Exploring Conventional Banks and E-commerce Synergies in Jakarta, Indonesian Financial Landscape

MSc Research Project
MSc in FinTech (MSCFTD1)

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MSc Project Submission Sheet

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Exploring Conventional Banks and E-commerce Synergies in Jakarta, Indonesian Financial Landscape

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Abstract

In the evolving landscape of the banking industry, traditional banks are facing challenges in adapting to rapid technological changes and shifting consumer preferences. The collaboration between conventional banking and e-commerce has emerged as a crucial strategy to enhance customer experience by improving operational efficiency, expanding market reach, and increasing customer satisfaction. While e-commerce offers benefits such as global market access and lower operating costs, challenges such as cybersecurity and data protection must be addressed to maximize its potential. The aim of this research is to examine the variables that influence the customer experience in Indonesian traditional banking and e-commerce partnerships by incorporating the (TAM) Technology Acceptance Model to elucidate the aspects that substantially effect the customer experience. The Confirmatory Factor Analysis (CFA) approach was used in this study's factor analysis to create a structural model for analysis and to ascertain the relationships between the factors, then finalise with regression and random forest to predict the significancy of each factor. The study examines the factors influencing customer experience in Indonesia through the lens of the (TAM) Technology Acceptance Model. Confirmatory Component Analysis (CFA) confirms strong correlations between the variables, indicating a well-fitting model. The analysis reveals that perceived usefulness (E-commerce Effect), ease of adoption (Readiness to Adopt), and trust in the system (Security of Banking System) are key drivers of customer experience. Regression and Random Forest models show that these factors significantly impact customer satisfaction, highlighting the importance of system security alongside the benefits and ease of using digital financial innovations collaboration in enhancing customer experience.

1 Introduction

The conventional banking world has experienced rapid development in the last 2 decades. Conventional banks are long-standing financial organizations that run on a broad financial framework. This bank provides a range of financial services and products, including credit cards, loans, savings accounts, deposits, and money transfer services. Interest on loans and deposits is how traditional banks make their money. Indonesia's banking industry saw notable changes between 2008 and 2018, including an increase in traditional banking funding. Even so, it remains unclear if finance influences the way the banking industry changes in a meaningful way (Baehaqy, H.N., 2019). Traditional banks are often slow to adapt to new technologies due to rigid infrastructure and tight regulations. While technology has advanced and promises greater security, there are challenges in building consumer trust in new and untested systems. Rapid technological change requires regulatory adaptations that often do not keep pace with the pace of technological innovation (Walker, A., 2014).

Demographic changes and disruptions that occur due to rapid technological developments require banks to transform. One of the changes that can be observed is the collaboration that management has begun to do in banking by involving e-commerce to support customer needs. E-commerce has experienced rapid growth and become an essential component of modern business. The development of information and communication technology, especially the internet, has changed the way companies operate and interact with consumers. E-commerce offers a variety of benefits, including access to global markets, lower operating costs, and the ability to serve customers 24/7 (Gupta, 2014).

The study concluded that e-commerce plays a vital role in today's business by improving operational efficiency, expanding market reach, and increasing customer satisfaction. E-commerce is not only changing the way consumers shop but also changing traditional business models. However, to maximize the potential of e-commerce, companies must overcome challenges such as cybersecurity, personal data protection, and integration with existing business systems. This potential reach can be an added value that conventional banks may find difficult to develop due to limitations in technology and innovation.

Not only related to technological developments, in a highly competitive banking industry, understanding how customers assess bank services is essential to attract and retain customers. Customers' perceptions of value can be influenced by a number of variables, including service quality, cost, customer satisfaction, and connections with service providers. The quality of service provided by a bank can affect customer value perceptions that include aspects such as reliability, responsiveness, and the ability to meet customer needs. In addition, competitive and transparent service prices increase the value perceived by customers. In addition, factors such as ease of interaction with staff and ease of use of services contribute greatly to perceived value. A good relationship between customers and banks is what can be the pillars of increasing customer loyalty and perceived value (Carlos Fandos Roig et al., 2006).

However, the traditional banking industry has been put under pressure by the emergence of E-commerce as a refined and contemporary platform. In this day of digital revolution, e-commerce has become a vital component of both consumer and commercial shopping. Worldwide e-commerce is growing at a very fast pace thanks to the advancements in information and communication technologies. Yet, it remains to be seen if traditional banking and e-commerce companies can cooperate to create a better ecosystem for customers in light of technological advancements and shifting consumer preferences. Customer satisfaction with the existence of banks and e-commerce is influenced by a number of aspects, including customer security and comfort (Amin & Kansana, 2016).

So, this study will aim to determine to what extend the collaboration of conventional banking and e-commerce has influenced customer experience in banking industry. The Technology Acceptance Model will help to construct insight of several factors, research methodology, execution and implementation, evaluation and also conclusion.

