Continuance Intention Analysis Using Unified Theory Of Acceptance And Use Of Technology Model And Unfavorable Attitude Toward Cash Payment Variable In The Case Study Of Pt. Xyz Bank M-Banking Application

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Abstract
The mobile banking application of PT. XYZ offers two main services, which are the core banking functions: collecting funds from the public and disbursing funds to the public. However, a decline in the number of users of the XYZ mobile banking app has been observed in both Monthly Active Users and Monthly Transacting Users. The study involves respondents who represent the target market of Bank XYZ, such as active users and users who make transactions on the XYZ mobile banking application. Thus, the objective of this research is to evaluate the IT functional-level strategy of PT. XYZ's mobile banking application concerning continuance intention. Further, the study aims to explain the relationships between the variables of performance expectancy, effort expectancy, social influence, and facilitating conditions from the UTAUT model, as well as the variable of unfavorable attitude toward cash payment (UATC), in relation to satisfaction and continuance intention, and the interaction between these variables. Employing a quantitative research method, the sampling technique was non-probability sampling, specifically purposive sampling, as the population was already sufficiently specific to mobile banking users of PT. XYZ, with 310 respondents who are users of PT. XYZ's mobile banking application. Data analysis was performed using CB-SEM with a Maximum Likelihood approach. The research findings indicate that performance expectancy has the most significant influence on continuance intention. The results also show that satisfaction, as an intervening variable, strengthens the significant effect of performance expectancy, effort expectancy, and social influence. Based on the findings, it is recommended to focus on performance expectancy, in line with the results of the descriptive analysis, which suggest that it is an area requiring urgent and critical evaluation. Enhancing performance expectancy can help sustain continuance intention among Monthly Active Users and Monthly Transacting Users of the XYZ mobile banking application.
Keywords: *PT. XYZ Apps, Continuance Intention, UTAUT, UATC and CB-SEM.*

I. INTRODUCTION

A report by McKinsey (2019), Digital Banking in Indonesia: Building Loyalty and Generating Growth, highlights the increasing openness of Indonesian consumers toward digital banking. Over the past three years, the adoption of digital banking in Indonesia has expanded at a rate twice as fast as that of other developing Asian nations. The survey findings indicate that 55% of non-digital banking users in Indonesia are inclined to adopt digital banking services within the next six months, marking the second-highest rate in Asia after Myanmar. Furthermore, approximately 50% of all respondents cited the convenience of non-physical banking interactions as a key driver for their preference. This shift in consumer expectations has prompted significant innovation within Indonesia's digital banking sector.

Regarding the expectations for digital banking usage in Asia, including Indonesia, a study on the user experience of digital banking in Indonesia (Windasari et al., 2022) revealed that ease of use and features significantly influence the intention to use digital banking services. Factors influencing user experience have been extensively examined in studies on mobile banking applications. Research by Sharma (2023), Hussain et al. (2023), and Shahid et al. (2021) consistently highlights that ease of use and convenience significantly predict the overall user experience with mobile banking applications.

In relation to security, which has been identified as a factor influencing user experience in previous studies (Hussain et al., 2023; Yin and Ling, 2022; Egala et al., 2021), an analysis of SMS OTP codes (Aparicio et al., 2023) reveals that the implementation of SMS OTP codes is vulnerable. Additionally, the adoption of artificial intelligence technology in digital banking services (Aparicio et al., 2023) has a positive impact on user satisfaction, although the application of this technology is still in its early stages.

Previous studies have demonstrated that factors such as time, application attributes, and system quality significantly influence user experience (Chauhan and Akhtar et al., 2022; Egala et al., 2021; Kapoor and Vij, 2020; Huang et al., 2019). The development of PT. XYZ Bank's m-banking application utilizes a hybrid approach rather than a native one. By observing the package through the command prompt on the Android version of the PT. XYZ Bank application, the researchers identified a distinctive feature of the application, namely the webview page (Kaczmarczyk et al., 2022). A comparison between native and hybrid applications (Kaczmarczyk et al., 2022) reveals that hybrid applications generally exhibit slower performance, less customizable user experiences, and frequent changes within the application ecosystem, including its attributes.

The concept of ease of use, as a parameter in technology acceptance, has been explored in several studies (Sharma, 2023; Hussain et al., 2023; Windasari et al., 2022; Yin & Ling, 2022; Egala et al., 2021), originally introduced by Fred Davis, the pioneer of the Technology Acceptance Model (TAM). TAM is one of the most widely used models for understanding technology adoption. Over time, TAM has evolved into the Unified Theory of Acceptance and Use of Technology (UTAUT), which further refines and expands on the original framework. Numerous studies in the banking sector have utilized the UTAUT model to explore technology acceptance (Gan & Lau, 2024; Namahoot & Boonchieng, 2023; Liang et al., 2022; Windasari et al., 2022; Shahid et al., 2021), highlighting its relevance in understanding user behavior in the context of financial technologies.

