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Understanding Continued BNPL Usage Behavior in E-Commerce: Extended UTAUT2 with Usage Intention Mediation

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Abstract
Purpose: This study aims to utilize an enhanced UTAUT2 model to examine the determinants influencing Indonesian customers' intentions and behaviors regarding the continued use of BNPL e-commerce services.
Research/methodology: A quantitative cross-sectional survey was conducted with 450 users of BNPL services Indonesian e-commerce platforms, and the data were analyzed using structural equation modeling to assess direct and indirect relationships.
Results: Performance expectancy, effort expectancy, trust, and habit significantly influenced continued usage, whereas perceived benefits and risks showed no significant impact among experienced digital users.
Conclusions: Performance Expectancy, Effort Expectancy, and Trust are important drivers of the continued use of Buy Now Pay Later (BNPL) e-commerce services among Indonesian users, according to this study, which also shows that habit is the most important predictor of actual usage behavior.
Limitations: The geographic breadth is limited to Indonesia, with possible selection bias toward current users, the sample focus on younger demographics impacts generalizability, and the cross-sectional methodology restricts causal inference.
Contribution: This study contributes to fintech adoption theory by demonstrating the theoretical redundancy of traditional risk-benefit constructs in mature digital user contexts and emphasizing habit formation over initial adoption factors.

Keywords: : *BNPL, Continued Usage Behavior, Continued Usage Intention, E-Commerce, UTAUT2*

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1. Introduction

The rapid growth of financial technology (fintech) has revolutionized payment systems globally, with Buy Now Pay Later (BNPL) services emerging as a significant disruptor in Indonesia's digital payment landscape. Pay Later services, which allow consumers to purchase goods and services with deferred payment options, have experienced exponential growth since their introduction in 2019, particularly accelerated by the COVID-19 pandemic's shift toward digital commerce (Kredivo, 2024). According to recent data, Pay Later services in Indonesia demonstrated remarkable growth of 47.92% year-over-year in 2024, substantially outpacing the traditional credit card growth of 10.92% (OJK, 2024). Among these services, one of the BNPL services in e-commerce has emerged as the dominant player, capturing the largest market share and achieving top-of-mind awareness among Indonesian consumers (Muhamad, 2023).

However, this rapid growth faces significant challenges in the country. Consumer trust remains fragile due to data security breaches and privacy concerns, with notable incidents affecting major platforms, including a BNPL service in e-commerce in 2021 and 2023. High interest rates, ranging from 2.25% to 4% per month, which are substantially higher than those of traditional credit cards, have led to consumer dissatisfaction and debt accumulation issues (Kredivo, 2024). The Financial Services Authority (OJK) reported 160 complaints related to one of the BNPL services in e-commerce alone from January to July 2024, primarily concerning information system services. Additionally, regulatory oversight remains insufficient, creating uncertainty regarding consumer protection and industry standards in the metaverse.

Despite these challenges, the factors influencing the continued usage intention and behavior of Pay Later services remain underexplored, particularly in Indonesia. While existing research has examined initial adoption factors using technology acceptance models, there is a critical gap in understanding how trust, perceived risk, and regulatory concerns affect sustained usage behavior in challenging environments. Therefore, this study adds the variables of perceived benefit and perceived risk, as these have been proven in previous Indonesian fintech studies, where technological readiness factors such as inconvenience and insecurity have been shown to be important in determining user acceptance and behavioral intentions in digital financial services (Hermanto, Prasetio, & Ariyanti, 2023). Using an expanded Unified Theory of Acceptance and Use of Technology (UTAUT) model and adding the variables of trust, perceived risk, and perceived benefits, this study fills this knowledge gap by thoroughly examining the variables influencing Indonesian Pay Later users' intention to continue using the service and their behavior. This study aims to provide strategic insights into service providers, regulatory bodies, and consumers navigating the complexities of this rapidly evolving and challenging fintech landscape.

