



Humanizing Agentic AI: Emotional Intelligence, Trust Architecture from Chatbot to Multi-Agent Banking Ecosystems

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Abstract

The adoption of AI chatbots in the banking sector is a critical issue despite the high numbers of AI chatbots deployed in the sector. In this mixed-method research, study explore about technological sophistication triggers human frustration in Indian retail banking by sequentially applying exploratory research design, involving qualitative analysis of 19,858 customer complaints and quantitative validation of the hypothesis with 1,000 banking customers using a PLS-SEM. The study builds on the UTAUT model by incorporating AI-specific constructs such as emotional intelligence, anthropomorphism and privacy capabilities to study adoption barriers. Results show that AI Effectiveness or effort expectancy turns out to be the central predictor and is even more significant than performance expectancy but does not mean that performance expectancy is not essential. The effect size of effort is approached by two variables, trust and privacy capabilities and the hypothesis on the privacy paradox which try to measure the consumer can share data over performance and efforts ease is rejected. The qualitative analysis reveals the negative sentiment and complaints focus on the operational breakdowns related based on thematic analysis (40 percent), technological shortcomings (25 percent), and loss of trust (15 percent). These Challenges are the outcome of the existing banking chatbot realities banking operation and branch services together with many minor challenges do exist that were uncovered in the qualitative analysis such lingual difference and other. The model so proposed has very good explanatory power ($R^2 = 0.639$ intention, $R^2 = 0.443$ behavior) as well as very good predictive validity ($Q^2_{predict} = 0.630$). The results show that effortlessness is replacing usefulness in the generative AI age as the key driver of adoption, which requires fundamental re-architecturalization to multi-agent orchestration with tiered human-supervised autonomy instead of slow chatbot incremental improvements.

Keywords: *AI Chatbot Adoption; Indian Retail Banking; UTAUT Extension; Service Challenges; Institutional Trust; PLS-SEM*

I. Introduction:

The emergence of superior models of AI in the form of generative AI has greatly changed the way consumers expect conversational AI systems output. The ubiquitous nature of ChatGPT and other similar engines has established new standards in the quality of AI interaction at the interface in any sector, as (Dwivedi, 2023) notes. This type of technological democratization implies that consumers now come to banking interfaces with developed mental models of AI capabilities, having tried the subtle, context-specific response of advanced language models (Kapoor, 2024).

This expectation gap presents serious challenges to the financial institutions implementing chatbot systems as, as institutions invest in AI implementation, most of their implementations use rule-based or narrow AI systems, which do not achieve consumer experiences with publicly available GPT models. In emerging markets, the technical constraints conflict with the increased expectations, as (Mogaji, 2021) found that the users were experiencing a lot of challenges with banking chatbots due to the technical constraints. The lack of connection is especially strong when the organizations launch traditional conversational agents, which users are aware of and can be reproduced with the help of available GPT tools in minutes, losing the perception of institutional innovation (Kelly, 2023). When chatbots used in banking fail to impress external AI, they eradicate both technology-specific and institutional trust (Alagarsamy, 2023). Financial firms, in turn, cannot simply view chatbot implementation as an automation exercise and should instead view it as a competitive edge that needs actual AI complexity (Lee, 2023). Such a success requires going beyond shallow applications and into full-blown AI-based solution frameworks, which not only match but surpass consumer standards set by publicly available generative AI.

Methods: A step-wise exploratory mixed-design was used. The study commenced by performing qualitative study on 19,858 customer complaints to determine the major adoption barriers. The results were used to create a long-Unified Theory of Acceptance and Use of Technology (UTAUT) model that included AI-specific constructs: emotional intelligence, anthropomorphism, and privacy capabilities. Data on 1,000 banking customers was then quantitatively verified by Partial Least Squares Structural Equation Modelling (PLS-SEM) using the model.

Results: The findings are significant with an underlying inversion of the traditional technology acceptance models. AI Effectiveness (conceptualized as effort expectancy) became the strongest predictor of adoption intention, performance expectancy, trust, and privacy capabilities were also considerably significant, and the privacy paradox hypothesis was rejected. On a qualitative report, analysis of the negative sentiments and complaints and challenges were majority found out on operational failures (40%), technology challenges (25%), and Trust loss and data related issue (15%).

The model was found to be a good predictor ($Q^2_{predict} = 0.630$) and has high explanatory power ($R^2 = 0.639$).

Discussion: The findings suggest that during the generative AI era, while usefulness (Performance Expectancy, $\beta = 0.097$) remains significant, effortlessness (AI Effectiveness, $\beta = 0.514$) has emerged as the dominant factor influencing adoption.

Consumer-grade generative AI has established new baseline expectations: multilingual understanding without language selection, direct statement comprehension without grammatical precision, emotional sentiment recognition that detects urgency in phrases like "I'm in distress, block my card," and semantic keyword extraction without requiring coding patterns or rigid commands.

Existing banking chatbots exhibit systematic deficiencies context amnesia, emotional blindness, and keyword-dependent rigidity. Incremental enhancements cannot bridge this gap. The solution demands radical architectural redesign toward multi-agent coordination systems with tiered human-supervised autonomy, where specialized AI agents orchestrate seamlessly to deliver ChatGPT-level effortlessness while maintaining institutional trust and regulatory compliance.

II. Research Questions

RQ1: What are the critical barriers preventing effective AI chatbot adoption in Indian retail banking from the customer perspective?

RQ2: To what extent do effort expectancy, performance expectancy, trust, privacy capabilities, social influence, anthropomorphism, emotional intelligence, and privacy paradox explain Indian consumers' intention to adopt AI chatbots in banking?

RQ3: Does the extended UTAUT model demonstrate predictive validity for forecasting AI chatbot adoption across Indian banking customer?

III. Problem Identification:

Analysis of 19,858 customer complaints (refined from 34,000 raw reviews) using NVivo (Fig 1. Thematic Construct Mapping and Gioia methodology) and (Table 1.1 Gioia Methodology Order Table) reveals a cascading challenge in Indian retail banking where operational, technological, and trust barriers reshape AI chatbot adoption dynamics, limiting large-scale implementation in the banking ecosystem.

Table: Qualitative Research Design Structure

DESIGN COMPONENT	SPECIFICATION
Research Approach	Qualitative – Exploratory Sequential Design (Mixed-Methods)
Data Type	Negative sentiment customer complaints (textual feedback, service failure narratives)
Data Source/ Platform	• Banking mobile apps (Google Play, App Store reviews)
	• Customer grievance portals (bank websites)
	• Social media complaints (Twitter/X, Facebook)
	• Banking Ombudsman records
	• Consumer forum submissions
Sample Size	Initial corpus: 34,000 raw customer reviews
	Refined dataset: 19,858 complaints (after removing duplicates, spam, and irrelevant content)
Sampling Method	Purposive sampling focusing on:
	• AI chatbot interaction complaints
	• Digital banking and branch banking service failures
	• Technology adoption barriers and resistance
Analysis Tools	NVivo (Qualitative Data Analysis Software)
	Gioia Methodology (Inductive thematic coding and analysis)
Analysis Process	Three-stage Gioia approach:
	1st Order: Customer voice coding (1,247 first-order concepts)
	2nd Order: Researcher thematic categories (87 second-order themes)
	Aggregate: Theoretical constructs (3 aggregate dimensions) and sentiment analysis with thematic analysis mapping
Key Issues/ Challenges Identified	1. Operational Breakdown (40% of complaints)
	→ Loan approval delays (10 days → 2 months)
	→ Unresponsive customer care channels
	→ Service inconsistency across branches
	→ Forced physical visits for digital-eligible tasks
	2. Technological Deficiencies (25% of complaints)
	→ System outages causing permanent fund loss
	→ Complex interfaces requiring 4+ attempts
	→ Broken authentication mechanisms
	→ Repetitive chatbot deflection patterns
	3. Trust Collapse & Exclusion (35% of complaints)
	→ Undisclosed charges and hidden terms
	→ Fraudulent transactions and mis-selling
	→ English-only interfaces
	→ Standardized processes ignoring regional needs
	4. AI Chatbot Vulnerabilities
	→ Identical responses without escalation
	→ AI-human channel information misalignment
	→ Context-handling rigidity
	→ Lack of cultural-linguistic adaptation
Research Outputs	• Fig 1: Thematic Construct Mapping (NVivo visualization)
	• Table 1.1: Gioia Methodology Order Table (3-stage coding)
	• Aggregate Dimensions: Institutional Trust Deficit, Digital Service Paradox, Cultural-Digital Divide
Integration with Quantitative Study	Qualitative findings inform Extended UTAUT survey (n=1,000 banking customers):
	→ Performance Expectancy (operational delay insights)
	→ Effort Expectancy (technological complexity patterns)

	→ Trust Constructs (transparency failure mechanisms)
	→ Social Influence (linguistic exclusion evidence)
	→ AI Effectiveness ($\beta=0.514$ dominance validation)

