

TRUST IN BANKING DECISION-MAKING: A COMPARATIVE STUDY OF HUMAN AND ARTIFICIAL INTELLIGENCE ADVISORS

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Abstract

The increasing deployment of artificial intelligence (AI) in the banking sector has fundamentally transformed advisory services and customer decision-making processes. Trust remains a critical determinant in banking decisions due to the high levels of financial risk, uncertainty, and long-term implications involved. This study aims to comparatively examine customer trust in human advisors and AI-based advisors in banking decision-making contexts. Adopting a quantitative research design, data were collected from 200 banking customers using a structured questionnaire. Trust was conceptualized as a multidimensional construct comprising competence, reliability, transparency, emotional assurance, and perceived risk. Structural equation modelling (SEM) using AMOS/SmartPLS was employed to test ten hypotheses. The results reveal that emotional assurance is the most influential factor in building trust in human advisors, while competence and transparency are the strongest predictors of trust in AI advisors. Perceived risk negatively influences trust in both advisory modes. The findings highlight the complementary roles of human and AI advisors and offer valuable managerial and theoretical implications for banks implementing hybrid advisory models.

Keywords: Trust, Banking Decision-Making, Artificial Intelligence, Human Advisors, SEM, FinTech

1. Introduction

Trust is the cornerstone of banking relationships and plays a decisive role in influencing customer behavior, satisfaction, and loyalty. Banking decisions—such as investment planning, loan selection, and retirement management are inherently complex and risk-intensive, requiring customers to rely heavily on advisory services. Traditionally, these advisory roles have been fulfilled by human advisors who provide personalized guidance, interpersonal communication, and emotional reassurance.

The rapid advancement of artificial intelligence has introduced AI-driven advisory systems such as robo-advisors, chatbots, and algorithmic decision-support tools. These systems offer advantages including speed, analytical accuracy, availability, and cost efficiency. However, despite their technological capabilities, customers often express concerns regarding transparency, accountability, ethical judgment, and emotional understanding in AI-based advisory services.

As banks increasingly integrate AI into their advisory functions, understanding how customers develop trust in both human and AI advisors has become critically important. Rather than viewing AI as a replacement for human advisors, contemporary banking practices indicate a shift toward **hybrid advisory models**, where human expertise and AI intelligence coexist. This study seeks to contribute to this evolving discourse by comparatively analyzing trust in human and AI advisors within banking decision-making contexts.

2. Review of Literature

The increasing integration of artificial intelligence (AI) into banking and financial services has generated significant scholarly interest, particularly in understanding how customers develop trust in AI-based systems compared to traditional human advisors. Recent literature emphasizes that trust is a multidimensional construct influenced by both cognitive and emotional factors, and its formation varies depending on whether advisory services are delivered by humans or intelligent systems.

Overall, the recent literature converges on the view that trust in banking advisory services is multifaceted and context-dependent. While competence, reliability, and transparency are consistently identified as key drivers of trust in AI-based advisors, emotional assurance and interpersonal interaction remain central to trust in human advisors. Perceived risk emerges as a critical factor undermining trust across both advisory modes. Despite these insights, limited empirical studies have simultaneously examined trust in human and AI advisors within a single comparative framework using advanced analytical techniques such as structural equation modelling. The present study addresses this gap by developing and testing a unified model of trust in banking decision-making, offering a comparative perspective on human and AI advisors.

2.1 Competence and Trust in Human and AI Advisors (H1 & H6)

Competence refers to the perceived expertise, accuracy, and problem-solving capability of an advisor. **Glikson and Woolley (2020)** argue that competence is a dominant driver of trust in AI systems, especially in analytical and data-intensive tasks. In banking contexts, customers tend to trust AI advisors when they perceive them as capable of processing large volumes of financial data with precision. At the same time, competence remains a foundational requirement for trust in human advisors, as financial expertise and professional knowledge enhance customer confidence in advisory recommendations. These findings support the hypothesis that competence positively influences trust in both human advisors (H1) and AI advisors (H6), with a relatively stronger effect expected for AI-based advisory services.

