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PERCEPTION OF GENERATION Z TOWARDS AI-BASED DIGITAL BANKING SERVICES: AN EMPIRICAL INVESTIGATION

Dr. Ashwini M. Jamuni*

*Assistant Professor,
Department of PG Studies and Research in Commerce,
Rani Channamma University,
Vidyasangama, Belagavi, INDIA
Email Id: ashwinijamuni@rcub.ac.in

Mr. Raju A. Sanadi**

**Research Scholar,
Department of PG Studies and Research in Commerce,
Rani Channamma University,
Vidyasangama, Belagavi, INDIA
Email Id: rajusanadi5@gmail.com

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ABSTRACT

The research shows how Gen Zsee digital banking services powered by artificial intelligence using calculus theory. Partial Least Squares Structural Equation Modelling studies four options. AI usefulness, usability, and confidence influence BI's AI-driven banking adoption more than privacy concerns. The model explains 78.3% of behavioural intention variance with strong internal consistency and convergent validity. The results show that Gen Z clients care more about AI-powered financial services' efficiency, dependability, and user-friendliness than privacy. In addition to providing useful insights for banks and fintech companies to improve digital engagement through trust-building, simplicity, and value-oriented AI services, the research makes a theoretical contribution by verifying an integrated TAM–Trust–Privacy framework. Future research may look at longitudinal behaviour, span geographical boundaries, or incorporate other factors like digital literacy.

KEYWORDS: *AI In Banking, Gen Z, Behavioral Intention, Privacy Concerns*.

1. INTRODUCTION:

Artificial Intelligence are changing the banking industry's digital transformation strategy.This progress has transformed internal banking processes and revolutionised consumer experiences by providing quicker, more secure, and more personalised services (Vukovic, 2020) [9]. People born in the years 1997–2012 make up Generation Z, a sizable cohort that has grown up with the internet and has high expectations for frictionless digital experiences(Francis & Hoefel, 2018) [13]. Generation Z has matured in a technology-centric environment, rendering them particularly equipped to assess the efficacy and usability of AI-driven financial services. Their expectations encompass advanced digital banking features such as intelligent chatbots, real-time fraud detection, voice and facial recognition, and predictive financial support (Deloitte, 2022) [2]. Consumers want functionality, transparency, trustworthiness, and customisation in financial transactions, which are increasingly facilitated by AI technology (Accenture, 2021) [5]. AI applications in banking are many, encompassing automated loan approvals, algorithmic trading, robo-advisory services, and intelligent virtual assistants. These initiatives have augmented operational efficiency, diminished human mistake, and elevated client engagement (Dwivedi et al., 2021) [6]. AI facilitates banks in delivering proactive and customised services that correspond with Gen Z's demands for personalisation and immediacy, encompassing fraud protection systems, credit risk analysis, and customer relationship management (Pousttchi et al., 2020) [11]. Notwithstanding their technological proficiency, Gen Z consumers exhibit a degree of caution. Their worries encompass data privacy, algorithmic bias, and ethical AI utilisation, which they anticipate banks will address with transparency (PwC, 2020) [10]. This indicates that although AI adoption is embraced, it must be morally founded and centred on human values to secure and maintain the trust of Generation Z. As digital natives, they possess a discerning perspective on electronic encounters that are inconsistent, unclear, or impersonal. Consequently, comprehending Gen Z's perspective is not just beneficial for client happiness but crucial for enduring digital change inside the banking industry. Research indicates that digital trust is a crucial factor influencing Gen Z's devotion to AI-driven financial services (Statista, 2023) [1]. People born in the years 1997–2012 make up Generation Z, a sizable cohort that has grown up with the internet and has high expectations for frictionless digital experiences.In this setting, banks must achieve a careful equilibrium between innovation and accountability by guaranteeing that AI solutions are transparent, inclusive, and safe (Microsoft, 2021) [8]. Thus, the efficacy of digital transformation programs in banking relies not alone on technology acceptance but also on comprehending generational behaviours and values. This research seeks to examine Generation Z's viewpoint on AI services in banking, focussing on their happiness, trust, ethical considerations, and the overall influence on their banking experience. As AI advances and becomes integrated into financial services, comprehending this generational perspective is essential for banks to formulate and implement AI strategies that are both effective and aligned with the values of future consumers (McKinsey, 2021) [7].