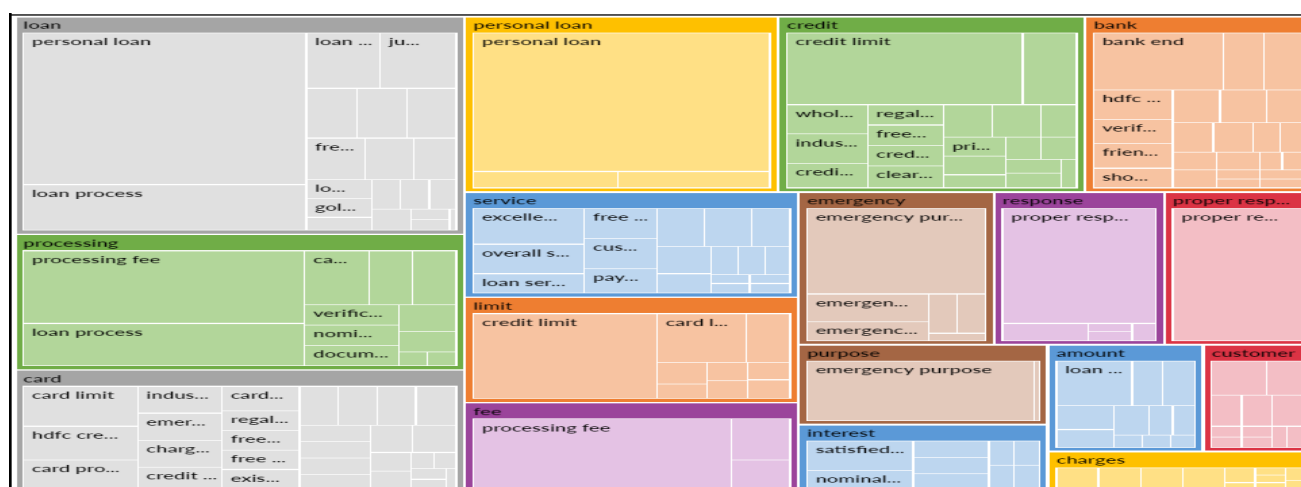


Fig 1. Thematic Construct Mapping

Table 1. NVIVO Coding Key Customer Service Issues

Theme	Subtheme	Issue Description	Example from Coding (First-Order Reference)	Impact on Customer Satisfaction	File Path (Reference)
Customer Service Challenges	Difficulty Reaching Support	Difficulty contacting customer service and poor issue resolution	"If I contact there is no proper response from their end"	Impact trust and satisfaction	<i>Results Preview.docx</i> , Page 11
	Negative Branch Experiences	Negative experiences during visits to bank branches	"Documentation was very simple, but they made a spelling mistake, so I returned the card"	Results in frustration and dissatisfaction	<i>Previewfd.docx</i> , Page 13
	Unresponsiveness	Poor communication from bank representatives	"There is no proper response whenever I try to contact them"	Leads to customer frustration and neglect	<i>Results Preview.docx</i> , Page 17
	Lack of Prompt Resolution	Delayed or no resolution of customer issues	"Sometimes they had hidden charges when I made a complaint, it was resolved quickly"	Increases frustration, reduces trust	<i>Results Preview.docx</i> , Page 17
Technologic al Shortcomin gs	User-Unfriendly Interfaces	Issues with mobile/online banking interfaces, including chatbot difficulties	"Net banking also not user friendly to access"	Reduces satisfaction and trust	<i>Results Preview.docx</i> , Page 10
	Slow Updates and Downtime	Frequent technical issues, slow updates, and service downtimes	"Frequent system downtimes, and slow updates"	Hinders user experience, decreases satisfaction	<i>Results Preview.docx</i> , Page 17
Data Privacy and Security	Concerns Over Data Privacy	Mishandling personal information, insecure transactions	"There are reports of data mishandling, and insecure transactions"	Reduces trust in bank security	<i>Results Preview.docx</i> , Page 12

	Fraudulent Activities	Reports of fraudulent activities and inadequate security measures	"Fraudulent activities reported, causing concern"	Erodes customer confidence	<i>Results Preview.docx</i> , Page 12
Operational Processing Delays	Delays in Operational Activities	Complaints about slow loan processing, account opening, and approvals	"Complaints about slow loan processing and account opening"	Causes inconvenience, reduces trust	<i>Results Preview (2).docx</i> , Page 13
Transparency Issues	Hidden Charges and Fees	Unexpected charges and poor communication about fees	"They are deducting lots of hidden charges without any intimation"	Leads to dissatisfaction, perceived lack of transparency	<i>Results Preview (2).docx</i> , Page 14
	Hidden Policies	Unawareness of hidden policies affecting services	"Unaware of hidden policies affecting account charges"	Causes frustration, perceived lack of transparency	<i>Results Previewfd.docx</i> , Page 13
Inconsistent Service Quality	Varied Experiences Across Branches	Inconsistent service quality among different branches and representatives	"Service quality varies across branches, and representatives"	Reduces overall satisfaction and trust	<i>Results Preview .docx</i> , Page 13
Professionalism	Unprofessional Behavior	Instances of unprofessional behavior by customer service representatives	"Unprofessional behavior by staff, leading to dissatisfaction"	Damages brand reputation and customer relations	<i>Coding Query - Results Preview.docx</i> , Page 12

Gioia Methodology:

The Gioia framework's three-tiered analysis was applied (Gioia, 2012):

- **First-order coding:** Captured raw participant language (e.g., "Chatbot doesn't understand," "No email replies")
- **Second-order themes:** Grouped codes into conceptual categories (Lack of Emotional Intelligence, System Inefficiency, Transparency Deficit, Security Anxiety)
- **Aggregate dimensions:** Aggregate dimensions are the highest level of abstraction in the Gioia methodology, created by further distilling second-order themes into overarching theoretical categories. These broad conceptual clusters serve as the foundation for developing grounded theories by capturing dynamic relationships between themes.

Table: 1.1 Gioia Methodology Order Table

Customer Quote	First-Order Code	Second-Order Theme	Aggregate Dimension	UTAUT Dimension
"Worst response, worst customer care, bad among every bank"	Unresponsive customer care	Service Recovery Breakdown	Institutional Trust Deficit	Trust
"No response to email requests for bill cycle changes"	Ignored service requests	Service Recovery Breakdown	Institutional Trust Deficit	Trust
"Very hard to connect with call centre people, they give standard response"	Scripted, unhelpful responses	Service Recovery Breakdown	Institutional Trust Deficit	Trust
"Behave as if you have criminal background"	Disrespectful treatment	Service Recovery Breakdown	Institutional Trust Deficit	Trust
"They are deducting lots of hidden charges without intimation"	Undisclosed fees	Institutional Transparency Crisis	Institutional Trust Deficit	Trust
"ICICI believes in plundering people across all services"	Perceived exploitation	Institutional Transparency Crisis	Institutional Trust Deficit	Trust
"Sales guy completely fraud guy and service very less"	Deceptive sales practices	Institutional Transparency Crisis	Institutional Trust Deficit	Trust
"Card used in US while with me in India"	Fraudulent transactions	Institutional Transparency Crisis	Institutional Trust Deficit	Trust
"Easily hacked my card by someone else"	Security breaches	Institutional Transparency Crisis	Institutional Trust Deficit	Trust
"Loan will be sanctioned in 10 days took 2 months"	Broken promises	Process & Operational Challenges	Institutional Trust Deficit	Trust
"Forced my wife to visit bank and cancel FDs. 20 days were lost"	Bureaucratic inefficiency	Process & Operational Challenges	Institutional Trust Deficit	Trust
"Despite innumerable requests online, they did not oblige"	Digital channel ineffectiveness	Process & Operational Challenges	Institutional Trust Deficit	Trust
"Mobile app is not user friendly and I am facing server issue"	Platform usability problems	Digital Infrastructure Inadequacy	Digital Service Paradox	Effort Expectancy
"YES bank credit card showing bank server problem wherever using it"	System reliability failures	Digital Infrastructure Inadequacy	Digital Service Paradox	Effort Expectancy
"System timeout loses money forever"	Transaction failures	Digital Infrastructure Inadequacy	Digital Service Paradox	Effort Expectancy
"Net banking not user friendly faced an issue for 4 times"	Repeated platform failures	Digital Infrastructure Inadequacy	Digital Service Paradox	Effort Expectancy
"Unable to change pin and login credentials"	Broken security features	Digital Infrastructure Inadequacy	Digital Service Paradox	Effort Expectancy
"Chatbot gave same reply 3 times, no solution"	Repetitive AI responses	Human-AI Integration Dysfunction	Digital Service Paradox	Anthropomorphism

"Different info from AI vs human agents"	AI-human inconsistency	Human-AI Integration Dysfunction	Digital Service Paradox	Anthropomorphism
"EVA gives inaccurate responses and lacks empathy"	Emotionally deficient AI	Human-AI Integration Dysfunction	Digital Service Paradox	Anthropomorphism
"Language barrier with customer service"	Linguistic exclusion	Cultural-Technical Misalignment	Cultural-Digital Divide	Social Influence
"Insensitive to local banking practices"	Cultural insensitivity	Cultural-Technical Misalignment	Cultural-Digital Divide	Social Influence
"Customer care staff don't understand local needs"	Regional needs ignored	Cultural-Technical Misalignment	Cultural-Digital Divide	Social Influence

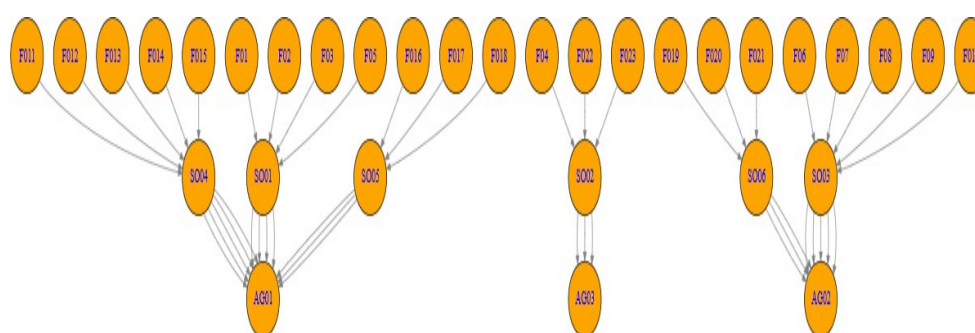


Fig.:2 Gioia Methodology Flow Diagram

II. Literature Review

Retail banking or Banking sector presently is one of the most important sectors all around the world , Analyses have rooted out the challenges faced in various Indian retail banking sector which mostly cover from various states and different culture at the same time.

