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Factors influencing the continued intention to use mobile payment among generation Z: An extension of the expectation-confirmation model

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ABSTRACT

Background: The fintech industry in Indonesia has been growing rapidly, driven by digitalization acceleration during the pandemic and positive funding trends in the ASEAN fintech sector. As a developing country with a high unbanked population, mobile payment (m-payment) adoption has the potential to support financial inclusion by providing easy access to affordable and beneficial financial services. This study integrates the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) and the Expectation-Confirmation Model (ECM) to understand the factors significantly influencing the continued usage intention of m-payment among Generation Z, a key potential customer segment in Indonesia. **Methods:** This research employs a quantitative approach by distributing structured questionnaires to Generation Z respondents. Structural Equation Modeling (SEM) was utilized to analyze the relationships between the variables. The key factors examined include Habit, Hedonic Motivation, Satisfaction, Facilitating Conditions, Performance Expectancy, Effort Expectancy, and Confirmation. **Findings:** The results reveal that continued intention to use m-payment is positively influenced by Habit, Hedonic Motivation, Satisfaction, and Facilitating Conditions. Furthermore, Performance Expectancy indirectly affects continued intention through the mediating role of Satisfaction. Additionally, Performance Expectancy mediates the relationship between Effort Expectancy and Confirmation with Satisfaction. **Conclusion:** The study highlights the crucial factors that drive the sustained use of m-payment among Generation Z in Indonesia. Understanding these factors is essential for financial service providers to enhance adoption and engagement. **Novelty/Originality of this article:** This study extends ECM by incorporating UTAUT2 constructs to provide a comprehensive understanding of continued m-payment adoption. The findings contribute to the literature on fintech adoption by offering empirical evidence from an emerging market perspective.

KEYWORDS: mobile payment; UTAUT2; ECM; Generation Z; continued usage intention.

1. Introduction

The enforcement of physical distancing measures during the pandemic has led to changes in consumer behavior in conducting economic activities and has driven business organizations to adopt technologies that enable minimal or contactless transactions (Puriwat & Tripopsakul, 2021). Consumption patterns have shifted towards digital shopping, thereby increasing the demand for fast and secure mobile payment methods. Consequently, non-cash payment systems utilizing mobile applications (mobile payment) are perceived as offering convenience, with safer and faster transaction processes

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compared to cash or physical card payments (Lisana, 2021). Mobile payment (m-payment) also provides significant advantages for merchants, including lower transaction costs, an enhanced shopping experience, and access to customer data (Hayashi & Bradford, 2014).

According to the Global Payments Report by Worldpay, m-payment has become the most widely used payment method worldwide, particularly in online shopping (49%) and in-store purchases (29%) in 2021, with projections indicating an increase to 53% and 39% by 2025, respectively. Financial technology (FinTech) funding in ASEAN reached US$4.3 billion within the first nine months of 2022, surpassing the total funding from 2018 to 2020 (Asian Fintech Report, 2022). Despite potential global economic challenges, these figures suggest strong confidence in the growth of the FinTech industry in ASEAN, with the payment FinTech category consistently securing the highest investment in 2022.

In line with global trends, Indonesia has also experienced a significant increase in m-payment adoption, with the potential to dominate future payment systems (MDI & Mandiri Sekuritas, 2019). A report titled "Indonesia's Fintech Industry Is Ready to Rise" by the Boston Consulting Group states that e-wallet transaction values in Indonesia from 2017 to 2021 exceeded $20 billion, with an exceptionally high growth rate of 123% (Boston Consulting Group, 2023). E-wallets, which store funds before being used for m-payment transactions, ranked as the second most frequently used payment method (33%) after cash among Indonesian respondents.

Despite its vast potential, Indonesia lacks a dominant e-wallet platform, unlike other ASEAN countries (Asian Fintech Report, 2022), leaving room for intense competition among technology developers to capture the m-payment market. As illustrated in Figure 1.3, the user base of m-payment continues to expand annually, and its adoption is expected to rise further, supported by Indonesia's large population of over 270 million and its evolving infrastructure.

Given its enormous potential, various organizations are striving to develop m-payment applications to maximize profitability and secure user loyalty. For instance, technology giant Google invested USD 100 million in building a mobile payment platform, while local m-payment provider DANA secured USD 250 million in Series D funding in 2022. However, fierce competition among m-payment platforms represents a classic "winner-takes-all" market scenario (Wirtz, 2018). In such markets, a strong network effect occurs where merchants and potential users tend to adopt platforms with an already established user base, reinforcing the dominance of larger platforms while marginalizing smaller ones (Lin, 2012). Consequently, it is not only crucial to attract potential users, but also essential for mobile payment service providers to retain existing users and facilitate continued usage to achieve profitability.

To harness the economic potential and sustain user engagement in m-payment, it is imperative to understand user behavior, particularly how individuals interact with new technologies such as mobile applications (Seethamraju, Garg, & Diatha, 2018; Xu, Peak, & Prybutok, 2015). The consumer lifecycle of a technology typically consists of three phases: adoption, usage, and post-usage, which includes switching or discontinuation (Kim & Crowston, 2012). Extensive research has been conducted on the initial adoption of m-payment technology, exploring various influencing factors (Singh & Srivastava, 2020; Tam, 2020; Gupta, Yang, Lu, & Cao, 2019; Wei, Luh, Huang, & Chang, 2021).

This study is particularly relevant in Indonesia, where approximately 30% of the country's gross domestic product (GDP) is driven by the digital economy. A study by Google, Temasek, and Bain & Company predicts that Indonesia's digital economy will continue to grow, solidifying its position as the largest digital economy in Southeast Asia by 2030. The driving force behind this digital economy is Generation Z and Millennials, who constitute the majority of Indonesia's population as digital natives. Having grown up in the digital era with rapid technological advancements, Gen Z, defined as individuals born between 1997 and 2012, holds significant economic potential, representing a quarter of the total Asia-Pacific population by 2025 (McKinsey & Company, 2022).