2. Literature Review

2.1 Literature Review

2.1.1 UTAUT 2

The Unified Theory of Acceptance and Use of Technology (UTAUT) was developed in 2003 by Venkatesh et al. to describe how people accept and use technology. It integrates eight contemporary models of technology adoption, including the Innovation Diffusion Theory, the Theory of Planned Behavior, the Technology Acceptance Model, and the Theory of Reasoned Action (Penney, Agyei, Boadi, Abrokwah, & Ofori-Boafo, 2021). Several significant models helped develop the theoretical underpinnings: Ajzen's Theory of Planned Behavior (1991) added perceived behavioral control (Ajzen, 1991). Davis's Technology Acceptance Model (1989) introduced perceived usefulness and ease of use (Davis, 1989). Fishbein and Ajzen's Theory of Reasoned Action (1975) concentrated on attitudes and subjective norms, and Rogers' Innovation Diffusion Theory (1962) identified five characteristics affecting innovation adoption (Rogers, 1962): three components were added to the original four in UTAUT 2, which was created in 2012 and expanded the model for customer situations (Penney et al., 2021).

Venkatesh, Morris, Davis, and Davis (2003) developed the UTAUT framework, which is made up of four essential parts. Performance expectancy" refers to a person's conviction that implementing technology will maximize their output. The apparent ease of use of the technology is known as "effort expectancy."Social influence describes how a person's attitude toward embracing technology is influenced by their social surroundings and the opinions of others. According to Venkatesh et al. (2003), "facilitating conditions" refer to the organizational support and infrastructure that make it possible for technology to be implemented successfully (Venkatesh et al., 2003). Venkatesh, Thong, and Xu (2012) developed the UTAUT 2 model, which incorporates three additional aspects to offer a more comprehensive view of technology adoption. Price value describes the process by which consumers weigh advantages over disadvantages. The internalized and impulsive use of technology brought on by regular repetition is referred to as a habit. The affective component of users' pleasure and emotional fulfillment while interacting with technology is known as hedonic motivation (Venkatesh et al., 2012).

2.1.2 Trust, Perceived Benefits, and Perceived Risk

Perceived Benefits are individual perceptions of the advantages or positive outcomes expected from using products or services. In technology adoption, customers are more likely to adopt technology when they believe it offers convenience, cost savings, efficiency improvements, or other benefits that match their needs (Raj, Jasrotia, & Rai, 2024). Unlike Performance Expectancy, which focuses specifically on performance improvement, Perceived Benefits encompass broader advantages, including personal convenience and general utility. Perceived Risk refers to customers' subjective evaluation of the potential negative consequences or uncertainties associated with using services. This includes concerns regarding data security, privacy, financial implications, and the reliability of service providers. Higher perceived risk reduces customers' likelihood of service adoption, as it negatively affects their trust, confidence, and willingness to use the technology (Raj et al., 2024). Trust is a positive belief in the actions and decisions of others and the reliability of technology (McAllister, 1995). In payment systems, trust is important for reducing perceived risk and supporting technology adoption (Kilani, Kakeesh, Al-Weshah, & Al-Debei, 2023).

2.1.3 Continued Usage Intention and Behavior

Continued usage intention refers to an individual's intention to continue using technology after initial adoption, which is influenced by satisfaction, trust, and perceived value. Continued usage behavior refers to the repeated use of technology, reflecting the success of long-term adoption (Kilani et al., 2023).

2.2 Hypothesis Development

The rapid growth of financial technology has introduced innovative payment solutions, particularly Pay Later services that offer installment payment convenience. A leading BNPL e-commerce service and prominent Pay Later service in Indonesia experienced significant adoption during the COVID-19 pandemic because of its flexibility and accessible credit offerings. However, these services face substantial challenges, including concerns about personal data security, financial risks from high-interest rates, and overdue payment penalties. According to the Indonesian Financial Services Authority (OJK) report in 2024, there were 160 complaints related to a leading e-commerce BNPL service, indicating the need for enhanced customer trust and risk mitigation strategies.