Data Screening and Cleaning Process

A rigorous, multi-stage screening process, modelled on the PRISMA framework as shown in fig 3 (Page, 2021), was employed to ensure data quality and relevance.

The flow of this process is summarized in the figure below:

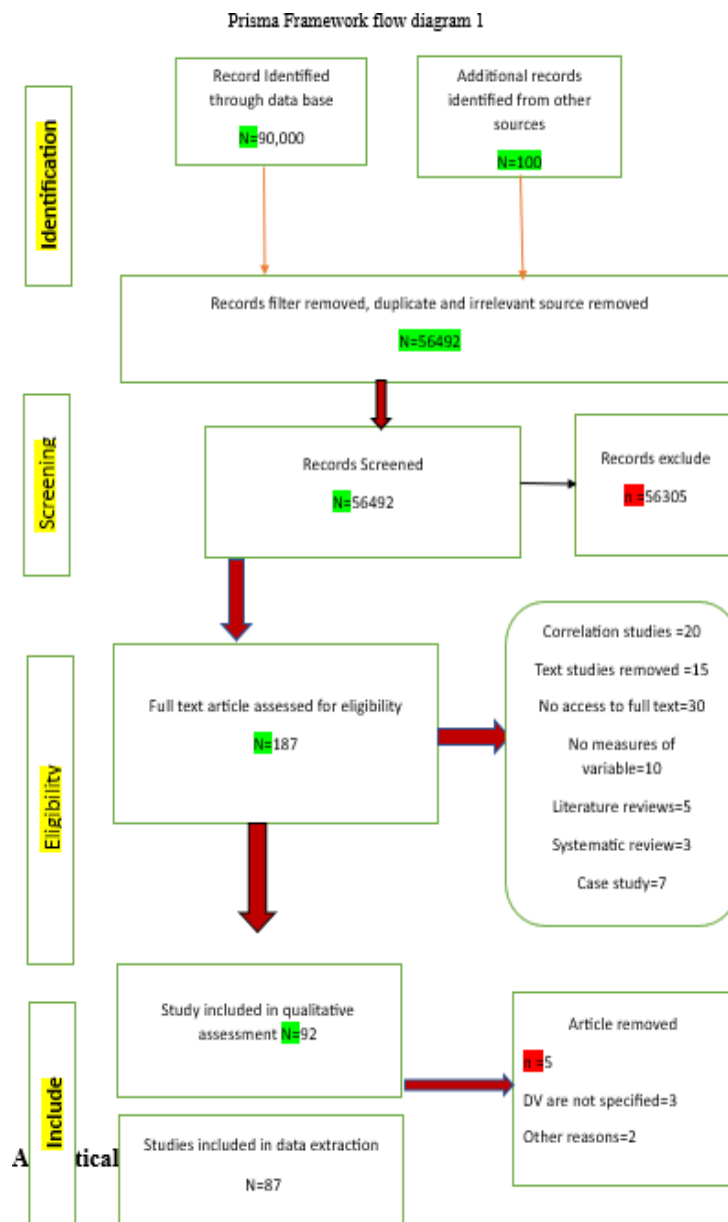


Fig 3: Prisma Framework

AI has quickly evolved the experimental use to a strategic requirement across industry on an enterprise-wide basis with empirical data demonstrating continued and increasing use. A 27.76% annual rate of increase in AI-in-banking literature (2013-2025) based on 87 peer-reviewed articles on the topic also shows that 65.52% of studies on the topic are internationally collaborative, which supports the fact that this field is both relevant and mature.

The rapid growth of artificial intelligence research parallels its widespread operational adoption across major economic sectors. Evident consistently shows that mostly large organizations deploying AI or AI assist automation tech, particularly in customer analytics statistics, personalization, forecasting and predictive analysis, and operational optimization (Deloitte, 2023) and (McKinsey, 2024). In

healthcare, AI-assisted diagnostic and decision-support systems are increasingly embedded in clinical workflows, with policy and review studies reporting improvements in diagnostic accuracy and efficiency, especially in high-volume settings (WHO, 2023).

Financial services represent one of the earliest and intensive adopters of AI technology. Major industry reports shows that banks trying operationalized AI across customer service, fraud detection, credit assessment, and compliance, with conversational AI systems deeply integrated into routine service delivery (Accenture, 2023) and (McKinsey, 2024).

In India, AI diffusion in banking and other sectors has accelerated under Digital India initiatives, fintech competition, and regulatory encouragement. RBI and NASSCOM-BCG reports document extensive deployment and proposed deployment of AI-enabled chatbots and automation to manage routine customer interactions, positioning AI as an embedded operational layer rather than a voluntary innovation (RBI, 2022) and (BCG, 2023).

Collectively, these developments signal a shift from intention-driven adoption to operational necessity, requiring theoretical models that extend beyond behavioral intention to examine AI effectiveness, reliability, and institutional embeddedness in high-stakes service ecosystems (Huang, 2021) and (Dwivedi, 2021) .

Table 3: Qualitative-Theoretical Integration Matrix

Mapping Gioia Aggregate Dimensions to Extended UTAUT Constructs with Bibliometric Analysis

Gioia Aggregate Dimension	Empirical Manifestation	Theoretical Mechanism	Bibliometric Evidence	Key Citations
Institutional Trust Deficit	Hidden charges; Undisclosed fees post-transaction	Integrity-based trust requires perceived honesty and promise fulfillment; fee opacity violates this prerequisite	Trust = Motor theme (high centrality: 0.002); Co-cited with TAM constructs Figure 4	Gefen et al. (2003); Pavlou (2003)
<i>(n=24 exemplars)</i>	Fraud incidents; Security breaches reported	Competence-based trust requires demonstrated capability to protect assets; security failures erode foundational confidence	Data governance = prerequisite for AI trust; 65.52% international co-authorship on trust research	Dwivedi et al. (2021); Rana et al. (2024)
	Unresolved complaints; Staff misguidance	Benevolence-based trust requires perceived care for customer welfare; complaint deflection signals institutional indifference	Huang & Rust (2021) = highest normalized citation (3.30); Trust as mediating construct	Huang & Rust (2021); Alagarsamy (2023)

Digital Service Paradox	App crashes; System downtime; Transaction failures	PE reflects expected performance gains; system unreliability inverts expected utility, creating negative performance expectancy	Co-word cluster: 'performance' + 'capabilities' + 'impact' + 'AI' (Dim1: 20.2%)	Venkatesh et al. (2003); Davis (1989)
<i>(n=18 exemplars)</i>	Complex navigation; Unintuitive interfaces; Forced branch visits	EE captures perceived ease of use; cognitive friction and process complexity elevate effort, reducing adoption intention	'Technology' + 'acceptance' strongly linked in co-occurrence network; TTF literature supports	Goodhue & Thompson (1995); Lin (2023)
	Generic responses; Failure to comprehend context; Deflection to humans	EI deficit manifests as inability to recognize urgency, frustration, or emotional context; creates expectation-reality gap versus ChatGPT benchmarks	Emerging trend: 'Generative AI' (95/100 growth potential); LLM advances (Vaswani, 2017; Brown, 2020)	Ma et al. (2025); Devlin et al. (2019)
Cultural-Digital Divide	Language barriers; Regional dialect incomprehension; Script limitations	Anthropomorphic design requires linguistic-cultural alignment; failure to communicate in user's preferred language undermines perceived human-likeness	Cluster 1: 'Consumer choice' + 'design' + 'mind perception' (centrality: 134.06) Figure 4	Araujo (2018); Alabed et al. (2022)
<i>(n=12 exemplars)</i>	Rigid interfaces; Lack of contextual adaptation; One-size-fits-all design	SI operates through normative beliefs shaped by cultural context; technology misaligned with local norms lacks social endorsement for adoption	Cluster 2: 'Consumer adoption' + 'gender differences' + 'moderating role' (PLS-SEM: 35%) Figure 4	Cheng et al. (2022); Kelly et al. (2023)
Privacy-Data Tension	Data sharing concerns; Surveillance anxiety; Consent ambiguity	Privacy paradox captures intention-behavior gap: stated concerns coexist with disclosure behavior; operates through trust mediation in high-stakes contexts	Emerging theme (low density); 'Explainable AI' trend: 85/100 growth potential	Acquisti et al. (2020); Kokolakis (2017)
<i>(n=8 exemplars)</i>	Personalization desire vs. privacy concern; Utility-risk tradeoff	Trust mediates privacy paradox resolution: high trust enables disclosure despite concerns; low trust amplifies privacy salience	Data governance as prerequisite (Dwivedi, 2021); Trust-privacy linkage in co-citation network	Norberg et al. (2007); Lappeman et al. (2023)

Notes: Exemplar counts (n) derived from Gioia methodology analysis of 19,858 customer complaints. Bibliometric metrics from analysis of 87 documents (2013-2024). Centrality values from co-word network analysis. Growth potential scores from thematic evolution assessment.