2 Literature Review

2.1 Conventional Banking Service Quality

The banking industry is one of the highly competitive sectors, where service quality is a key factor in attracting and retaining customers. With increasing customer expectations and technological advancements, banks must continue to innovate and improve their service quality (Sangeetha & Mahalingam, 2011). This study attempts to understand the concepts, dimensions, and measurement methods used in various service quality models in the banking sector.

(Sangeetha & Mahalingam, 2011) also concludes that various service quality models play an important role in enhancing customer satisfaction and loyalty in the banking sector. These models help banks identify areas for improvement and provide guidance for improving service quality. Some of the main models reviewed in this study are servqual Model which measures the gap between customer expectations and their perceptions of service performance. Then, the servperv Model which is a modification of servqual which only measures customer perceptions of service performance without comparing it to their expectations. Also, the bankserv Model which was developed specifically for the banking industry and the E-servqual Model which is designed to assess service quality in the context of online banking, with a focus on efficiency, security, and user experience in using digital banking services. From these models, it is hoped that recommendations can be provided on how to implement the service quality model that best suits the bank's specific needs.

To improve the quality of conventional banks, technology integration is needed. One method proposed by (Chahar et al., 2023) is a micropayment mechanism that effectively reduces the risk of double payments. This mechanism uses a combination of cryptographic techniques and secure transaction protocols to ensure that each payment is only made once. The implementation of this mechanism is expected to increase consumer confidence, as well as reduce losses caused by double payments.

2.2 Security of Banking System

(Ula et al., 2011) declared that one of the primary concerns that businesses, especially those in the banking industry, need to effectively manage in the current digital era is information security. It is imperative that banks uphold the security and confidentiality of client information, transactional data, and internal business information. Data security breaches may cause banks to suffer reputational damage, financial losses, and a decline in client trust. Security is critical because the banking system manages sensitive consumer data, which makes it essential. A few crucial areas are network security, physical security, personnel training, access control, authentication, regular password changes, and data security.

In another study of Ahmadisheykhsarmast & Sonmez, (2020), they offer to use smart contracts and blockchain technology, which can offer benefits in terms of payment security, to guarantee that payments are secure, transparent, and automatic. Smart contracts increase the confidence between the parties involved by facilitating effective and efficient payments through transparency, immutability, and monitoring by all parties. Additionally, firewalls, intrusion detection systems, encryption, Multi-Factor Authentication (MFA), ATM security, and data center security are all possible tools used by banks. In the current digital era, banks have substantially moved its customer service offerings to online and mobile platforms. Although this gives consumers more accessibility and convenience, it also presents new security risks. Cyberattack-prone banking systems can seriously jeopardize personal information of consumers and harm a bank's brand. In order to tackle security concerns within the banking sector, banks must have a strategy that encompasses cutting-edge security technologies, employee education, and continuous monitoring for security events (Ahmad et al., 2010).

2.3 E-commerce effect on for ease of transactions

The way people shop has been completely transformed by e-commerce, which also makes transactions more convenient and easier. It provides round-the-clock services, international reach, streamlined procedures, a variety of payment choices, safe transactions, improved user experience, and stored data for later purchases. Online retailers offer a large selection of goods from foreign vendors, which facilitates the search for better offers. Online payments are quicker, and a range of payment methods, including digital wallets, debit cards, credit cards, and buy now, pay later services, are available to accommodate a range of consumer preferences. Convenience is further increased via mobile shopping. However, there are still possible flaws in the goods, like security holes and physical inspection difficulties. E-commerce has increased accessibility, speed, and convenience of shopping for a larger range of people. Furthermore, online transactions have emerged as one of the most widely used methods for customers to shop and conduct financial transactions in the contemporary digital era.

Moreover, user views of technology and psychological variables play a role in the adoption and success of online transactions. Perceived usefulness, perceived danger, perceived simplicity of use, and degree of trust in the platform or service provider are some of the important variables that affect consumers' behavioral intentions when making purchases online (Nugroho, 2016). Despite, according to (Eka Putri et al., 2019), the adoption of payment methods in e-commerce in Indonesia still faces various challenges. Many consumers in Indonesia still prefer conventional payment methods such as bank transfers or cash on delivery, compared to more sophisticated digital payment methods. This is influenced by several key factors, including consumer trust, ease of use, perceived security, and perceived benefits and to increase the adoption of digital payment methods, service providers need to focus on increasing consumer trust by improving the security and ease of use of their payment systems. In addition, education and promotion about the benefits of using digital payment methods are also very important to encourage changes in consumer behavior.

2.4 Readiness to Adopt Digital Financial Innovations

A number of aspects are crucial for the adoption of digital banking innovations, including financial inclusion initiatives, socioeconomic conditions, digital literacy, trust and security concerns, individual level financial literacy, access to technology, and regulatory elements. Customers' concerns about security threats, potential fraud, and data privacy may give rise to uncertainties. Financial inclusion programs, robust digital infrastructure, and government laws are examples of regulatory variables. The deployment of digital-based banking financial innovation will become more realistic in a more favourable environment once these obstacles are removed, which will inevitably result in greater financial inclusion and a more dynamic financial ecosystem.

