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The Influence Of Perceived Risk On Digital Banking On Customers' Intention To Use Digital Banks In Jabodetabek 2023-2024

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Abstract

This study aims to identify the perceived risk dimensions significant to the intention to use digital banks in Jabodetabek, addressing the gap between customer willingness and actual use. Digital banks, which operate primarily through online applications without physical offices, have become prominent, with 78% of Indonesians using them by 2021. Despite this, a disparity exists: 69% express a willingness to use digital banks, but only 32% do. This gap is attributed to perceived risks, as highlighted in previous Technology Adoption Model (TAM) research. This study delves into the Perceived Risk Theory (PRT) to analyze these risk dimensions. The objective is to understand how perceived risks influence the intention to use digital banks, identify the most impactful risk factor, and explore correlations between risk factors and usage intention. Six risk dimensions were examined: financial, performance, social, time, security, and privacy. The quantitative research targeted bankable individuals in Jabodetabek, using cross-sectional data from 2023-2024. A sample of 400 respondents, determined through the Slovin method and simple random sampling, provided data via an online questionnaire. The analysis involved descriptive statistics (SPSS) and Structural Equation Modeling (SEM) in SmartPLS 4.0, with hypotheses tested via bootstrapping and a two-tailed t-test at a 5% significance level. Findings indicate that perceived risk levels are generally low, with security risk being the sole significant factor, showing a negative correlation of 30.3%. Practical recommendations for digital bank managers include enhancing encryption, securing firewalls, and conducting regular security audits to reduce perceived security risks, potentially increasing user intention and market share. Future research should consider larger samples, extended time frames, additional variables, and cultural differences. This study aims to aid digital bank managers in mitigating perceived risks and boosting customer intention to use digital banks.

Keywords: Digital banking; Intention to use; Perceived risk theory (PRT); Technology Adoption Model (TAM)

A. INTRODUCTION

McKinsey's Personal Financial Services survey reveals that 78% of Indonesian consumers actively use digital banking for various transactions (McKinsey, 2021). Indonesia leads in digital wallet adoption across Asia, experiencing a surge in usage, particularly among millennials. Digital banks, accessible exclusively online without physical branches, offer convenient financial management. This trend began with Jenius in 2016, now adopted by 64.2% of Indonesians, making it the most popular digital bank (Pahlevi, 2022). Other notable digital banks include Allobank, Bank Jago, Blu, Digibank, LINE Bank, and Neo Bank.

The COVID-19 pandemic accelerated digital banking adoption in Indonesia, with a reported increase of 21 million new users in 2022 (Rosana, 2022). Despite its acceptance, digital banks are often secondary to traditional banks for Indonesian millennials (Ramadhani, 2023). Physical bank branches remain relevant due to accessibility. McKinsey's survey shows that while 69% of consumers in emerging Asia-Pacific countries are willing to use digital financial platforms, only 32% have made transactions (McKinsey, 2021, p. 9). Indonesia's digital banking ranking is expected to drop to third by 2026 (Kurniawan, Kelly, & Vionita, 2024).

A gap exists between the intention and actual usage of digital banks among Indonesian customers, partly due to perceived risks. Understanding these barriers requires examining factors influencing customer intention. The Theory of Reasoned Action (TRA), developed by Fishbein and Ajzen in 1975, predicts behavior based on attitudes and subjective norms (Rozenkowska, 2023, p. 2670). The Theory of Planned Behavior (TPB), extending TRA in 1980, includes perceived behavioral control. Davis et al.'s 1989 Technology Adoption Model (TAM) identifies perceived ease of use, usefulness, and attitude in technology adoption (Al-Adwan et al., 2023, p. 15385).

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Recent research expands TAM to include external factors like perceived risk, trust, and brand awareness. Studies show that perceived risk negatively impacts customer intention. (Suroso et al., 2022) find perceived risk undermines online purchase intention. (Julina et al., 2022) identify cybercrime risk as a barrier to mobile banking adoption. (Putra et al., 2023) note perceived risk's impact on digital banking adoption. These findings suggest that perceived risks, including uncertainty and potential dissatisfaction, deter the primary use of digital banks. Bauer's Perceived Risk Theory (PRT) views consumer behavior as risk-taking (Permatasari & Muthohar, 2023). This theory emphasizes uncertainty and potential dissatisfaction in purchasing decisions. This research examines six perceived risk dimensions: performance, financial, time, social, security, and privacy risks (see Table 1), showing security risk as the most critical factor in digital banking adoption (Aldás-Manzano et al., 2009).

This study advances understanding of perceived risks in digital banking, focusing on addressing significant risks like security. Constraints include sample size, timeframe, and global variations. Future research should consider longitudinal studies and explore moderating or mediating variables to clarify perceived risks' impact on global digital banking adoption.

