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How AI Is Disrupting Traditional Banks: Perceptions of the Younger Generation

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Abstract

This research examined the perspectives of Generation Z and Millennials regarding banking services, emphasising awareness, trust, and satisfaction towards AI technologies. Employing a quantitative methodology, the study randomly sampled 200 respondents in Bangkok, Thailand. Findings indicated notable demographic variations in attitudes towards AI-driven banking services. Participants aged 18–25 exhibited lower Awareness (S1) levels than older groups, with an F statistic of 22.91 (significance level 0.000). Additionally, both female and male respondents demonstrated reduced Trust (S2) in AI financial solutions, reflected by an F value of 31.71, P = 0.000. Understanding (S3) of current AI services was most pronounced among those aged 42 and above. At the same time, females reported higher satisfaction levels than males, which is evident from an F-test of 18.75%, which is significant at the 0.000 level. The study suggests tailored educational and trust-building initiatives for younger demographics and emphasises the need for accessible offerings for this group.

Keywords: AI-Powered, Banking Services, Gen Z, Millennials

Introduction

Several key factors influence AI adoption for banking services among young people and the two most essential generations of users – Generation Y and Z. These factors include perceived benefits of the intelligent features, personalisation, and perceived ease of use critical in determining their interaction with digital banking. Specifically, younger users-specifically Gen Y, are particular about the benefits offered by features AI brings into banking, including the effectiveness in undertaking banking operations. The hedonic aspects we have just identified show that people’s expectations of ‘‘intelligence’’ and the recognisability of AI systems contribute considerably to their satisfaction and motivated interaction with digital banking services (Bhatnagr & Rajesh, 2024a).

On the other hand, Generation Z is highly concerned about personalising services and empathy, similar to humans when financially interacting with AI. This aspect of AI is pivotal for constant updates to provide the user with continuously growing interest and satisfaction in AI-proposed financial solutions, which would fit the expectations of consumer desire for personalised outcomes (Yang & Lee, 2024a). Of the three factors, security, functionality and social pressures, perceived security is used to determine the likelihood of consumers engaging in digital banking services and was found to be the most persuasive factor (Irwin et al., 2023). While most people show a favourable attitude towards AI technology, recent research has evidenced that Generation Z may not optimally utilise AI-based banking services, showing a gap between attitudinal and utilitarian behaviour (Hameed & Nigam, 2022). However, although young people tend to be significantly pro-AI in banking, they have not entirely lost the desire for interpersonally mediated communication. This suggests the need for banking institutions, primarily in the 21st century, to consider both the application of technology and customer interface to capture the divergent needs of their clientele base.

Banks and other affiliated institutions among the players in the fintech space continue to embrace artificial intelligence in delivering customer-micro-services. These companies can analyse a large amount of data as customer-centred, and it will be possible to adapt the financial services offered to match the customers' desires and demands. That way, it also increases customers and enhances financial services for liberalised people. First, it helps to assess and identify customer preferences in dealing with banks and other financial institutions, with the aid of which it becomes easier to address the expectations of various customers (Okeke et al., 2024a; Muhammad et al., 2024a). Moreover, there is also an embedded feature of machine learning, which provides options based on concrete ‘seeable’ financial behaviours and achieving specific goals (Jashwanth, 2024). Also, AI-driven chatbots offer round-the-clock support that improves consumers’ engagement and makes complex financial transactions easier (Sivaji & Seethalapu, 2024a).

AI systems convincingly improve abilities related to fraud detection to detect suspicious activity using advanced pattern recognition; implementing such abilities boosts customer confidence (Jashwanth, 2024; Muhammad et al., 2024b). Furthermore, the high capability allows better credit scoring models to be generated using predictive analytics, which, in effect, can minimise lending risk (Sivaji & Seethalapu, 2024b). Using AI for personalisation and improving organisational operations is beneficial. However, on the same note, they bring forth issues rote to the use of AI, such as privacy and modelling issues. More so, it is crucial to consider the following ethical aspects if the self-serving instincts and the conflicts of interest issues are to be managed, if the equity in the delivery of services is to be maintained, and most importantly, if customers’ trust is to be upheld (Muhammad et al., 2024c; Rohella et al., 2024).

Generation Z and Millennials have realised various perceptions regarding the hybrid of AI as traditional banks seek to stay relevant with the new entrant Fintech companies. A more refined outlook of these inter-generation attitude disparities is key to the improvement of user satisfaction as well as services trusted by the banking institutions. The subsequent sections evoke the features that significantly affect these perceptions. Security, privacy, ease of use, and convenience were perceived as critical concerns concerning user trust and satisfaction with fintech services by Kee et al. (2024). Furthermore, compound differences in these elements are observed across generations. While AI’s anthropomorphism highly influences decision-making in Generation Z, the distinctly Millennials’ approach revolves around AI functionality and its practical benefits.

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Due to perceptions of animacy and intelligence man, AI influences user satisfaction and subsequent interactions with digital banking applications (Bhatnagr & Rajesh, 2024b).