(Jamshidi & Hussin, 2016) examined the factors that influence consumer preferences, especially for Islamic banking, towards e-commerce banking services. With the increasing popularity of e-commerce, the need for payment methods that comply with Islamic principles is becoming increasingly important. For example, Islamic credit cards offer payment solutions that comply with Islamic law, but their adoption is still very low. This study found that several key factors influence consumer readiness to use e-commerce services, including perceptions of religiosity, trust, perceived benefits, and ease of use. Consumers who have a high level of religiosity tend to be more interested in e-commerce services that can better accommodate Islamic principles because they are in accordance with their values and beliefs. In addition, trust in service providers and perceptions of practical benefits also play an important role in driving this adoption. With this, banks must focus on improving aspects of trust, education about benefits, and ease of use to facilitate the readiness process for consumers. However, there are several obstacles in this process such as lack of knowledge, trust, and lack of perceived benefits so that there is a need for consumer education and promotion of the benefits of implementing e-commerce services.

(Hussain & Papastathopoulos, 2022) stated that important factors such as digitalization have changed the global financial landscape, forcing organizations or institutions such as banks to adapt to digital innovations in order to remain competitive. Digital transformation in the financial sector includes the adoption of new technologies such as blockchain, artificial intelligence, and big data analytics, which not only improve operational efficiency but also introduce new risks and challenges. In this context, organizational readiness for digital financial innovation is a key factor in achieving financial resilience. The study concluded that organizational readiness for digital innovation has a significant impact on financial resilience. Organizations that are ready to adopt digital financial technologies tend to be better able to withstand economic shocks and take advantage of new opportunities. Factors such as a culture of innovation, supportive leadership, strong technological infrastructure, and human resource training play an important role in determining organizational readiness. In addition, continued investment in technology such as collaborating with e-commerce is key to achieving sustainable financial resilience.

3 Research Methodology

3.1 Data Collection

A quantitative strategy will be used to accomplish the research goals, and data from respondents will be gathered through the use of a questionnaire technique. This will calculate customer experiences with the collaboration between banking and e-commerce (Jamshidi & Hussin, 2016). The study will focus on a specific segment of Jakarta's society, using a structured questionnaire that addresses four key factors: the quality of conventional banking services, the security of the banking system, the impact of e-commerce on transaction ease, and the readiness to adopt digital financial innovations.

3.2 Data Analysis

After acquiring the dataset, some of the measured variables will be transformed into a 5-point Likert scale for processing, where 1 denotes strongly disagree, 2 disagree, 3 neutral, 4 agree, and 5 strongly agree. Factor analysis will then be utilized. By using this statistical technique, patterns of correlations between variables can be found and they can be reduced to smaller factors. It seeks to comprehend the variables impacting consumers' experiences with traditional banking and online shopping, as well as to explain the discrepancies in the data. Factor analysis helps in simplifying data complexity by identifying the relationships between variables, thus providing a clearer insight into the underlying data structure (Natasia et al., 2021).

3.2.1 Confirmatory Factor Analysis

A statistical method called confirmatory factor analysis (CFA) is used to examine if a particular theoretical model can be explained by the correlations between observed variables and their underlying latent components. The subsequent step is to conduct this statistical technique, constructing a structure to check if the proposed factors are suitable with the collected data by analyzing the relationships between the observed factors. CFA requires the researcher to specify the number and nature of factors expected before the analysis. The basis of CFA lies in its ability to confirm or disconfirm the factor structure proposed by the researcher, thereby validating the measurement model. Its primary purpose is to verify the factor structure of a set of observed variables, assess the model's goodness-of-fit, and refine the model to improve its alignment with the data. By systematically exploring these relationships, researchers can glean deeper insights into the underlying dynamics at play, thereby informing more informed conclusions and actionable recommendations. CFA allows researchers to confirm or reject the proposed factor structure, thereby assisting in the validation of the service quality measurement model. Using this approach, this study seeks to provide deeper insights into the dynamics underlying customer service quality perceptions, which can ultimately be used to improve service quality improvement strategies across various industry sectors (Sureshchandar et al., 2002).

3.2.2 Statistical Method

This study uses a survey method to collect data from users of various sharing platforms. The designed questionnaire includes various items that measure the dimensions of user satisfaction and their sharing experience. To ensure that these items are appropriate to measure the desired construct, Exploratory Factor Analysis (EFA) will be conducted. This step is essential to identify the initial factor structure and evaluate the fit of the items. One of the key steps in EFA is the Kaiser-Meyer-Olkin (KMO) measure. KMO is a measure of sample adequacy that indicates whether the existing data is suitable for factor analysis. KMO values range from 0 to 1, with values higher than 0.6 considered adequate for factor analysis. In this study, KMO is used to assess whether the collected data is sufficient to proceed to factor analysis (Yoon et al., 2017). By using this method, this study aims to provide in-depth insights into the factors that influence user indexes and satisfaction in the sharing economy, as well as develop a measurement tool that can be used by researchers and practitioners in the future.