Table 1. Perceived Risk Indicator

	Performance Risk	Financial Risk	Time Risk	Social Risk	Security Risk	Privacy Risk
(Aldás-Manzano, et al., 2009)	S (2)		X	S (4)	S (1)	S (3)
(Lee, 2009)	S (3)	S (2)	S (4)	X	S (1)	
(Hanafizadeh & Khedmatgozar, 2012)	S (2)	S (4)	S (1)	X	S (3)	S (5)
(Hong, et al., 2019)	X	X	X	X		S (1)
(Andrian & Selamat, 2021)		S (3)	S (2)	X	S (1)	
(Nguyen, et al., 2021)		X	S (3)		S (2)	
(Rahmi, et al., 2022)		S (4)	S (1)			S (3)
(Reepu & Arora, 2022)		S (3)	S (5)	S (4)	S (2)	S (1)

Source: research data, 2024

Therefore, this study proposes the following hypothesis, which is illustrated in the conceptual framework in Figure 1.

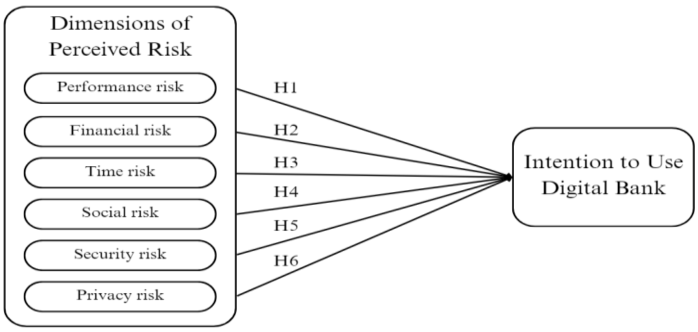

Figure 1. Research Framework

The following hypotheses were put forth by the literature reviews that were previously described:
H1: Performance risk significantly affects customers' intention to use digital banking services.
H2: Financial risk significantly affects customers' intention to use digital banking services.
H3: Time risk significantly affects customers' intention to use digital banking services.
H4: Social risk significantly affects customers' intention to use digital banking services.
H5: Security risk significantly affects customers' intention to use digital banking services.
H6: Privacy risk significantly affects customers' intention to use digital banking services.

This study also aims to examine the overall impact of perceived risks associated with digital banks in Jabodetabek, identify the risk factor that most strongly influences customer intention to use digital banks and analyze the correlation between perceived risks and customer intention to use digital banks. The findings of this research will assist digital banks in identifying significant dimensions of perceived risk, enabling them to focus their resources on mitigating these dimensions rather than on insignificant ones. This contribution is crucial for enhancing digital bank adoption by providing insights into the significant perceived risk dimensions. By reducing these significant dimensions of perceived risk, it is anticipated that customer intention to use digital banks will increase, enabling them to maintain and expand their market share in Indonesia.

B. RESEARCH METHODS

The study employs quantitative research methodology, focusing on numerical data collection and analysis to test relationships and draw conclusions regarding how perceived risks influence digital banking adoption. Conducted between 2023-2024 using a cross-sectional design, the research captures a snapshot of technology adoption trends. Data collection involves a survey method via Google Forms, chosen for its convenience and ability to reach a diverse demographic across Jabodetabek. The study targets bankable individuals aged 17-50 in Jabodetabek, totaling approximately 31.24 million, reflecting active banking users (Central Bank of Indonesia, 2024). This region was selected to represent urban digital banking users in Indonesia's largest metropolitan area. A sample size of 400 respondents was determined using the Slovin formula at a 5% significance level, employing simple random sampling to ensure fairness and simplicity in participant selection.

The research commenced with problem identification through literature review and conceptual framework development. Data collection utilized a structured questionnaire assessing respondent characteristics, perceived risks, and intention to use digital banks. The questionnaire employed a five-point Likert scale for respondents to indicate their agreement with the statements. Before full-scale data collection, a pilot study with 30 respondents validated questionnaire items for reliability and validity. Reliability, assessed using Cronbach's Alpha, demonstrated satisfactory internal consistency (Cronbach's Alpha > 0.7). Validity was confirmed through Pearson Correlation analysis, ensuring effective measurement of intended constructs (Pearson Correlation > 0.361). Questionnaire items for perceived risks were adapted and translated based on established indicators from previous international studies tailored to the Indonesian context. This approach aligns with global research standards while addressing local nuances in digital banking perceptions.

Table 2. Questionnaire Items For Perceived Risk

Variable	Code	Item Descriptions	Sources
Performance risk (X1)	X1.1	It is not easy to find out about the financial characteristics (interest, profitability, etc..) of the product/service acquired or about the online banking operation*	(Aldás-Manzano, et al., 2009)
	X1.2	I am concerned that the banking operation does not provide the financial advantages listed on the website.	(Aldás-Manzano, et al., 2009; Hanafizadeh & Khedmatgozar, 2012)
	X1.3	I am concerned that digital banking systems may not work properly due to low download speed maintenance operations or face server pauses.	(Hanafizadeh & Khedmatgozar, 2012)
	X1.4	I am concerned that digital banking servers may not work properly, and the payment process may be wrong.	(Hanafizadeh & Khedmatgozar, 2012)
Financial risk (X2)	X2.1	When transferring money using digital banks, I am afraid that I will lose money due to careless mistakes such as wrong input of account number and wrong input of the amount of money.	(Lee, 2009)
	X2.2	I worry that I cannot get bank compensation when transaction errors occur.	(Lee, 2009)
	X2.3	I am afraid of losing control of my account by using digital banks.	(Hanafizadeh & Khedmatgozar, 2012)
Financial risk (X2)	X3.1	When I use digital banking, I feel I waste much time choosing the banking operation I need	(Aldás-Manzano, et al., 2009)
	X3.2	When I use digital banking, I am concerned about waiting too long for the banking operation to take effect, wasting time on additional procedures, etc.	(Aldás-Manzano, et al., 2009)
	X3.3	Using digital banking services would make me lose convenience because I would have to waste much time fixing payment errors.	(Lee, 2009)
	X3.4	It would take me lots of time to learn how to use digital banking services	(Lee, 2009)
Social risk (X4)	X4.1	I think using digital banking services worsens the image your friends and relations have of you.	(Aldás-Manzano, et al., 2009)
	X4.2	Some people whose opinions I value think I am not acting correctly when I use digital banking services instead of offline branches.	(Aldás-Manzano, et al., 2009)
	X4.3	If I decided to use digital banking and something went wrong with online transactions, my friends, family, and colleagues would think less of me.	(Lee, 2009)