2. Need for the Study

The digital transformation of the banking sector, driven by Artificial Intelligence (AI) and fintech innovations, is reshaping customer experiences at an unprecedented pace. However, while banks are increasingly adopting AI-driven financial services—such as robo-advisors, intelligent fraud detection, and predictive analytics— Unfortunately, there is still a significant disconnect between these advancements and Generation Z's unique demands and tastes.

Gen Z, as digital natives, demands intuitive, personalized, and trustworthy digital experiences. Yet, many banking institutions tend to focus more on implementing advanced technologies rather than understanding how these are perceived and received by younger consumers. This disconnect poses a risk of alienating a vital customer segment whose loyalty is influenced not only by functionality but also by transparency, data security, and ethical AI usage. Furthermore, the fintech landscape is evolving rapidly, challenging traditional banks to keep up with customer-centric innovations. It is crucial for banks to embrace technology that cater to the habits and expectations of Gen Z in this setting. Retaining this generation requires more than technological capability—it requires strategic alignment with their values, concerns, and digital behavior.

3. Significance of the Study

The rising digital economy in India makes this subject important academically and practically. As banks and financial institutions adopt artificial intelligence (AI) to improve service delivery, it becomes essential to understand how Generation Z—digitally savvy and future-oriented consumers—perceives these AI-enabled services. Bankers and fintech service providers will find this research particularly helpful since it sheds light on the preferences, expectations, and trust factors that impact Gen Z's adoption of digital banking powered by AI. By aligning technology strategies with the actual perceptions of this generation, banks can not only enhance user experience but also **retain Gen Z customers** in an increasingly competitive digital landscape. In addition, the study has implications for **policymakers**, as it highlights the behavioural and psychological factors influencing technology adoption among India's youth. These insights are crucial for designing **regulatory frameworks and digital inclusion policies** that are in line with the goals of **Digital India** and broader economic development.

4. Conceptual Framework and Hypothesis Development

This research examines how AI-related variables affect Generation Z's BI to utilise AI-enabled digital banking services. The model incorporates three theoretical perspectives:

TAM:

Davis's TAM states that new technologies' perceived usefulness and simplicity influence their adoption. People believe a system will improve their performance, which is termed perceived usefulness, and the effort necessary to utilise it is called perceived ease of use. All of these things affect how the user feels about the technology, which in turn affects whether or not they plan to utilise it. To assess consumer adoption of new technologies like AI in digital banking, TAM is commonly used.

Trust Theory:

Belief in the security and dependability of AI systems, according to Trust Theory, impacts people's actions in dangerous or uncertain contexts, especially in AI-based digital banking. When people have faith in AI systems, they are more likely to utilise them and keep using them. Trust reduces perceived risk and enhances confidence in automated services, especially when dealing with sensitive financial data.

Privacy-Calculus Theory:

This Theory states that consumers uses the advantages & downsides of disclosing personal data online. Using AI-enabled banking is more likely if they think the positives outweigh the risks. This theory is particularly relevant in AI-based systems where large volumes of personal data are collected and analyzed.

4.1 Perceived Usefulness (PU)

Generation Z feels AI-based services would boost banking efficiency and performance PU. 1989 (Davis).The perceived utility of a technology has a substantial impact on its acceptability, according to research. This is particularly true for digital natives.

H_{01}: No significant relationship exists between PU and BI to utilise AI in banking.

4.2 PEOU

The ease and friendliness of AI-driven financial services from Generation Z are evaluated using this approach (Venkatesh & Davis, 2000). PEOU is crucial, since a service that appears hard may deter consumers, regardless of their technological proficiency.

H_{02}: To use AI in banking, PEOU and BI do not correlate significantly.

4.3 TAI

The confidence that Gen Z places in AI systems is evident in their trust, which encompasses the ability of these systems to handle data securely, deliver dependable services, and uphold ethical standards (Gefen et al., 2003). This holds significant relevance in financial contexts that deal with personal and sensitive information.

H_{03}: The banking industry has not shown any discernible relationship between trust in AI and the intention to use AI in their operations.

4.4 Privacy Concern(PC)

Privacy Concern highlights the unease among Gen Z regarding the potential misuse, sale, or exploitation of their data by AI systems employed by banks (Smith et al., 1996). It is generally believed that people's behavioural intentions would be negatively affected by increased privacy concerns.

H_{04}: No association exists between PC and BI's AI utilisation. in banking.