The theoretical challenge lies in understanding the complex interplay of factors that influence customers' continued intentions and behaviors toward Pay Later services. Traditional technology adoption models may not fully capture the nuanced relationships between trust, perceived benefits, and perceived risks in the context of financial technology services. Furthermore, the unique characteristics of Indonesian customers, particularly millennials and Gen Z, who dominate Pay Later usage, require a comprehensive theoretical framework that considers both technological and socio-psychological factors. The expanded Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model was used as the theoretical basis for this research. The UTAUT model, created in 2003, is one of the most prominent theoretical frameworks for understanding and predicting individual technology adoption behavior.

The UTAUT incorporates several aspects that affect both an individual's desire to utilize technology and their actual usage of it, as well as several earlier models of technology acceptance. The four fundamental components of the original UTAUT model–performance expectancy, effort expectancy, social influence, and enabling conditions–are thought to be essential for understanding the adoption of technology. Based on the original UTAUT model, UTAUT2 adds new components, including price value, habits, and hedonic motivation. The purpose of these extra variables is to offer a more thorough understanding of technology adoption, especially in client scenarios. To effectively address this research challenge, the basic UTAUT2 model needs to be further extended, given the unique characteristics of financial services and the dangers that come with Pay Later services.

The theoretical framework for this study extends the UTAUT2 by incorporating three critical variables: trust, perceived benefits, and perceived risks. The initial framework extension draws from previous research that utilized the UTAUT model with the addition of perceived benefit and risk variables. This study employed an expanded UTAUT2 model incorporating perceived risk (PR) and perceived benefits (PB) elements to evaluate customer behavioral intention in using Pay Later services (Raj et al., 2024). The second reference study also employed the UTAUT2 model with the addition of a trust variable. This framework was designed to explore the factors influencing Continued Usage Intention (CUI) and Continued Usage Behavior (CUB) of e-wallet services. Trust is a pivotal factor in Pay Later transactions, which involve sensitive personal and financial data, and can significantly enhance user loyalty and continued usage intention (Kilani et al., 2023).

The current research framework integrates trust, perceived risk, and perceived benefit variables to provide a broader understanding. The integration of these variables creates a comprehensive framework that evaluates the relationships between these factors and continued usage intention (CUI) and continued usage behavior (CUB) in the context of Pay Later Services. The independent factors included Effort Expectancy, Facilitating Conditions, Performance Expectancy, Trust, Social Influence, Price Value, Hedonic Motivation, Habit, Perceived Benefits, and Perceived Risk. These factors influence Continued Usage Intention, which then directly impacts Continued Usage Behavior.

Hypothesis development followed a systematic approach based on an extensive literature review and established theoretical relationships. Each hypothesis was formulated by considering both the direct and indirect relationships between the variables, supported by empirical evidence from previous studies.