	X4.4	When my bank account incurs fraud or a hacker invades, I will potentially lose status in my social group.	(Lee, 2009)
	X4.5	When I use digital banks, I cannot directly relate with bank staff and use their help. This gives me an unpleasant feeling.	(Hanafizadeh & Khedmatgozar, 2012)
Security risk (X5)	X5.1	I feel insecure about sending and receiving my financial information on digital banking platforms.	(Hanafizadeh & Khedmatgozar, 2012)
	X5.2	I think unauthorized people, like hackers, can easily access digital banking systems.	(Hanafizadeh & Khedmatgozar, 2012)
	X5.3	In my opinion, online platforms (applications or websites) are not safe and appropriate for financial transactions*	(Hanafizadeh & Khedmatgozar, 2012)
	X5.4	I worry about giving my credit card number or login information to banking websites/applications.	(Aldás-Manzano, et al., 2009)
	X5.5	When I send data to banking websites, I am worried that they will be intercepted and modified by unauthorized third parties like hackers.	(Aldás-Manzano, et al., 2009)
Privacy risk (X6)	X6.1	I think if I use digital banking, it might be possible for the bank to make my personal information accessible to other organizations or companies without my consent.	(Hanafizadeh & Khedmatgozar, 2012)
	X6.2	Using digital banking for financial transactions increases the possibility of unwanted emails.	(Hanafizadeh & Khedmatgozar, 2012)
	X6.3	Digital banking endangers my privacy by using my personal information without permission.	(Aldás-Manzano, et al., 2009)

Sources: Research data, 2024

**indicators dropped due to unsatisfactory outer loadings*

The questionnaire items for the customer's intention to use a variable (Y) are in Table 3.

Table 3. Questionnaire Items For Customer Intention To Use

Variable	Code	Item descriptions	Sources
Customer Intention to Use (Y)	Y1	I intend to use digital banking regularly in the future	(Hanafizadeh & Khedmatgozar, 2012)
	Y2	I intend to use digital banking to access my bank information easily.	(Hanafizadeh & Khedmatgozar, 2012)
	Y3	I am going to use digital banking for my bank transactions in the future	(Hanafizadeh & Khedmatgozar, 2012)
	Y4	I think that I will use digital banking more than bank branches in the future.	(Hanafizadeh & Khedmatgozar, 2012)
	Y5	I would switch from physical to digital banks for my payment needs	(Alaeddin, et al., 2018)
	Y6	I can see myself switching from physical to digital banks to handle my payments.	(Alaeddin, et al., 2018)
	Y7	I expect to switch from physical to digital banks to handle my payments in the future.	(Alaeddin, et al., 2018)
	Y8	I will strongly recommend that others use a digital wallet	(Alaeddin, et al., 2018)

Sources: Research data, 2024

After collecting data from 467 bankable respondents, statistical analysis was conducted using SPSS and SmartPLS 4.0. SPSS performed descriptive statistics to analyze the frequencies of demographic data. SmartPLS 4.0 was utilized for comprehensive tasks such as measurement model assessment (validity and reliability testing), hypothesis testing, and correlation analysis through structural equation modeling (SEM). The data underwent reliability and validity analysis using SmartPLS 4.0's measurement model assessment. Subsequently, the dataset was refined to include 400 valid and reliable responses after conducting data cleaning in Microsoft Excel. This process involved removing questionnaire responses with high variability within constructs, which could compromise reliability and validity. Descriptive statistics were then generated using SPSS, with results presented in tables and charts for clarity. Hypotheses were tested using SEM with the bootstrapping method in SmartPLS 4.0, employing a two-tailed t-test at a 5% significance level. The research findings were subsequently interpreted and reported following standard research reporting guidelines.

The research utilized the bootstrapping method due to its nonparametric nature, which assesses the significance of estimated path coefficients using t-statistics and p-values. This method involved generating 5,000 resamples from the original data. SEM was chosen for its ability to handle non-normal data without assuming normal distribution. SmartPLS 4.0's path modeling capabilities were particularly beneficial for this study, accommodating a complex model with seven constructs and up to eight indicators per construct, making it well-suited for PLS-SEM analysis in this research context.