Research has identified a correlation between preference for cashless transactions and respondents' socioeconomic class. Higher socioeconomic status Gen Z individuals tend to prefer cashless transactions. This behavior is attributed to factors such as limited supporting infrastructure for cashless transactions (e.g., older phone models with restricted features, poor internet connectivity), costs associated with e-wallet usage, and a lack of confidence in cashless transactions due to concerns about fraud and financial security.

Based on the aforementioned discussion, understanding the adoption of financial technology, particularly m-payment, among Gen Z as a potential consumer group is crucial. Research on m-payment adoption among Gen Z in Indonesia remains scarce. A systematic review conducted by Pramana (2021) indicates that between 2016 and 2020. only two articles on m-payment adoption in Indonesia were published in leading online academic journal databases. Therefore, this study aims to further investigate the behavioral factors influencing Gen Z's intention to adopt m-payment and the determinants of continued usage intention by integrating the Unified Theory of Acceptance and Use of Technology (UTAUT2) and the Expectation-Confirmation Model (ECM).

The objectives of this research are to examine the factors that positively influence the intention to continuously use m-payment among Gen Z and to identify the strongest predictor factors that significantly affect the sustained intention to use m-payment. This study will employ a combination of the UTAUT2 and ECM models to provide a comprehensive understanding of user behavior in adopting and maintaining the use of mobile payment systems.

2. Methods

2.1 Research design and model

This study adopts a conclusive research design using a descriptive quantitative approach to examine the post-adoption usage of mobile payments (m-payment) among Generation Z in Indonesia. The research is conducted with a cross-sectional design, utilizing an online questionnaire distributed via judgment sampling. Data analysis is performed through regression and factor analysis using Partial Least Squares Structural Equation Modeling (PLS-SEM).

The research model, adapted from Sleiman et al. (2021), extends the Expectancy-Confirmation Model (ECM) with the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). It refines the model by incorporating Confirmation and Effort Expectancy as factors influencing Performance Expectancy, with Performance Expectancy and Satisfaction acting as mediators. Twelve hypotheses are proposed to investigate the factors affecting continued use of m-payment.

2.2 Operationalization of variables

This study measures ten variables using thirty-two indicator items adapted from Sleiman et al. (2022). These indicators are based on theoretical constructs and transformed into statements forming reflective constructs. The variables are aligned with studies employing UTAUT2 and ECM models in the context of m-payment research, as detailed in Table 1.

Table 1. Operational variables

Variable	Definition	
Performance Expectancy	Performance expectancy is defined as the user's expectation or belief about how using technology will provide benefits in performing certain activities (Venkatesh et al., 2012).	
Indicator	Operational variable	Source
PE1	M-payment helps me carry out my daily financial transactions.	Sleiman, et al. (2022);
PE2	M-payment makes it easier for me to make transactions than conventional methods	Lisana (2022); Tam, et al. (2020)

PE3	M-payment allows me to transact faster than conventional methods	
PE4	Using m-payment improves my activity efficiency.	
Variable	Definition	
Effort Expectancy	Effort expectancy is defined as the degree of belief that users have regarding how easy and effort-free it is to use m-payment (Wei et al., 2021).	
Indicator	Operational variable	Source
EE1	I can quickly learn how to use m-payment.	Sleiman, et al. (2022); Lisana (2022); Tam, et al. (2020)
EE2	Instructions and features of m-payment are easy to understand.	
EE3	M-payment is easy to use.	
EE4	I can easily become proficient in using m-payment.	
Variable	Definition	
Facilitating Condition	Facilitating Condition refers to the perception of consumers regarding the resources available to support their actions in adopting technology (Wu et al., 2016).	
Indicator	Operational variable	Source
FC1	I have the necessary resources (device, internet, etc.) to use m-payment.	Sleiman, et al. (2022); Lisana (2022); Tam, et al. (2020)
FC2	I have sufficient knowledge to use m-payment.	
FC3	The m-payment app is compatible with my phone and can integrate with other apps I use for transactions.	
FC4	I can get help from others when I face difficulties using m-payment.	
Variable	Definition	
Social Influence	Social influence refers to the extent to which consumers perceive that people important to them (such as family and friends) believe they should use a particular technology (Venkatesh et al., 2012; Sleiman et al., 2021).	
Indicator	Operational variable	Source
SI1	People whose opinions I respect prefer me to use m-payment.	Sleiman, et al. (2022); Lisana (2022); Tam, et al. (2020)
SI2	People close to me encourage me to use m-payment.	
SI3	Influential figures in my life recommend using m-payment.	
Variable	Definition	
Price Value	Venkatesh et al. (2012) define price value as the cognitive trade-off consumers make between the financial costs or prices incurred and the perceived benefits of using the technology.	
Indicator	Operational variable	Source
PV1	M-payment offers reasonable transaction fees.	Sleiman, et al. (2022); Lisana (2022); Tam, et al. (2020)
PV2	The benefits provided by m-payment are greater than the costs I incur (including effort to use it).	
PV3	The costs I incur for m-payment provide benefits according to my needs.	
Variable	Definition	
Hedonic Motivation	Hedonic motivation is defined as the pleasure and material enjoyment gained from using technology (Venkatesh et al., 2012).	
Indicator	Operational variable	Source
HM1	My experience with m-payment is enjoyable.	Sleiman, et al. (2022); Lisana (2022); Tam, et al. (2020)
HM2	I enjoy the payment process with m-payment.	
HM3	Using m-payment enhances my shopping experience.	
Variable	Definition	
Habit	Habit refers to the tendency to engage in a behavior repeatedly and unconsciously, done automatically based on past actions (Liao et al., 2006).	
Indicator	Operational variable	Source
H1	Using m-payment for transactions has become a habit for me.	Sleiman, et al. (2022); Khayer et al. (2019))
H2	I am very familiar with using m-payment.	