The models of technology acceptance discussed in the previous paragraph (TAM and UTAUT) primarily focus on the initial intention or willingness to adopt technology. However, researchers have emphasized the need to explore users' continued intention to use a system. The importance of this continuity, as opposed to initial acceptance, is underscored by the fact that acquiring new customers is five times more costly than retaining existing ones (Parthasarathy & Bhattacherjee, 1998). Understanding continued usage, or continuance intention, as distinct from initial usage or acceptance, is the primary focus of the Expectation Confirmation Model (Bhattacherjee, 2001). While initial acceptance of an information system is crucial for its success, long-term survival and effectiveness depend on continued usage, rather than just first-time adoption (Bhattacherjee, 2001).

Previous studies have integrated the UTAUT model with the Expectation Confirmation Model, including research by Reza et al. (2024), Marandu et al. (2023), Istijanto and Handoko (2022), Zanetta et al. (2021), and Marinković et al. (2019). These studies contribute to a deeper understanding of technology adoption by combining elements of both models to explore user behavior in greater detail.

Analysis of PT. XYZ Bank's mobile banking application usage reveals a notable decline in both Monthly Active Users (MAU) and Monthly Transacting Users (MTU) from January 2023 to September 2023. The shift in the z-score from approximately 2.3 to -1 evidences this downward trend, indicating a statistically significant reduction in user engagement. This decline is a critical concern as it potentially exerts a substantial

negative impact on continuance intention, a key determinant of sustained platform usage.

Concurrently, the stock performance of PT. XYZ Bank Tbk. experienced a negative trajectory from January to May 2023. However, a subsequent positive surge was observed starting from late May. This upward movement, as reported by cnbcindonesia.com (2023), is attributed to the strategic acquisition of 500,000 shares by PT. XYZ Bank's Chief Executive Officer, at prices ranging from Rp 1,035 to Rp 1,060 per share. Consequently, the positive impact on stock prices became apparent from May 25th to 29th, 2023.

The selection of MAU and MTU data from January to September 2023 (equivalent to Q1 to Q3 2023) is deliberate. This timeframe allows for a focused analysis of the period exhibiting a sharp decline in user activity. By concentrating on this specific period, the study aims to identify the underlying causes of this decline and subsequently facilitate the design and implementation of effective corrective measures to mitigate similar occurrences in the future.

Based on these observations and the aforementioned phenomena, this research investigates continuance intention and satisfaction within the framework of the Expectation Confirmation Model (ECM) (Bhattacherjee, 2001), integrated with the Unified Theory of Acceptance and Use of Technology (UTAUT) model (Venkatesh et al., 2003). The UTAUT component encompasses performance expectancy, effort expectancy, social influence, and facilitating conditions as independent variables. Additionally, this study incorporates unfavorable attitude toward cash payment as an independent variable, reflecting specific characteristics of mobile payment usage (Istijanto and Handoko, 2022). Recent studies employing the UTAUT model in the banking industry (Gan & Lau, 2024; Namahoot & Boonchieng, 2023; Liang et al., 2022) provide further context for this research.

2. Basic Theory and Framework

In the theoretical study of system evaluation strategies, it is crucial to understand the diverse approaches employed to assess the effectiveness and efficiency of implemented systems. Evaluation strategies encompass a comprehensive analysis of system performance, including technical, functional, and practical usage aspects. This evaluation aims to ensure that the system fulfills user needs and organizational objectives, while also identifying areas requiring improvement. User acceptance models serve as frameworks for understanding how users adopt and utilize technology.

2.1 Strategic Management Theory

According to Fred R. David in his book Strategic Management: Concepts and Cases, Thirteenth Edition (2011), the strategic management process comprises three stages: strategy formulation, strategy implementation, and strategy evaluation. The strategy formulation stage involves establishing a vision and mission, identifying external opportunities and threats to the organization, determining internal strengths and weaknesses, setting long-term objectives, developing alternative strategies, and selecting the strategy to pursue.

Strategy implementation necessitates the establishment of annual objectives, the creation of policies, the enhancement of employee motivation, and the provision of resources to achieve these objectives. Strategy implementation represents the “action stage” of strategic management. Often considered the most challenging phase in strategic

management, strategy implementation demands personal skills, commitment, and dedication.

The concluding stage of the strategic management process is strategy evaluation, a primary method used by managers to identify strategic shortcomings. Given the constant flux of external and internal factors, all strategies are subject to future modifications. Three principal strategy evaluation activities include: (1) evaluating the external and internal factors that form the basis of current strategies, (2) measuring performance, and (3) implementing corrective actions.

2.2 User Acceptance Model

User acceptance of new technologies has been a subject of extensive research within the fields of information systems and technology marketing for several decades. User acceptance not only measures the effectiveness of new technology adoption by individuals but also predicts the technology's long-term success or failure.