In addition, it complements the financial recommendations by AI systems, making them genuine, which increases user interest – especially among young audiences (Yang & Lee, 2024b). The importance of cybersecurity can hardly be overestimated, as Generation Z's level of trust in digital banking depends significantly on their estimate of cybersecurity measures. They are crucial in mobilising this group since the rising army of young people forms an autresignificant popular demographic (Yadav & Tandon, 2024). On the one hand, legacy banks are already investing in the application of AI to enhance their service portfolios; on the other hand, it remains a struggle to maintain relevancy in the context of a rapidly evolving clientele base, mainly the Gen Z and the Millennial generation. This demographic prefers personalised, secure, and engaging digital services, which requires a targeted effort by banks to achieve loyalty and satisfaction.

This paper is crucial since it reveals young customers' attitudes towards banking services that artificial intelligence powers, and more so, consumers within the Gen Z and Millennial bracket. Thus, by analysing their perception, traditional banks have understood to understand the changes required in the AI strategies, such as improving and differentiating the user interface, personalisation of the experience, and a perception of privacy and trust. The study's purpose will be to assist financial institutions in addressing the areas of communication, product, and the proper implementation of AI solutions to address the issues of attracting and retaining young customers within a digital environment. However, the emphasis on these two demographic groups has to consider the opinions of other age categories, and the study area might also reduce the possibility of separating the results by area. Besides, there is a possibility of limiting a better appreciation of what qualitative findings could otherwise bring out through only the quantitative data collection procedures.

Research Objective

- To assess the awareness of Gen Z and Millennials about AI-powered banking services.
- To evaluate their level of trust in AI-driven financial solutions offered by traditional banks.
- To compare their satisfaction with AI-powered services provided by traditional banks versus fintech companies.

Hypotheses

- H1: Awareness of AI-powered banking services varies considerably across different age groups, with Generation Z displaying the lowest levels of awareness.
- H2: Trust in AI-driven financial services varies significantly by age and gender, with younger individuals and males exhibiting lower levels of trust.
- H3: Satisfaction with AI-powered banking services differs notably between traditional banks and fintech companies across various demographic segments.

Literature Review

Customer experience in banking is revolutionised by AI chatbots that deliver accurate financial solutions to consumers based on their needs with the help of techniques, including NLP and predictive analytics (Okeke et al., 2024b; Balaji et al., 2024a). These chatbots are conversant with large amounts of customer data to offer timely support, enhance round-the-clock support interaction, and recommend products out of customer databases (Udeh et al., 2024; Temara et al., 2024a). On the same note, they enhance organisational productivity since several basic questions can be programmed (Zarie et al., 2024a). However, chatbots also have drawbacks, such as failure to recognise individual emotions and even, concerning the financial industry, the complexity of some cases, requiring assistance and immediate, further help from assistants.

Fintech organisations have emerged as critical in supporting the application of AI in meeting customers' needs, mainly through AI-driven chatbots. These chatbots use complex artificial intelligence and NLP to study vast amounts of customer information and deliver individualised finance and support in local languages and at any time of the day or night, as well as one-size-fits-all financial literacy programmes (Okeke et al., 2024c). Thus, enhancing the automation workflow advances operational performance, impacting customer satisfaction with reliable services. However, there is a range of critical issues to be solved, such as privacy and the role of humans in communication with clients. Solving some of these problems is essential to the ability of Fintechs to harness the full potential of AI-driven customer experiences (Bansal et al., 2024a; El-Shihy et al., 2024b).

Age and educational level are major predictors of attitudes towards AI-based banking technologies. Using the technology acceptance model, the available literature suggests that young participants, as well as those with at least a college education, are more likely to be confident as well as willing to embrace AI technologies in the financial dealership because of their ease with technology and lower perceived risk (Vaidya et al., 2024). On the other hand, most of the elderly work negatively towards AI due to security concerns and limited AI knowledge (R & Salman, 2023). It is also important to stress the correlation between the level of education and the extent of the use of AI recommendations, for that educational activity should be focused on increasing AI awareness and making it more accessible to people of different age groups and backgrounds (Biswas & Murray, 2024a; Alshari & Lokhande, 2022a). However, some research has provided evidence that age and experience are not always related to one’s level of trust; the relationship between these variables in a multi-dimensional trust model is inconsistent and intriguing, and more research needs to be done (Bhandari et al., 2023).

The banks' staff recognises essential information about job security as an influential factor determining their resistance to changes in policies and regulations. Minors who are secure with their job will self-accept the organisational changes but are likely to resist change whenever they feel insecure with their position. The Conservation of Resources Theory is used here; job security lowers resistance since employees consider changes less risky (Feng et al., 2021). Perceived organisational support also increases the acceptance of changes because people with a higher perception of organisational support are likely to accept changes because they feel valued (Rehman et al., 2021). Nevertheless, mergers and acquisitions often trigger job insecurity and, therefore, resistance; the cross-sectional correlation indicated that perceived M&A negatively relates to job security (Fayankinnu & Akinde, 2020a). Leadership can help to reduce such problems, as the experience of charismatic leaders can help to overcome perceptions of job destruction and, therefore, minimise resentment of change (Adda et al., 2019). However, some organisational employees may have negative attitudes towards a change since they may misconstrue change or have previously undergone unpleasant experiences concerning change. To some extent, attitudes towards organisational change in the banking sector are challenging.