C. RESULTS AND ANALYSIS

Descriptive Statistics

The initial phase of this research involved conducting descriptive statistics using SPSS to analyze the demographic characteristics of the 400 respondents. These characteristics included age, occupation, domicile, and highest education level, all providing contextual insights into the study findings. For instance, understanding that most respondents fall within the 17-25 age range (84%) suggests a familiarity with technology among Gen Z and Millennials, potentially influencing their perceptions of risk in digital banking. Regarding age distribution, the majority of respondents were in the 17-25 age range (84%), followed by 43-50 (7.8%), 26-34 (5.3%), and 35-42 (3%). In terms of occupation, the largest group consisted of college students (78%), followed by employees (12%), homemakers (4.5%), high school students (2%), entrepreneurs (1.8%), and those not currently working (1.5%), with freelancers comprising 0.3%. Geographically, respondents primarily resided in Jakarta (46.3%), followed by Tangerang (22.5%), Bogor (14.8%), Depok (9.8%), and Bekasi (6.8%). Regarding educational attainment, the majority had completed senior high school (77.8%), while 17.8% had finished an undergraduate program, with smaller percentages having completed a diploma or graduate program (1.8% each), junior high school (0.8%), or a postgraduate program (0.3%).

The descriptive statistics reveal that a significant portion of the respondents are young adults aged 17-25, predominantly college students residing in Jakarta, with a substantial proportion having completed senior high school. These demographic insights provide a foundational understanding that informs this study's subsequent hypothesis testing and analysis.

Measurement Model Assessment

The second phase of this research involves assessing the measurement model using SmartPLS 4.0 to ensure the validity and reliability of the data through confirmatory factor analysis within the PLS-SEM framework. Reliability assessment is crucial for internal consistency, measured using Cronbach's Alpha (α) and composite reliability (CR). Both coefficients are considered reliable if they exceed 0.7 (Pratiwi, Sanusi, & Hasibuan, 2022, p. 70). Cronbach's Alpha provides a conservative internal consistency estimate, while composite reliability (rho_c) typically offers a more liberal estimate, with the true reliability of a construct generally falling between these values (Hair et al., 2021).

Table 4 displays Cronbach's Alpha and composite reliability results, confirming values above 0.7, indicating strong internal consistency among the constructs. These reliability analyses are visually represented in Figure 2, further affirming the robustness of the constructs.

Table 4. Reliability And Validity Results

	Cronbach's Alpha	Composite reliability (rho_c)	Average variance extracted (AVE)
Variable X1	0.829	0.880	0.712
Variable X2	0.829	0.885	0.721
Variable X3	0.810	0.873	0.633
Variable X4	0.906	0.926	0.715
Variable X5	0.899	0.927	0.760
Variable X6	0.867	0.914	0.780
Variable Y	0.891	0.913	0.567

Sources: Research data, 2024

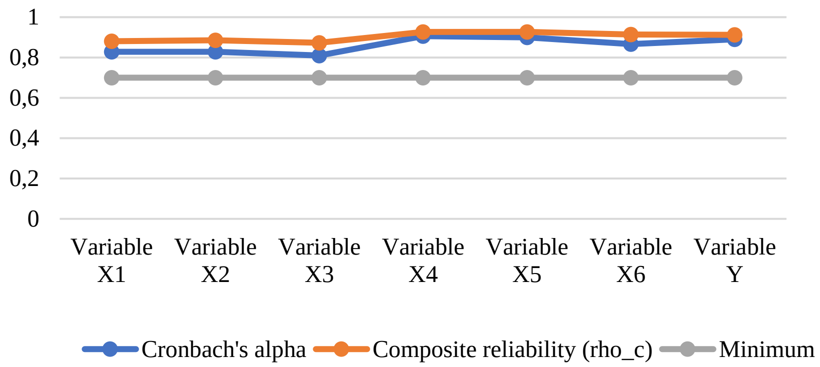

Figure 2. Reliability Analysis Results
Sources: Research data, 2024

The construct validity is assessed through convergent and discriminant validity to ensure that the scale measures what it is intended to measure. Convergent validity is established when items converge to represent the underlying construct, describing the degree to which one test is related to other tests that measure similar constructs. It is assessed using Average Variance Extracted (AVE) and outer loadings factor. Convergent validity is established when AVE is greater than 0.5, and the outer loadings factor is greater than 0.7 (Pratiwi, Sanusi, & Hasibuan, 2022, p. 69). As shown in Table 4, the AVE values for all indicators are greater than 0.5, indicating that convergent validity is fulfilled. The results for the convergent validity are also visualized in Figure 3.