3.2.3 Statistical Hypothesis Test

After conducting CFA and validating the factor model, the Chi-square test of independence will be used. The Chi-square Test of Independence is a statistical method used to determine whether there is a significant relationship between two categorical variables. The Chi-square Test of Independence is an effective and versatile tool because researchers can determine whether there is a significant association between the variables. It is emphasized that a proper understanding of the assumptions and interpretation of Chi-square results is essential to avoid incorrect conclusions. This test has limitations, such as sensitivity to sample size and category imbalance, but it remains a powerful method in the analysis of categorical data. Some specific challenges in using the Chi-square Test are how to ensure that the data meets the basic assumptions of the test, such as a large enough sample and expected frequencies that are not too small and avoiding misinterpretation of the results that can lead to invalid conclusions (McHugh, 2012). The process involves several steps: first, comparing the observed frequencies to compute the chi-square statistic; then, determining the P-value, which indicates the probability of significance. If the P-value is less than 0.05, it signifies that the relationship between the variables is statistically significant.

3.2.4 Factor Analysis

Exploratory Factor Analysis (EFA) is a statistical technique used to uncover the underlying structure of a set of observed variables, aiming to identify latent constructs that explain the correlation patterns in the data. It begins by examining the correlation matrix, extracting factors using methods such as Principal Component Analysis for clear interpretation. Factors are determined using criteria such as the Kaiser criterion or scree plot analysis, with factor loadings indicating the strength of the relationship between variables and factors. EFA is a powerful tool for uncovering latent structure in complex data. It allows researchers to identify the factors underlying the relationships between variables and provides a solid foundation for the development of theories and research instruments. In practice, EFA helps to simplify data by reducing the number of variables into fewer, more easily interpretable factors. EFA provides deep insights into the hidden structure of data and can lead to new discoveries in a variety of research fields. With EFA, researchers can also overcome the problem of multicollinearity and develop simpler, more robust models to explain the relationships between variables. EFA is also useful in validating theoretical constructs and developing reliable measurement instruments (Hooper, 2012).

3.2.5 The Goodness of Fit Tests

Goodness-of-fit tests are statistical methods used to determine how well a sample data set fits the distribution of a particular theoretical model. They compare observed data with expected data based on a chosen model to assess the accuracy of the model. The Chi-square goodness-of-fit test, which compares observed and expected frequencies in categorical data, and the Kolmogorov-Smirnov test, which assesses the agreement of a sample distribution with a continuous theoretical distribution. The results of these tests help determine whether deviations between observed and expected values are due to random chance or indicate poor fit, thus guiding researchers in model validation and selection. (Babu & Rao, 2004) concluded that when parameters are estimated from data, goodness-of-fit tests require special adjustments to remain valid. This is because a major problem faced in goodness-of-fit testing with parameter estimation is how to ensure that the statistical test used remains valid and unbiased. This study makes an important contribution by providing a more reliable tool for goodness-of-fit testing when model parameters are estimated from data. To measure the goodness of fit, several methods are commonly used, such as the Tucker-Lewis Index (TLI) and Root means square error of approximation (RMSEA) with a fit defined as TLI > 0.9 and RMSEA <0.05. Statistical significance tests were conducted to ensure that the observed data and the model's predicted results were not purely coincidental so that statistical tests couldbe used to measure these differences.

3.2.6 Regression and Random Forest

Regression is a statistical method that models the relationship between independent and dependent variables to predict continuous values, with Linear Regression as the most common form that uses linear equations to find the best line that minimizes prediction error, evaluated through metrics such as Mean Squared Error and R-squared. (Sykes, 1993) said that linear regression focuses on where the relationship between the variables is assumed to be linear. Sykes explains how regression can be used to identify patterns in data, estimate model parameters and predictions about dependent variables based on independent variables. In addition, linear regression also has underlying assumptions and validity of its model.

Random Forest is an ensemble machine learning method that combines multiple decision trees to improve prediction accuracy and stability, both in classification and regression tasks, with its important feature being its ability to handle overfitting and provide estimates of the importance of features in the model. In the study presented (Pal, 2005), Random Forest can be used to process rich and complex spectral data. The use of accurate classification of this data is very important for deeper applications. Random Forest is known for its ability to handle high-dimensional and non-linear data, as well as its resistance to overfitting. In the paper (Pal, 2005), Random Forest showed better results in terms of classification accuracy compared to traditional methods, so Random Forest is a very effective and reliable choice for complex data classification, especially in situations where the data has high dimensions and there is a possibility of overfitting on simpler models.