AI's adoption in banking services depends on customer viewpoints about job security, trust levels, privacy concerns, system functionality, and how users see empathy in AI interactions. The acceptance of AI services differs between generations since younger technology-adopting users demonstrate higher receptiveness than older generations. Asian users adopt new technology because they know its advantages and find it helpful, while their doubts about risks impede acceptance. User confidence grows when trust is paramount because users need to understand AI functions and the level of trust in the system. AI brings operational advantages to businesses, yet ethical issues and human oversight requirements continue to exist, so organisations must develop considered strategies for integration and trust development (Choi, 2022).

Research Methodology

Quantitative research techniques of finance are crucial when it comes to formulating efficient financial investment tools and enhancing the management of portfolios. The methods employed here leverage an understanding of statistical models and better algorithms to improve returns and control for risks as needed. According to the efficient model like the modern portfolio theory (MPT), it helps decide the right proportion of asset mix. Thus, applying mean-variance optimisation and risk-parity strategies ensures that no asset class dominates portfolio risk (Li, 2024; Senescall & Low, 2024).

Further, quantitative measures enhance risk management as much as they can quantify actual loss more accurately. They employ multi-factor models and reasonable machine learning algorithms as the market behavioural predictor and exposure measurement instrument (Liu, 2023; Huang, 2024). Fundamental approaches, such as momentum and mean reversion strategies, are based on calculations made with the help of quantitative analysis and are complemented and improved by using big data and artificial intelligence depending on the change in the market (Xiang, 2024; Li, 2024). However, over-fitting of models and problems related to data quality can be a real issue in dynamic markets.

Issues with sample size and generality impact the reliability of financial data for research due to their effect on population size. According to Lakens (2022), large populations require a smaller sample size to generate more reliable estimates of the variable than small populations, which require a larger sample size to minimise sampling error. Errors allow data contamination, but more samples can detect and eliminate these errors, thus giving better results (Liu, 2020). Furthermore, sample size is incorporated or can influence results as the size may vary within meta-analyses and, without proper weighting, leads to incorrect conclusions (Tipton et al., 2023). While higher numbers of people increase data credibility, low numbers are also acceptable if used wisely in the analysis.

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Hence, this study only included 200 respondents using a stratified random sampling technique, whereby respondents were equally sampled from Gen Z and Millennials and were further divided into uniform age groups and genders in Bangkok, Thailand. The authors used questionnaires, administered both online and on paper, to collect the data. This instrument was comprised of four elements, the first of which was the basic demographics of the participants, the second identified their level of awareness about AI in banking, which additionally included information about chatbots, fraud alerts or personalised Banking as well as the participants' perception of AI-powered financial services which also encapsulated their trust, satisfaction and comparative self-employment experience with traditional banking institutions as well as FinTech companies; the last consisted of participants' concern about AI The replies were captured predominantly on a five-point Likert scale augmented with multiple choice questions to measure the consciousness and know-how. Surveys were conducted through Google Forms and Other online tools and distributed through email, social media, and Thematic Groups. Descriptive statistics were then used in further analysis to describe other aspects of the participant base and its awareness.

Results

The analysis of the descriptive statistics (Table 1) shows that the dataset was obtained from two hundred valid responses, and there were no cases of missing data. The age distribution mean was 2.17 (SD = 0.69), ranging from the groups 18-25 years and 42 years and above. Regarding gender, the mean was 1.57 (SD = 0.56), ranging from 'Male' to 'Other.' The education variable average was 2.34 (SD = 0.92) and includes the levels of education from 'High School or Equivalent' to 'Other' qualification. The frequency of use indicated a mean of 1.21 (SD = 0.48) using a scale ranging from daily to monthly. All age measures show that the distribution of this variable is reasonably homogenous (limited range), while that of education, though slightly bell-shaped, shows sufficient variation to warrant further analysis.

Table 1: Descriptive Statistics

	Mean	S.E. Mean	Std Dev	Variance	Range
Age	2.17	.05	.69	.47	2.00
Gender	1.57	.04	.56	.32	2.00
Education	2.34	.06	.92	.84	4.00
Frequency	1.21	.03	.48	.23	2.00
Valid N	200				

Source: Own Research

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The summary of the theoretical model confirmed a significant correlation between the level of age (as a dependent variable) and five independent variables, which are the awareness of mobile and online AI-based banking services and the trust in the AI-driven solutions for financial services and products, the satisfaction with the AI-based offered solutions in the traditional compared to new generation of bank companies, the engagement factors, and the perceived usefulness of the security, privacy and personalisation in the use The R-value is 0.81 which would indicate a high degree of correlation between the variables; as you recall, the independent variables combined account for exactly two-thirds of the variance in age (R Square = 0.66). The R Square of 0.65 after adjustment shows that the model's predictive capability is rather robust compared to overfitting. The relatively small standard error of the estimate of 0.41 shows how well the model predicted age from these independent variables.