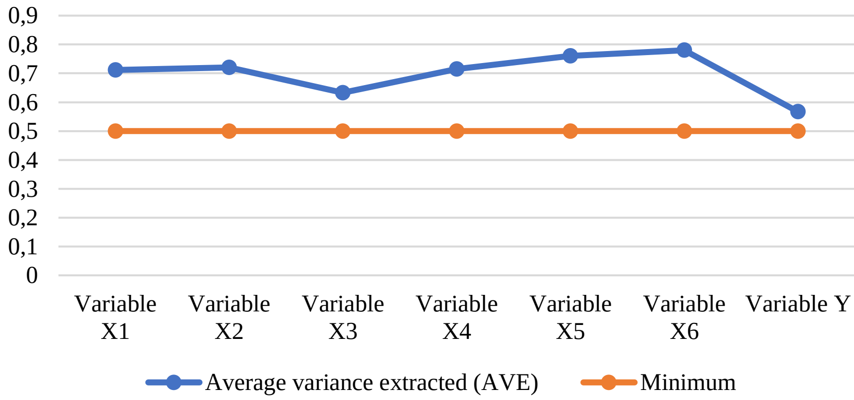

Figure 3. Convergent Validity Analysis Results
Sources: Research data, 2024

Aside from convergent validity, discriminant validity is also assessed. Discriminant validity is established when two tests that should not be highly related are unrelated. The purpose of discriminant validity is to determine how unique the constructs are and to show that the constructs are not too highly correlated with other constructs in the study. Using SmartPLS, discriminant validity is assessed by observing the Heterotrait-Monotrait (HTMT) Ratio. Discriminant validity is established when the HTMT ratio is less than 0.9 (Franke & Sarstedt, 2019). As shown in Table 5, all of the HTMT values are less than 0.9. Thus, both the convergent and discriminant validity assessments are fulfilled, and it can be concluded that the data in this research is valid and reliable.

Table 5. Heterotrait-Monotrait (HTMT) Results

	Variable X1	**Variable X2**	**Variable X3**	**Variable X4**	**Variable X5**	**Variable X6**	**Variable Y**
Variable X1							
Variable X2	0.825						
Variable X3	0.675	0.597					
Variable X4	0.611	0.505	0.897				
Variable X5	0.741	0.742	0.617	0.609			

	Variable X1	Variable X2	Variable X3	Variable X4	Variable X5	Variable X6	Variable Y
Variable X6	0.653	0.698	0.587	0.579	0.831		
Variable Y	0.087	0.118	0.121	0.102	0.079	0.078	

Sources: Research data, 2024

Hypothesis Testing

The third phase of this research involves hypothesis testing conducted using SmartPLS 4.0 with Structural Equation Modeling (SEM) and a bootstrapping method. Hypotheses were tested with a two-tailed t-test at a 5% significance level to assess the significance of relationships. The t-statistics measure the difference between estimated and hypothesized values in standard error units (Al-Kassab, 2022, p. 134). A higher t-value indicates stronger evidence against the null hypothesis, suggesting significant influence. Meanwhile, the p-value indicates data compatibility with the null hypothesis (Leo & Sardanelli, 2020). A lower p-value signifies stronger statistical significance. Hypotheses are considered significant (null hypothesis rejected) if the t-value exceeds 1.96 and the p-value is below 0.05.

Table 6 presents the bootstrapping results, highlighting Variable X5 (security risk) as the only variable with a significant relationship with Variable Y. The variables are ranked by significance as follows: Variable X5 (security risk), Variable X2 (financial risk), Variable X6 (privacy risk), Variable X4 (social risk), Variable X1 (performance risk), and Variable X3 (time risk). These results are visually represented in Figures 4 and 5, illustrating the outcomes of hypothesis testing.

Table 6. Hypothesis Testing Results

	T statistics	P-values	Results	Hypothesis
Variable X1 -> Variable Y (H1)	0.536	0.592	Insignificant	Rejected
Variable X2 -> Variable Y (H2)	1.715	0.086	Insignificant	Rejected
Variable X3 -> Variable Y (H3)	0.408	0.683	Insignificant	Rejected
Variable X4 -> Variable Y (H4)	0.690	0.490	Insignificant	Rejected
Variable X5 -> Variable Y (H5)	2.239	0.025	Significant	Accepted
Variable X6 -> Variable Y (H6)	1.047	0.295	Insignificant	Rejected