In 1962, Everett Rogers developed the Innovation Diffusion Theory (IDT) to explain how innovations spread within a population over time and the factors influencing adoption rates. Introduced by Fishbein and Ajzen in 1975, the Theory of Reasoned Action (TRA) was among the first theories to explain how beliefs and attitudes influence individual intentions and behaviors. In 1989, Fred Davis introduced the Technology Acceptance Model (TAM), which quickly became one of the most influential models in technology acceptance studies.

In 2000, Venkatesh and Davis introduced an extension of TAM, known as TAM2. This model incorporated social and cognitive factors influencing perceived usefulness (PU) and perceived ease of use (PEOU). In 2003, Venkatesh et al. developed the Unified Theory of Acceptance and Use of Technology (UTAUT) in an attempt to consolidate eight distinct technology acceptance models, including TAM, TPB, and IDT, into a single comprehensive framework. UTAUT also considers four moderating variables: gender, age, experience, and voluntariness of use, which can influence the relationships between the core constructs and technology usage intention and behavior. In 2012, Venkatesh et al. developed UTAUT2 to further explain technology acceptance within consumer contexts. UTAUT2 extends the original model by adding three additional constructs: hedonic motivation, price value, and habit.

2.3 Digital Banking

The advent of technology has profoundly impacted the banking industry. The introduction of the telegraph in the mid-19th century enabled banks to communicate more rapidly and efficiently, thereby accelerating financial transactions. Subsequently, the emergence of computers and the internet revolutionized banking by enabling customers to access accounts and conduct transactions online.

As technology advanced, so too did the banking industry. The introduction of automated teller machines (ATMs) in the 1960s and 1970s allowed customers to access their accounts outside of traditional banking hours, providing enhanced convenience and increased customer satisfaction. The rise of online banking in the 1990s and early 2000’s further transformed the industry, allowing customers to conduct transactions and manage their accounts from any location with an internet connection. However, with the arrival of the web and mobile platforms, initial approaches often simply replicated existing branch-based distribution systems for these new channels. Instead of re-evaluating application processes for the online environment, web pages were frequently designed to mirror the processes conducted in physical branches.

King (2018, p. 29) posits that banks fundamentally provide three core services: (1) a value store—the ability to securely store money; (2) money movement—the ability to securely transfer customer funds; and (3) access to credit—the ability to lend money when customers require it.

One of the most significant impacts of technology on the banking industry has been the emergence of mobile banking. According to King (2018, p. 41), "the number of mobile banking users worldwide was projected to exceed 1.75 billion by 2019." This trend is driven by the increasing prevalence of smartphones and the convenience of accessing banking services from any location at any time.

2.4 The Unified Theory of Acceptance and Use of Technology (UTAUT)

Based on user acceptance theory (Venkatesh et al., 2003), a review and comparison of eight technology acceptance models and their extensions culminated in the development of the Unified Theory of Acceptance and Use of Technology (UTAUT). Through rigorous testing and empirical data analysis, UTAUT demonstrated superior predictive validity compared to its predecessors. According to Venkatesh et al. (2003), of the seven constructs initially considered, four play a crucial role as direct determinants of user acceptance and usage behavior: performance expectancy, effort expectancy, social influence, and facilitating conditions, which directly influence behavioral intention.

Performance expectancy is defined as the degree to which an individual believes that using the system will help him or her to attain gains in job performance (Venkatesh et al., 2003). 1 Effort expectancy is defined as the degree of ease associated with the use of the system (Venkatesh et al., 2003). Social influence is defined as the degree to which an individual perceives that 2 important others believe he or she should use the system (Venkatesh et al., 3 2003). Facilitating conditions are defined as the degree to which an individual believes that an organizational and technical infrastructure 4 exists to support use of the system, 5 reflecting access to resources that facilitate the implementation of a specific technology (Bouteraa et al., 2024; Zhang et al., 2020; Venkatesh et al., 2003). Behavioral intention captures the motivational factors that influence a behavior, indicating how hard people are willing to try and how much effort they are planning to exert to perform the behavior (Zhang et al., 2020).

2.5 Expectation Confirmation Model

Information System (IS) acceptance models, such as the Technology Acceptance Model (TAM), Innovation Diffusion Theory (IDT), and Theory of Planned Behavior (TPB), have extensively examined the variables motivating initial individual acceptance of IS. However, according to Bhattacherjee (2001), while initial IS acceptance constitutes a crucial first step toward IS success, the long-term viability and ultimate success of IS depend on continued usage, rather than initial adoption. Understanding continued usage, or "continuance" (as distinct from initial usage, or "acceptance"), is the central focus of the model proposed by Bhattacherjee (2001).

The Expectation Confirmation Model (ECM) comprises four key constructs. (1) Satisfaction is defined as an emotional state encompassing pleasure, positive affect, and contentment arising from interactions with the Information System (Bhattacherjee, 2001). (2) Confirmation explains the chronological process from pre-purchase to post-consumption; in this context, confirmation occurs when expectations are met (Bhattacherjee, 2001). (3) Perceived usefulness, following initial adoption, user satisfaction with the technology and assessments of the system's value may evolve, influencing their continued use of the technology (Bhattacherjee & Lin, 2015). (4)

Continuance intention, simply defined, refers to the user's intention to continue using the information system after initial adoption (Vasuthevan et al., 2024).