4.5 Behavioral Intention to Use (BI)

This research uses BI as its dependent variable, which represents Gen Z's desire to either continue using or adopt digital banking services that are enabled by AI. (Ajzen, 1991). The above factors exert influence, with each being examined through the relevant hypothesis.

5. Proposed Conceptual Model:

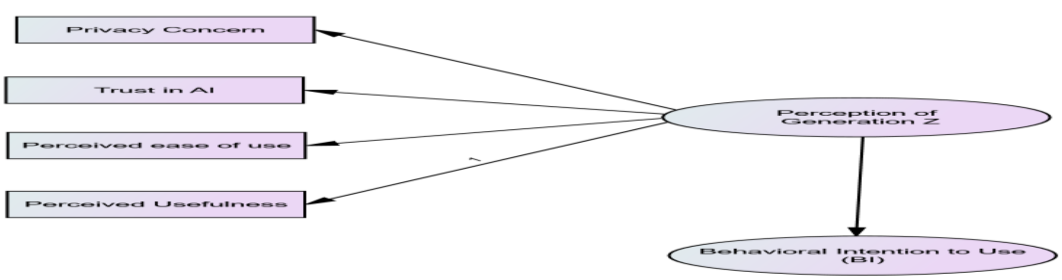

Figure-1Proposed Conceptual Model

6. Research Methodology:

Perceived utility, simplicity of use, faith in AI, and privacy concerns were the primary areas of emphasis in this descriptive-analytical research of Generation Z consumers' views of digital banking services in India that were facilitated by AI—affect Generation Z's propensity to utilise these services. A total of 185 respondents were chosen through purposive sampling from consumers of several public and private sector banks. The inclusion criteria targeted individuals from GenZ (born between 1997 and 2012) who actively utilise digital banking services, including mobile applications, chatbots, AI-based financial planning tools, and fraud detection functionalities. A standardised 5-point Likert scale questionnaire was used to collect primary data on PU, PEOU, TAI, PC, and BI. The questionnaire items were modified from reliable sources. Scales used in prior studies (Davis, 1989; Venkatesh & Davis, 2000; Gefen et al., 2003; Smith et al., 1996; Ajzen, 1991) to guarantee construct reliability and content validity.

Secondary data were sourced from industry papers, journal articles, and government digital banking policy documents to offer contextual support and validate findings. Structural Equation Modelling (SEM) was utilised for statistical analysis with Smart PLS 4. We assessed reliability and discriminant validity using Cronbach's alpha and CR ratings and the Fornell-Larcker Criterion. Path analysis examined direct links between posited structures.

7. Analysis and Interpretation:

Table1: Statistical Details about the Respondents (n = 185)

Variable	Category	Frequency	Percentage (%)
Gender	Male	98	53.0%
	female	87	47.0%
Age Group	18–21	64	34.6%
	22–25	95	51.4%
	26–28	26	14.0%
Education Level	Undergraduate	83	44.9%
	Postgraduate	95	51.4%
	Others	7	3.8%
Occupation	Student	117	63.2%
	Working Professional	68	36.8%
Monthly Income	Less than ₹ 10,000	89	48.1%
	₹ 10,000–₹ 30,000	51	27.6%
	₹30,001–₹ 50,000	28	15.1%
	Above ₹50,000	17	9.2%
Location	Urban	112	60.5%
	Semi-Urban	51	27.6%
	Rural	22	11.9%
Banking Experience	Less than a year	23	12.4%
	One to three years	84	45.4%
	More than three years	78	42.2%

Table 2: Construct-Wise Item code

Factor	Item Code	Questionnaire Item
Behavioral Intention	BI1	I plan to routinely utilise AI-based digital banking.
	BI2	I advocate AI-based digital banking.
	BI3	I want to utilise AI-enabled digital banking more.
	BI4	I may employ AI-based digital banking when accessible.
Privacy Concern	PC1	AI-based financial systems utilise my personal data, which worries me.
	PC2	I feel uncomfortable sharing financial details through AI-enabled banking services.
	PC3	AI algorithms in digital banking may exploit my personal info.
	PC4	I believe AI-based banking services may compromise my privacy.
Perceived Ease of Use	PEOU1	Digital banking AI features are simple for me to learn.
	PEOU2	AI-based banking is straightforward to use.
	PEOU3	I learn AI-enabled digital banking products rapidly.
	PEOU4	Cognitive effort is minimal while using AI-based financial services.
Perceived Usefulness	PU1	AI-based digital banking services help me manage my finances better.
	PU2	AI features in banking save me time and effort.