4 Design Specification

Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) are two key components in the (TAM) Technology Acceptance Model that can be applied in the study of synergy between conventional banks and e-commerce. In the context of synergy between conventional banks and e-commerce, perceived usefulness can be measured through the benefits felt by consumers and businesses from this collaboration. For example, ease of payment transactions, increased access to financial services, and more varied product offerings through e-commerce platforms. While for PEOU, it can be applied by measuring the ease of use of the digital platform resulting from the synergy between banks and e-commerce. This includes an intuitive user interface, a simple registration process, and seamless integration between bank accounts and e-commerce services.

In a study by (Jamshidi & Hussin, 2016), it was concluded that perceived usefulness and perceived ease of use play an important role in influencing consumer intentions to adopt Islamic credit cards as e-commerce banking services. Which means that both are relevant to be used to measure the influence of collaboration between conventional banks and e-commerce. Therefore, the TAM theory will be used in this study to understand the factors that can influence the influence of collaboration between conventional banks and e-commerce to customer experience by involving the four-factor construct represented by the TAM model in Figure 1 which represents the relationship between variables that are hypothesized. By choosing a TAM model that includes more of these variables would be more suitable for use in this study.

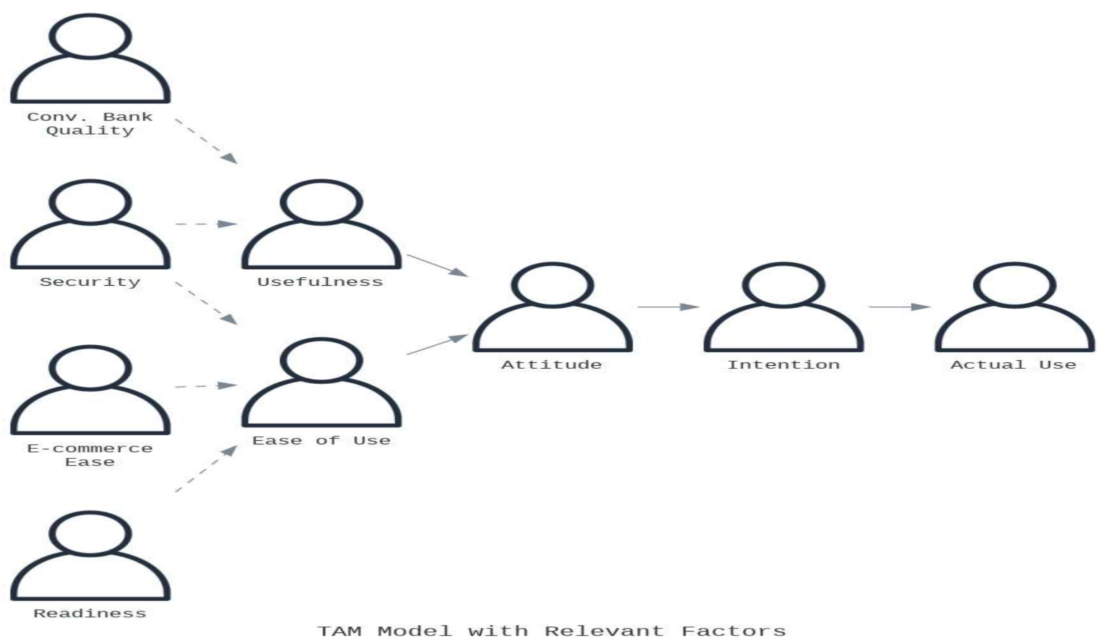

Figure 1: Proposed Research Model based on TAM (Technology Acceptance Model)

5 Implementation

In the implementation process, survey data undergoes data cleaning to meet the expected standards and is prepared for statistical analysis using the Confirmatory Factor Analysis (CFA) method. CFA is primarily used to assess measurement models and determine the relationships between observed variables and latent constructs. This process utilizes Google Colab for programming and provides insights into factor loadings, correlations among latent factors, and overall model fit measures. The aim of CFA is to test and validate the pre-designed measurement models based on research hypotheses, offering a better understanding of the next measurement model, Factor Analysis. CFA outputs include several fit indexes :

- Comparative Fit Index (CFI): Assesses how well the proposed model fits the observed data compared to the null hypothesis, which assumes no relationship between observed variables. The CFI value ranges from 0 to 1, with higher values indicating a better fit. A value closer to 1 suggests a superior model fit.
- Tucker-Lewis Index (TLI): Measures the proposed model's fit to the data, with values typically between 0 and 1, where higher values indicate better fit.
- Root Mean Square Error of Approximation (RMSEA): Indicates the extent to which the proposed model fits the data, with lower values signifying a better fit.

Additionally, Cronbach's Alpha is used to measure internal reliability, providing an indication of the correlation among items in a scale. Scores range from 0 to 1, with values above 0.70 generally indicating satisfactory internal reliability. Once the data is deemed reliable, it undergoes statistical factor analysis to identify latent patterns and structures. The main objective is to explore the relationships among representative variables and identify latent factors to simplify and structure the data. The stages involved include:

- Kaiser-Meyer-Olkin (KMO) Index: Measures data suitability for factor analysis, with values ranging from 0 to 1. Higher values indicate better suitability. Bartlett's Test is also used to ensure the correlation among variables is significant.
- Extraction: Involves measuring eigenvalues using a scree plot to determine the number of significant latent factors in the data. This helps researchers decide the number of factors to include in the analysis.
- Rotation: Utilizes Varimax rotation to achieve a clearer, more interpretable factor structure. Varimax maximizes the separation between factors, making them more independent.