H3	I always use m-payment whenever I have the chance.	
Variable	Definition	
Satisfaction	Satisfaction is the psychological state resulting from comparing performance with expectations, combined with the consumer's feelings about the experience of consuming a product or service (Oliver, 1981).	
Indicator	Operational variable	Source
ST1	Using m-payment generally meets my expectations for transaction ease.	Sleiman, et al. (2022); Khayer et al. (2019))
ST2	I am satisfied with the transaction process using m-payment.	
ST3	Using m-payment is very efficient for me in making transactions.	
Variable	Definition	
Confirmation	Confirmation is the process of evaluation by consumers to determine their evaluative response or satisfaction based on expectations (Bhattacherjee, 2001).	
Indicator	Operational variable	Source
CF1	My experience using m-payment is better than I expected.	Sleiman, et al. (2022); Khayer et al. (2019))
CF2	The features provided for m-payment are better than I expected.	
CF3	In general, many of my expectations have been met in using m-payment.	
Variable	Definition	
Continuance Intention	Continuance Intention refers to the situation where an individual identifies their intention for continued use of an action or goal they have undertaken (Chen et al., 2013).	
Indicator	Operational variable	Source
CI1	I will continue to use m-payment in the future.	Sleiman, et al. (2022); Khayer et al. (2019)
CI2	I plan to use m-payment for at least the next year.	
CI3	I plan to always use m-payment whenever I get the chance.	

2.3 Data collection methods

Primary data is obtained through a self-administered online questionnaire distributed via Google Forms. The questionnaire consists of structured, close-ended questions utilizing a six-point Likert scale ranging from "strongly disagree" to "strongly agree" to capture respondents' perceptions while minimizing response bias common in five-point scales (Collis & Hussey, 2013). Secondary data is collected from various sources, including journals, literature reviews, and credible official websites. These sources encompass books, reputable news outlets, academic journals, and industry reports on m-payment, providing a broader context for the research.

2.3.1 Questionnaire design and structure

A questionnaire is a structured instrument designed to collect responses relevant to research objectives (Malhotra, 2007). This study utilizes dichotomous questions for screening and a combination of multiple-choice and scaled-response questions for the main inquiries. Responses are measured using a seven-point Likert scale, where 1 represents strong disagreement or never, while 7 indicates strong agreement or very often. The questionnaire is divided into four sections, beginning with an introduction that provides information about the researcher, the study's objectives, and a brief overview of m-payment to familiarize respondents with the topic. This section also includes contact details for inquiries. Screening questions ensure that respondents meet the study's criteria, such as being between 16 and 26 years old, having used mobile payment at least once in the past three months, and residing in Indonesia. If a respondent does not meet these criteria, they are directed to the final section without completing the core questions. The core section contains statements related to the research variables, with responses measured using a six-point Likert scale. These questions are adapted from prior studies (Sleiman et al., 2022; Lisana, 2022; Tam et al., 2020) and contextualized for Indonesia. At the end of the questionnaire, respondents provide demographic information, including initials, gender, education level, occupation, and monthly expenditures.

2.3.2 Sampling method

The target respondents for this study are Generation Z individuals born between 1996 and 2012 (Dimock, 2019). This generation has been exposed to advanced technology from an early age, fostering a digitally integrated lifestyle referred to as "Always On". Mobile applications play a crucial role in their daily activities, making them a key market for digital payment adoption. Generation Z constitutes 29.94% of Indonesia's population (BPS, 2020), surpassing Millennials, who account for 25.87%. As Gen Z enters the workforce, their consumption patterns are expected to increase significantly. By 2030. ASEAN's Gen Z is projected to contribute 34% to consumption growth.Understanding the factors influencing their adoption of m-payment is essential, given their growing economic influence.

This study employs a non-probability sampling technique using purposive sampling, where only specific populations that meet the predetermined parameters are eligible to become respondents whose data will be used in the research. According to Hair et al. (2019), the minimum number of respondents can be determined by multiplying the total number of questionnaire items by five. In this study, with 32 questions, a minimum of 160 respondents is needed. However, to reduce bias in the SEM estimation, the target number of respondents was rounded to a minimum of 200 (Loehin, 1998; Kline, 2005). The target respondents for this research are Generation Z individuals residing in Indonesia. In addition to having a dominant percentage of the Generation Z population, Indonesia has also become the largest digital payment market in ASEAN.

2.4 Data analysis methods

2.4.1 Preliminary questionnaire analysis

Before the questionnaire is distributed more broadly, the questions designed by the researcher will undergo a wording test. This phase is conducted to avoid misinterpretation or refusal to answer from the respondents (Malhotra, 2007). The wording test will be conducted on 10 potential respondents, after which improvements to the questions and the questionnaire layout will be made based on suggestions and critiques from the test respondents. Once the questionnaire is confirmed to be easily understood, it will proceed to the pre-test phase.

2.4.2 Pre-test validity and reliability testing

The pre-test will be conducted with at least 30 respondents who meet the research criteria, as SPSS data processing requires a minimum of 30 respondents. The pre-test aims to assess the consistency of the questions before they are distributed more widely. The validity of the questions in the questionnaire will be evaluated based on the Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) and Component Matrix values. According to Malhotra (2007), each question item is considered valid if the KMO value is greater than or equal to 0.5 and the Component Matrix value is also above 0.5. Meanwhile, reliability is measured using Cronbach's Alpha, with a recommended value of ≥0.60 to be considered reliable (Malhotra, 2007).

2.4.3 Frequency distribution and descriptive analysis

In frequency distribution analysis, the data will be grouped into categories so that the frequency or number of data points in each category can be identified (Suharyadi & Purwanto, 2003). This step is taken to simplify the data grouping process for the respondents. Meanwhile, in descriptive analysis, the respondents' answers will be categorized into several intervals, and the maximum, minimum, standard deviation, and average values will be computed (Malhotra, 2007).

2.4.4 Partial least squares Structural Equation Modelling (PLS-SEM) analysis

The use of Partial Least Squares Structural Equation Modelling (PLS-SEM) has increased in recent years across various research fields (Hair & Alamer, 2022). PLS-SEM estimates a partial model structure defined through path diagrams, combining principal component analysis with least squares regression. A path model is a diagram used to visually display hypotheses and illustrate the relationships between latent variables when SEM is applied (Hair et al., 2021). PLS-SEM has become an alternative to Covariance-based Structural Equation Modelling (CB-SEM).