The results of the ANOVA also show a highly significant value for F with 75.15, and the p-value is equal to 0.000; this means that all independent variables used in the model can predict age at a 95% confidence level. The regression sum of squares (61.70) is significantly larger than the residual sum of squares (31.85), proving that the model accounts for the most significant part of the variance in the variable of interest, age. These results imply that trust, satisfaction, usage behaviour of AI services, security, and personalisation significantly impact age-related differences in attitudes toward AI-powered banking solutions.

Table 2: Coefficients (Age)

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	.52	.16	.00	3.23	.001
S1	.35	.05	.43	6.59	.000
S2	.30	.06	.44	5.10	.000
S3	.36	.06	.46	5.98	.000
S4	-.79	.06	-1.03	-13.10	.000
S5	.24	.05	.28	4.70	.000

Source: Own Research

The coefficients table (Table 2) further shows the extent of the effect of the independent variables on age, with all the predictors underlined having them having a statistical significance ($p < 0.05$). Out of the selected variables, S1 (perception about banking service through AI technology), S2 (confidence in the AI-based financial products and services), S3 (level of satisfaction of AI services in traditional bank and Fintech), S5 (security privacy and personalisation) has positive beta value and a direct correlation with the age factor. However, looking at the standardised coefficients, we see that satisfaction has the highest positive value at 0.46, meaning that satisfaction with AI services has the most significant influence on age, followed by S2, which is trust at 0.44 and S1, which is awareness at 0.43. Whereas S4 (comparison and user engagement factors) has a negative Beta value (Beta = -1.03), it shows an inverse relationship with Age; therefore, younger participants perceive the user engagement factors poorly compared to older participants.

The nature of these relationships is revealed further by the unstandardised coefficients for the models, where S1, S2, S3, and S5 all suggest a corresponding increase in age for each unit increase in the predictors in question. Whereas referring to S4 being high, we depict a sharp decline in this component as the weight on user engagement factors rises. With this understanding, one can state that traditional participants prioritise satisfaction, trust, and security more than young participants focus on user engagement dynamics. These outcomes speak to how age moderates one's attitudes toward AI specifically targeted to self-employed banking services and specific implications for action pertinent to generating tactics geared to particular generational segments.

Table 3: Oneway ANOVA (Age)

		Sum of Squares	df	Mean Square	F	Sig.
S1	Between Groups	26.26	2	13.13	22.91	.000
	Within Groups	112.88	197	.57		
	Total	139.14	199			
S2	Between Groups	48.34	2	24.17	31.71	.000
	Within Groups	150.16	197	.76		
	Total	198.50	199			
S3	Between Groups	24.07	2	12.03	18.75	.000
	Within Groups	126.43	197	.64		
	Total	150.50	199			
S4	Between Groups	5.72	2	2.86	3.71	.026
	Within Groups	151.72	197	.77		
	Total	157.44	199			
S5	Between Groups	43.38	2	21.69	50.20	.000
	Within Groups	85.12	197	.43		
	Total	128.50	199			

Source: Own Research

The analysis of the differences by ANOVA shows the statistically significant attitudes of the age groups to different characteristics of AI banking services. For S1 (awareness of AI-powered banking services), the obtained F-value = 22.91, which is highly significant; thus, it can be stated that the level of awareness differs from one age group to the other ($p = 0.000$). Characterising post hoc tests, participants 18 – 25 claim significantly ($p < 0.05$) lower awareness than participants 26 – 41 and 42 or above on average by -0.69 and -1.09, respectively. Arguably, the F-value of S2 (trust in AI-technology financial solutions) equals 31.71, $p = 0.000$, indicating significant fluctuations. The participants in the younger age group of 18-25 years show lower trust levels than the other age groups,

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making the differences equal to -0.72 and -1.44, respectively and further cementing the results that the platform's younger users are less trusting of the other parties.

The F-value for S3 (satisfaction with the current AI services in traditional banks and that of the fintech) shows significant differences at 18.75, being significant at p = 0.000). Post-42 participants expressed the most satisfaction and were significantly different from participants aged 18-25 by 0.97 margin and 26-41 by 0.58 margin. For S4 (comparison and user engagement factors), an F-value is significant, equal to 3.71 (p = 0.026). However, the effect size is significantly lower. In particular, participants with the youngest age mentioned, 26-41 years old, have considerably less favourable perceptions than participants 42+ years old (mean difference = (-0.36). Last, security, privacy and personalisation, S5 suggests the most significant differentiation between age groups, comparing the importance of mis en œuvre with an F-value equal to 50.20, p = 0.000. Our results on age differences show older participants (42+) have a greater appreciation of security and personalisation than younger participants; the respective mean differences are -1.33 and -0.75 compared to the 18-25 and 26-41 groups. As such, the study reveals key differences between generation's perceptions of AI in banking and, therefore, should fundamentally support services that reflect the preferences and concerns of any given generation.