2.6 Unfavorable Attitude toward Cash Payment (UATC)

The independent variable, unfavorable attitude toward cash payment, was employed by Istijanto and Handoko (2022) to develop a comprehensive model explaining the continuance intention of mobile payment usage by customers during the COVID-19 pandemic. As posited by Schiffman and Wisenblit (2015), consumer attitudes toward an object can be either favorable or unfavorable, contingent upon the perceived situation.

During the COVID-19 pandemic, perceptions surrounding the virus influenced public attitudes, leading to the perception that using cash for purchasing transactions during this period constituted a detrimental behavior (a push factor) that should be avoided (Musyaffi et al., 2021). Consequently, consumers were more inclined to continually utilize m-payment as a safer alternative compared to cash (Istijanto and Handoko, 2022).

II. RESEARCH HYPOTHESIS AND FRAMEWORK

To operationalize the methodology, this study adopts a combined UTAUT and Expectation Confirmation Model, as depicted in Figure 2.1. The following hypotheses are proposed:

a. Performance expectancy has a significant effect.
b. Effort expectancy has a significant effect.
c. Social influence has a significant effect.
d. Facilitating conditions has a significant effect.
e. Unfavorable attitude toward cash payment has a significant effect.
f. Satisfaction has a significant effect.

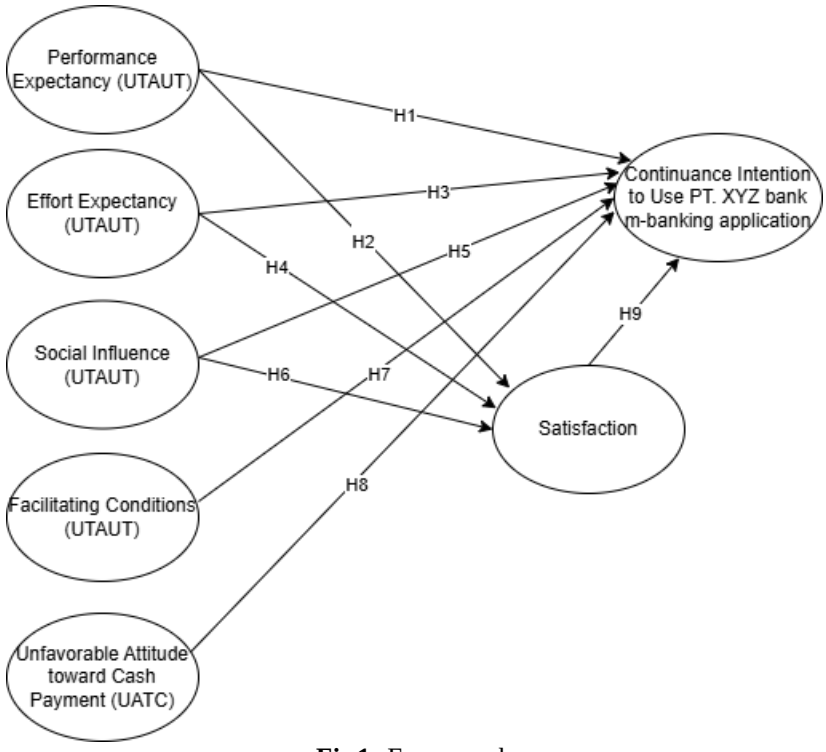

Fig 1. Framework

Drawing upon prior research (Bhattacherjee, 2001; Venkatesh et al., 2003; Istijanto & Handoko, 2022; Reza et al., 2024), the following hypotheses are formulated:

H1: Performance expectancy influences significantly continuance intention to use PT. XYZ Bank m-banking application (Vasuthevan et al., 2024; Reza et al., 2024).

H2: Performance expectancy influences significantly satisfaction (Vasuthevan et al., 2024; Reza et al., 2024).

H3: Effort expectancy influences significantly continuance intention to use PT. XYZ Bank m-banking application (Vasuthevan et al., 2024; Reza et al., 2024).

H4: Effort expectancy influences significantly satisfaction (Vasuthevan et al., 2024; Reza et al., 2024).

H5: Social influence influences significantly continuance intention to use PT. XYZ Bank m-banking application (Zou et al., 2024; Marandu et al., 2023; Istijanto & Handoko, 2022; Zanetta et al., 2021).

H6: Social influence influences significantly satisfaction (Marinković et al., 2019).

H7: Facilitating conditions influences significantly continuance intention to use PT. XYZ Bank m-banking application (Vasuthevan et al., 2024; Reza et al., 2024; Zou et al., 2024; Marandu et al., 2023; Istijanto & Handoko, 2022).

H8: Unfavorable attitude toward cash payment influences significantly continuance intention to use PT. XYZ Bank m-banking application (Istijanto & Handoko, 2022).

