer experience

Usefulness means achieving a banking objective, while ease of use reflects interaction effort. Cheng and Trinidad (2026) report positive adjusted associations of both with trust. Zungu et al. (2025), using 422 responses from Ghana, connect personalization and convenience with self-service experience, and experience with trust. This offers an experiential account in which customers evaluate features through service encounters. The inclusion of conventional self-service channels nevertheless limits an AI-specific interpretation.

Kesharwani et al. (2026, preprint) separate trust from perceived reliability in a chatbot model based on 342 usable responses from India. Performance expectancy and social influence have positive trust paths but nonsignificant reliability paths. Effort expectancy and facilitating conditions relate positively to both evaluations. The pattern shows why trust and reliability should not be treated as interchangeable outcomes. The study analyzes several chatbot features together, so it cannot show how much each feature, such as accuracy or customization, influences trust on its own. Because the paper has not yet been peer reviewed, its findings should be interpreted cautiously.

Personalization and customer control

Personalization is associated with favorable experience in Zungu et al. (2025) and cognitive trust in the financial advisory model of Fitriani and Basir (2025). These findings regard the relevance of a service to the customer. They do not establish that collecting more information necessarily increases trust. Ashrafuzzaman et al. (2025) discuss personalization, privacy, consent, and engagement in their review. It contributes thematic context, but the studies it cites were not independently verified in this synthesis.

Customer control is an important distinction within this theme. A customer may value a relevant recommendation while questioning how the information behind it was obtained. The selected studies do not establish how much control is needed or whether control consistently changes the personalization-to-trust relationship. Customization also appears in Kesharwani et al.'s (2026) bundled feature construct, without an independently estimated trust effect. Accordingly, control is

identified as an unresolved condition of personalization rather than an empirically confirmed moderator across the collection.

Human assistance and institutional assurance

Sharma and Agarwal (2026) report that 22 percent of respondents selected easy escalation to a human agent as their principal trust consideration. This establishes a descriptive preference within that sample, not the effect of implementing a review process. The distinction between reaching an agent and obtaining a correction is also unresolved. Basri and Almutairi (2023) discuss transparency, trust, and financial self-efficacy, but the relationship between their employee and customer samples is insufficiently clear for detailed interpretation. Their account provides context for the service arrangements around AI rather than evidence about a particular escalation design.

Practical support extends beyond intervention after an error. Kesharwani et al. (2026, preprint) associate facilitating conditions with trust and perceived reliability. Resources, access, compatibility, and available assistance can therefore be examined separately from the effort required by an interface. However, the selected evidence does not establish a general effect across populations or determine which support component matters most.

Institutional assurance consist of expectations about the bank and the arrangements surrounding a service. Cheng and Trinidad (2026) report a positive adjusted relationship between institutional trust and service trust. Geetha and Venkatragavan (2026) include accountability and regulatory or social legitimacy within their governance model. These studies connect the evaluation of technology with confidence in its provider. They do not identify separate effects for reputation, regulation, and complaint handling, or demonstrate compliance with particular laws. Whether bank-level confidence transfers to a new AI service and changes after an error remains a question for later research.

Perceived risk and conflicting findings

Perceived risk produces disagreement that should remain visible. Sharma and Agarwal (2026) associate risk negatively with willingness to use chatbots, while Fitriani and Basir (2025) report negative risk interactions in trust-formation pathways. Cheng and Trinidad (2026), however, find a positive association between risk-concern scores and trust and explicitly leave it unresolved. These models differ in outcome, specification, and measurement, so their coefficients are not directly comparable. The positive result cannot be relabeled as safety to create agreement. Perceived likelihood of harm also needs to be separated from risk tolerance, which concerns willingness to accept uncertainty.

Trust, emotional responses and behavioral outcomes

Fitriani and Basir (2025) distinguish cognitive and emotional trust and place satisfaction between trust and intention. Salazar-Altamirano et al. (2026, preprint), using 274 responses, report links from ethical perceptions to trust and subjective well-being, with both related to intention. Their direct ethics-to-intention path is nonsignificant. The proposed parallel pathways are potentially useful, but the displayed discriminant-validity table raises doubts about separation between ethical perceptions, trust, and well-being. The preprint consequently supplies an exploratory explanation, not confirmation of distinct psychological mechanisms.

Lopes et al. (2025) also demonstrate the need to distinguish feelings from intention. Their results do not identify comfort with AI or need for service as significant predictors of intention, despite stronger negative-effect wording in the abstract. The displayed results do not establish that comfort reduces adoption. More broadly, Geetha and Venkatragavan's (2026) cross-sectional

retention measures include continuation intentions, and Kesharwani et al.'s (2026) use behavior is questionnaire-based. Such outcomes cannot demonstrate durable trust, independently observed customer retention, or improved financial decisions.