Factor analysis is crucial for uncovering latent structures in complex data, aiding in understanding variable relationships, and providing insights into factors significantly influencing the adoption of digital payment services. The last step is to execute predictive modelling regression dan random forest. After the data is prepared by dividing the training and testing sets, a regression model is built as a baseline. Simple and multiple linear regression models are used to evaluate the linear relationship between the independent and dependent variables, as well as to get an initial idea of the predictive ability of the data. The performance of these models is then measured using metrics such as R-squared and MSE to assess how well the model can predict the data.

Next, the Random Forest model is applied to improve the prediction accuracy. Random Forest, with its advantages in handling high-dimensional data and providing feature importance estimates, is built and optimized over the training set. The performance of this model is compared with the regression model using the same test set, and the results show whether Random Forest provides significant improvement in prediction. This evaluation helps identify the superior model, both in terms of accuracy and generalization ability.

6 Research Methodology

6.1 Data Collection

The Confirmatory Factor Analysis (CFA) approach is utilized for the measurement analysis method by conducting further testing and verification to determine if the observed variables are related to the latent variables, or unobserved variables, through several indicators.

Table 2: Result of Latent Variable

Lval	Rval	Estimate	Std.Err	z-value	P(>|z|)
Q5	F1	1.000			
Q7	F1	10.430	14.939	0.698	0.485
Q8	F2	1.000			
Q11	F2	1.224	0.135	9.047	0.000
Q12	F2	1.437	0.153	9.422	0.000
Q6	F3	1.000			
Q9	F3	-6.545	7.120	-0.920	0.358
Q10	F3	-6.566	7.130	-0.921	0.357
Q13	F3	-7.978	8.663	-0.921	0.357
Q14	F4	1.000			
Q15	F4	0.859	0.088	9.787	0.000

In Table 2, the latent variables (F1, F2, F3, F4) are measured using CFA with 10 indicators. The parameter estimation results show mixed significance. Indicators Q11, Q12, and Q15 have significant factor loadings ($P < 0.05$), indicating a strong and positive contribution to their respective latent variables (F2 and F4). Q5, Q8, and Q14 are set as reference points with estimates of 1. However, indicators Q7, Q9, Q10, and Q13 show insignificant factor loadings ($P > 0.05$), indicating a weaker relationship with their latent variables (F1 and F3). The highest significant factor loading is Q12 with an estimate of 1.437982, indicating a strong relationship with F2. In contrast, Q9, Q10, and Q13 have negative and insignificant factor loadings with F3, indicating potential measurement problems. The analysis confirms that while some indicators effectively measure the latent variables, other indicators may be less statistically effective in measuring their latent factors.

Table 3: Result of Fit indexes derived from Confirmatory Factor Analysis (CFA)

Criteria	Result
Comparative Fit Index (CFI)	0.997
Tucker-Lewis Index (TLI)	0.995
Root Mean Square Error of Approximation (RMSEA)	0.024

To assess the model's fit, the fit index application measures whether the resulting data is appropriate for confirmatory factor analysis, as shown in Table 3. The findings indicate that the metrics meet the thresholds: CFI is 0.997 and TLI is 0.995, both exceeding the recommended limit of 0.95, suggesting an excellent fit with the data (Almaiah et al., 2022). Additionally, the RMSEA value is 0.024, indicating a very low model error rate since it is below the 0.08 threshold (Sarkar et al., 2020). These results demonstrate that the model has a strong fit, though some aspects may still need to be addressed to enhance validity.

Table 4: Result of Cronbach's Alpha Test

No of Items	Sample units	Cronbach's alpha
11	102	0.884

In Table 4, Cronbach's Alpha is used as a statistical measure to assess the reliability or internal consistency of the study, with values ranging from 0 to 1, where a value closer to 1 indicates higher reliability. A value close to 1 is considered sufficiently reliable for research purposes (Y. Wang et al., 2023). In this study, which involved 11 items tested on 102 samples, the Cronbach's alpha value was 0.884, signifying a high level of reliability and internal consistency. This high value indicates that the items are well-related and consistently measure the same constructs. Good reliability implies that the analysis results are dependable and can be trusted to provide accurate information about the variables being measured, thereby supporting the research.

6.2 Statistical Analysis

Factor analysis is carried out to explore the basic structure of the variables in the dataset and before conducting factor analysis a Kaiser-Meyer-Olkin (KMO) measurement calculation is carried out which aims to assess the suitability of the data for factor analysis by measuring the proportion of variance in the observed variables with KMO values ranging from 0 to 1 and acceptable level > 0.60 (Kaiser, 1974). Bartlett's test is carried out to determine whether the correlation matrix is significantly different from the identity matrix with a significant acceptable level p <0.05 indicating that the variable is suitable for factor analysis (Bartlett, 1954).