H9: Satisfaction influences significantly continuance intention to use PT. XYZ Bank m-banking application (Vasuthevan et al., 2024; Reza et al., 2024; Marandu et al., 2023; Marinković et al., 2019).

III. RESEARCH METHODS

Research Object and Analysis

This section details the research approach employed in this study, which is a quantitative approach. Quantitative research is utilized to gain an in-depth understanding of the phenomenon under investigation. This study employs an exploratory quantitative approach to collect data through various data collection techniques, including the administration of questionnaires. In this research, questionnaires were distributed to examine patterns among PT. XYZ Bank users.

Variable Operationalization

The relationships between variables in research can be categorized as follows (Sugiyono, 2013):

a. Independent Variables: Often termed stimulus or predictor variables, these are commonly referred to as independent or explanatory variables. Independent variables influence or cause changes in the dependent variable. In this study, the independent variables include performance expectancy (X1), effort expectancy (X2), social influence (X3), facilitating conditions (X4), and unfavorable attitude toward cash payment (X5).

b. Intervening Variable: According to Sugiyono (2013), an intervening variable theoretically influences the relationship between independent and dependent variables, creating an indirect and unobservable relationship. This variable acts as a mediator or intermediary situated between the independent and dependent variables, such that the independent variable does not directly influence changes in or the emergence of the dependent variable. In this study, the intervening variable is satisfaction (Z).

c. Dependent Variable: Frequently referred to as the outcome, criterion, or consequent variable, this is commonly known as the dependent or outcome variable. The dependent variable is influenced by or is a consequence of the independent

variable. In this research, the dependent variable is continuance intention to use PT. XYZ Apps (Y).

Populations and Samples

According to (Sugiyono, 2013), population is a generalization area consisting of objects or subjects that have certain quantities and characteristics set by researchers to study and then draw conclusions. According to Kontan.co.id (2024), PT. XYZ Bank Indonesia Tbk has 9 million customers by mid-May 2024. Thus, the respondent population (N) in this study are users of PT. XYZ Bank application totaling 9 million people.

The determination of data sampling in this study was carried out using nonprobability sampling techniques using the Hair sample and population determination formula (Hair et al., 2010). The sample calculation can be seen in equation 3.1 as follows:

n = 5 x indicator.....(3.1)

n = 5 x 51

n = 255 samples

n >= 255 samples

The sampling technique through nonprobability sampling refers more to purposive sampling according to the theory (Sugiyono, 2013) because this research is limited to users of the PT. XYZ Bank m-banking application only which shows that the population is quite specific and the selection of samples based on the criteria of PT. XYZ Bank m-banking application users relevant to the research objectives. The purposive sampling technique was also used by (Prasetio et al., 2022) by examining Batik Air users who were exposed through the Batik Air Instagram account.

Test Techniques

Covariance-Based Structural Equation Modeling (CB-SEM) is a statistical method used to test and estimate structural models involving latent variables and measured variables. CB-SEM uses the Maximum Likelihood (ML) approach for model parameter estimation and relies heavily on the assumption that the data follows a multivariate normal distribution and requires a sufficiently large sample size to provide reliable results.

This approach PT. XYZws a thorough evaluation of the Mahalanobis D-Squared to identify outliers in order to obtain standardized multivariate normality and model reliability as well as the provision of various fit indices to assess how well the model fits the data. The tool to be used is AMOS.

IV. RESULTS

Characteristics of Respondent Data

For distributing questionnaires, the number of respondents obtained was 310 respondents with the characteristics of PT. XYZ Bank m-banking application users. Using AMOS software through CB-SEM data analysis techniques, data processing through the first order by using the Maximum Likelihood (ML) approach for model parameter estimation and relies heavily on the assumption that the data follows a multivariate normal distribution. Using skewness-curtosis normality test, outlier identification using Mahalanobis D-Squared founded 8 datas to be eliminated so it becomes 302 respondents, model fit test, and path correlation test to ensure the data used are valid and produce valid output.

To analyze reliability using Croanbach's Alpha with a minimum interpretation of a value above 0.7 for data that shows reliability and a value above 0.9 indicates excellent reliability. Then do a normality test using skewness-curtosis to show that the data is normal and good through multivariate normality worth under 2.58 to ensure the data is normally distributed. We also analyzed these respondents' data to meet the Fit Model and ensure goodness of fit by examining RMSEA, CFI, and Chi-square to achieve values of less than 0.05, more than 0.90, and <= 3, respectively. The Path Coefficient on each variable must also meet p-values below 0.05 which indicates statistical significance.