Table 2. Themes and limits of the reviewed evidence

Domain	Pattern in the reviewed papers	Examples and principal qualification
Performance and service quality	Perceived accuracy and service quality recur in trust findings.	Ni 2024; Sharma and Agarwal 2026; Lopes et al 2025. Preferences and perceptions do not verify system performance.
Privacy and security	Protection is associated with trust or intention in several studies.	Cheng and Trinidad 2026; Lopes et al 2025. Trust and security items sometimes overlap.
Transparency and explainability	Positive findings depend on specification and the meaning of explanations.	Ehsan et al 2026; Cheng and Trinidad 2026. Adjusted results differ; sector scope varies.
Fairness and ethical practice	Specific practices and perceived ethical context enter trust models.	Ehsan et al 2026; Geetha and Venkatragavan 2026. Broad ethical approval is not an equivalent measure.
Usefulness and ease of use	Practical value, effort, and experience are related to trust evaluations.	Cheng and Trinidad 2026; Zungu et al 2025; Kesharwani et al 2026, preprint. Pathways and AI exposure differ.
Personalization and control	Personalization relates to experience or trust; control remains less tested.	Zungu et al 2025; Fitriani and Basir 2025; Ashrafuzzaman et al 2025. No general control effect is established.
Human recourse	Easy escalation is a stated trust preference.	Sharma and Agarwal 2026. Limited descriptive evidence; correction effectiveness is not tested.
Facilitating conditions	Resources and assistance are linked to trust and reliability.	Kesharwani et al 2026, preprint. Independent components and wider applicability remain uncertain.
Institutional assurance	Confidence in the provider and governance arrangements is relevant.	Cheng and Trinidad 2026; Geetha and Venkatragavan 2026. Specific institutional mechanisms are not isolated.

This table summarizes the selected papers without ranking effects or assigning quality scores. Risk and behavioral outcomes are discussed separately.

Discussion

What the literature supports

The clearest pattern is the recurrence of perceived performance and protection across different service settings. Accuracy, service quality, security, and acceptable data use give customers grounds for evaluating whether reliance is reasonable. Recurrence alone does not establish that these factors dominate others. Some findings are about stated preferences, others concern regression associations, and others appear in models of intention. A conclusion about the strongest determinant would require comparable definitions, measures, and outcomes that this collection does not provide.

The literature also directs attention beyond the technology to the institution operating it. Ethical culture, accountability, human escalation, and facilitating conditions describe different parts of that environment. Their evidence should not be combined into a claim that one comprehensive governance mechanism has been tested. A more precise interpretation is that customers may evaluate the response they expect from the bank alongside the output they receive from the system. How those judgments interact, particularly for consequential financial tasks, remains insufficiently examined.

Trust should also be distinguished from making adoption convenient. A customer may find a service useful without being willing to follow its advice. Conversely, confidence in the bank may coexist with difficulty using a particular interface. The distinctions made by Davis (1989), Mayer et al. (1995), and McKnight et al. (2002) help interpret these possibilities. Kesharwani et al.'s (2026) different paths to trust and reliability provide a concrete example of why apparently similar evaluations deserve separate measures.

Why findings are difficult to combine

Firstly, findings may differ because the studies examine different types of banking services. An interaction about routine account information differs from a personalized financial recommendation, but the reviewed studies do not provide a controlled comparison of those tasks. Clear explanations and access to help when problems occur may matter more for services involving major financial decisions. However, the studies reviewed do not confirm this, so further research is needed. Some studies do not clearly identify which AI banking services their participants actually used. This makes it difficult to apply their findings to other types of banking services.

Secondly, measurement overlap is another source of disagreement. Cheng and Trinidad (2026) report high ratios between several constructs. Lopes et al.'s (2025) protection-related trust item partly overlaps with security, while the ethics and well-being preprint does not consistently demonstrate the construct separation it claims. Correlations between similar questions can make distinct determinants appear to have clearer support than they do.

Finally, most studies collected information at one point in time, so they cannot show which came first: a positive customer experience or greater trust. Finding a possible link through another factor does not prove that events happened in that order. Similarly, a lack of clear evidence for a direct relationship does not prove that an indirect relationship exists. Some results are also difficult to interpret because of reporting problems. For example, the governance study reports identical numbers for direct and indirect relationships. These uncertainties should be acknowledged, rather than using only results that support the expected conclusion.

Implications for banking services and Uzbekistan

For banks, the recurring themes suggest evaluating whether customers receive dependable answers, understand the use of their information, and can obtain useful assistance. Recommendations should remain proportionate to the evidence. For example, a preference for human escalation supports

attention to that option, but does not show which staffing or correction process improves trust. Perceived security should also be compared with actual safeguards. Following Lee and See (2004), the objective is confidence that supports appropriate reliance; favorable questionnaire responses alone cannot establish service safety or decision quality.

None of the reviewed papers shows direct evidence from Uzbek banking customers. The review can help frame local questions, but cannot establish which determinant matters most in Uzbekistan. Relevant questions include whether customers understand explanations in their preferred language, distinguish the bank from its AI service when assigning responsibility, and know how to seek correction. The relative importance of these issues should be investigated across service types and levels of digital experience. They are proposed applications of the reviewed themes, without claims about existing Uzbek customer behavior.

Limitations and research priorities

This review is limited by its purposive collection, the absence of a reproducible search strategy, and reliance on interpretive appraisal without independent double-coding. It cannot characterize all research on AI banking trust or estimate the prevalence of particular findings in the wider literature. The two preprints may change through peer review. Inclusion was based on analytical relevance, with reporting limitations carried into the interpretation.

Future studies would benefit from identifying the exact AI service encountered and separating trust in the service from trust in the bank. Trust measures should avoid repeating the content of proposed predictors, especially security and reliability. Experiments could compare explanation formats or access to effective human review within the same banking task. In Uzbekistan, language comprehension and the meaning of the constructs should be examined before testing relationships.

Conclusion

The selected literature associates customer trust in AI-based banking with perceived performance, protection, ethical practices, usability, personalization, support, and institutional assurance. Its most defensible contribution is a set of recurring themes with different evidential limits. Performance and security recur, while transparency, risk, and psychological pathways require closer attention to model specification and measurement. Human recourse and customer control remain less directly established than their practical prominence might suggest. No universal ranking follows from the fourteen papers. Clearer service definitions, better separation of constructs, and evidence about trust over time are needed before stronger causal or behavioral conclusions can be drawn.

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