The model summary indicates a moderate relationship between gender (the dependent variable) and the independent variables (S1Q1: Awareness of artificial intelligence facilitated banking services (S2); trust in artificially intelligent-based banking solutions (S3); comparison satisfaction with artificially intelligent services in conventional banks and fintech (S4); user participation differentiators (S5); security and privacy; and individualisation. By looking at the value of R = 0.47, on the other hand, points to the fact that the independent variables give out a positive correlation, hence controlling the level of variance of gender at 22% (R Square = 0.22). This means the model complexity has been adjusted while possessing reasonable prediction power; the adjusted R Square is 0.20. The standard error of the estimate is 0.50, which shows a satisfactory accuracy of the predictions due to the included variables.

Table 4: Coefficients (Gender)

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	.81	.20	.00	4.08	.000
S1	-0.6	.07	-.09	-.91	.366
S2	.08	.07	.14	1.06	.291
S3	.11	.07	.16	1.43	.155
S4	-.19	.08	-.29	-2.48	.014
S5	.30	.06	.42	4.66	.000

Source: Own Research

The calculated F-value for the regression ANOVA is 10.83, and the significance value for the model is 0.000, which shows that all put together, the independent variables affect gender at a 95% confidence level. The regression sums of squares, which is 13.75, suggests that a portion of total variability (63.02) has been ascribed to factors relating to gender differences, such as trust, satisfaction and security. However, when we look at the residual sum of squares of 49.27, there is still variability left unaccounted for, implying that other variables outside the purview of this model might be at play. These gaps argue that other factors, besides the independent variables process in gender-perceived differences of AI-powered banking services, may be at play.

According to the coefficients table (Table 4), the independent variables S4 (comparison and user engagement factors) and S5 (security, privacy and personalisation) are highly related to gender in the present study as it has p-values of 0.014 and 0.000, respectively. The findings further show that S5 has the highest positive impact on gender (Beta = 0.42), meaning that perceptions of security, privacy and personalisation have more differences. On the other hand, S4 has a negative beta value (Beta = -0.29), which means the post-implementation focus on these user engagement factors negatively correlates with gender, suggesting that they may not appeal to the same gender equally. The other variables, S1 (perceived knowledge of banking services supported by artificial intelligence), S2 (perceived trust in intelligent financial services), and S3 (perceived satisfaction with AI services in conventional banks compared with Fintechs), were not significant predictors of gender as their $p > 0.05$.

This paper further establishes knowledge of security and personalisation considerations impacting Gender regarding AI-presented banking services. Additionally, user engagement proportion discovered a negative but substantial relationship. However, gender differences show minor disparities regarding people's general awareness, trust, and satisfaction with AI services. In this sense, there are recommendations that traditional banks and fintech companies interested in targeting people of different gender orientations should improve the security and privacy indicators while considering the likely gender differences in the approach.

Table 5: Multiple Comparisons (Gender)

	(I) Family	(J) Family	S1 (Sig.)	S2 (Sig.)	S3 (Sig.)	S4 (Sig.)	S5 (Sig.)
LSD	Male	Female	.001	.000	.001	.004	.000
		Other					
	Female	Male	.001	.000	.001	.004	.000
		Other	.004	.002		.001	
	Other	Male					
		Female	.004	.002		.001	

Source: Own Research

The descriptively evaluated ANOVA results illustrate a significant F-value in gender perceptions of the perceived dimensions of AI-powered banking services. In S1 (perception on AI banking services), the F-value of gender is 8.68, 0.000.F-value. Males report significantly lesser awareness than females (mean difference = -0.40; p = 0.001), while “Other” gender respondents report significantly lesser awareness than females but not substantially different from males. Likewise, there is a significant F-value for S2 (trust in AI-driven financial solutions) = 19.58, p = 0.000, suggesting a highly considerable gender effect on the level of trust with males found to express significantly lower levels of trust than females (mean difference = -0.77, p = 0.000) while ‘Other’ did not differ significantly from males.

In S3 (level of satisfaction with the AI services in the traditional banks and the fintech), the F-value (6.68, p = 0.002) shows moderate differences across the gender; Male respondents reported lesser satisfaction (M = 24.86, SD = 3.22) than the females (M = 25.60, SD = 3.13) by a margin of -0.40 (p Gender differences are also found in S4: comparison and User engagement have significantly different means for gender (males, t = -4.38, df = 174, p = 0.004, mean diff = -0.36; females compare favourable to males, p = 0.002) but non-significantly different from ‘Other gender’ (p = 0.062). S5 (security, privacy, and personalisation) provides the most significant gap between females and males, where males perceive low levels of security and privacy compared to females (mean difference = -0.75, p = 0.000). These results emphasise the need to bring banking services based on AI for women and men to create preferences and concerns about using banking services and the need to increase confidence in banking services that men can use the services while also considering the engagement and security expectations of different gender groups.