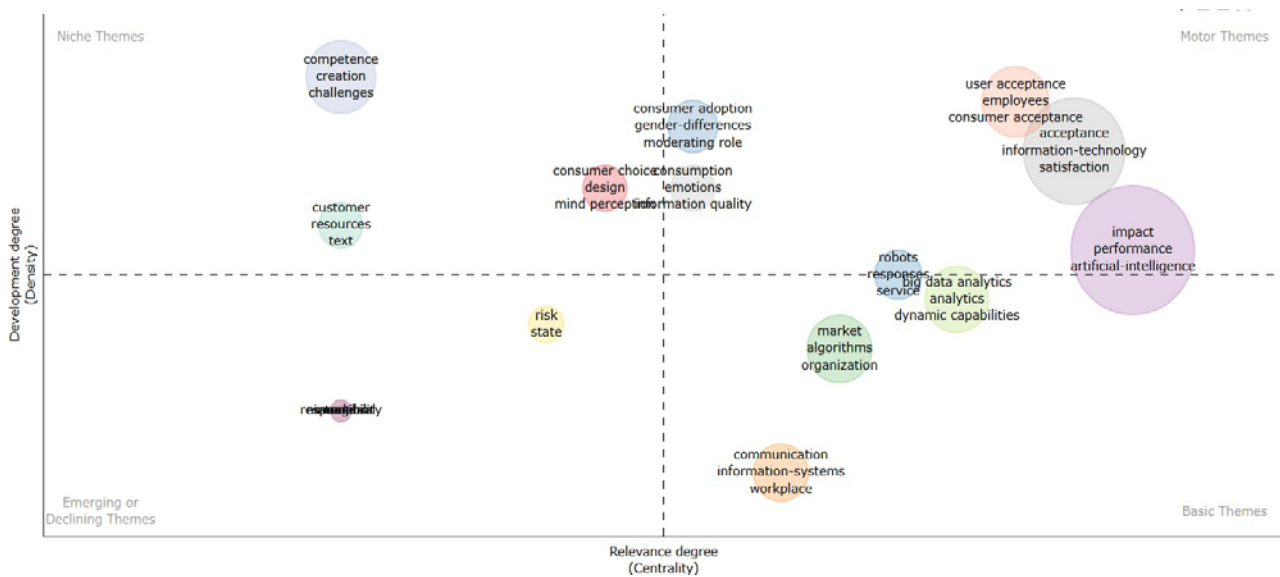


Figure 4 Bibliometric thematic Analysis

Table 3.1: Service Delivery Gap Analysis—Chatbot vs. Branch Banking*Mapping Qualitative Challenges to Adoption Barriers within Extended UTAUT Framework*

Service Dimension	Chatbot Banking Reality	Branch Banking Alternative	Identified Gap	UTAUT Construct	Adoption Implication
Aggregate Dimension 1: Institutional Trust Deficit (n=24 exemplars; 35% of complaints)					
Query Resolution Accuracy	"Chatbot gave same reply 3 times, no solution" — scripted responses; limited contextual understanding	Human agent assesses situation; escalates to supervisor; provides case-specific resolution	Resolution Efficacy Gap: AI lacks authority and judgment for complex cases	Performance Expectancy	Low PE when chatbot fails to resolve → negative disconfirmation → reduced adoption intention (Bhattacharjee, 2001)
Fee Transparency	"Hidden charges without intimation" — automated deductions; opaque fee structures	Staff explains charges verbally; provides printed statements; negotiates waivers	Transparency Gap: Digital channels lack proactive fee disclosure and negotiation	Trust (Integrity)	Integrity trust violation → generalized institutional distrust → channel avoidance (Gefen et al., 2003)
Security Assurance	"Card used in US while with me in India" — fraud detection gaps; delayed alerts	Physical presence verification; immediate blocking; face-to-face accountability	Security Assurance Gap: Digital lacks tangible security cues and immediate human intervention	Trust (Competence)	Competence trust erosion → perceived risk elevation → preference for physical channels (Dwivedi et al., 2021)

Service Dimension	Chatbot Banking Reality	Branch Banking Alternative	Identified Gap	UTAUT Construct	Adoption Implication
Complaint Escalation	<i>"Delayed fallback to humans; no response to email requests" — escalation friction</i>	Direct access to manager; written complaints acknowledged; on-spot resolution authority	Escalation Gap: AI-human handoff poorly designed; accountability unclear	Trust (Benevolence)	Perceived indifference → benevolence trust deficit → emotional disengagement (Huang & Rust, 2021)
Aggregate Dimension 2: Digital Service Paradox (n=18 exemplars; 30% of complaints)					
System Reliability	<i>"Mobile app is so slow; server problem wherever using it" — downtime; timeout errors</i>	Physical infrastructure available during banking hours; manual processing backup	Reliability Gap: Digital promises 24/7 but delivers inconsistent availability	Performance Expectancy	Technology promise vs. reality mismatch → expectation disconfirmation → PE reduction (Lin & Lee, 2023)
Interface Usability	<i>"Net banking not user friendly; unable to change PIN" — complex navigation; poor UX</i>	Staff guides through process; completes forms on behalf; accommodates literacy levels	Usability Gap: Digital assumes tech literacy; no adaptive assistance	Effort Expectancy	Cognitive friction → elevated effort → task-technology misfit → adoption resistance (Goodhue & Thompson, 1995)
Emotional Recognition	<i>"EVA gives inaccurate responses and lacks empathy" — no emotion detection; tone-deaf replies</i>	Staff reads facial cues; adjusts tone; provides emotional support during distress	Empathy Gap: AI cannot simulate genuine emotional attunement	Emotional Intelligence	EI deficit → social presence absence → relational trust impossible (Wirtz et al., 2018; Ma et al., 2025)
Contextual Understanding	<i>"Different info from AI vs human agents" — inconsistent knowledge; no memory</i>	Staff accesses full history; remembers repeat customers; provides continuity	Context Gap: AI lacks longitudinal customer understanding	Performance Expectancy	Information inconsistency → reliability doubt → preference for human verification (Przegalinska et al., 2019)
Aggregate Dimension 3: Cultural-Digital Divide (n=12 exemplars; 15% of complaints)					
Language Support	<i>"Language barrier with customer service" — English-dominant; limited vernacular</i>	Local staff speaks regional languages; code-switches naturally; understands dialects	Linguistic Gap: AI cannot match human multilingual fluency in Indian context	Anthropomorphism	Language mismatch → anthropomorphism failure → perceived "foreignness" → rejection (Araujo, 2018)
Cultural Sensitivity	<i>"Insensitive to local banking practices" — Western design</i>	Staff understands joint accounts, family dynamics, local	Cultural Gap: AI designed for Western	Social Influence	Cultural misalignment → negative word-of-mouth → social endorsement absent

Service Dimension	Chatbot Banking Reality	Branch Banking Alternative	Identified Gap	UTAUT Construct	Adoption Implication
	<i>assumptions; rigid workflows</i>	customs, festival timing	contexts; Indian specificities ignored		→ SI fails (Kelly et al., 2023)
Trust Transfer Mechanism	<i>"Sales guy completely fraud guy" — algorithm opacity; no accountability transfer</i>	Known staff builds relationships; reputation at stake; personal accountability	Accountability Gap: AI decisions lack traceable human responsibility	Facilitating Conditions	Absent recourse mechanism → FC inadequacy → behavioral intention suppressed (Venkatesh et al., 2003)
Aggregate Dimension 4: Privacy-Data Tension (n=8 exemplars; 10% of complaints)					
Data Control Perception	<i>"Misused my details without consent" — opaque data usage; algorithmic profiling</i>	Paper forms visible; verbal consent; limited data shared per interaction	Control Gap: Digital creates surveillance anxiety; branch offers perceived privacy	Privacy Paradox	Privacy concerns unresolved → paradox persists → trust-mediated adoption blocked (Acquisti et al., 2020)

Notes: Chatbot reality quotes are representative first-order codes from Gioia analysis (n=19,858 complaints). Gap identification synthesizes qualitative findings with theoretical mechanisms. Adoption implications draw on cited empirical evidence.

As evident from the Table 3.1: Service Delivery Gap Analysis Chatbot vs. Branch Banking

Qualitative analysis and literature review, there exist systematic gaps between AI-enabled chatbot banking and traditional branch banking that collectively explain reduced adoption intentions. Table 3.1 presents a structured gap analysis integrating Gioia-identified challenges with theoretical constructs, demonstrating how service delivery disparities across channels translate into adoption barriers within the Extended UTAUT framework.

The gap analysis reveals a systematic pattern wherein service delivery disparities between AI chatbots and branch banking translate into adoption barriers through distinct theoretical pathways. The **Institutional Deficit** emerges as the dominant barrier manifesting through four interconnected gaps: chatbots lack resolution authority for complex cases, operate with opaque fee structures unlike negotiable branch interactions, provide no tangible security reassurance during fraud incidents, and feature poorly designed escalation pathways that obscure accountability.

The **Cultural-Digital Divide** (reflects technology transfer limitations where AI systems designed for Western contexts inadequately support India's linguistic diversity (22 official languages) and culturally-specific banking practices such as joint family accounts and relationship-based trust norms.