The choice of PLS-SEM is deemed most appropriate for this study due to several reasons. These include the study's focus on testing a theoretical framework from a predictive perspective (predicting the strongest factors influencing sustainable usage intention among Gen Z), the complex structural model with many constructs and indicators, and the goal to understand the increasing complexity by exploring theoretical expansions of widely-used theories related to m-payment (Hair et al., 2019).

In marketing literature published by Hair et al. (2019), PLS-SEM is said to enable researchers to model and estimate causal relationships in complex models for latent variables (represented as circles) and measurement models for observed variables (represented as rectangles). Latent variables represent phenomena that cannot be directly observed or measured, such as perceptions, attitudes, and intentions, while observed variables are those directly measurable by the researcher, such as responses in questionnaires, which represent latent variables in statistical models. PLS-SEM estimates the relationships between latent variables and further examines how well the model explains the constructs being studied. As Hair et al. (2019) suggest, the increasing popularity of PLS-SEM is primarily due to its ability to estimate highly complex models with data requirements that are easier to obtain.

One of the most common applications of PLS-SEM is for estimating technology acceptance models (TAM), which predict factors that influence the adoption or acceptance of a technology (Ringle, 2021). This model is similar to the research conducted in this study, which examines factors influencing m-payment adoption intentions, combining the UTAUT2 and ECM models. Research linking initial technology adoption with the likelihood of continued use remains scarce in this field (Sleiman, 2022). Therefore, PLS-SEM is deemed suitable for this study, considering that PLS-SEM employs a weighted composite approach of indicator variables, allowing for looser exploratory assumptions compared to the strong assumptions of CB-SEM's confirmatory approach. Furthermore, SMART PLS 3 software will be used to analyze the data with the SEM-PLS method. The SEM analysis in this study is divided into two stages: structural model analysis and measurement model analysis.

2.4.5 Measurement model analysis

The measurement model analysis (or outer model) is conducted to determine whether the observed variables adequately measure the latent variables in the study. The variables in the model have a reflective nature as manifestations of the research constructs. According to Hair et al. (2021), testing reflective models involves evaluating internal consistency, discriminant validity, and convergent validity. Internal consistency is assessed for latent variables using Cronbach's Alpha and Composite Reliability values, with a minimum value of 0.6 (Hair et al., 2021).

Convergent validity examines how well the observed variables (indicators) correlate with the latent variables (Wang et al., 2015). The minimum factor loading threshold used is 0.5 (Simamora & Saputra, 2023; Ghozali & Laten, 2006), and the same value applies for the average variance extracted (AVE). These tests ensure that the variables are considered reliable. Additionally, the researcher will evaluate cross-loadings and Fornell-Larcker criteria for validity testing. The minimum cross-loading criterion is that the outer loading between one item and its own item should be higher than the loading with other items.

2.4.6 Structural model analysis

In this stage, testing is conducted to analyze the structural model and assess the model's feasibility. During testing, the researcher examines any collinearity issues by looking at the inner Variance Inflation Factor (VIF) values, which should meet a minimum requirement of ≤ 0.5. The collinearity test ensures there is no intercorrelation among the variables (Hair et al., 2021).

The researcher also evaluates the path coefficient values to examine the relationships within the structural model. The path coefficient should have a minimum value of +1 (positive effect) or -1 (negative effect). When the path coefficient approaches 0. it indicates a weakening relationship. Significance for each relationship is assessed based on the T-value, as this study uses a one-tailed test with a significance level of 5%. Therefore, the critical value is set at 1.65 (Hair et al., 2021).

Furthermore, the researcher assesses the model's feasibility by evaluating its predictive capabilities using the coefficients of determination (R^2) and the effect size (F^2) analysis. The R^2 value measures the predictive accuracy of the model and the square correlation between the actual and predicted values of endogenous constructs (Hair et al., 2021). Variables with values closer to 1 are considered to have stronger predictive power. The F^2 test is used to assess the relative influence of exogenous variables on endogenous variables in the model. The guideline for interpreting F^2 values is that 0.02 indicates a small effect, while values of 0.15 and 0.35 indicate medium and large effects, respectively (Selya et al., 2012). Lastly, the researcher conducts a Q^2 test to evaluate the predictive relevance of the model using out-of-sample data. This test ensures that the model has predictive relevance, with a value above zero being categorized as good.

3. Results and Discussion

3.1 Research implementation

The research was conducted in three stages: wording test, pre-test, and main-test. The wording test was conducted online with 10 respondents who met the previously established criteria. The purpose of the wording test was to ensure the selection of appropriate wording and language usage in the questionnaire, so respondents could understand the questions clearly and reduce any ambiguity. In the wording test, the researcher tested it on 5 respondents. Feedback and suggestions regarding the questionnaire were provided by the respondents and were applied to revise the questionnaire accordingly.

The next stage was the pre-test. The pre-test aimed to ensure the validity and reliability of the indicators and variables used. This test was conducted by distributing the questionnaire online through social media platforms such as Line and Instagram, with responses obtained from 30 respondents. The data collected from this pre-test were analyzed using SMART PLS 3 software.

The final stage was the main-test, which was implemented by distributing the questionnaire via social media platforms including Instagram, Telegram, Tiktok, and Whatsapp. The questionnaire was distributed through broadcast messages to various online communities, private text messages, and posts on popular social media platforms used by

Generation Z, such as Instagram and Tiktok. Data collection was carried out over a period of 15 days, from March 14, 2023, to March 28, 2023. A total of 334 responses were obtained, with 330 valid and screened responses. The data from the main-test will be processed using structural model testing with SMART PLS 3 software.

3.2 Wording test

The wording test was conducted online with 10 respondents who met the predetermined criteria. The primary objective of this test was to ensure that the language and wording used in the questionnaire were appropriate, so that the respondents would clearly understand the questions, thus minimizing ambiguity. During this stage, the researcher tested the questionnaire with 5 respondents. The suggestions provided by the respondents, which were related to word choice, sentence structure, effectiveness, clarity, and interpretation of the intended meaning, were considered. The results of the wording test were used as the basis for making revisions to the questionnaire, ensuring that it was more comprehensible and better aligned with the respondents' understanding.