Table 5: Result of KMO and Bartlett's Test

Kaiser-Meyer-Olkin	0.93
Bartlett's Test Chi-Square	744.117
Bartlett's Test p-value	1.782258e-121
Bartlett's Test df.	55

In Table 5, the KMO value is 0.93, indicating that the variables in the dataset have strong correlations with each other and are suitable for factor analysis. The Bartlett test results show a chi-square value of 744.117 with 55 degrees of freedom and a very small p-value of 1.782258e-121, which is less than 0.001. These results suggest that the correlation matrix significantly differs from the identity matrix, providing strong evidence to reject the null hypothesis and confirming a significant correlation between variables. Consequently, the KMO and Bartlett Test results support proceeding with factor analysis to explore the underlying structure of the variables in the dataset.

In the following step, exploratory factor analysis (EFA) is conducted to uncover the underlying structure of the variables. This is done by extracting factors that have eigenvalues greater than one, as these factors account for a significant portion of the variance in the data and thus contribute more substantially to explaining the data's variability.

Table 6: Result of Exploratory Factor Analysis

Number of Factor	Eigenvalue
Component 1	6.4759
Component 2	1.0553
Component 3	1.0014
Component 4	0.4957
Component 5	0.4234
Component 6	0.4048
Component 7	0.3169
Component 8	0.3005

Component 9	0.2584
Component 10	0.2128
Component 11	0.1640

Component 1 has the highest eigenvalue of 6.4759, indicating that it explains the most variability in the data and likely represents the primary concept or pattern among the variables in the dataset. Components 2 and 3 also have relatively high eigenvalues, demonstrating their significant contribution to explaining the data's variability as shown in Table 6.

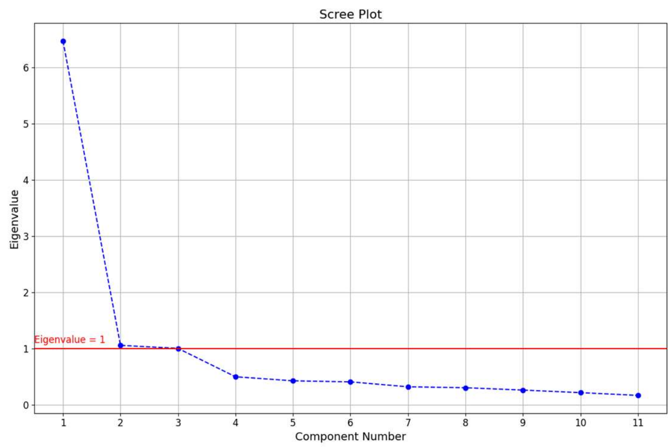

Figure 2: Scree plot Showing the Eigenvalues

The scree plot in Figure 2 illustrates the eigenvalues for each component, with the x-axis representing the component numbers and the y-axis representing their corresponding eigenvalues. Scree plots assist in identifying the number of significant components to retain in component analysis. This plot highlights the "elbow" points on the curve, where the eigenvalues begin to drop sharply, indicating the most significant components to retain. In this case, Components 1 to 3 are identified as the most significant.

Table 7: Principal Component Analysis

Variable	PC1	PC2	PA3
Q5	-0.08	-0.75	-0.65
Q6	0.12	0.66	-0.73
Q7	-0.82	0.09	0.01
Q8	-0.80	0.01	0.08
Q9	-0.81	-0.11	-0.01
Q10	-0.86	0.06	-0.09
Q11	-0.85	0.01	-0.06
Q12	-0.88	-0.01	-0.07

Q13	-0.88	0.01	0.08
Q14	-0.88	0.16	0.02
Q15	-0.83	-0.06	0.01

Table 7 presents the results of the Component analysis conducted using the Principal Component Analysis (PCA) method to extract three Components that explain the variability in the data. The values for PC1, PC2, and PC3 indicate the strength of the relationship between the variables and the Components, where a higher value signifies a stronger connection. The findings reveal that the variables Q10, Q8, Q9, Q11, Q7, and Q15 have substantial loadings on Component 1, indicating that this component captures the primary construct within the dataset. In contrast, the variables Q12, Q13, and Q14 show significant loadings on Component 3, suggesting that this component reflects a different aspect of the data. Finally, the variables Q5, Q6, and Q4 display considerable loadings on Component 2, indicating a unique relationship compared to the other variables in this analysis.

Table 8: Result of SS loadings (Sum of Squared Loadings)

	PC1	**PC2**	**PC3**
SS loadings	6.06	0.38	0.30

The value of SS loadings Table 8 shows that PC1 (Component 1) has the highest contributing Componentin explaining the variability in the data, ss loadings of 3.15 and is dominated by Component loadings on variables related to accessibility, PC2 (Component 2) has ss loadings of 0.38 and is related to payment services, PA2 (Component 3) has ss loadings of 2.18 and is related to the load Component on thevariable that describes security. These Components have an important role in shaping the data structure and contribute to explaining the variability in the observed variables.