	PU3	AI-based banking services provide useful insights for my financial decisions.
	PU4	AI-enabled digital banking enhances my banking experience.
Trust in AI	TAI1	I trust AI systems in digital banking to perform accurately.
	TAI2	I believe AI-based banking services are secure and reliable.
	TAI3	I have confidence in the decisions or suggestions made by AI in banking apps.
	TAI4	I feel safe using AI-based digital banking services.

Table3: Effectiveness of Samples and Factor Extraction in Exploratory Factor Analysis (EFA)

Measure	Value
KMO	0.935
Bartllets test of sphericity(Chi-sq)	3533.315
Degrees of freedom (df)	378
significance(p-value)	0.000

Source: SPSS 2020

The sample's KMO score of 0.935 supports appropriateness, however Bartlett's Test of Sphericity shows the correlation matrix is not an identity matrix. Perceived Personalisation, Perceived Usefulness, Bias, and Perceived Usefulness are the six components that pertain to conceptual traits. The results prove that factor analysis is a good choice. These factors explain 93.5% of the variation, indicating a strong factor structure and suggesting construct validity in the dataset.

Table 4: Internal Factor Consistency and Rotated Component Matrix

Factor	Item Code	Factor Loading	Cronbach's Alpha
Behavioral Intention (BI)	BI1	0.826	0.890
	BI2	0.846	
	BI3	0.822	
	BI4	0.778	
Privacy Concern (PC)	PC1	0.774	0.831
	PC2	0.708	
	PC3	0.766	
	PC4	0.718	
PEOU	PEOU1	0.733	0.878
	PEOU2	0.772	
	PEOU3	0.912	
	PEOU4	0.795	
Perceived Usefulness (PU)	PU1	0.843	0.872
	PU2	0.729	
	PU3	0.821	
	PU4	0.779	
TAI	TAI1	0.850	0.863
	TAI2	0.716	
	TAI3	0.723	
	TAI4	0.835	

Source: Smart PLS Output

The rotated component matrix and internal consistency findings reveal that all five components in the model exhibit robust reliability and convergent validity. Every item is confirmed to be significant for the latent variable since it has a high factor loading (≥0.70).

All constructs are internally consistent since their Cronbach's Alpha values above 0.70, ranging from 0.831 for Privacy Concern to 0.890 for Behavioural Intention(Hair et al., 2019).This guarantees that the indicators accurately assess Gen Z's impression of AI-based financial services.

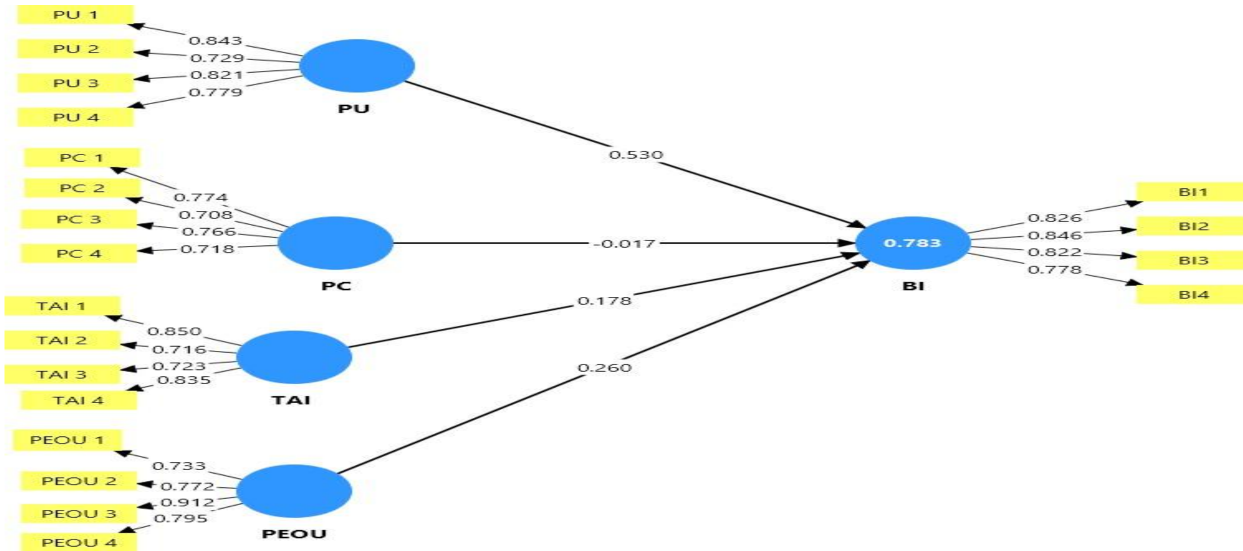

Figure-2 Analyzed Model (Smart PLS)