3.3 Pre-test validity and reliability testing

Before conducting Structural Equation Modeling (SEM) analysis, the researcher performed validity and reliability testing for the pre-test using SMART PLS 3 software to process the data obtained from 30 respondents. Through the pre-test, if any indicator was found to be invalid or unreliable, it would be revised or removed from the questionnaire. Below are the results of the pre-test validity and reliability testing that was carried out.

3.4 Pre-test validity test

The researcher conducted the pre-test validity test using data from 30 respondents who had passed the screening process and met the established criteria. The pre-test validity was assessed by examining the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy, Bartlett's Test of Sphericity, and the Component Matrix. Each item in the variables is considered valid if the KMO value is above 0.5, the Bartlett's Test of Sphericity has a significance value below 0.05, and both the anti-image and component matrix values are ≥ 0.5. The following table presents the results of the pre-test validity test, which were processed using SPSS version 22.

Table 2. Validity test result

Variable	Indicator	KMO	Anti Image	Component Matrix	Bartlett's Test	Validity
Performance Expectancy (PE)	PE1	0.812	0.866	0.772	0.000	VALID
	PE2		0.800	0.880		VALID
	PE3		0.784	0.867		VALID
	PE4		0.817	0.871		VALID
Effort Expectancy (EE)	EE1	0.814	0.812	0.864	0.000	VALID
	EE2		0.814	0.902		VALID
	EE3		0.814	0.862		VALID
	EE4		0.816	0.901		VALID
Facilitating Condition (FC)	FC1	0.768	0.798	0.795	0.000	VALID
	FC2		0.747	0.853		VALID
	FC3		0.738	0.868		VALID
	FC4		0.840	0.638		VALID
Social Influence (SI)	SI1	0.740	0.717	0.905	0.000	VALID
	SI2		0.758	0.888		VALID
	SI3		0.749	0.891		VALID
Price Value (PV)	PV1	0.729	0.732	0.872	0.000	VALID
	PV2		0.713	0.882		VALID

	PV3		0.743	0.867		VALID
Hedonic Motivation (HM)	HM1	0.704	0.665	0.904	0.000	VALID
	HM2		0.669	0.901		VALID
	HM3		0.825	0.826		VALID
Habit (H)	H1	0.711	0.674	0.891	0.000	VALID
	H2		0.700	0.872		VALID
	H3		0.776	0.834		VALID
Satisfaction (ST)	ST1	0.742	0.789	0.892	0.000	VALID
	ST2		0.704	0.925		VALID
	ST3		0.743	0.908		VALID
Confirmation (CF)	CF1	0.753	0.768	0.909	0.000	VALID
	CF2		0.758	0.912		VALID
	CF3		0.733	0.921		VALID
Continuance Intention (CI)	CI1	0.649	0.599	0.924	0.000	VALID
	CI2		0.622	0.894		VALID
	CI3		0.824	0.770		VALID

The reliability test results in the table above show that all variables, including PE, EE, FC, SI, PV, HM, H, ST, CF, and CI, have Cronbach's Alpha values above 0.6, indicating that the variables used in this study are reliable. This suggests that the variables are consistent and can be used for further analysis in the main test.

3.5 Respondent profile

The research questionnaire was distributed online through social media posts, online community groups, and direct messaging via platforms like WhatsApp, Tiktok, and Instagram, collecting a total of 334 respondents. Out of the collected responses, 330 respondents met the established criteria and passed the screening questions. The criteria for inclusion were being within the age range of 16 to 26 years, having used mobile payment services (such as OVO, Gopay, Shopeepay, etc.) at least once in the past three months, and residing in Indonesia. Afterward, the researcher analyzed the respondent profiles to provide further insights into the research.

The majority of the respondents were female. Out of the 330 respondents, 240 were female (72.7%) and 90 were male (27.3%). In terms of educational background, most respondents had completed or were currently pursuing a bachelor's degree or diploma (77%), followed by those with a high school diploma or equivalent (21.8%). Consistent with their educational background, most respondents were students or university undergraduates (86.5%). Geographically, the majority of respondents resided on the island of Java (79%). Regarding monthly expenditures, nearly half of the respondents reported spending below IDR 1,000.000 (47.58%), while the second-largest group (40.61%) spent between IDR 1,000.001 and IDR 2,999,999 per month.

Table 3. E-wallet used by respondents

Total respondent	E-wallet	Percentage of users based on the total respondents
330	OVO	51.5%
	DANA	58.8%
	Shopeepay	83.3%
	Gopay	69.1%
	LinkAja	10.3%

3.6 Descriptive analysis

Descriptive analysis was carried out to provide a comprehensive overview of the main test data based on 330 responses from the questionnaires obtained from the respondents. This analysis aims to classify the average answers for each indicator of the questionnaire. The measures employed in the descriptive analysis include the number of respondents, the minimum value, the maximum value, the mean per indicator, and the total mean across all indicators. The descriptive statistics help to provide insight into the overall perception of respondents regarding various aspects of mobile payment (m-payment).

3.6.1 Descriptive analysis of performance expectancy (pe) variables

The total mean for Performance Expectancy (PE) was found to be 6.2, which indicates that, on average, the respondents had positive expectations regarding the performance of m-payment. This suggests that most respondents believe m-payment improves their ability to carry out financial transactions in their daily lives. In particular, the highest mean value was observed for indicator PE 1, which shows that respondents highly agree that m-payment helps with everyday financial transactions. This could reflect the increasing trust and reliance on m-payment systems for routine financial activities, such as bill payments or shopping.