Reliability Test

Using the Croanbach's Alpha calculation to measure the consistency of the items in the construct, a value of more than 0.7 is acceptable, but if it is more than 0.9 it will indicate excellent reliability. Here are some reliability results and variables available.

a. Performance Expectancy (PE) is 0.934 indicating that it has very good and consistent reliability

b. Effort Expectancy (EE) is 0.920 indicating it has very good and consistent reliability

c. Social Influence (SI) is worth 0.890 indicating that it has acceptable reliability

d. Facilitating Conditions (FC) is worth 0.910 indicating that it has very good and consistent reliability

e. Unfavorable Attitude toward Cash Payment (UATC) is worth 0.911 indicating that it has very good and consistent reliability

f. Satisfaction (SF) is worth 0.927 indicating that it has very good and consistent reliability

g. Continuance Intention (CI) is 0.918 indicating that it has very good and consistent reliability.

Table 2. Reliability Test Value using Croanbach's Alpha

Indicator	Reliability Value
Performance Expectancy (PE)	0.934
Effort Expectancy (EE)	0.920
Social Influence (SI)	0.890
Facilitating Conditions (FC)	0.910
Unfavorable Attitude toward Cash Payment (UATC)	0.911
Satisfaction (SF)	0.927
Continuance Intention (CI)	0.918

Mahalanobis D-Squared Test

In CB-SEM, this research uses Mahalanobis D-squared to detect outliers data that can affect the results of model analysis such as skewness-curtosis normality tests, path coefficient estimates, and overall model fit tests. The purpose of using Mahalanobis D-Squared is to check the presence of outliers in the data because the presence of outliers can affect the results of model estimation and parameter interpretation.

In the available data, the normality test using skewness-kurtosis produces a value of 20.513 which is below the threshold of normal data values which is < 2.58, so it is necessary to identify which data are outliers. Some data will be identified as outliers using Mahalanobis D-Squared, data with values above 87.97 are eliminated, so 8 data identified as outliers with Mahalanobis D-squared values above 87.97 are eliminated in Table 4.2. (*Obs No: Observation Number, Mah. Val: Mahalanobis value)

Table 3. Mahalanobis D-Squared Values

Obs. No.	Mah. Val	Obs. No.	Mah. Val	Obs. No.	Mah. Val	Obs. No.	Mah. Val

21	159,885	**111**	65,537	**290**	61,505	**267**	56,856
62	143,831	**140**	65,163	**128**	61,089	**179**	56,758
190	137,322	**177**	64,992	**188**	61,073	**152**	56,486
145	127,543	**69**	64,883	**83**	60,758	**146**	56,408
200	123,629	**108**	64,614	**162**	60,710	**205**	56,326
255	109,193	**171**	64,608	**112**	60,136	**157**	56,082
254	104,841	**158**	64,539	**149**	60,128	**174**	56,040
42	101,168	**104**	64,407	**201**	60,122	**127**	55,927
142	159,885	**259**	64,303	**173**	60,093	**264**	55,858
60	143,831	**36**	64,103	**133**	59,352	**297**	55,823
121	137,322	**263**	63,685	**107**	59,316	**75**	55,808
123	127,543	**151**	63,672	**156**	59,138	**122**	55,725
164	70,198	**153**	63,511	**65**	58,829	**81**	55,168
160	69,862	**235**	63,422	**93**	58,732	**293**	55,158
117	69,351	**119**	63,160	**258**	58,668	**184**	55,033
110	69,160	**165**	63,055	**37**	58,562	**16**	54,967
139	68,673	**94**	62,873	**220**	58,083	**53**	54,776
90	68,562	**41**	62,697	**144**	58,044	**105**	54,742
265	68,367	**84**	62,374	**54**	57,601	**286**	54,684
143	68,345	**269**	61,981	**154**	57,446	**291**	54,678
167	68,342	**302**	61,972	**125**	57,397	**124**	54,545
116	67,738	**285**	61,928	**115**	57,218	**289**	54,359
113	66,669	**106**	61,750	**102**	57,212	**298**	54,325
256	66,625	**29**	61,549	**288**	57,066	**135**	54,306
186	66,558	**1**	61,512	**88**	56,976	**68**	53,960

Normality Test

After eliminating 8 pieces outlier data, the next stage is the normality test. This study uses the CB-SEM data analysis technique by using the Maximum Likelihood (ML) approach for estimating model parameters and relies heavily on the assumption that the data follows a multivariate normal distribution. This normality test used skewness-curtosis to indicate that the data is normal and either through multivariate normality is below 2.58 to ensure the data is normally distributed.

The multivariate normality test results produced a value of 2.245 according to Table 4.3, which is below the threshold of less than 2.58 to ensure the data is normally distributed. Previously, the data tested for normality before being identified using Mahalanobis D-Squared and eliminated, the value of the multivariate normality test resulted in a value of 20.513 so that the identification process through Mahalanobis D-Squared had an effect on the value of the multivariate normality test after eliminating a total of 8 respondent data that had a Mahalanobis D-Squared value above 87.97.