The model summary of the education (the dependent variable) and the independent variables: S1Q1 awareness of the AI banking services, S2 trust in AI financial solutions, S3 satisfaction with AI service in traditional banks and Fintech S4 comparison and user engagement S5 Security & privacy and personalisation. MART employing an R-value of 0.52 yields an explained variance of 27 per cent (R Square = 0.27) with the adjusted R Square of 0.25 reflecting the measure of the number of independent variables. The standard error of the estimate seems moderate (0.79), so the education level has been predicted with a reasonably good degree of accuracy from the independent variables.

The significance of the model is supported by the ANOVA results of the regression F value of 14.32 and the P value of 0.000, which implies that the overall predictors significantly predict education at a 95% confidence level. The regression sum of squares (44.99) meaningfully a portion of the total variance (166.88); however, the residual sum of squares (121.89) indicates that the majority of variability in education is still unaddressed. These results suggest that trust, satisfaction, and levels of engagement with AI-based banking services comprise moderate variance on educational levels, and it would be fruitful to examine specific influences within such factors.

The analysis of the coefficients table (Table 6) brings up the fact that among the independent variables, S4 (comparison, user engagement) and S5 (security, privacy, personalisation) have a predictive influence on the levels of education with p=0.005 and p=0.000, respectively. Among the variables, S5, which has the highest positive impact on education (Beta = 0.43), shows that education level significantly influences security, privacy, and personalisation towards AI-based banking services positively. On the other hand, S4 is marked by a negative Beta value equal to -0.33, which denotes the interaction.

At the same time, highly educated users may have a less favourable attitude toward engagement factors, so the index goes up. The other predictors—S1 (perceived availability of AI-based banking services), S2 (perceived trustworthiness of AI-driven BFSI solutions), and S3 (perceived satisfaction with existing AI services in conventional banks and new-age fintech institutions)—did not affect educating, as their p-values were higher than .05.

Table 6: Coefficients (Education)

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	.66	.31	.00	2.10	.037
S1	.14	.10	.13	1.32	.188
S2	.16	.11	.18	1.42	.157
S3	.04	.12	.04	.35	.726
S4	-.34	.12	-.33	-2.85	.005
S5	.49	.10	.43	4.92	.000

Source: Own Research

The above-stated results indicate that security/privacy regard and personalisation are paramount to customers with higher levels of education using AI-enhanced banking services sessions. They may be less driven or/and motivated by user engagement dynamics, although they may represent the bias towards content rather than form in interactions. The non-significance of the awareness, trust and satisfaction variables indicate that these two factors might not offer any significant differences across the educational levels. Such findings can help financial institutions adapt financial AI services by incorporating learning algorithms to provide distinct expected customer satisfaction levels to cater to highly educated customers.

The analysis of variance shows that there are differences regarding the attitudes toward AI-based banking services depending on the education level. Regarding S1 (awareness of AI-powered banking services), a high F-value of 9.81 (Sig. 0.000) clearly suggests a strong relationship between educational level and awareness. The single comparison confirms that in all cases, participants with higher education levels – doctoral and master's degrees are more aware than participants with lower education levels, including high school or equivalent, with mean differences -0.91 to -2.23, $p < 0.05$. Regarding S2, similar to the previous study, the analysis of variance showed that $F = 13.81$ ($p = 0.000$) when comparing trust in AI financial solutions indicates significant educational differences. PhDs display the most outstanding confidence identified as differing considerably from participants with high school or equivalent education at $p < 0.05$, with mean differences between -1.26 and -3.04.

Table 7: Multiple Comparisons (Education)

	(I) Family	(J) Family	S1 (Sig.)	S2 (Sig.)	S3 (Sig.)	S4 (Sig.)	S5 (Sig.)
LSD	High School or Equivalent	Bachelor's Degree	.000	.000			.000
		Master's Degree	.000	.000			.000
		Doctoral Degree	.000	.000	.000	.002	.000
		Other	.000	.000			.000
	Bachelor's Degree	High School or Equivalent	.000	.000			.000
		Master's Degree					.001
		Doctoral Degree	.000	.000	.000	.000	.000
		Other					.000
	Master's Degree	High School or Equivalent	.000	.000			.000
		Bachelor's Degree					.001
		Doctoral Degree	.001	.000	.000	.000	.000
		Other					
	Doctoral Degree	High School or Equivalent	.000	.000	.000	.002	.000
		Bachelor's Degree	.000	.000	.000	.000	.000
		Master's Degree	.001	.000	.000	.000	.000
		Other		.004		.002	.002
	Other	High School or Equivalent	.000	.000			.000
		Bachelor's Degree					.000
		Master's Degree					
		Doctoral Degree		.004		.002	.002

Source: Own Research

For S3 (satisfaction with AI services – traditional banks vs. fintech), The derived F-value of 6.89 ($p = 0.000$) demonstrated a moderate difference among the educated level. Specifically, participants with doctoral degrees show higher satisfaction levels of 5 out of the 8 scale items of the ATTRQ compared to participants with only a bachelor's degree or high school education or no formal education at all, with mean differences of -1.54 and -1.61 ($p < 0.05$). For S4 (comparison and user engagement factors), There is a significant variation F =7.95 ($p = 0.000$), and education level is significantly related to positive perception. Finally, the S5 associated with security, privacy, and personalisation is also significantly different, $F = 23.93$, $p = 0.000$. Doctoral degree holders assign a relatively higher value to these factors than the rest by having mean differences of -2.73 with high

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school and -1.75 with bachelor's degree holders. These results imply that the provision of AI-based banking services should factor in the heterogeneity of consumers by their educational levels, especially in terms of security, engagement, and trust.