Table 5: External Loads and Convergent Self-Sufficiency an Overview of Measurement Elements

Construct	Item Code	Outer Loading	Convergent Validity Summary
Behavioral Intention (BI)	BI1	0.826	α = 0.890; CR = 0.890; AVE = 0.670
	BI2	0.846	
	BI3	0.822	
	BI4	0.778	
Privacy Concern (PC)	PC1	0.774	α = 0.831; CR = 0.830; AVE = 0.551
	PC2	0.708	
	PC3	0.766	
	PC4	0.718	
PEOU	PEOU1	0.733	α = 0.878; CR = 0.880; AVE = 0.649
	PEOU2	0.772	
	PEOU3	0.912	
	PEOU4	0.795	
Perceived Usefulness (PU)	PU1	0.843	α = 0.872; CR = 0.872; AVE = 0.631
	PU2	0.729	
	PU3	0.821	
	PU4	0.779	
TAI	TAI1	0.850	α = 0.863; CR = 0.864; AVE = 0.614
	TAI2	0.716	
	TAI3	0.723	
	TAI4	0.835	

Source: SPSS/Smart PLS Output

Table 5 demonstrates that all five components of the measuring model have good internal reliability and validity. Each item's outer loading is more than the minimally acceptable threshold of 0.70, suggesting that structures are well represented. All constructs have Cronbach's Alpha scores over 0.83, indicating strong internal consistency. For all constructs, the Average volatility Extracted (AVE) is more than 0.50, which means that more than half of the observed data volatility is greater than that threshold.Variables are elucidated by the latent variables. The measurement model is suitable for SEM structural analysis based on these results.

Table 6: Discriminant Validity Testing With Fornell–Larcker

Construct	BI	PC	PEOU	PU	TAI
BI	**0.818**				
PC	0.794	**0.742**			
PEOU	0.804	0.849	**0.806**		
PU	0.849	0.806	0.772	**0.794**	
TAI	0.774	0.920	0.842	0.742	**0.784**

Source: SPSS/Smart PLS Output

Table 6 shows the Fornell-Larcker Criterion for measurement model validity. The test is discriminantly valid when the bold diagonal values of the square root of Average Variance Extracted are bigger than the off-diagonal values in the same row or column. The square root

of PEOU's AVE is 0.806, higher than its correlations with BI (0.804), Perceived Control (PC) (0.849), PU (0.772), and TAI (0.842), confirming discriminant validity.The findings show that each model idea is unique, avoiding multicollinearity problems and proving the measurement framework's applicability for structural model research.

Table 7: Evaluation of Structural Model Paths: Significance, Effect Sizes, and Coefficients

Hypothesis Path	Path Coefficient (β)	Standard Deviation (SD)	T-value	P-value	f^2 Effect Size	Remark
H1: PC → BI	-0.017	0.130	0.131	0.896	0.000	**Not Supported**
H2: PEOU → BI	0.260	0.100	2.600	0.010	0.081	**Supported**
H3: PU → BI	0.530	0.180	2.944	0.004	0.321	**Supported**
H4: TAI → BI	0.178	0.080	2.225	0.027	0.091	**Supported**

Source: SPSS/Smart PLS Output

According to the results, three out of the four suggested connections hold up to statistical scrutiny, while the fourth does not. While PU has the most favourable effect on BI, PEOU and TAI have a considerable impact on the likelihood that members of Generation Z would utilise financial services powered by artificial intelligence.Nonetheless, Privacy Concern (PC) exerts a negative albeit statistically minor influence (β = -0.017, p = 0.896), suggesting it does not meaningfully impede Gen Z’s behavioural intention in our analysis. The findings support the structural model, showing that Generation Z's behavioural intentions are mostly affected by AI's usefulness, simplicity of use, and trustworthiness in banking, while privacy concerns appear to have less effect.

Construct	R-square	R-squareAdjusted
BI(BehavioralIntention)	0.783	0.778

Source: SPSS/Smart PLS

According to the research, 78.3% of Generation Z would adopt AI-enabled financial services if the exogenous variables of Perceived Usefulness, PEOU, TAI, and Privacy Concern were included. This indicates that the suggested structural model has a strong ability to anticipate user intention in the Gen Z banking context, proving its predictive importance and explanatory power.