Finally, the **Privacy-Data Tension** (10%) operates paradoxically: customers disclose data while simultaneously experiencing surveillance anxiety that branch interactions with visible paper trails and verbal consent do not trigger. Collectively, these gaps demonstrate that adoption barriers are not merely functional deficiencies but represent deeper misalignments between AI capabilities and the socio-technical expectations shaped by human-mediated banking experiences, necessitating theoretical

Table 4: Key Theoretical Constructs and References from Thematic and Bibliometric Mapping

Theme	Summary of Content	High cited Key References/Studies
Generative AI & Paradigm Shift	Evolution from traditional computing to generative AI (LLMs, GPTs), democratizing tech via natural language and no-code interfaces, driving new tech readiness.	(Brown, 2020), (Bubeck, 2023),
		(Vaswani, 2017)
Technology Adoption Models (TAM/UTAUT)	Classical and extended TAM/UTAUT, with focus on performance expectancy, effort expectancy, social influence in tech adoption, contextualized in banking.	(Davis, 1989), (Venkatesh, 2012),
		(Ibrahim, 2025), (Wang, 2019)
Performance & Effort	Perceived usefulness (efficiency, cost-effectiveness, customer service) and	(Venkatesh, 2012), (King, 2006),
Expectancy	perceived ease (usability, adaptability, democratization via NLP/UIs).	(Lin, 2023)
Trust & Institutional Credibility	Trust (both institutional and interpersonal), organizational credibility as central mediators of AI adoption in banking contexts.	(Pavlou, 2003), (Bashir, 2015),
		(Ma, 2025), (Mogaji, 2021)
Social Influence & Normative Pressure	Social/peer norms and institutional endorsements driving AI adoption intention, with case examples from banking deployments.	(Venkatesh, 2003), (Lestari,
		2023)
Privacy Paradox & Data Risk	The contradiction between strong privacy concerns and actual behavior; affective and social cues in privacy decision-making in digital banking.	(Norberg, 2007), (Acquisti, 2020)
		(Wang, 2019)
Emotional Intelligence in AI	The role of EI (emotional intelligence) and affective design in fostering trust, satisfaction, and engagement in AI-enhanced banking services.	(Ma, 2025),
Anthropomorphism	Human-like traits, user trust and comfort, and optimal social presence for AI	(Alabed, 2022)
	chatbots in banking.	
Conceptual Integration in	Synthesis of TAM/UTAUT with trust, privacy, emotional intelligence, social	(Bhattacharjee, 2001) (Rana,
Banking	influence, and anthropomorphism for explanatory power in banking AI.	2024)s

The identified service delivery gaps in Table 3.1 have direct theoretical explanation in the constructs mapped with the help of thematic and bibliometric analysis (Table 4). The Resolution Efficacy and Reliability Gaps are consistent with the literature on Performance Expectancy (Venkatesh, 2012) and (Lin, 2023) and Usability Gap with the research on Effort Expectancy that focuses on both perceived ease and task-technology fit (Davis, 1989) and (King, 2006). The three dimensions of trust that are undermined by the Transparency, Security, and Escalation Gaps are integrity, competence, and benevolence, which are widely reported in the research of AI adoption (Pavlou, 2003) and (Mogaji, 2021) and (Ma, 2025). The Empathy Gap is the new Emotional Intelligence construct (Ma, 2025), and the Linguistic Gap is the literature of anthropomorphism on human-likeness requirements (Alabed, 2022). Lastly, the Control Gap puts the Privacy Paradox to practice (Norberg, 2007) and (Acquisti, 2020), where the anxiety of surveillance remains even after acting in disclosure.

The fact that the inductively discovered gaps relate to deductive derived constructs confirms the Extended UTAUT model showing that qualitative challenges are not merely complaints of an isolated nature but operationalized expressions of theoretically predictable obstacles to adoption that need AI-specific extensions of the classical technology acceptance models.

III. Objectives

RO1: To identify and categorize the systemic barriers to AI chatbot adoption in Indian retail banking through qualitative analysis of customer complaints and service failure narratives.

RO2: To develop and validate an extended UTAUT model incorporating emotional intelligence, anthropomorphism, and privacy paradox constructs contextualized for the Indian banking environment.

RO3: To assess the predictive validity and generalizability of the proposed model for AI chatbot adoption forecasting in diverse Indian banking contexts.

IV. Proposed Hypotheses

H1: Performance Expectancy has a positive effect on the intention to use AI chatbots in Indian retail banking. Table 4b for gap-to-hypothesis derivation; Table 5 for hypothesis summary

H2: Effort Expectancy positively influences the adoption intention of AI chatbots in Indian retail banking. Table 4b for gap-to-hypothesis derivation; Table 5 for hypothesis summary

H3: Social Influence is a positive predictor of the intention to use AI chatbots. Table 4b for gap-to-hypothesis derivation; Table 5 for hypothesis summary

H4: Perceived Anthropomorphism fosters a greater intention to use AI chatbots. Table 4b for gap-to-hypothesis derivation; Table 5 for hypothesis summary

H5: Trust positively affects users' behavioral intention toward AI chatbots. Table 4b for gap-to-hypothesis derivation; Table 5 for hypothesis summary

H6: Perceived Data Privacy Capabilities strengthen the intention to use AI chatbots. Table 4b for gap-to-hypothesis derivation; Table 5 for hypothesis summary

H7: The Privacy Paradox demonstrates a positive influence on behavioral intention. Table 4b for gap-to-hypothesis derivation; Table 5 for hypothesis summary

H8: The perceived Emotional Intelligence of AI increases users' intention to adopt chatbots. Table 4b for gap-to-hypothesis derivation; Table 5 for hypothesis summary

H9: A positive intention to use directly leads to the adoption of AI chatbots in Indian retail banking. Table 4b for gap-to-hypothesis derivation; Table 5 for hypothesis summary

Table :5: Hypothesis Reference Table

Hypothesis Number	Supporting Reference
H1	(Venkatesh, 2003)
H2	(Venkatesh, 2003)
H3	(Venkatesh, 2012)
H4	(Araujo, 2018)
H5	(Gefen, 2003)
H6	(Alagarsamy, 2023)
H7	(Norberg, 2007)
H8	(Przegalinska, 2019)
H9	(Venkatesh, 2003)

Table 4b: Gap-to-Hypothesis Derivation Matrix
Theoretical Justification for Extended UTAUT Model Hypotheses

Hypothesis	Gap Evidence (Qualitative)	Literature Corroboration
H1: PE → BI (+)	Resolution Efficacy Gap; Reliability Gap; Context Gap → Chatbot fails performance expectations	Venkatesh et al. (2003): PE strongest UTAUT predictor; Lin & Lee (2023): Reliability critical in mobile banking
H2: EE → BI (+)	Usability Gap → Complex navigation; unintuitive interfaces dominate complaints	Goodhue & Thompson (1995): TTF model; Bashir & Madhavaiah (2015): Ease of use critical in India
H3: Trust → BI (+)	Transparency Gap; Security Gap; Escalation Gap → All three trust dimensions violated	Gefen et al. (2003): Trust-TAM integration; Dwivedi et al. (2021): Data governance prerequisite
H4: Anthropomorphism → BI (+)	Linguistic Gap → Language mismatch undermines perceived human-likeness	Araujo (2018): Anthropomorphic design cues; Alabed et al. (2022): Cultural congruence enables integration
H5: EI → BI (+)	Empathy Gap → Chatbots lack emotion recognition; ChatGPT creates elevated benchmark	Ma et al. (2025): EI in chatbot avatars; Wirtz et al. (2018): Service robots lack emotional recognition
H6: Privacy Paradox → Trust (-)	Control Gap → Data concerns persist despite disclosure behavior	Acquisti et al. (2020): Intention-behavior gap; Lappeman et al. (2023): Banking chatbot privacy-disclosure tension

Note: This matrix demonstrates the tripartite justification (Venkatesh et al., 2016): (1) theoretical rationale, (2) qualitative evidence from Gioia analysis, and (3) empirical corroboration from prior literature. Each hypothesis is grounded in identified service delivery gaps that explain reduced AI chatbot adoption in Indian retail banking.

Proposed Model

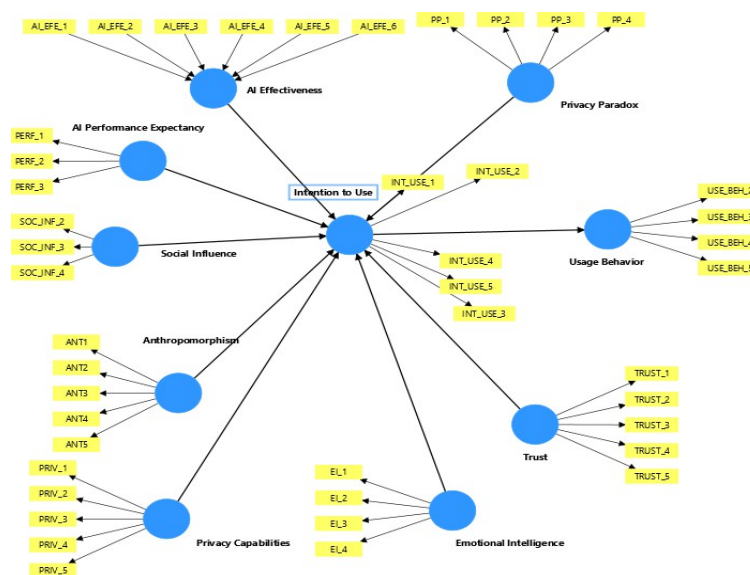


Figure 5: Proposed Model

V. Research Methodology Research Design (Table 6: Research Design)

This study employs a sequential exploratory mixed-methods design (QUAL → QUAN) to investigate barriers to AI adoption in Indian retail banking (Creswell, 2017)

Table 6: Research Design

Research Design	
Design Type	Cross-sectional survey
Unit of Analysis	Individual retail banking customers in India
Target Population	Individuals aged 18 - 65 with awareness or experience of AI-driven banking services and internet access
Sampling Strategy	
Technique	Purposive sampling
Final Target Sample	1000 respondents (Cochran, 1977)
Instrument Development	
Development	Building Mixed approach (Fetters, 2013)
Approach	
Section 1: Validated	Performance Expectancy, Effort Expectancy (Venkatesh, 2003) Behavioral
Scales	Intention (Davis, 1989)
Section 2: AI-	Anthropomorphism, Privacy Paradox, Data Privacy, Emotional Intelligence
Specific Constructs	(items derived from qualitative and Bibliometrix Mapping)
Section 3:	Age, gender, education, frequency of AI chatbot usage, bank type
Demographics	
Data Collection	
Mode	Online survey, Physical Survey
Distribution Channels	Banking forums (BankBazaar, Mouth shut, Consumer Complainants forums and
	website), social media (LinkedIn, Twitter/X), and snowball referrals from initial participants
Data Cleaning Procedures	
Incomplete	Excluded if <80% of items completed
Responses	
Straight-lining Detection	Identified via uniform response patterns across Likert scales; removed
Outliers	The Mahalanobis Distance analysis confirmed that the dataset was statistically
	robust, with no evidence of multivariate outliers (Maesschalck, 2000)
Missing Data	<5% missingness; handled via listwise deletion