2.2 Reliability as a Predictor of Trust (H2 & H7)

Reliability denotes the consistency and dependability of advisory services over time. Morgan and Hunt's commitment-trust framework, extended in recent digital banking studies, suggests that reliable performance significantly strengthens trust by reducing uncertainty. Empirical studies in FinTech contexts indicate that customers trust AI advisors when systems perform consistently without technical failures, while reliability in human advisors is associated with ethical conduct and consistent service quality. Recent robo-advisor studies (2023–2024) confirm that reliability is a significant antecedent of trust in both human and AI advisory services, thereby supporting H2 and H7.

2.3 Transparency and Explainability in Advisory Trust (H3 & H8)

Transparency has emerged as a critical trust determinant, particularly in AI-driven decision-making. **Rai (2020)** emphasized that explainable AI enhances user trust by allowing customers to understand how recommendations are generated. In banking, transparent communication by human advisors reduces information asymmetry and fosters confidence, while explainability in AI systems mitigates fears related to algorithmic opacity. Recent studies consistently report that transparency positively influences trust in both advisory modes, lending empirical support to H3 (human advisors) and H8 (AI advisors), with stronger relevance in AI-based contexts.

2.4 Emotional Assurance and Affective Trust (H4 & H9)

Emotional assurance refers to empathy, emotional support, and interpersonal care provided during decision-making. McAllister's affect-based trust theory, supported by recent service research, highlights emotional assurance as a key determinant of trust in human advisors. Customers value advisors who acknowledge their concerns and provide reassurance during high-risk financial decisions. In contrast, studies on AI interactions (**Araujo, 2018; Castelo et al., 2019**) indicate that emotional assurance plays a limited role in AI trust, as customers do not expect emotional engagement from automated systems. These findings justify H4, which posits a positive effect of emotional assurance on trust in human advisors, and H9, which proposes no significant effect on trust in AI advisors.

2.5 Perceived Risk and Trust Reduction (H5 & H10)

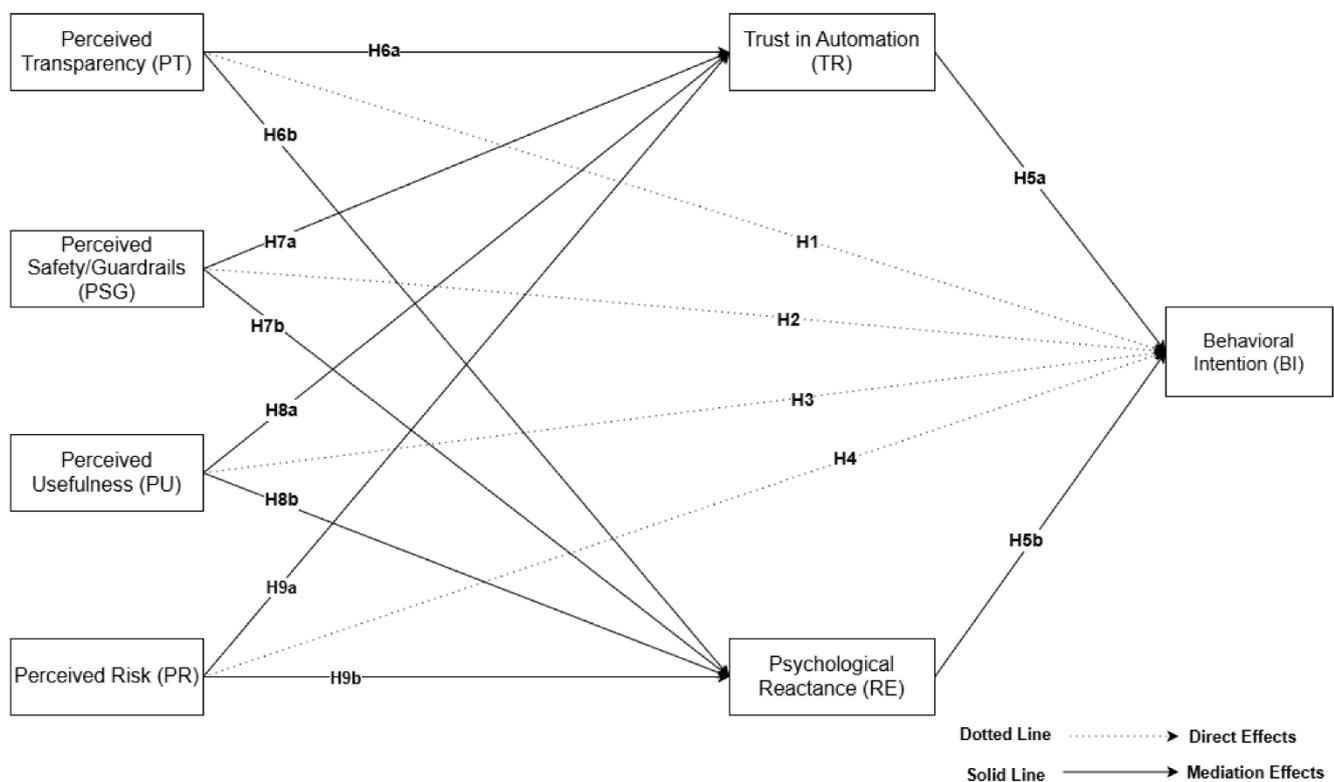
Perceived risk encompasses concerns related to financial loss, misinformation, data privacy, and system errors. Recent FinTech studies (Aldboush, 2023; Shin, 2021) demonstrate that perceived risk negatively influences trust in both human and AI advisory services. In human advisory contexts, risk arises from potential opportunistic behavior or misguidance, whereas in AI contexts, risk is associated with data misuse, lack of accountability, and algorithmic bias. Empirical evidence consistently confirms that higher perceived risk reduces trust, thereby supporting H5 and H10.