3.6.2 Descriptive analysis of effort expectancy (ee) variables

For Effort Expectancy (EE), the total mean was 6.37, signifying that, on average, the respondents found m-payment to be easy to use and requiring little effort. This reflects a high level of satisfaction with the simplicity of mobile payment systems. Indicator EE 3 recorded the highest mean value, indicating that the majority of respondents agreed that m-payment is indeed user-friendly and easy to navigate. This result underscores the importance of having an intuitive and simple interface in mobile payment applications to encourage adoption among users, especially among those who might not be highly tech-savvy.

3.6.3 Descriptive analysis of facilitating condition (fc) variables

The total mean for Facilitating Condition (FC) was 6.22, indicating that the respondents generally agreed that they have the necessary resources to adopt and use m-payment. The resources refer to things like having access to mobile devices, stable internet connections, and knowledge of how to use mobile payment systems. The highest mean value was observed in indicator FC 1, suggesting that most respondents have the required devices and internet connection to make full use of m-payment systems. This finding highlights the role of external factors, such as infrastructure and access to technology, in the widespread adoption of digital payment systems.

3.6.4 Descriptive analysis of social influence (si) variables

The total mean for Social Influence (SI) was 5.19, indicating that, on average, respondents were somewhat influenced by those around them, such as friends, family, or colleagues, in deciding to use m-payment systems. The lowest value came from indicator SI 3, which indicates that respondents did not feel strongly that the key figures influencing their behavior were actively recommending or promoting the use of m-payment. On the other hand, the highest value came from SI 2, suggesting that respondents felt that people close to them, such as family or friends, played a significant role in encouraging them to use m-payment. This highlights the role of social networks and peer influence in shaping technological adoption.

3.6.5 Descriptive analysis of price value (pv) variables

The total mean for Price Value (PV) was 5.80. showing that, on average, respondents agreed that the value or benefits of m-payment outweigh the costs associated with using these services. The highest value was found in indicator PV 3, suggesting that respondents felt that the costs associated with using m-payment were reasonable relative to the benefits it offers, such as convenience and time-saving. The lowest value was found in PV 1, indicating that some respondents were less convinced that m-payment provides transaction fees that are reasonable. This finding suggests that there may be concerns about the fees or charges associated with mobile payments, particularly for small transactions or for users who are sensitive to costs.

3.6.6 Descriptive analysis of hedonic motivation (hm) variables

For Hedonic Motivation (HM), the total mean was 6.27, suggesting that, on average, respondents derived some enjoyment or pleasure from using m-payment. This indicates that respondents did not only use m-payment for practical reasons, but also found the experience of using it enjoyable. Indicator HM 2 had the highest mean value, which indicates that respondents particularly liked the process of making payments using m-payment. This could be attributed to the ease, speed, and convenience of using mobile payment systems, which can make transactions more enjoyable and less stressful compared to traditional payment methods.

3.6.7 Descriptive analysis of habit (h) variables

The total mean for Habit (H) was 6.03, indicating that respondents, on average, had formed a habit of using m-payment for their transactions. This suggests that mobile payments have become a regular part of their financial behavior. The lowest mean value was seen in indicator H 1, indicating that some respondents were still in the process of adopting m-payment as a consistent habit for their everyday transactions. On the other hand, indicator H 2 had the highest mean, suggesting that the majority of respondents had already become quite familiar with m-payment, to the point where it was a habitual part of their daily routines.

3.6.8 Descriptive analysis of satisfaction (st) variables

For Satisfaction (ST), the total mean was 6.21, showing that respondents were generally satisfied with their experience using m-payment. This indicates that respondents had positive feelings regarding the service and functionality of m-payment platforms. Indicator ST 3 had the highest mean, which suggests that respondents particularly appreciated the efficiency of m-payment for transactions. This could reflect the growing satisfaction with the speed and convenience of completing transactions via mobile payment systems, which are often faster and more convenient than traditional methods.

3.6.9 Descriptive analysis of confirmation (cf) variables

The total mean for Confirmation (CF) was 5.98, suggesting that, on average, respondents viewed the experience of using m-payment as meeting or exceeding their expectations. This shows that respondents generally found m-payment to be aligned with their initial beliefs about its usefulness. The highest mean values were recorded in indicators CF 1 and CF 3, indicating that respondents felt that their experiences with m-payment had exceeded their expectations and that the service had fulfilled many of their initial expectations. This finding emphasizes the importance of confirming users' expectations to encourage continued use and loyalty toward m-payment systems.

3.6.10 Descriptive analysis of continuance intention (ci) variables

Finally, the total mean for Continuance Intention (CI) was 6.14, suggesting that, on average, respondents intended to continue using m-payment in the future. This indicates a high likelihood of long-term adoption and usage of m-payment services among respondents. Indicator CI 2 had the highest mean, which suggests that the respondents had plans to continue using m-payment at least for the next year. This shows the potential for sustained usage of mobile payment systems, driven by the positive experiences respondents had and their intention to keep using the service for the foreseeable future.

3.7 Measurement model analysis

The measurement model analysis is conducted to assess how well the observed variables measure the latent variables in the study. This is done by evaluating the feasibility of the model through reliability testing and construct validity testing in the outer model. The variables in the model are reflective as representations of the constructs in the research. These variables include Performance Expectancy, Effort Expectancy, Facilitating Condition, Social Influence, Price Value, Confirmation, Satisfaction, and Continuance Intention. Therefore, the testing follows the steps outlined in the previous chapter.

In this section, the researcher tests internal consistency for the latent variables by examining the results of Cronbach's Alpha and Composite Reliability, with a minimum value of 0.6 (Hair et al., 2021). This test is used to determine the reliability of the data in the measurement model. Below is the table presenting the results of the internal consistency test from the Smart PLS output.