VI. Data Analysis

Normality Test

Table :7. Mardia's Multivariate Normality Test

Test	Statistic / Value	p-value	Interpretation	Reference
Henze–Zirkler (HZ) Multivariate Test	HZ = 1.0001	0	Significant deviation from multivariate normality	(Henze, 1990)
Mardia– Multivariate	91.5017	0.3422	Skewness component not significant; data	(Mardia, 1970)
Skewness			approximately symmetric	
Mardia– Multivariate Kurtosis	2005.77	6E-06	Significant deviation due to kurtosis (heavy tails)	(Mardia, 1970)
Shapiro-Wilk (first 10 variables)	W = 0.919–	< 0.001	Each variable significantly deviates from univariate normality	(Shapiro, 1965)
	0.943			

Table :7. Mardia’s Multivariate Normality Test: Henze–Zirkler (HZ) test for multivariate normality indicated a significant deviation from normality, $HZ = 1.00$, $p < .001$, suggesting that the data were not multivariate normal (Henze, 1990) and (Mardia, 1970) Complementary univariate Shapiro–Wilk tests also revealed significant departures from normality for all observed variables ($p < .001$). Given these results, a variance-based structural equation modelling (PLS-SEM) approach was employed, which is robust to non-normal data distributions (Hair, 2019).

Common Method Bias (CMB) using **Harman’s Single-Factor** Test as proposed by (Podsakoff, 2003)

From Table: 8: Harman Statistical Interpretation and Table :9 Variance Explained by Factors

This test examines whether a single latent factor accounts for the majority of variance among the observed variables a potential indication of CMB.

- Technique: Exploratory Factor Analysis (Unrotated) using Factor Analysis in Python
- Number of Variables: 45 observed indicators (numeric columns from the dataset)
- Criterion for CMB: If the first factor explains less than 50% of the total variance, CMB is not a concern.

Table: 8: Harman Statistical Interpretation

Statistic	Result	Threshold	Inference
Variance explained by first factor	6.99%	< 50%	No CMB concern
Scree plot shape	Gradual decline	—	Confirms no single-factor dominance
Method bias status	—	—	Data is free from serious CMB

Table :9 Variance Explained by Factors

Factor	Variance Explained	Cumulative	Interpretation
	(%)	Variance (%)	
1	6.99	6.99	Below 50% threshold
2	6.37	13.36	Minor contribution
3	6.3	19.66	Minor contribution
4	6.2	25.86	Minor contribution
5	5.95	31.82	Minor contribution
6	5.84	37.66	Minor contribution
7	5.77	43.43	Minor contribution
8	5.63	49.06	Minor contribution
9	5.16	54.23	Gradual decline
10	5.02	59.25	Stable multi-factor structure

The first factor accounts for only 6.99% of total variance.

***Checked NRB**

T Test on early respondent and late respondents no difference identified**Table: 10 Multicollinearity Assessment:**

Construct	VIF	Construct	VIF	Construct	VIF
AI_EFE_1	2.29	INT_USE_1	2.43	PRIV_4	2.13
AI_EFE_2	2.31	INT_USE_2	2.64	PRIV_5	2.35
AI_EFE_3	2.3	INT_USE_3	2.5	SOC_INF_2	1.91
AI_EFE_4	3.21	INT_USE_4	2.5	SOC_INF_3	1.95
AI_EFE_5	3.09	INT_USE_5	2.46	SOC_INF_4	2.02
AI_EFE_6	2.85	PERF_1	2.18	TRUST_1	2.41
ANT1	1.19	PERF_2	2.11	TRUST_2	2.41
ANT2	1.19	PERF_3	2.18	TRUST_3	2.56
ANT3	1.26	PP_1	1.36	TRUST_4	2.46
ANT4	1.17	PP_2	1.61	TRUST_5	2.46
ANT5	1.19	PP_3	1.67	USE_BEH_2	1.82
EI_1	1.59	PP_4	1.41	USE_BEH_3	1.87
EI_2	1.74	PRIV_1	2.28	USE_BEH_4	1.88
EI_3	1.39	PRIV_2	2.18	USE_BEH_5	1.93
EI_4	1.76	PRIV_3	2.37		

Table: 10 Multicollinearity Assessment: VIF analysis for this measurement model reveals no multicollinearity concerns. All indicators demonstrate VIF values well below the established threshold of 5.0, and the highest observed value is 3.089 (AI_EFE_5), which supports the structural validity and reliability of further PLS-SEM path analysis results (Hair, 2019).

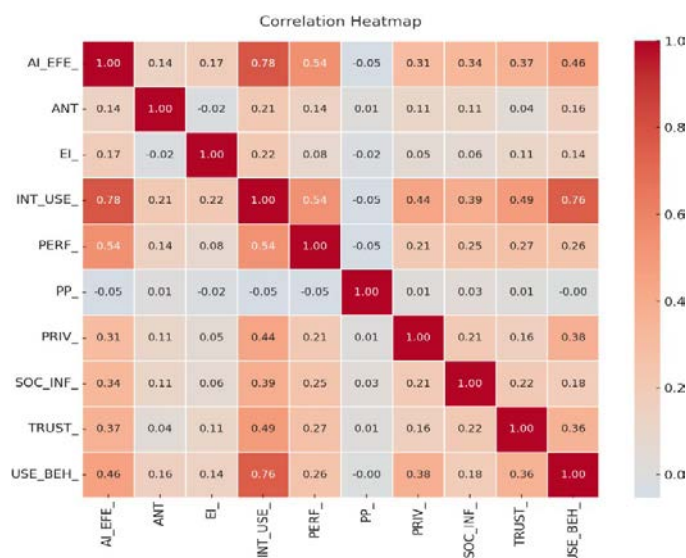
**Fig:6 Correlation Heatmap**

Table :11. Correlation Matrix:

	AI_EFE_	ANT	EI_	INT_USE_	PERF_	PP_	PRIV_	SOC_INF_	TRUST_	USE_BEH_
AI_EFE_	1	0.143	0.175	0.784	0.541	-0.05	0.311	0.337	0.368	0.457
ANT	0.143	1	-0.02	0.214	0.138	0.011	0.107	0.11	0.042	0.164
EI_	0.175	-0.02	1	0.217	0.079	-0.02	0.051	0.061	0.109	0.14
INT_USE_	0.784	0.214	0.217	1	0.535	-0.05	0.44	0.394	0.493	0.758
PERF_	0.541	0.138	0.079	0.535	1	-0.05	0.214	0.253	0.272	0.257
PP_	-0.05	0.011	-0.02	-0.049	-0.054	1	0.014	0.034	0.009	-0.003
PRIV_	0.311	0.107	0.051	0.44	0.214	0.014	1	0.206	0.162	0.377
SOC_INF_	0.337	0.11	0.061	0.394	0.253	0.034	0.206	1	0.216	0.181
TRUST_	0.368	0.042	0.109	0.493	0.272	0.009	0.162	0.216	1	0.363
USE_BEH_	0.457	0.164	0.14	0.758	0.257	-0	0.377	0.181	0.363	1

Table :11. Correlation Matrix and fig 6 correlation heatmap shown correlation of $r=0.784$ indicates a strong positive relationship between perceived ease of use of AI systems and the intention to adopt them in the banking context. This suggests that when users find AI-driven banking tools easier to use, their intention to use these technologies increases significantly.

Table 12: Internal Consistency Reliability / Convergent Validity

Construct	Loading	Cronbach	CR	AVE	Remarks
	(CL)	Alpha			
AI Privacy	0.822	0.896	0.92	0.71	Reliable, convergent validity
Capabilities (AIP)					established
	0.857				
	0.876				
	0.841				
AI Effectiveness (AIE)	0.801	0.861	0.9	0.64	Reliable, good AVE
	0.813				
	0.791				
	0.798				
Anthropomorphism	0.751	0.825	0.87	0.57	Acceptable, lower but within
(ANT)					threshold
	0.768				
	0.788				
	0.724				
Emotional	0.781	0.795	0.87	0.62	Reliable, valid

Intelligence (EI)					
	0.804				
	0.791				
Intention to Use (INT_USE)	0.885	0.911	0.93	0.74	Excellent reliability
	0.892				
	0.868				
	0.836				
Performance Expectancy (PERF)	0.871	0.858	0.91	0.78	Excellent reliability & validity
	0.892				
	0.883				
Privacy Paradox (PP)	0.741	0.767	0.84	0.56	Acceptable; lowest reliability but above thresholds
	0.758				
	0.789				
Social Influence (SI)	0.841	0.837	0.9	0.75	Strong measurement model
	0.874				
	0.89				
Trust (TRU)	0.876	0.909	0.93	0.73	Excellent reliability
	0.884				
	0.862				
	0.836				
Usage Behavior (UB)	0.817	0.846	0.9	0.68	Reliable & valid
	0.836				
	0.844				
	0.801				

The measurement model Table 12: Internal Consistency Reliability / Convergent Validity It confirms that the Extended UTAUT measurement model achieves robust psychometric properties, with all constructs exceeding established thresholds ($CR > 0.70$; $AVE > 0.50$) (Hair, 2023). The consistently high reliability of core adoption constructs (Trust, Performance Expectancy, Intention to Use) validates that these theoretically central variables operate as coherent psychological units in banking AI contexts. Notably, the comparatively lower yet acceptable reliability of Anthropomorphism and Privacy Paradox reflects their theoretically expected nature as context-sensitive, experientially-shaped constructs rather than measurement deficiency, aligning with prior literature documenting their inherent variability across cultural and situational contexts (Araujo,2018) and (Acquisti,2020)