Table 4. Multivariate Normality Value Before and After Outliers Data were Eliminated

	Before outliers data eliminated	After outliers data eliminated
Multivariate Normality	20.513	2.245

Model Fit Test

Model Fit test to evaluate how well the respondent's data fits the hypothesis model and describes how well this model describes the data. Some parameters for testing Model Fit are RMSEA worth <0.05 indicating very good or <0.08 indicating acceptable, CFI worth> 0.90 indicating good, and chi-square worth <= 3 indicating good, The R-Square value ranges from 0 to 1, minimum > 0.75. The following are the results of the analysis of the respondent data including in the Table 4.4 in this study

a. RMSEA is 0.047, indicating a very good fit with minimal error in the model because it meets the requirements even below 0.05
b. CFI is 0.928, indicating that the model has good performance on the independent model because it meets the requirements for a value> 0.90
c. CMIN (Chi-square) is worth 1.673, indicating a good fit model because it meets the requirements <= 3
d. The R-Square value is 0.80, The R^2 value of 0.80 indicates that the model used can explain 80% of the variability in the dependent variable, which shows that this model has very good predictability.

Table 4.4. Model Fit Test Results

Model Fit Test	Value
RMSEA	0.047
CFI	0.928
CMIN	1.673
R-Square (R^2)	0.80

Path Coefficient Test

The path coefficient is a parameter that indicates the direct effect of one variable on another in a structural model. In the context of CB-SEM, the path coefficient measures the strength and direction of the causal relationship between the variables in the model. If two variables have a greater or lesser value together, it is positive. Conversely, if one variable increases while the other decreases, it is negative. If there is no linear relationship between two variables, the value will be close to zero. The path coefficient is directional and asymmetric; that is, βXY is different from βYX, because it shows a different direction of influence between the variables. The following path coefficient results also show indirect effects:

Table 5. Standardized Indirect Effects

	UATC	FC	SI	EE	PE	SF	CI
SF	0,000	0,000	0,000	0,000	0,000	0,000	0,000
CI	0,000	0,000	0,002	0,037	0,002	0,000	0,000

From Table 4.5 above, it can be seen that variables that have a value of 0.000 have no relationship at all, while for SI, EE, and PE variables show an indirect relationship through intervening variables. SI, EE, and PE variables will mediate SF first and then affect CI indirectly.

Table 6. Standardized Direct Effects

	UATC	FC	SI	EE	PE	SF	CI
SF	0,000	0,000	0,303	0,181	0,326	0,000	0,000
CI	0,155	0,155	0,164	0,172	0,138	0,318	0,000

While Table 4.6 above shows the direct effects path coefficients, where it can be seen that FC and UATC have a value of 0.000 on SF which confirms the proposed research framework. For SF and CI variables, they have no relationship with their own variables (CI → CI, SF → SF) and the relationship of CI to SF also has no relationship worth 0.000 (CI → SF).

Regression Weight Validity Test

In the context of Covariance-Based Structural Equation Modeling (CB-SEM), the loading factor is often used as an indicator to assess the validity of a construct or latent variable within the measurement model. The loading factor, derived from the standardized regression weight, provides information on the extent to which an indicator or measurement variable can explain the latent factor it represents. This relationship is crucial for evaluating the convergent validity of the construct, as higher loading factors indicate that the indicators effectively capture the underlying latent construct. The table below showed standardized regression weight as validity test.

Table 7. Standardized Regression Weight as Validity Test

Indicator			**Estimate**
SF	<---	PE	,326
SF	<---	SI	,303
SF	<---	EE	,181
CI	<---	PE	,138
CI	<---	SI	,164
CI	<---	FC	,155
CI	<---	UATC	,155
CI	<---	SF	,318
CI	<---	EE	,172
PE2	<---	PE	,670
PE1	<---	PE	,842
PE3	<---	PE	,815
CI5	<---	CI	,840
CI4	<---	CI	,814
CI3	<---	CI	,765
CI2	<---	CI	,806
CI1	<---	CI	,726
PE4	<---	PE	,736
CI6	<---	CI	,768
PE5	<---	PE	,760
PE6	<---	PE	,830

Indicator			Estimate
PE7	<---	PE	,889
PE8	<---	PE	,777
EE2	<---	EE	,779
EE1	<---	EE	,837
EE3	<---	EE	,797
EE4	<---	EE	,649
EE5	<---	EE	,726
EE6	<---	EE	,751
EE7	<---	EE	,775
EE8	<---	EE	,701
SI1	<---	SI	,773
SI2	<---	SI	,773
SI3	<---	SI	,765
SI4	<---	SI	,695
SI5	<---	SI	,764
SI6	<---	SI	,761
FC2	<---	FC	,709
FC1	<---	FC	,700
FC3	<---	FC	,747
FC4	<---	FC	,739
FC5	<---	FC	,739
FC6	<---	FC	,662
FC7	<---	FC	,787
FC8	<---	FC	,706
UATC2	<---	UATC	,804
UATC1	<---	UATC	,792
UATC3	<---	UATC	,753
UATC4	<---	UATC	,781
UATC5	<---	UATC	,666
UATC6	<---	UATC	,676
UATC7	<---	UATC	,668
UATC8	<---	UATC	,754
SF5	<---	SF	,870
SF4	<---	SF	,843
SF3	<---	SF	,755
SF2	<---	SF	,705
SF1	<---	SF	,821
SF6	<---	SF	,840
SF7	<---	SF	,707