Sources: Research data, 2024

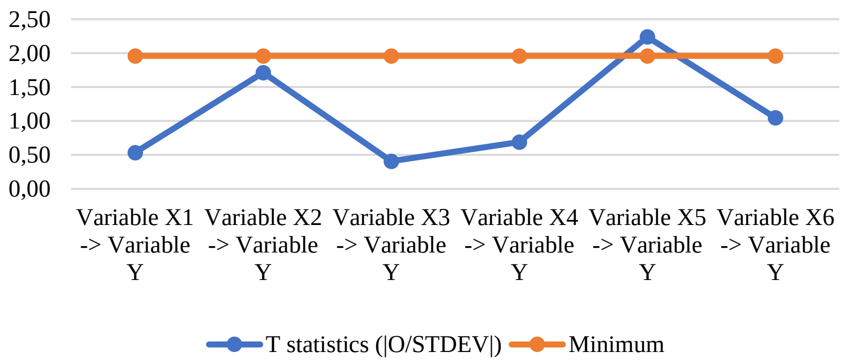

Figure 4. T-statistics Results
Sources: Research data, 2024

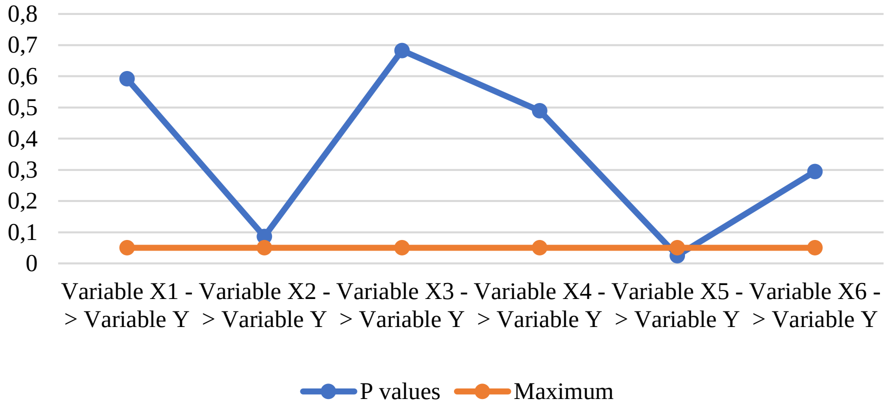

Figure 5. P-values Results
Sources: Research data, 2024

Based on hypothesis testing using t-statistics and p-values, the findings for each hypothesis are as follows: H1: Performance risk does not significantly affect customers' intention to use digital banking services. With a t-statistic of 0.536 and a p-value of 0.592, there is no significant relationship between performance risk and customer intention to use digital banking services. Thus, H1 is rejected. This finding diverges from research by Hanafizadeh and Khedmatgozar (2012) in Iran but aligns with findings by Lee (2009) in Taiwan, indicating that performance risk has limited significance in influencing customer intention. In Indonesia, promotional events and discounts by digital banks may have mitigated concerns related to performance issues.

H2: Financial risk does not significantly affect customers' intention to use digital banking services. The t-statistic value is 1.715 with a p-value of 0.086, indicating no significant relationship between financial risk and customer intention to use digital banking services. Thus, H2 is rejected. This result contrasts with studies by Lee (2009) in Taiwan and Roy et al. (2017) in India, which found significant financial risk impacts on customer intention. In Indonesia, the availability of money-back guarantees and robust customer service may have alleviated concerns related to financial risks.

H3: Time risk does not significantly affect customers' intention to use digital banking services. With a t-statistic of 0.408 and a p-value of 0.683, there is no significant relationship between time risk and customer intention to use digital banking services. Thus, H3 is rejected. This finding aligns with previous research by Aldás-Manzano et al. (2009) in Spain, Lee (2009) in Taiwan, and Reepu and Arora (2022) in India, indicating that concerns over time-related issues have diminished with technological advancements and familiarity with digital platforms in Indonesia's Jabodetabek area.

H4: Social risk does not significantly affect customers' intention to use digital banking services. The t-statistic value is 0.690 with a p-value of 0.490, indicating no significant relationship between social risk and customer intention to use digital banking services. Thus, H4 is rejected. This finding aligns with studies by Khedmatgozar (2021) in Iran and Lee (2009) in Taiwan, suggesting that concerns about social status associated with digital banking use are insignificant in Indonesia's context. As digital payment platforms have become mainstream, social perceptions regarding digital banking use have normalized.

H5: Security risk significantly affects customers' intention to use digital banking services. Security risk shows a t-statistic value of 2.239 with a p-value of 0.025, indicating a significant relationship between security risk and customer intention to use digital banking services. Thus, H5 is accepted. This finding aligns with research by Lee (2009) in Taiwan, Aldás-Manzano et al. (2009) in Spain, Reepu and Arora (2022) in India, and Demirdogen et al. (2010) in Turkey, highlighting security concerns as the most critical factor influencing customer intention. Indonesian customers' fears of hacking and unauthorized transactions underline the importance of robust security measures in digital banking services.

H6: Privacy risk does not significantly affect customers' intention to use digital banking services. The t-statistic value is 1.047 with a p-value of 0.295, indicating no significant relationship between privacy risk and customer intention to use digital banking services. Thus, H6 is rejected. This finding contrasts with research by Reepu and Arora (2022) in India but aligns with Aldás-Manzano et al. (2009), suggesting that privacy concerns rank lower among perceived risks influencing customer intention in the Jabodetabek region. Digital banks in

Indonesia have implemented stringent privacy policies and technological safeguards, which may have reassured customers regarding their data security.

These results provide insights into the varying impacts of perceived risks on customer intention to use digital banking services in Indonesia, highlighting security as the predominant concern among users.

Correlation Analysis

The fourth part of this research involves correlation analysis, observed through the path coefficient values using the PLS-SEM algorithm in SmartPLS 4.0. The path coefficient indicates the direction and strength of the relationship between dependent and independent variables, showing whether there is a positive or negative correlation. The path coefficient value ranges from -1 to +1, with coefficients closer to -1 indicating a strong negative relationship and coefficients closer to +1 indicating a strong positive relationship (Sarstedt, Ringle, & Hair, 2017, p. 22). Since only security risk proved significant, it is the only variable tested for correlation, as shown in Table 7. The results indicate a path coefficient of -0.303. This means that for every one-unit increase in security risk, the customer's intention to use digital banks decreases by 30.3%, indicating a negative correlation.

Table 7. Correlation Results

	Path coefficients
Variable X5 -> Variable Y	-0.303

Sources: Research data, 2024

The research findings indicate that among the perceived risks associated with digital banks in Jabodetabek, only security risk significantly influences customer intention to use these services, showing a negative correlation of 30.3%. This study successfully addresses its research questions, confirming that only H5 was accepted. These results contrast with findings from studies in other countries, underscoring the influence of factors like risk appetite, cultural considerations, and levels of technology adoption on perceived risk impact.