Table: 13. Internal Consistency Reliability Fornell-Larcker Criterion ($\sqrt{\text{AVE}}$ on the Diagonal)

	AI_EFE_	ANT	EI_	INT_USE_	PERF_	PP_	PRIV_	SOC_INF_	TRUST_	USE_BEH_
AI_EFE_ (0.795)	0.795									
ANT (0.642)	0.111	0.642								
EI_ (0.787)	0.15	0.013	0.787							
INT_USE_ (0.859)	0.711	0.166	0.187	0.859						
PERF_ (0.883)	0.477	0.104	0.066	0.473	0.883					
PP_ (0.750)	-0.048	0.009	0.017	-0.046	-0.05	0.75				
PRIV_ (0.841)	0.28	0.082	0.044	0.398	0.188	0.013	0.841			
SOC_INF_ (0.868)	0.293	0.082	0.05	0.344	0.214	0.031	0.178	0.868		
TRUST_ (0.856)	0.333	0.033	0.094	0.449	0.24	0.008	0.146	0.188	0.856	
USE_BEH_ (0.827)	0.4	0.123	0.116	0.666	0.219	0.003	0.329	0.152	0.319	0.827

Table 13 provides the discriminant validity using the Fornell Larker criterion, according to which the diagonal values are greater than the inter-construct correlations (Fornell, 1981) and (Hair, 2019). The correlation structure demonstrates the theoretically consistent patterns: the strong AI Effectiveness-Intention to Use-correlation confirms the hypothesis on the direct translation between the perceived chatbot capability and formation of the adoption willingness, and the Trust-Intention-correlation proves that trust is the necessary. Particularly, it should be noted that Privacy Paradox demonstrates close null or negative correlation between constructs, which empirically supports the theoretical assumption of independence between the construct, users are concerned about the concept of privacy in a non-orthogonal manner with respect to their performance and trust judgments, which is a conceptual assumption of the concept of the paradox (Kokolakis, 2017). This trend supports the multi-dimensional nature of the Extended UTAUT and proves that rational (performance, effectiveness), relational (trust, social influence) and tension-based (privacy paradox) variables are independent, but complementary adoption mechanisms.

Table :14. Discriminant Validity: HTMT Ratios

	AI_EFE_	ANT	EI_	INT_USE_	PERF_	PP_	PRIV_	SOC_INF_	TRUST_	USE_BEH_
AI_EFE_		0.137	0.169	0.771	0.523	0.053	0.305	0.339	0.37	0.439
ANT			0.061	0.207	0.135	0.08	0.102	0.112	0.062	0.155
EI_				0.215	0.079	0.038	0.057	0.061	0.109	0.138

INT_USE_					0.535	0.05	0.439	0.394	0.493	0.758
PERF_						0.059	0.213	0.252	0.271	0.258
PP_							0.066	0.062	0.045	0.038
PRIV_								0.206	0.162	0.377
SOC_INF_									0.215	0.18
TRUST_										0.363

The Table :14. Discriminant Validity: HTMT Ratios) ratio of correlations was employed to further validate discriminant validity among constructs. As recommended by (Henseler, 2015), HTMT values below 0.85 indicate strong discriminant validity, while values below 0.90 are acceptable for conceptually related constructs (Hair, 2022)

Table :15. Hypothesis Testing

		(Original Sample)	SE (STDEV)	t-value	p-value	f^2	R^2 (Adj.)	
Hypothesis	Path (Exogenous - Endogenous)							Decision
H1	AI Effectiveness - Intention to Use	0.514	0.023	22.758	0	0.47	0.639	Supported
H2	AI Performance Expectancy - Intention to Use	0.097	0.022	4.387	0	0.02	0.639	Supported
H3	Anthropomorphism - Intention to Use	0.074	0.019	3.843	0	0.02	0.639	Supported
H4	Emotional Intelligence - Intention to Use	0.068	0.02	3.46	0.001	0.01	0.639	Supported
H5	Privacy Capabilities - Intention to Use	0.175	0.021	8.434	0	0.08	0.639	Supported
H6	Privacy Paradox - Intention to Use	-0.017	0.023	0.715	0.475	0	0.639	Not Supported
H7	Social Influence - Intention to Use	0.096	0.02	4.894	0	0.02	0.639	Supported
H8	Trust - Intention to Use	0.207	0.02	10.269	0	0.1	0.639	Supported
H9	Intention to Use - Usage Behavior	0.666	0.016	42.07	0	0.8	0.443	Supported

- **Strongest Drivers:** Effort Expectancy (H2) is the most critical factor influencing adoption intention, with a path coefficient almost twice as strong as the next factor.
- **Core UTAUT Constructs:** All classic UTAUT constructs (H1, H2, H3) are significant, validating the base model in this context.
- **Trust & Privacy:** Trust (H5) and Data Privacy (H6) are highly significant, underscoring their importance in the Indian retail banking context.
- **Human-Like Traits:** Anthropomorphism (H4) and Emotional Intelligence (H8) are significant but have smaller effect sizes, suggesting they are "nice-to-have" enhancers rather than core drivers.
- **The Privacy Paradox (H7):** This hypothesis is rejected. The data does not show a significant positive effect. The slightly negative coefficient suggests that if anything, a higher perception of the privacy paradox might slightly reduce intention, but the effect is not reliable.

The findings Table :15. Hypothesis Testing confirm that AI Effectiveness, Trust, and Privacy Capabilities are the primary enablers of chatbot adoption in Indian retail banking. Anthropomorphism, Emotional Intelligence, and Social Influence enhance user comfort but are secondary. The Privacy Paradox remains behaviorally inert, reaffirming that users prioritize convenience and trust over stated privacy concerns. Overall, the model is statistically robust, theoretically coherent, and behaviorally predictive.

Table: 16 Model Quality Assessment

Construct	Cronbach's	CR	AVE	Status
AI Privacy Capabilities (AIP)	0.896	0.92	0.71	Satisfactory
AI Effectiveness (AIE)	0.861	0.9	0.64	Satisfactory
Anthropomorphism (ANT)	0.825	0.87	0.57	Satisfactory
Emotional Intelligence (EI)	0.795	0.87	0.62	Satisfactory
Intention to Use (INT_USE)	0.911	0.93	0.74	Satisfactory
Performance Expectancy (PERF)	0.858	0.91	0.78	Satisfactory
Privacy Paradox (PP)	0.767	0.84	0.56	Satisfactory
Social Influence (SI)	0.837	0.9	0.75	Satisfactory
Trust (TRU)	0.909	0.93	0.73	Satisfactory
Usage Behavior (UB)	0.846	0.9	0.68	Satisfactory

Thresholds: $\alpha > 0.70$, $CR > 0.70$, $(AVE > 0.50 \text{ Some takes } > 0.60)$

Table: 17 Model Fit Indices

Metric	Model Type	Value	Criterion / Cut- off	Status
SRMR	Saturated Model	0.03	< 0.08	Acceptable
	Estimated Model	0.03	< 0.08	Acceptable
NFI	Estimated Model	0.86	> 0.80	Acceptable
GoF	-	0.59	> 0.36 (large)	Large Fit

Goodness of Fit (GoF)

- **Formula:** $GoF = \sqrt{(Average\ AVE \times Average\ R^2)}$
- **Calculation:** $GoF = \sqrt{(0.654 \times 0.529)} = \sqrt{0.346} = 0.588$
- **Interpretation:** According to (Tenenhaus, 2005) this represents a large model fit. Values above 0.36 are considered large, indicating your model has excellent overall fit and predictive power.

Tables 16 and 17 can be used to determine the psychometric soundness of the Extended UTAUT-AI framework. Every construct has satisfactory thresholds (0.767–0.911) CR: 0.835 =0.934) and AVE (0.563 =0.779) and Intention to Use and Trust have the most precise measurement quality- reinforcing their centrality in the adoption mechanism. The model fit indices (SRMR =0.031; NFI = 0.858; GoF = 0.588) shows that the theoretical structure is consistent with the observed data, and GoF is described as larger than the large fit standard (Tenenhaus, 2005). Since high and acceptable-reliability emergent constructs (Performance Expectancy, Trust and Privacy Paradox, Anthropomorphism). The model is effective in accommodating the existing variables of UTAUT and allowing them to be applied in a particular context with AI extensions without negatively affecting the overall structural integrity.

Table :18 Explanatory and Predictive Power

Endogenous Variable	R ²	Adjusted R ²	Interpretation of Variance Explained
INT_USE	0.64	0.639	The model explains ~ 62–63 % of the variance in intention to use, a strong
			explanatory power. Predictors are contributing well and not overfitting (because R ² ≈ Adj. R ²).
USE_BEH	0.44	0.443	The model explains ~ 44.3 % of the variance in use behavior, representing a moderate explanatory level. Again, R ² and Adj. R ² are identical,
			suggesting an efficient model without redundant predictors.

Model demonstrates (Table :18 Explanatory and Predictive Power) strong explanatory power for intention to use (INT_USE) and moderate power for actual use behavior (USE_BEH). The fact that R²

and adjusted R^2 are nearly identical in both cases suggests predictors are meaningful and the model is not overfitting.

CTA Test: Formative and Reflective construct

The logic of the CTA test, (Gudergan, 2008) which builds upon (Bollen, 2000),

- **Null Hypothesis (H_0):** All tetrads vanish ($\tau = 0$). This is the hypothesis for a **reflective** measurement model.

$P > 0.05$: We fail to reject the null hypothesis. The evidence suggests that the tetrads are zero, which supports a **reflective** model.