Table 4. Internal consistency test tresult

Construct	Internal Consistency		Indikator	Convergent Validity	
	Cronbach's Alpha > 0.6	Composite Reliability > 0.6		Outer Loading's ≥ 0.6	AVE ≥ 0.5
Performance Expectancy	0.870	0.911	PE1	0.786	0.720
			PE2	0.878	
			PE3	0.859	
			PE4	0.868	
Effort Expectancy	0.905	0.934	EE1	0.862	0.779
			EE2	0.895	
			EE3	0.864	
			EE4	0.909	
Social Influence	0.875	0.923	SI1	0.907	0.800
			SI2	0.880	
			SI3	0.896	
Facilitating Condition	0.799	0.869	FC1	0.806	0.629
			FC2	0.870	
			FC3	0.865	
			FC4	0.600	
Hedonic Motivation	0.850	0.909	HM1	0.902	0.770
			HM2	0.912	
			HM3	0.814	
Price Value	0.845	0.906	PV1	0.868	0.763
			PV2	0.887	
			PV3	0.866	
Habit	0.833	0.899	H1	0.877	0.748
			H2	0.856	
			H3	0.861	
Satisfaction	0.894	0.934	ST1	0.880	0.825
			ST2	0.920	
			ST3	0.911	
Confirmation	0.901	0.938	CF1	0.913	0.835
			CF2	0.904	
			CF3	0.922	
Continuance Intention	0.829	0.897	CI1	0.906	0.745
			CI2	0.864	
			CI3	0.817	

Based on the internal consistency testing results using the SmartPLS application, it is shown that all the variables studied meet the recommended reliability test threshold, which is above 0.6 for both Composite Reliability and Cronbach's Alpha (Table 4). Therefore, the data is concluded to be reliable, and the researcher decided to proceed to the next phase of the study.

Convergent validity reflects how well measured variables (indicators) correlate with latent variables (Wang et al., 2015). The minimum threshold for factor loading is 0.5 and for average variance extracted (AVE), it is also 0.5. Referring to Table 4.19, all the study variables meet the minimum values for both outer loading and AVE, thus being considered valid in terms of convergent validity. The next validity test in the measurement model is carried out by evaluating cross-loadings and the Fornell-Larcker criterion. The minimum criterion for cross-loadings is that the outer loading for one item should be higher when compared to the loading of other items.

3.8 Structural Model Analysis

Once all the variables in the measurement model are concluded to be reliable and valid, the next step is to conduct structural model analysis. Below are the steps for testing the model. Collinearity testing is conducted by evaluating the values of VIF with the maximum value criteria. All indicators have met the criteria. Therefore, it can be concluded that there is no multicollinearity issue in this study.

A commonly performed structural model test is the coefficients of determination (R^2) and Effect Size (F^2) tests. The R^2 test is conducted to measure the predictive ability of the model and as the square correlation between the actual values of the endogenous construct and the predicted values (Hair et al., 2021). In the range from 0 to 1, variables with values closer to 1 are said to have higher predictive power within the sample. Meanwhile, adjusted R^2 is used as a criterion to avoid bias in complex models because it is modified according to the number of exogenous constructs relative to the sample size. This allows the researcher to determine if adding new variables to the model will improve model fit. The change from R^2 to adjusted R^2 for endogenous variables indicates the relative influence of exogenous variables in the model (Hair et al., 2021). The F^2 test is used to determine the relative influence of exogenous variables on endogenous variables in the model. Researchers also examine the path coefficient values to estimate the influence of an endogenous variable from a particular exogenous variable, while holding other variables constant. Negative path coefficient values indicate a negative influence, while positive values indicate a positive influence. The closer the path coefficient value is to zero, the weaker the relationship is.

3.8.1 Predictive Relevance (Q^2) Test

For the Q^2 test, the researcher used the blindfolding procedure in SmartPLS to assess whether the model has predictive relevance. As shown in Table 4.19, the Q^2 values for the endogenous variables Continuance Intention (0.528), Performance Expectancy (0.355), and Satisfaction (0.359) are all greater than 0. This means that the model and its latent variables have predictive relevance, suggesting that the model can predict values for these constructs in future samples.

3.8.2 Significance of Path Coefficients (Direct Effects) and Mediation Effect Analysis

Direct and indirect effect testing was performed using bootstrapping with 5,000 subsamples to improve the accuracy of the final results (Hair et al., 2021). The bootstrapping procedure was conducted at a significance level of 0.100 and using a one-tailed test with a significance level of 0.05, where the critical Z-value was 1.645. If the Z or T-value is greater than 1.645, the hypothesis is rejected. The P-value must also be less than 0.100 for the results to be considered statistically significant.

Table 5. Bootstrap result

Path Coefficient		Sample Mean	Standard Deviation	T-value	P-value	Conclusion
Performance Expectancy						
Confirmation -> Performance Expectancy	0.323	0.324	0.057	5.687	0.000	Significant
Effort Expectancy -> Performance Expectancy	0.457	0.453	0.064	7.119	0.000	Significant
Satisfaction						
Performance Expectancy -> Satisfaction	0.668	0.664	0.055	12.217	0.000	Significant
Continuance Intention						
Facilitating Condition -> Continuance Intention	0.227	0.226	0.611	3.710	0.015	Significant
Habit -> Continuance Intention	0.840	0.841	0.020	41.579	0.000	Significant
Hedonic Motivation -> Continuance Intention	0.200	0.204	0.081	2.473	0.007	Significant
Price Value -> Continuance Intention	-0.006	-0.006	0.061	0.106	0.458	Not Significant
Satisfaction -> Continuance Intention	0.356	0.353	0.084	4.231	0.000	Significant
Social Influence -> Continuance Intention	0.074	0.073	0.051	1.451	0.073	Not Significant
Mediating Variable						
Confirmation -> Performance Expectancy -> Satisfaction	-	0.216	0.046	5.517	0.000	Significant
Effort Expectancy -> Performance Expectancy -> Satisfaction	-	0.305	0.055	5.573	0.000	Significant
Performance Expectancy -> Satisfaction -> Continuance Intention	-	0.235	0.062	3.851	0.038	Significant

The bootstrapping results, as shown in Table 5, indicate that several direct effects are significant, including the relationship between Confirmation and Performance Expectancy, Effort Expectancy and Performance Expectancy, and Satisfaction and Continuance Intention. The indirect effects, such as Performance Expectancy mediating the relationship between Confirmation and Satisfaction, and Effort Expectancy mediating the relationship between Performance Expectancy and Satisfaction, are also significant.