Previous research has yielded varied results regarding the significance of perceived risks on customer intention to use digital banks. For instance, studies in Indonesia did not find a significant effect on customer intention to use Fintech payments (including digital banking), whereas significant effects were observed in Portugal, Spain, and Iran. These discrepancies highlight the challenges in generalizing findings due to sample limitations, different cultural contexts, and varying stages of technological adoption across countries. Notably, similar to this study, research in Taiwan also identified security risk as the primary perceived risk factor affecting customer intention to use digital banks (Lee, 2009). This research contributes uniquely to the existing literature by dissecting multiple dimensions of perceived risks rather than treating perceived risk as a singular concept. Focusing on specific risk dimensions such as security, the study provides nuanced insights into how these factors influence customer behavior in the Indonesian digital banking landscape.

CONCLUSION

This research underscores that security risk is the most influential perceived risk factor negatively affecting customers' intention to use digital banks in Jabodetabek. By adopting a nuanced approach that evaluates each perceived risk indicator individually, this study expands upon the Technology Adoption Model (TAM), highlighting that not all perceived risks equally impact customer behavior. Specifically, while security risk significantly influences customer intention, other factors such as performance, financial, social, time, and privacy risks show negligible effects in this context (Aldás-Manzano et al., 2009).

However, this study is limited by its sample size, geographic scope, and the absence of analysis on moderating or mediating variables. Future research should consider larger and more diverse samples across Indonesia, conduct longitudinal studies to track evolving perceptions over time and explore the role of cultural differences in shaping perceived risks. Additionally, investigating moderating factors could uncover nuances in the relationship between perceived risks and customer behavior.

Practically, the findings suggest that digital banks should prioritize enhancing security measures such as encryption, secure firewalls, and two-factor authentication to build trust and reduce user security concerns. Regular security audits and proactive measures against emerging threats are essential to maintain customer confidence. By addressing these security concerns effectively, digital banks can potentially expand their market share, particularly among Indonesia's significant unbanked population. As digital banking adoption continues to evolve globally, mitigating perceived risks becomes crucial for sustaining competitive advantage and fostering widespread customer acceptance and trust.

REFERENCES

Al-Adwan, et al. (2023). Extending the Technology Acceptance Model (TAM) to Predict University Students' Intentions to Use Metaverse-Based Learning Platforms. Education and Information Technologies Volume 28, 15381–15413.

Alaeddin, et al. (2018). From physical to digital: Investigating consumer behaviour of switching to mobile wallet. Polish Journal of Management Studies, Volume 17, Issue 2, 18-30.

Aldás-Manzano, et al. (2009). The role of consumer innovativeness and perceived risk in online banking usage. International Journal of Bank Marketing, 53-69.

Al-Kassab, M. M. (2022). The Use of One Sample t-Test in the Real Data. Journal of Advances in Mathematics Vol 21, 134-138.

Andrian, & Selamat, F. (2021). The Influence of Consumer's Perceived Risk on Consumer's Online Purchase Intention in Indonesia. Advances in Social Science, Education and Humanities Research, volume 655, 669-676.

Bank Indonesia. (2024). Consumer Expectation Survey April 2024. Bank Indonesia.

Dayanand, A., & Chaudhary, P. (2023). Introduction of a Pilot Study. International Journal of Ethics, Trauma & Victimology Volume 9 Issue 2, 33-35.

Demirdogen, O., Yaprakli, S., Yilmaz, M. K., & Husain, J. (2010). Customer Risk Perceptions Of Internet Banking - A Study in Turkey. The Journal of Applied Business Research, Volume 26 No 6.

Faradynawati, I. A. (2018). The Impact of Perceived Risk and Trust on Consumer Intention to UseFinTech Payment in Indonesia. The International Review of Financial Consumers, Volume 3 Issue 1, 27-37.

Franke, G. R., & Sarstedt, M. (2019). Heuristics Versus Statistics in Discriminant Validity Testing: A Comparison of Four Procedures. Internet Research Volume 29 No 3, 430-447.

Hair, et al. (2021). Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R. Springer Cham.

Hanafizadeh, P., & Khedmatgozar, H. R. (2012). The mediating role of the dimensions of the perceived risk in the effect of customers' awareness on the adoption of Internet banking in Iran. Electronic Commerce Research Volume 12 Issue 2, 151-171.

Hong, et al. (2019). Perceived Risk on Online Store Image Towards Purchase Intention. Research in World Economy Volume 10 No 2, 48-52.

Jenius. (2024). Kebijakan Privasi. Retrieved from Jenius: https://www.jenius.com/privacy-policy

Julina, Miftah, D., & Saputra, D. H. (2022). Perceived Cybercrime Risk: Modification of the Technology Acceptance Model on Generation Z. International Conference on Business Management and Accounting (ICOBIMA) Volume 1 Issue 1, 307-313.

Khedmatgozar, H. R. (2021). The impact of perceived risks on internet banking adoption. Electronic Commerce Research Volume 21, 147-167.