1. The awareness level of Gen Z and Millennials on AI-based banking services

The data analysis shows that awareness of community pharmacy services (S1) is highly sensitive to age, with an F-value of 22.91 ($p = 0.000$). Subgroup analysis of the awareness score reveals that participants aged 18 to 25 years had lower scores than those in the age range of 26- 41 years by 0.69 ($p<0.01$) and 42 years and above by 1.09 ($p = <0.001$). These results are consistent with prior research stressing that young people, in particular, need special education to improve their AI literacy.

2. The degree of confidence that has grown with the incorporation of artificial intelligence in the provision of financial services from the established financial institutions

As for Team Members Trust (S2), a component of trust, the study established that the scores significantly changed with age; $F(4,122) = 31.71$: $p = 0.000$). Participants within 18 to 25 years had the lowest self-reported trust with a mean difference of -0.72 compared to the 26-41 group and -1.44 compared to the ≥42years group. As for this hypothesis, comparing trust by gender placed males in a lower confidence level than females ($t = -12.65$, $df = 1398$; mean difference = -0.77; $p = 0.000$). These findings highlight that concerns about trust were significant for younger and male participants, which necessitated focusing on how to address them.

3. The use of AI for services in traditional banks compared to the FinTech companies

The results showed satisfaction (S3) differences when gender, age, education level and occupation were compared. Thus, for age groups, the participants in this study who were 42 years and above had the highest satisfaction levels, differing significantly from those in 18–25 years (mean difference = -0.97) and 26–41 years (mean difference - 0.58) $F = 18.75$, $P = 0.000$. Cross tabulations and t-tests of gender comparison showed that males had a lower mean satisfaction score than females ($t = - 6.897$, $p = 0.001$). These outcomes can hardly be viewed as evidence of the successful fulfilment of the satisfaction needs by traditional and fintech banks: they only reveal the comparative advantages of each type of company.

As presented in Figure 1, the research hypotheses wherein the results reveal that AI awareness, AI trust and satisfaction depend on the demographic characteristics of the banking consumers. H1 is also supported by two findings on awareness (S1). Young participants between 18 and 25 had low awareness compared to the older groups $F = 22.91$; $P = 0.000$. Using Tukey post hoc on the optimism score, it was possible to compare dependent variables across the groups; means were -0.69 between the 18–25 group and the 26–41 group, -1.09 between the 18–25 group and the aged 42 or above. These results underscore the importance of these specialised educational programs to make people of younger generations aware of these problems. H2 is also supported by the findings because there are statistically significant differences in the level of trust (S2) depending on the age and gender of consumers. Specifically, the trust level of the participants aged 18–25 was

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significantly lower than that of the participants aged 26–41, with a mean difference¼ of -0.72; and 42 and above mean difference ¼ -1.44: F¼ 31.71; p¼ .000. With regards to the results of gender analysis, males were proven to have lower levels of trust that females with a mean difference of -0.77 (p = 0.000). Hence, there is a need to address trust concerns, especially from the younger generation and males, to extend the usage of AI-driven financial solutions.

Figure 1: AI-Powered Banking Services Flowchart

Source: Own Research

H3 was supported by the satisfaction (S3) results, showing the differences in age and gender. These individuals reported the most satisfaction, though a one-way ANOVA showed a significant difference of -0.97 from the 18- 25-year-old group and - 0.58 from the 26 – 41-year-old group (F = 18.75, p = 0.000). Males also confessed to having lower mean satisfaction levels than females, and this was 0.39 lower than for females (p = 0.001). Presumably, these findings imply that AI services, both extended by conventional financial institutions and emerging fintechs, should be further aligned more effectively with the satisfaction requirements of different demographic subgroups. The results support the hypotheses and offer practical recommendations for enhancing the quality of AI-based banking services.

The analysis confirmed that H1 was correct because younger participants displayed substantially less awareness than older participants. The trust variable showed meaningful differences between age groups and gender according to H2. The values regarding satisfaction with AI services varied based on demographic factors between traditional banking institutions and digital financial technology providers, which aligned with H3.

Discussion

The results obtained in his study are consistent with the study's hypotheses and previous studies, revealing diverse preferences over age, gender, and education levels in AI-powered banking services. Similar findings have been reported in some previous studies (Okeke et al., 2024d; Udeh et al., 2024c; Balaji et al., 2024b), and it is suggested that the use of AI-based tools such as chatbots offer customised financial solutions, organisational productivity, and increased consumer interaction. These benefits are captured by the study parameters, with satisfaction (S3), trust (S2), and security, privacy, and personalisation (S5) acting as key determinants of positive AI perceptions in banking and notably in the elder and highly educated audience segments. This implies that such demographic segments will be more receptive to the stability and personalised service provided by AI, which, according to the literature, the principle of trust and satisfaction are key components to acquiring customer loyalty (Temara et al., 2024b; El-Shihy et al., 2024c).