3.9 Discussion

This study delves into the key factors influencing the sustained use of mobile payments among Gen Z, offering new insights into the user experience while aligning with existing technology adoption theories. The findings highlight the significant role of confirmation and effort expectancy in shaping user satisfaction and their intention to continue using mobile payment services.

The concept of confirmation, refers to the validation of users' expectations after actual use of the technology. When users' expectations are met, satisfaction follows, which enhances their likelihood of continued usage. This aligns with prior research (Hsu et al., 2006), which links confirmation with post-consumption satisfaction. In the case of mobile payments, this means that when the service meets users' expectations in terms of functionality and ease of use, satisfaction rises, and users are more likely to continue using the service. The findings of this study mirror these trends, emphasizing the importance of meeting or exceeding users' expectations to foster long-term engagement with the technology.

Effort expectancy, which refers to how easy users perceive the technology to be, plays a pivotal role in performance expectancy—the perceived benefits users anticipate from using mobile payments. Since Gen Z is highly familiar with digital technologies, they have high expectations for mobile payments in terms of ease of use and performance. The findings confirm that the easier the technology is to use, the more likely it is that users will perceive it as beneficial and continue using it. This echoes the findings of Cho (2016), who highlight the crucial role of ease of use in driving satisfaction and sustained use, especially among younger users who are accustomed to seamless digital experiences.

The relationship between effort expectancy and performance expectancy is particularly strong in this context. Gen Z users, having grown up in a highly digitalized world, expect mobile payment systems to be intuitive and efficient. Any friction or complexity in using these systems may lead to dissatisfaction, making it crucial for mobile payment providers to prioritize usability and ensure that their platforms are optimized for a smooth, hassle-free experience. The findings reinforce the idea that mobile payments must meet these high expectations to retain users over time.

Performance expectancy directly influences user satisfaction, and our study reinforces this by showing that users who perceive mobile payments as efficient, secure, and easy to use are more likely to remain satisfied and continue using the service. This aligns with previous research (Tam et al., 2020; Sleiman et al., 2022), which also found that perceived performance benefits drive user satisfaction and continued use. Moreover, performance expectancy mediates the relationship between confirmation and satisfaction, meaning that when users' expectations are confirmed, their satisfaction is further amplified by the perceived performance benefits of the service.

Satisfaction is a central factor in the adoption and continued use of mobile payments. Our study shows that satisfaction not only directly impacts continuance intention but also mediates the relationship between other factors like performance expectancy and continued use. Essentially, satisfied users are more likely to continue using the service, regardless of other external factors. This emphasizes the importance of creating a positive, fulfilling user experience that leads to sustained engagement.

Interestingly, social influence, a factor that often plays a significant role in technology adoption among other generations, was found to have little impact on the continued use of mobile payments for Gen Z. This could be because Gen Z is more independent in their technology choices, often relying on personal experience and recommendations rather than social pressure or peer influence. This finding challenges the traditional assumption that social factors are the main drivers of technology adoption, particularly in younger generations.

On the other hand, facilitating conditions, such as access to necessary technology and knowledge, were found to positively influence continuance intention. Gen Z values compatibility and ease of integration with existing devices or platforms. Therefore, providing a user-friendly, easily accessible service is crucial for encouraging long-term use. Mobile payment platforms that ensure easy access and minimal technical barriers are more likely to retain Gen Z users.

Another important factor influencing continued use is hedonic motivation, which relates to the enjoyment users derive from interacting with the technology. For Gen Z, this means that mobile payments should not only be functional but also engaging and entertaining. Features like gamification, rewards, or interactive elements can enhance user satisfaction and increase the likelihood of continued use. This reflects Gen Z's preference for enjoyable and interactive experiences, rather than merely utilitarian ones.

Finally, habit emerged as a strong predictor of continued use. Once Gen Z users become accustomed to using mobile payments, their likelihood of continuing to use the service increases significantly. Habitual use makes users more likely to integrate mobile payments into their daily lives, reducing the need for external motivations or incentives. This reinforces the idea that mobile payment services must be seamless and convenient enough to become ingrained in users' routines, ensuring long-term adoption.

In summary, the study highlights several key factors that influence the continued use of mobile payments among Gen Z. Satisfaction, habit, facilitating conditions, and hedonic motivation were found to directly impact users' intention to continue using mobile payments. Meanwhile, performance expectancy and satisfaction play mediating roles in the relationship between other factors and continued use. These findings provide valuable insights for understanding how to design mobile payment systems that cater to the needs and preferences of Gen Z, ensuring both high adoption rates and long-term user engagement.

4. Conclusions

Effort Expectancy and Confirmation play an exogenous role in explaining Performance Expectancy. The accuracy of these two exogenous variables in explaining the endogenous variable is 50.6%, indicating a moderate level of explanation. Both variables are found to positively and significantly influence Performance Expectancy. Based on these findings, mobile payment service providers should continue to consider the ease of use of the application (Effort Expectancy) in developing their services. A practical example of this would be creating a user-friendly UI/UX, such as using simple language, ensuring accessibility across various devices, and implementing intuitive and helpful visual elements, among others. On the other hand, Confirmation also plays a role in defining the Performance Experience. This implies that providers need to develop features that align with user expectations. Conducting regular market research is essential to continually understand and meet user needs and desires in a dynamic market competition.

Generation Z is known as the "Always On" generation, always connected online through social media and various services. However, while Social Influence was found to significantly affect the adoption of m-payment usage among Gen Z (Lisana, 2022), it did not show a significant impact on the intention for continued use. This suggests that variables influential in the adoption stage may not necessarily have the same effect on continued usage. Meanwhile, the number of Gen Z users and their social media activity is substantial and expected to grow over the next five years (Insider Intelligence, 2023). Despite the lack of significant impact, Social Influence is not entirely irrelevant and should still be considered in business decision-making, particularly when targeting Gen Z consumers. One approach could be using social influence to share information related to variables that significantly affect continued usage intention. Mobile payment providers can develop structured campaign strategies to ensure that existing users are informed about the ongoing benefits and new features that meet their needs and desires.

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