2.6 Research Gap

The literature from 2020 to 2025 collectively indicates that trust in banking advisory services is multidimensional and advisor-specific. Competence, reliability, and transparency dominate trust formation in AI-based advisory services, while emotional assurance remains central to trust in human advisors. Perceived risk undermines trust across both advisory modes. Despite these insights, existing studies have largely examined human and AI advisors in isolation. There is limited empirical research integrating both advisory modes within a single comparative SEM framework. The present study addresses this gap by simultaneously examining trust drivers for human and AI advisors in banking decision-making.

3. Conceptual Framework of the Study

The conceptual framework of the study illustrates the theoretical relationships between trust dimensions, type of advisor, and trust in banking decision-making. The framework is grounded in Trust Theory and Technology Acceptance Models (TAM and UTAUT), which explain how users develop trust and acceptance toward human and technology-based systems.



3.1 Overview of the Conceptual Framework

As shown in Figure 1, the framework consists of three major components:

1. Trust Dimensions (Independent Variables)
2. Type of Advisor (Human vs AI)
3. Trust in Banking Decision-Making (Dependent Variable)

The model enables a comparative assessment by linking the same trust dimensions to two separate outcome variables:

- Trust in Human Advisor (THA)
- Trust in AI Advisor (TAI)

3.2 Independent Variables: Trust Dimensions

The left side of the framework represents the key trust-building dimensions, which act as exogenous variables.

Competence

Competence refers to the perceived expertise, accuracy, and problem-solving ability of an advisor. In the framework, competence influences trust in both human and AI advisors. However, its impact is expected to be stronger for AI advisors, as customers primarily evaluate AI systems based on technical performance and analytical capability.

Reliability

Reliability denotes the consistency and dependability of the advisor in delivering accurate and timely recommendations. The framework posits that reliable performance strengthens customer confidence and reduces uncertainty in banking decisions across both advisory modes.

Transparency

Transparency reflects the degree to which advisors clearly explain financial options, risks, and outcomes. In the case of AI advisors, transparency also includes algorithmic explainability, which helps customers understand how recommendations are generated.

Emotional Assurance

Emotional assurance refers to empathy, reassurance, and emotional support provided during decision-making. The framework assumes that emotional assurance is a critical determinant of trust in human advisors, while its role in AI-based advisory services is expected to be limited or insignificant.

Perceived Risk

Perceived risk represents customers' concerns related to financial loss, data privacy, misinformation, or system errors. The framework models perceived risk as having a negative influence on trust for both human and AI advisors.