Lastly, the Ordinary Least Squares (OLS) regression model was also used to evaluate the influence of various factors on the dependent variable, namely customer experience. The results of the analysis show that this model is very good at explaining variations in customer experience, with an R-squared value of 0.957, which means that 95.7% of the variation in customer experience can be explained by the independent variables used in the model. The most significant variables in influencing customer experience are Security of Banking System ($p < 0.001$), Ecommerce Effect ($p < 0.001$), and Readiness to Adopt ($p < 0.001$), while Conventional Banking Service Quality does not show statistical significance at the 0.05 level. The Durbin-Watson value is close to 2, indicating that there is no serious problem with autocorrelation in the residuals of the model.

In addition, by using the random forest regression model, we can improve the prediction and understand the importance of each feature more deeply. The results show that Random Forest has a slightly better performance than OLS regression, with an R-squared value of 0.959, indicating that this model explains 95.9% of the variation in customer experience. The most influential feature in this model is Readiness to Adopt with an importance score of 0.4867, followed by Ecommerce Effect with a score of 0.3193. This indicates that readiness to adopt technology and the influence of e-commerce play an important role in determining customer experience.

In addition to regression, the Random Forest Classifier model is used for customer experience level classification. This model shows an overall accuracy of 61.9%, with the best performance in the class with the highest customer experience value, where precision and recall each reach 1.00. However, this model has difficulty in predicting other classes, especially for the class with the middle value, with a low f1-score. In terms of feature importance, Ecommerce Effect has the greatest influence with an importance score of 0.3800, followed by Readiness to Adopt and Security of Banking System.

6.3 Discussion

The measurement model of the studied data was subjected to Confirmatory Component study (CFA), which demonstrated that every variable in the dataset has a strong correlation with other variables at KMO 0.93, allowing it to make the appropriate contribution to the study. Strong evidence contradicts the null hypothesis, as demonstrated by the Bartlett test's resultant significantly different correlation matrix (Chi-square 744.117 and p-value 1.782258e-121 <0.05). The goodness of fit results show that TLI has a value that is able to indicate that the resulting components have high reliability, as well as RMSEA has an indication of 0.024 which indicates very good model quality. The results of the Ordinary Least Squares (OLS) regression performed well, explaining 95.7% of the variation in customer experience, with significant contributions from Banking System Security, E-commerce Effects, and Readiness to Adopt, while Conventional Banking Service Quality was not statistically significant. Random Forest regression slightly outperforms OLS, explaining 95.9% of the variation, with Readiness to Adopt being the most influential factor. In addition, the Random Forest Classifier, used to classify customer experience levels, achieved an overall accuracy of 61.9%, with the best performance in predicting the highest customer experience class, highlighting the importance of the E-commerce Effect and Readiness to Adopt.

A satisfactory fit between the reproduced and observed covariance matrices is predicted by three of the four verified TAM Components. The first component regarding the security of the banking system in the collaboration of conventional banks and e-commerce is important to note as a fundamental thing that aims to ensure whether consumers feel safe in making transactions ((Ula et al., 2011). Researchers propose to create a layered security system to ensure customer security in making transactions. The second component regarding the Impact of E-Commerce on Ease of Transactions shows the importance of E-commerce integration in improving the quality of customer experience that can offer more sophisticated features. (Nugroho, 2016) revealed that E-commerce services improve customer experience by providing easy and 24/7 access to products and services, allowing customers to shop from anywhere at any time. E-commerce also offers a more personalized shopping experience through data-driven recommendations, customized promotions, and seamless interactions. In addition, e-commerce platforms often provide faster and more efficient customer service, increasing overall satisfaction and loyalty. However, it should also be underlined that the level of customer satisfaction can determine how massive E-commerce integration needs to be carried out.

The last component is Readiness to Adopt Digital Financial Innovation is a key factor that determines how quickly and effectively individuals or organizations can utilize new financial technologies. This level of readiness is influenced by various aspects, including understanding of the technology, ease of use, and trust in digital systems. (Hussain & Papastathopoulos, 2022) also revealed that when readiness to adopt innovation is high, users tend to be more receptive to change, which ultimately improves efficiency, accessibility, and the overall financial experience. Conversely, low readiness can be a significant barrier to adoption, reducing the potential benefits of the innovation. The results of the analysis show that in the TAM framework, perceived usefulness (Ecommerce Effect), ease of adoption (Readiness to Adopt), and trust in the system (Security of Banking System) significantly affect customer experience in Indonesia. The importance of these factors in the regression and Random Forest models emphasizes that in addition to benefits and ease of use, system security is also a crucial aspect that supports readiness to adopt technology and improve customer experience in Indonesia.

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