KMS Solutions. (2023, September 20). Key Strategies to Improve Mobile Banking App Security. Retrieved from KMS Solutions: https://blog.kms-solutions.asia/strategies-to-improve-mobile-banking-app-security

Kurniawan, Y., Kelly, & Vionita. (2024). Examining the Factors Driving Digital Banking Adoption in Indonesia: A Modified Technology Acceptance Model Approach. Journal of Logistics, Informatics and Service Science Volume 11 No 6, 442-459.

Lee, M. C. (2009). Factors influencing the adoption of Internet banking: An integration of TAM andTPB with perceived risk and perceived benefit. Electronic Commerce Research and Applications Volume 8 Issue 3, 130–141.

Leo, G. D., & Sardanelli, F. (2020). Statistical significance: p value, 0.05 threshold, and applications to radiomics—reasons for a conservative approach. European Radiology Experimental Vol 4 Article 18.

Martins, C., Oliveira, T., & Popovič, A. (2014). Understanding the Internet banking adoption: A unified theory of acceptance and use of technology and perceived risk application. International Journal of Information Management, Volume 34 No 1, 1-13.

McKinsey & Company. (2021). Emerging markets leap forward in digital banking innovation and adoption: 2021 Asia–Pacific Personal Financial Services Survey. Asia-Pacific: McKinsey & Company.

Microsoft Security. (2024). What is two-factor authentication? Retrieved from Microsoft Security: https://www.microsoft.com/en-us/security/business/security-101/what-is-two-factor-authentication-2fa

Nguyen, et al. (2021). The Effects of Perceived Risks on Food Purchase Intention: The Case Study of Online Shopping Channels during Covid-19 Pandemic in Vietnam. Journal of Distribution Science Volume 19 No 9, 19-27.

Pahlevi, R. (2022, January 5). Jenius, Bank Digital Paling Dikenal Konsumen pada 2021. Retrieved from Databoks: https://databoks.katadata.co.id/datapublish/2022/01/05/jenius-bank-digital-paling-dikenal-konsumen-pada-2021

Permatasari, D. N., & Muthohar, M. (2023). The Effect of Perceived Risk on Consumer's Online Purchase Intention at Zalora for Muslim Clothing Product. Asian Journal of Economics, Business and Accounting Volume 23 Issue 19, 117-133.

Pratiwi, A. G., & Muta'Ali, L. (2018). Perkembangan Ekonomi Wilayah dan Peran Sektor Tersier di Kawasan Jakarta, Bogor, Depok, Tangerang, dan Bekasi (Jabodetabek). Jurnal Bumi Indonesia Vol 7 No 3, 2.

Pratiwi, R., Sanusi, A., & Hasibuan, S. (2022). Teacher performance analysis using SmartPLS. Jurnal Darmajaya, 67-73.

Pusparisa, Y. (2021, February 8). Jabotabek, Wilayah Urban dengan Populasi Terbesar Kedua di Dunia. Retrieved from Databoks: https://databoks.katadata.co.id/datapublish/2021/02/08/jabotabek-wilayah-urban-dengan-populasi-terbesar-kedua-di-dunia

Putra, et al. (2023). Factors Affecting Intention to Use on the Digital Banking Services Offered by Digital Banks in Indonesia. International Journal of Industrial Engineering and Operations Management (IJIEOM).

Rahmi, et al. (2022). Perceived risk and its role in the influence of brand awareness on purchase intention: study of Shopee users. Jurnal Siasat Bisnis Volume 26 No 1, 97-109.

Ramadhani, P. I. (2023, June 20). Visa Catat Lebih dari 90 Persen Milenial dan Gen Z Pilih Perbankan Virtual. Retrieved from Liputan 6: https://www.liputan6.com/saham/read/5324029/visa-catat-lebih-dari-90-persen-milenial-dan-gen-z-pilih-perbankan-virtual?page=3

Reepu, & Arora, R. (2022). The Effect of Perceived Risk on Intention to Use Online Banking. Universal Journal of Accounting and Finance Volume 10 No 1, 62-71.

Rohl, J., & Sokal, R. (1981). Statistical Tables. San Fransisco: Freeman.

Rosana, D. (2022, June 9). BI: 21 juta konsumen baru transaksi digital sejak pandemi. Retrieved from Antara News: https://www.antaranews.com/berita/2929737/bi-21-juta-konsumen-baru-transaksi-digital-sejak-pandemi

Roy, S. K., Balaji, M. S., Kesharwani, A., & Sekhon, H. (2017). Predicting Internet banking adoption in India: A perceived risk perspective. Journal of Strategic Marketing, Volume 25 No 5-6, 418-438.

Rozenkowska, K. (2023). Theory of planned behavior in consumer behavior research: A systematic literature review. International Journal of Consumer Studies Volume 43, 2670-2700.

Sarstedt, M., Ringle, C., & Hair, J. (2017). Partial Least Squares Structural Equation Modeling. Springer International Publishing.

Suroso, I., Afandi, M. F., & Galushasti, A. (2022). Does Perceived Risk? A Study of Technology Acceptance Model on Online Shopping Intention. Academy of Strategic Management Journal Volume 21 Issue 3, 1-12.

Visa. (2021). Visa Customer Payment Attitudes Study 2022: Navigating a New Era in Payments. Visa.

World Bank. (2021). The Global Findex Database 2021. World Bank.