Interpretations

The interpretation showed the p-values which require a minimum of <0.05 which indicates statistical significance. The following is a summary of the analysis results:

a. Performance Expectancy (PE) worth p = 0.000 significantly affects Satisfaction
b. Performance Expectancy (PE) worth p = 0.018 significantly increases Continuance Intention
c. Social Influence (SI) has a value of p = 0.000 which strongly significantly affects Satisfaction
d. Social Influence (SI) is worth p = 0.022 strongly significantly increases Continuance Intention

e. Effort Expectancy (EE) worth p = 0.009 is also significantly positive affecting Satisfaction on a small scale.
f. Effort Expectancy (EE) worth p = 0.001 significantly increases Continuance Intention
g. Facilitating Conditions (FC) worth p = 0.003 significantly affects Continuance Intention
h. Unfavorable Attitude toward Cash Payment (UATC) worth p = 0.003 has a very negative influence on the use of banknotes, thus increasing Continuance Intention
i. Satisfaction (SF) with a value of p = 0.001 significantly increases Continuance Intention

Table 8. P-values Interpretations

Indicator	**P**
SF <--- PE	.000
SF <--- SI	.000
SF <--- EE	.009
CI <--- PE	.018
CI <--- SI	.022
CI <--- FC	.003
CI <--- UATC	.003
CI <--- SF	.000
CI <--- EE	,001

IV. CONCLUSIONS AND RECOMMENDATIONS

Conclusions

From the background to the results of the analysis, the following are the conclusions of this study on the variables tested:

a. The performance expectancy variable from the UTAUT model has a significant effect on the continuance intention to use the PT. XYZ Bank m-banking application.

b. The effort expectancy variable from the UTAUT model influences the continuance intention to use the PT. XYZ Bank m-banking application.

c. The social influence variable from the UTAUT model affects the continuance intention to use the PT. XYZ Bank m-banking application.

d. The facilitating conditions variable from the UTAUT model has an impact on the continuance intention to use the PT. XYZ Bank m-banking application.

The Unfavorable Attitude toward Cash Payment (UATC) variable from the UTAUT model plays a role in shaping the continuance intention to use the PT. XYZ Bank m-banking application.

Recommendations

a. **Academic Aspects:**

- The Performance Expectancy variable yielded the most significant influence among all variables, yet its descriptive analysis results were suboptimal. Performance Expectancy is the foremost priority for evaluation due to its paramount significance and unfavorable assessment, necessitating improvements in application performance to mitigate payment failures, among other issues.
- The Effort Expectancy variable demonstrated a significant influence but also exhibited suboptimal descriptive analysis results. Evaluating and enhancing the application's interface design and functionality are imperative to elevate user Effort Expectancy.
- The Social Influence variable manifested a significant influence while concurrently displaying suboptimal descriptive analysis results. Social factors have yet to constitute a

robust impetus for respondents to utilize the application. PT. XYZ should contemplate strategies to augment social influence, such as testimonials, influencer campaigns, or engagement with user communities.

- The Facilitating Conditions variable indicated a significant influence but presented suboptimal descriptive analysis results., suggesting that there remains scope for improvement in supporting facilities, such as technical infrastructure, organizational support, or more lucid information about the application, to enhance the overall user experience.
- The Unfavorable Attitude toward the Cash Payment variable demonstrated a significant influence, yet with suboptimal descriptive analysis results, implies that factors such as inconvenience, lack of benefits, and hygiene concerns have not yet become potent drivers for respondents to eschew cash payments, indicating that there remains potential for individuals who favor cash transactions.
- The Satisfaction variable exhibited a significant influence while displaying suboptimal descriptive analysis results, indicating that PT. XYZ needs to evaluate and enhance user satisfaction by considering the independent variables Performance Expectancy, Effort Expectancy, and Social Influence, given their significance to Satisfaction.
- The Continuance Intention variable significantly influenced but presented suboptimal descriptive analysis results. Strategies are required to ensure that users continue to utilize the XYZ application, thereby increasing and sustaining Monthly Active User and Monthly Transacting User metrics.
- The PE and SF variables are identified as possessing the highest significant influences, respectively, PT. XYZ can optimize these variables to retain Monthly Active Users and Transacting Users.

b. Practical Aspects:

- The corrective actions are an evaluation strategy for PT. XYZ will retain monthly active users and monthly transacting users of the XYZ m-banking application, thereby increasing the potential for higher paylater submissions from users, impacting PT. XYZ's increased profitability.
- Endeavor to win the hearts of PT. XYZ m-banking application users by offering flexible integration with ecosystems outside of PT. XYZ's ecosystem as desired by the market and meeting customer needs.

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