However, the findings also indicate cause for concern and disparities by age and education level of respondents. As the current literature has addressed the reduced emphasis on privacy and emotional self-oversights in AI services (Zarie et al., 2024b; Bansal et al., 2024b), S4 underscores that the youngest users, aged 18-25, demonstrate comparatively lower trust and satisfaction and negative perceptions of user engagement. Consequently, the ANOVA and regression analysis results of the respondents with low educational attainment revealed lower levels of awareness (S1) and trust (S2) in AI-driven solutions. These findings support the issues indicated in prior research methods, including privacy concerns and lack of the human being factor in interaction with an AI (Fayankinnu & Akinde, 2020b). To address these issues, especially in increasing consumer engagement and awareness levels through informative campaigns on the use of AI by financial institutions, the underrepresented groups are likely to be better aligned with the services offered in the financial markets. This approach echoes the current clamour to strive to design marketing strategies that guarantee every consumer demographic segment access and satisfaction (Biswas & Murray, 2024b; Alshari & Lokhande, 2022).

Therefore, banks require a segmented approach, which includes user-oriented AI design practice. Building trust requires financial institutions to establish open communication and protect personal data while developing mixed human-AI interface designs. Young people will adopt fintech through systems built with empathy and flexible artificial intelligence functions. Educational efforts focusing on digital literacy advancement will help eliminate knowledge gaps.

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Conclusion

This study aimed to establish the level of knowledge, confidence, and satisfaction regarding the AI-based banking products offered to the participants by traditional banks and start-ups in banking services. The study proves that age, gender, and education play important roles in shaping opinions on AI-based banking products. Thus, awareness levels (S1) were relatively low in the youngest group of participants (18–25 years, $p < 0.01$), hence the necessity of focused educational programs aimed at increasing AI service familiarity. Trust (S2) was relatively moderate, but again, there was a weak signal for young and male participants to use these solutions. However, satisfaction (S3) was higher in participants 42+ and female participants, meaning that traditional banks and fintech companies are performing better in satisfying the needs of these consumers.

Consequently, the results are consistent with the extant literature pointing to both the advantages of AI in promoting enhanced customer relations and business operations and the key issues. This indicates that younger and less educated users (Group C) have negative perceptions towards S4, implying that there is a need for application-oriented intelligence tools to have advanced Human Intelligence or interface. Moreover, the concerns about security and privacy (S5 preferred by older and more educated users) mean that data privacy and thus creating users' trust should be provided for all users, regardless of their age and education levels.

Some of the limitations of this study are as follows. First, access to self-reported data could create a focus bias since participants' perceptions could differ from actual experience. Second, the sample size is large enough to perform most of the statistical tests used in the study, albeit not large enough to accommodate all the nuances of Gen Z and Millennials from all geographically and culturally diverse areas. Thirdly, the study is purely quantitative, lacking qualitative data richness when analysing user preferences and experiences.

To respond to the results of this research, financial institutions should introduce numerous informative campaigns for chosen relevant AI-driven banking services among the younger generation and dispel myths about such services. Several elements are essential for trust creation: improving AI's explanation of its work and focusing on strong data protection and privacy, which is especially important for young people and men who are more sceptical. It is thus fitting that more enhanced features are required in AI tools, such as emotional recognition and micro-interactions, to address the interactivity of the younger generation of users. Secondly, as a dimension of personalisation, new AI-based banking services require different emphasis depending on the user demographic characteristics, so, for instance, security and privacy should be emphasised for older, more educated users than convenience and simplicity for young people. Future research should incorporate user preference and experience quantitative qualities, incorporate higher variability in culture and region for greater generalisation, and conduct longitudinal studies of changes in perception as the technologies and user familiarity progress. Thus, financial institutions may enhance their portfolio offerings to be more relevant to Gen Z and Millennial clients, significantly increasing the use of the segments.

In addressing these areas, financial institutions will be well-positioned to serve the needs of these two crucial customer demographics regarding the AI-powered services offered to the market. The research shows that banks must adopt AI approaches that address age and gender considerations when integrating artificial intelligence systems. AI technology enhances service delivery while raising customer satisfaction, but generalised solutions do not adequately adapt to individual user specifications. Future advancements in AI banking software need to prioritise security safeguards together with customisation capabilities and standing assurance measures for commercially successful acceptance among young people who are both digitally proficient and intensely sceptical.

Research that employs interviews and other qualitative methodologies should explore younger consumers' underlying thoughts and anticipated behaviours. Furthermore, it is imperative for researchers to examine how regional differences and cultural backgrounds may shape perceptions of AI banking. An ongoing assessment throughout the developmental phases of AI technologies will be essential in monitoring the evolution of user attitudes over time, providing valuable insights into the dynamic relationship between technology and its users.

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