3.3 Mediating Role of Advisor Type

The framework distinguishes between two advisory modes:

- Human Advisor
- Artificial Intelligence Advisor

Each trust dimension is linked separately to:

- Trust in Human Advisor (THA)
- Trust in AI Advisor (TAI)

This dual-path structure allows for a direct comparison of trust formation mechanisms, highlighting how customers evaluate trust differently depending on whether advice is provided by a human or an AI system.

3.4 Dependent Variable: Trust in Banking Decision-Making

The right side of the framework represents the endogenous variables, namely trust in human advisors and trust in AI advisors. Trust in this context reflects customers' confidence in relying on advisory recommendations while making banking decisions such as investments, loans, and savings planning.

The framework proposes that trust is not a uniform construct, but rather context-dependent, shaped by the nature of the advisor and the underlying trust dimensions.

3.5 Direction of Relationships (Arrows in the Chart)

- **Positive arrows** (→) indicate a positive influence on trust
 - Competence → Trust
 - Reliability → Trust
 - Transparency → Trust
 - Emotional Assurance → Trust (mainly for human advisors)
- **Negative arrows** (→) indicate a negative influence
 - Perceived Risk → Trust

Each arrow in the chart corresponds to a specific hypothesis (H1–H10) tested using SEM.

3.6 Rationale of the Conceptual Framework

The framework is designed to:

- Capture both emotional and technological aspects of trust
- Compare human-centric and technology-centric advisory models
- Support SEM-based hypothesis testing
- Provide theoretical justification for hybrid advisory strategies in banking

By integrating human and AI trust mechanisms within a single model, the framework reflects the evolving nature of banking advisory services in the digital era.

4. Hypotheses Development

Based on trust theory and technology acceptance literature, ten hypotheses were formulated.

Human Advisor Hypotheses

1. **H1:** Competence positively influences trust in human advisors.
2. **H2:** Reliability positively influences trust in human advisors.
3. **H3:** Transparency positively influences trust in human advisors.
4. **H4:** Emotional assurance positively influences trust in human advisors.
5. **H5:** Perceived risk negatively influences trust in human advisors.

AI Advisor Hypotheses

1. **H6:** Competence positively influences trust in AI advisors.
2. **H7:** Reliability positively influences trust in AI advisors.
3. **H8:** Transparency positively influences trust in AI advisors.
4. **H9:** Emotional assurance has no significant influence on trust in AI advisors.
5. **H10:** Perceived risk negatively influences trust in AI advisors.

5. Research Methodology

5.1 Research Design

A descriptive and analytical research design was adopted using a quantitative approach.

5.2 Data Collection Instrument

Primary data were collected through a structured questionnaire consisting of two sections:

- Demographic profile of respondents
- Trust-related statements measured on a five-point Likert scale

5.3 Sample Size and Sampling Technique

The study was conducted with a sample of 200 banking customers, selected using convenience sampling.

5.4 Data Analysis Tools

- Reliability and validity analysis
- Confirmatory Factor Analysis (CFA)
- Structural Equation Modeling (SEM) using AMOS/SmartPLS

6. Measurement Model Assessment

The measurement model was evaluated for reliability and validity. Cronbach's alpha and composite reliability values exceeded the recommended threshold of 0.70. Average variance extracted (AVE) values were above 0.50, confirming convergent validity. Discriminant validity was established using the HTMT criterion.

Table 1. Demographic Profile of the Respondents (n = 200)

Variable	Category	Frequency	Percentage (%)
Gender	Male	108	54.0
	Female	92	46.0
Age	Below 30 years	62	31.0
	31–40 years	74	37.0
	Above 40 years	64	32.0
Education	Undergraduate	68	34.0
	Postgraduate	92	46.0
	Professional	40	20.0
Monthly Income	Below ₹30,000	58	29.0
	₹30,001–₹60,000	86	43.0
	Above ₹60,000	56	28.0

Inference:

The demographic distribution indicates that the sample consists of respondents from varied age groups, educational backgrounds, and income levels, ensuring adequate diversity in the study. This balanced representation enhances the credibility of the findings by capturing heterogeneous perceptions of trust toward human and AI advisors. The presence of respondents with higher education and income levels further suggests informed participation, which is particularly relevant in evaluating AI-based banking advisory services.