8. DISCUSSIONS:

This study explains Generation Z's AI-driven digital banking habits. PU, PEOU, and TAI predict BI among young digital banking users, according to Privacy-Calculus theories. TAM and Trust were included to the study.These findings corroborate previous research, indicating that utility, simplicity, and trust all influence favourable intentions towards technology adoption. PU demonstrated the most significant impact ($\beta = 0.530$), underscoring Generation Z's preference for utility and efficiency in banking. Contrary to expectations, PC did not significantly affect behavioural intention ($\beta = -0.017$, $p > 0.05$).This may indicate that Gen Z users either see digital banks as sufficiently safe or are prepared to compromise privacy for convenience and functionality, reflecting conclusions from recent research on digital-native behaviour. The model's significant explanatory power ($R^2 = 0.783$) illustrates its effectiveness in encapsulating Gen Z views; nevertheless, more adjustments may be necessary to account for individual variations in privacy tolerance.

8. Theoretical and Practical Implications

Theoretical Implications:

This study adds a Generation Z-specific conceptual framework to digital banking literature. This is done by merging TAM, Trust Theory, and Privacy-Calculus Theory. Results confirm premise that Perceived Usefulness (PU) and TAI greatly impact BI.This further supports the basic principles of TAM and shows that it can be used to financial ecosystems that are enabled by AI. Notably, the insignificant role of **PC** challenges conventional theories that assume privacy apprehension as a primary deterrent to technology adoption. This suggests a generational shift in digital behaviour, where Gen Z may weigh utility and convenience more heavily than privacy risks. Such insights necessitate a re-evaluation of privacy-centric adoption models in the context of emerging technologies and younger consumer groups.

Practical/Managerial Implications:

It is critical for lawmakers, fintech companies, and banks to meet Gen Z's expectations for trustworthy, user-friendly, and efficient financial services using AI.Developers should prioritize intuitive user interfaces and high-utility features—such as predictive budgeting tools, real-time fraud alerts, and responsive AI chatbots—to enhance perceived usefulness. Building trust through secure, transparent, and ethical AI systems is essential for sustained engagement. While privacy was not a major deterrent in this study, it should not be overlooked; adopting **privacy-by-design** practices can offer silent reassurance without affecting functionality. Furthermore, educational outreach on responsible AI use can deepen digital trust. Policymakers are advised to formulate **ethical AI governance frameworks** that mandate transparency, explainability, and user control over personal data, ensuring AI deployment remains socially responsible and future-ready.

9. CONCLUSION

This research analyses how Indian Generation Z's psychological aspects impact their adoption of AI-based digital banking. TAM, Trust Theory, and Privacy-Calculus Theory form a powerful model in this study. According to the research ($R^2 = 0.783$), Perceived Usefulness, Ease of Use, and Trust in AI strongly influence behavioural intention. Privacy Concerns did not discourage digital natives, indicating a paradigm change in how they weigh risk and value in technology usage. The findings reveal that Gen Z prioritizes performance, reliability, and simplicity in financial technologies, and they are relatively more tolerant of data-sharing if the perceived value is high. These findings are critical for creating user-friendly, future-proof AI-powered financial services.The research not only extends theoretical discourse in digital adoption literature but also equips practitioners with actionable strategies to drive deeper engagement with next-generation banking consumers.

10. Limitations and Directions for Future Research

The research does have certain limitations, but it does make some good contributions. One limitation is that the sample only includes respondents from Generation Z in India. The results may not apply to other generations or nations.Future research should adopt a **comparative generational lens**—incorporating Millennials, Gen Alpha, and Gen X—to explore intergenerational differences in AI adoption behaviours. Secondly, while the study examines behavioural intention, it does not measure **actual usage behaviour**. Future studies might use digital banking use statistics or longitudinal approaches to assess the intention–behavior gap.

Moderating and mediating factors including digital literacy, trust disposition, financial literacy, and socioeconomic level should improve future models.

Exploring **perceived personalization**, **algorithmic fairness**, and **AI explainability** as new constructs may also add depth to understanding user acceptance. Finally, qualitative research approaches like focus groups and in-depth interviews may reveal more subtle emotional and psychological factors affecting trust and perceived risk, which can help explain digital banking conduct in the AI age.

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