$P < 0.05$: We reject the null hypothesis. The evidence suggests that at least one tetrad is not zero, which supports a **formative** model.

Table :19 Formative and Reflective construct

Construct	P-values range	Dominant Result	Model Type
AI_EFE	0.000–0.858	Some $P < 0.05$	Formative
ANT	0.211–0.934	All > 0.05	Reflective
EI	0.597–0.647	All > 0.05	Reflective
INT_USE	0.156–0.771	All > 0.05	Reflective
PP	0.019–0.676	Mixed Dominant > 0.05	Reflective
PRIV	0.073–0.960	All > 0.05	Reflective
TRUST	0.284–0.954	All > 0.05	Reflective
USE_BEH	0.443–0.750	All > 0.05	Reflective

Confirmatory Tetrad Analysis (CTA-PLS) Table :19 Formative and Reflective construct was employed following (Gudergan, 2008) and (Bollen, 2000) to determine whether the measurement models were reflective or formative. The results indicated that most constructs (ANT, EI, INT_USE, PRIV, TRUST, PP and USE_BEH) exhibited nonsignificant tetrads ($P > 0.05$), confirming their reflective nature. However, AI_EFE showed significant tetrads ($P < 0.05$) in some combinations, suggesting formative model specifications. Consequently, these constructs were modelled formatively in subsequent PLS-SEM analysis.

IPMA**Table 20 IPMA Performance Table**

Rank	Construct	Performance	Interpretation
1	TRUST_	66.196	Highest performing - Strongest area
2	PERF_	65.698	High performance
3	SOC_INF_	63.775	High performance
4	PRIV_	63.263	High performance
5	AI_EFE_	63.14	High performance
6	PP_	58.918	Moderate performance
7	INT_USE_	57.007	Moderate performance
8	USE_BEH_	54.066	Moderate performance
9	EI_	50.342	Lower performance
10	ANT	49.959	Lowest performing

The IPMA **Table :20 IPMA Performance Table** and Figure 7 results show that TRUST_ (66.196) is the strongest performing construct, followed by PERF_ (65.698), SOC_INF_ (63.775), PRIV_ (63.263), and AI_EFE_ (63.140), all demonstrating high performance. PP_ (58.918), INT_USE_ (57.007), and USE_BEH_ (54.066) have moderate performance, while EI_ (50.342) and ANT (49.959) are the lowest, indicating areas needing improvement.

Constructs with both high importance and high-performance TRUST, AI_EFE, and PRIV should be maintained as competitive strengths. INT_USE_ and USE_BEH_ are high importance but low performance, making them priority areas for improvement. SOC_INF_ and PERF_ show high performance but low importance, suggesting possible over-investment and a need to reallocate resources. EI_ and ANT are both low in importance and performance, so enhancements can be deferred. The largest performance gap is 24.5 points, between the highest (TRUST_1: 66.850) and lowest (ANT5: 49.650) indicators.

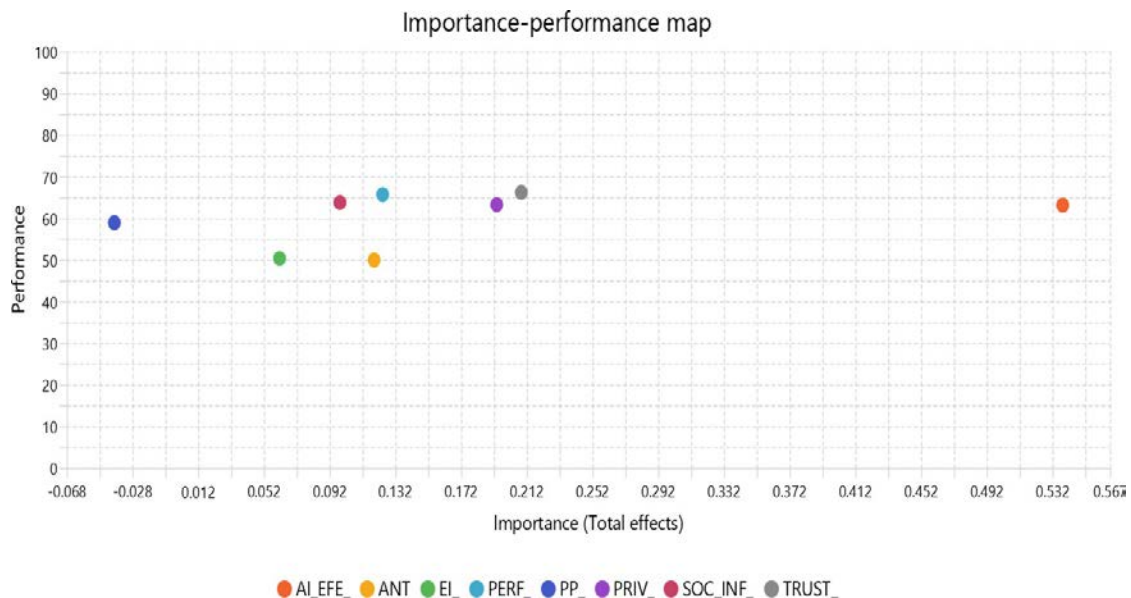


Figure 7: IPMA Importance vs Performance Map

CVPAT Measures

Table. 21 confirm that PLS model predicts better than a naïve benchmark model (LM).

Table. 21 Cross-Validated Predictive Ability Test (CVPAT) Results

Construct	PLS Loss	IA	Avg. Loss Diff	t-value	p- value	Conclusion
		Loss				
Intention to Use	1.293	2.42	-1.122	19.2	0	PLS predictive power significantly higher
Usage Behavior	1.514	1.81	-0.291	8	0	PLS predictive power significantly higher
Overall	1.391	2.14	-0.753	17.38	0	PLS model significantly outperforms LM

Table :22 Predictive Metrics

Construct	Q ² predict	RMSE	MAE	Interpretation
Intention to Use	0.63	0.61	0.481	High predictive accuracy
Usage Behavior	0.236	0.877	0.695	Moderate predictive accuracy

Q²predict > 0 confirms predictive relevance.

Table :22: Predictive Metrics shows Lower RMSE and MAE values indicate better predictive accuracy.

Together with CVPAT, these support that PLS model is statistically and practically predictive.

The combined evidence from CVPAT, Q^2 predict, and prediction error metrics (RMSE, MAE) (Shmueli, 2019) confirms that the PLS model achieves superior predictive accuracy and relevance, validating its practical applicability in explaining Intention to Use and Usage Behavior.

VII. Conclusion:

This paper confirms the Extended UTAUT-AI model ($R^2 = 0.639$ intention; $R^2 = 0.443$ behavior) and shows a re-calibrated adoption pyramid in AI-based banking. The fact that AI Effectiveness ($\beta = 0.514$, $f^2 = 0.471$) turns out to be the strongest predictor does not make Performance Expectancy irrelevant but rather creates a chain effect: effortlessness is the entrance through which performance evaluation can occur. Frictionless interaction is the requirement of users who are cognitively trained by generative AI (ChatGPT, Claude, Gemini), and the so-called 10-second rule is now qualitatively determined but quantitatively validated. Nevertheless, ineffectiveness devoid of functional worth makes technology meaningless; Performance Expectancy is crucial as a substantive reason to continue to use technology. The result indicates a complementary design: AI Effectiveness eliminates the barriers to adoption, whereas Performance Expectancy maintains the commitment to remain in the adoption- both are not enough to be used independently. Trust-Privacy duality proves to be functionally equal to usability: Trust multiplied by AI Privacy Capabilities gets to the same effect size of AI Effectiveness itself ($f^2 = 0.181$ combined), and psychological safety becomes necessarily required, as opposed to a facilitating factor. The Privacy Paradox Rejection: Rationality Depending on the context. The most theoretically relevant observation of the study is the refusal of the hypothesis of the Privacy Paradox.

This empirically counters the traditional view that users have known conflicting attitudes on privacy including expressing worries and at the same time revealing information (Norberg, 2007) and (Acquisti, 2020). This non-significant negative coefficient shows that in banking situations where there is an existence of Trust infrastructure the paradox disappears. Users show context-specific rationality: in the event transparent data governance, provable accountability measures, and institutional credibility exist, privacy issues do not play the role of independent adoption deterring factors. This is in line with reformulations of the privacy paradox as a contingent concept instead of a universal phenomenon (Kokolakis, 2017). The gap in intention and behavior reported in low-trust digital settings is not evident with Indian banking customers who operate within the context of already existing institutional relationships and regulatory frameworks. They want privacy options, such as granular consent, purpose

specification, deletion rights, but not privacy guarantees. When personal data are traded with the engineered Trust in explainability, reversibility, contestability, and auditability, users are ready to share personal data with the personalized service, which makes the paradox empirically inoperative. The significance of Emotional Intelligence (OE=0.068) and Anthropomorphism (OE=0.074) although they are present in 64% of qualitative empathy complaints is the phenomenon of the latent need: customers cannot state what they desire, which they have never encountered. The way forward is not selling these capabilities but implementing systems that establish reference experiences that transform the expectations of users. The combination of quantitative results, qualitative challenge mapping (40% operational breakdown, 25% technological deficiencies, 15% trust erosion), and the customer frustration rate of 86 percent regardless of the massive AI introduction all leads to a particular architectural requirement: multi-agent orchestration systems with tiered human-controlled autonomy, where the AI Effectiveness brings the sense of effortlessness that enables adoption, the Performance Expectancy offers the utility that validates further use, Trust-by-design offers the psychological safety, and the Emotional Intelligence leverages the empathetic ability. The competitive edge that will be presented to early movers will not be gradual but will be categorical. The empirical requirement is evident; the technological capacity is available; the only other variable is the institutional desire to implement.

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