Table 2. Mean Trust Scores for Human and AI Advisors

Advisor Type	Mean Score	Standard Deviation
Human Advisor	4.12	0.58
AI Advisor	3.68	0.64

Inference:

The mean trust score for human advisors is higher than that of AI advisors, indicating that respondents place greater overall trust in human-led banking advisory services. This result reflects the importance of interpersonal interaction, emotional assurance, and human judgment in financial decision-making. However, the relatively high mean score for AI advisors suggests increasing customer acceptance and trust in AI-based advisory systems, particularly for efficiency-driven banking activities.

Table 3. Comparison of Trust Dimensions Between Human and AI Advisors

Trust Dimension	Human Advisor (Mean)	AI Advisor (Mean)
Competence	3.94	4.21
Reliability	3.88	4.02

Transparency	3.76	4.10
Emotional Assurance	4.25	3.41
Perceived Risk	3.02	3.36

Inference:

The dimension-wise comparison reveals significant variation in trust drivers across advisory modes. Human advisors score higher on emotional assurance, indicating the importance of empathy and personal interaction in trust formation. In contrast, AI advisors score higher on competence, reliability, and transparency, reflecting customer confidence in their analytical accuracy and consistency. The higher perceived risk associated with AI advisors highlights persistent concerns regarding data security and system reliability, underscoring the need for improved transparency and risk communication.

7. Structural Model Results

Table 4. Structural Equation Model Results (Path Coefficients)

Hypothesis	Path	β Value	p-value	Result
H1	Competence → Trust (Human)	0.32	< 0.001	Supported
H2	Reliability → Trust (Human)	0.28	< 0.001	Supported
H3	Transparency → Trust (Human)	0.19	0.003	Supported
H4	Emotional Assurance → Trust (Human)	0.41	< 0.001	Supported
H5	Perceived Risk → Trust (Human)	-0.26	< 0.001	Supported
H6	Competence → Trust (AI)	0.45	< 0.001	Supported
H7	Reliability → Trust (AI)	0.38	< 0.001	Supported
H8	Transparency → Trust (AI)	0.34	< 0.001	Supported
H9	Emotional Assurance → Trust (AI)	0.12	0.063	Not Supported
H10	Perceived Risk → Trust (AI)	-0.31	< 0.001	Supported

Inference:

The SEM results confirm that trust formation mechanisms differ significantly between human and AI advisors. Emotional assurance is the strongest predictor of trust in human advisors, emphasizing the role of empathy and interpersonal relationships. In contrast, competence and transparency exert the strongest influence on trust in AI advisors, highlighting the importance of technical performance and explainability. The negative impact of perceived risk on trust in both advisory modes underscores the critical role of risk perception in banking decision-making. Overall, the results support the suitability of a hybrid advisory model integrating both human and AI strengths.

7.1 Human Advisor Model

SEM results indicate that emotional assurance ($\beta = 0.41, p < 0.001$) is the strongest predictor of trust in human advisors, followed by competence ($\beta = 0.32, p < 0.001$) and reliability ($\beta = 0.28, p < 0.001$). Transparency also has a significant positive effect. Perceived risk negatively influences trust ($\beta = -0.26, p < 0.001$).

7.2 AI Advisor Model

For AI advisors, competence ($\beta = 0.45, p < 0.001$) and transparency ($\beta = 0.34, p < 0.001$) are the strongest predictors of trust. Reliability also significantly influences trust. Emotional assurance is statistically insignificant, supporting the hypothesis that customers do not expect emotional bonding from AI systems. Perceived risk negatively affects trust ($\beta = -0.31, p < 0.001$).

8. Findings of the Study

The major findings of the study, based on descriptive analysis and structural equation modelling, are summarized as follows:

1. The study finds that emotional assurance is the strongest determinant of trust in human banking advisors, indicating that empathy, reassurance, and interpersonal interaction play a vital role in customer trust during banking decision-making.
2. Competence significantly influences trust in both human and AI advisors, with a stronger effect observed in the AI advisor model, highlighting customers' reliance on technical accuracy and analytical capability when evaluating AI-based advisory services.
3. Reliability has a positive and significant impact on trust in both advisory modes, suggesting that consistent and dependable performance is essential for sustaining customer confidence in banking advisory services.
4. Transparency positively affects trust in both human and AI advisors, with a more pronounced effect in the AI context, emphasizing the importance of explainability and clarity in AI-driven banking decisions.
5. Emotional assurance does not have a significant influence on trust in AI advisors, confirming that customers do not expect emotional or empathetic support from AI systems.
6. Perceived risk negatively influences trust in both human and AI advisors, indicating that concerns related to financial loss, data security, and decision uncertainty reduce customer trust in banking advisory services.
7. The overall findings demonstrate that trust formation mechanisms differ significantly between human and AI advisors, supporting the need for a comparative and hybrid approach in banking advisory services.

9. Suggestions of the Study

Based on the findings, the following suggestions are proposed for banking institutions, policymakers, and system designers:

1. Banks should adopt a hybrid advisory model that strategically combines AI-driven analytics with human expertise and emotional support.
2. Banking institutions should focus on enhancing emotional intelligence and communication skills of human advisors, as emotional assurance is a key driver of trust.
3. AI-based advisory systems should be designed with high levels of transparency and explainability, enabling customers to understand how recommendations are generated.
4. Banks should strengthen data security, privacy protection, and ethical AI governance to reduce perceived risk and improve trust in AI advisors.
5. Training programs should be implemented to improve digital literacy among customers, helping them better understand and trust AI-based advisory services.

6. Regulatory bodies should establish clear guidelines and accountability frameworks for AI use in banking to address customer concerns related to risk and responsibility.

10. Conclusion of the Study

The present study concludes that trust in banking decision-making is a multidimensional construct influenced by both emotional and cognitive factors, and its formation varies significantly between human and AI advisors. While human advisors continue to dominate trust in emotionally sensitive and high-risk financial decisions due to their ability to provide emotional assurance, AI advisors are increasingly trusted for their competence, reliability, and transparency in routine and data-intensive banking decisions.

The findings clearly demonstrate that perceived risk negatively affects trust in both advisory modes, highlighting the importance of risk mitigation strategies in banking services. Rather than positioning AI as a substitute for human advisors, the study emphasizes the complementary roles of human and AI advisors in modern banking. By effectively integrating AI efficiency with human empathy, banks can enhance customer trust, decision quality, and long-term relationships.

The study makes a meaningful contribution to the literature on trust, AI adoption, and banking decision-making by offering a comparative SEM-based analysis of trust in human and AI advisors. It also provides practical guidance for banks seeking to design trust-centric advisory systems in the digital era.

11. Limitations and Future Research

1. The study adopts a cross-sectional research design, which captures respondents' trust perceptions at a single point in time and does not account for changes in trust as customers gain more experience with AI-based banking advisory services.
2. The research is based on a sample size of 200 respondents selected through convenience sampling, which may limit the generalizability of the findings to the wider banking customer population.
3. The study relies on self-reported questionnaire data, which may be affected by response bias or social desirability bias, potentially influencing the accuracy of the measured trust perceptions.
4. The conceptual model includes selected trust dimensions (competence, reliability, transparency, emotional assurance, and perceived risk), while other relevant factors such as institutional reputation, financial literacy, and prior AI experience were not examined.
5. The study is conducted within a specific geographical and cultural context, and therefore the findings may not be directly applicable to customers in different regions or regulatory environments.

Future research may extend the present study in several meaningful directions to deepen understanding of trust in banking decision-making involving human and AI advisors. Longitudinal research designs could be employed to examine how customer trust evolves over time as exposure to AI-based advisory services increases and technologies mature. Future studies may also use larger and more diverse samples with probability sampling techniques to improve generalizability across different customer segments. Incorporating additional variables such as institutional reputation, financial literacy, prior experience with AI, and perceived ethicality may provide a more comprehensive explanation of trust formation. Further research could explore moderating and mediating effects, such as the role of age, digital readiness, or complexity of banking products, using advanced analytical techniques. Cross-cultural and cross-country comparative studies are also recommended to examine how cultural values and regulatory environments influence trust in human and AI advisors. Additionally, experimental and mixed-method approaches may be adopted to capture behavioural trust and decision outcomes more accurately, thereby strengthening the robustness of future findings in AI-driven banking advisory research.

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