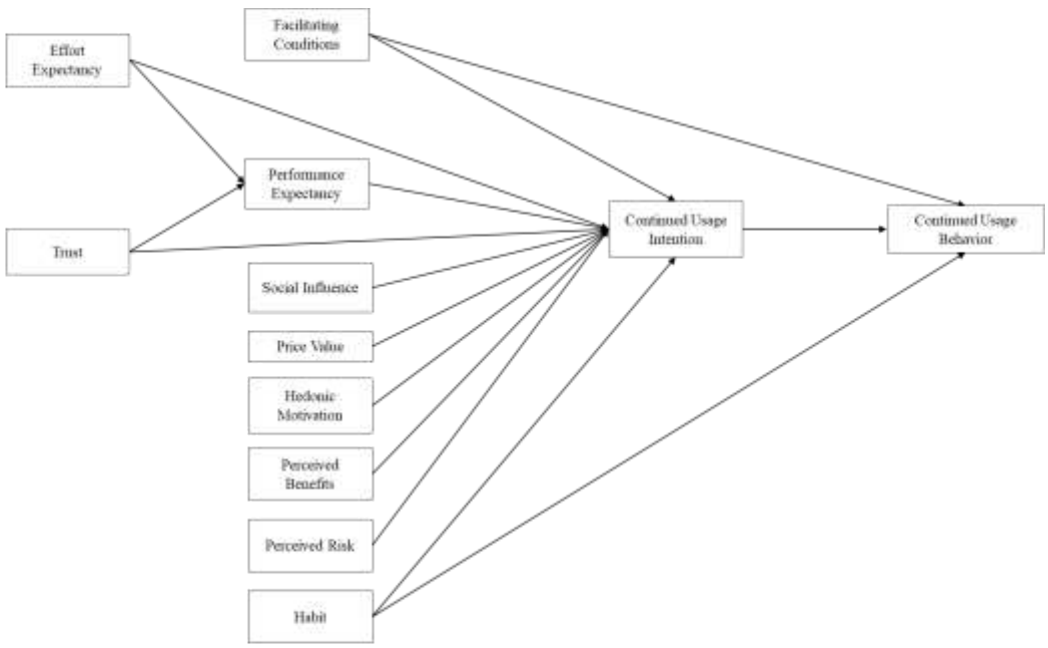

Figure 1. Research Framework
Source: Adapted from Raj et al. (2024) and Kilani et al. (2023)

2.2.1 *Facilitating Conditions Effects*

In the context of Pay Later services, facilitating conditions encompass the availability of technological infrastructure, customer support, and institutional support that enable users to effectively utilize the service. Several studies have demonstrated that facilitating conditions positively impact continued usage intention and behavior. When users feel they have the necessary resources and support to use technology, their adoption intention increases (Ferreira Barbosa, Garcia-Fernandez, Pedragosa, & Cepeda-Carrion, 2022; Kilani et al., 2023; Penney et al., 2021). Based on this theoretical foundation, the following hypotheses were formulated.

H1: Facilitating Conditions positively influences Continued Usage Intention

H2: Facilitating Conditions have an indirect effect on Continued Usage Behavior

2.2.2 Performance Expectancy Effects

In Pay Later services, performance expectancy relates to users' beliefs about how the service enhances their purchasing power, financial management, and overall transaction efficiency. Research on fitness center applications and BNPL services has revealed that performance expectancy significantly influences behavioral intentions. Users are more likely to use a service when they believe it will enhance their performance or provide tangible benefits (Ferreira Barbosa et al., 2022; Raj et al., 2024). Therefore, the following hypotheses are proposed:
H3: Performance Expectancy positively influences Continued Usage Intention
H4: Performance Expectancy has an indirect effect on Continued Usage Behavior

2.2.3 Effort Expectancy Effects

In Pay Later services, this encompasses the perceived simplicity of the application process, user interface intuitiveness, and overall ease of service utilization. Studies on Islamic banking and mobile money services consistently show that effort expectancy positively impacts behavioral intentions. When users perceive technology as easy to use and requiring minimal effort, they are more inclined to adopt and use the service (Penney et al., 2021). Research on fintech services also demonstrates the relationship between Effort Expectancy and Continued Usage Intention through Performance Expectancy (Kilani et al., 2023). Based on these findings, the following hypotheses are proposed.

H5: Effort Expectancy positively influences Performance Expectancy
H6: Effort Expectancy influences Continued Usage Intention
H7a: Effort Expectancy has an indirect effect on Continued Usage Behavior through Continued Usage Intention
H7b: Effort Expectancy has an indirect effect on Continued Usage Behavior through Performance Expectancy and Continued Usage Intention

2.2.4 Trust Effects

Trust is the readiness to be exposed to the activities of another party in the hope that the other party will carry out a specific activity that is significant to the trustor. In Pay Later services, trust encompasses confidence in data security, service reliability, fair treatment, and institutional credibility. Several studies have consistently demonstrated the crucial role of trust in technology adoption, suggesting that perceived risk influences trust, and trust significantly influences behavioral intention (Namahoot & Jantasri, 2023; Shuhaiber, Al-Omoush, & Alsmadi, 2025). Research on fintech services also shows the relationship between Trust and Continued Usage Intention through Performance Expectancy (Kilani et al., 2023). Therefore, the following hypotheses are proposed:

H8: Trust positively influences Performance Expectancy
H9: Trust influences Continued Usage Intention
H10a: Trust has an indirect effect on Continued Usage Behavior through Continued Usage Intention
H10b: Trust has an indirect effect on Continued Usage Behavior through Performance Expectancy and Continued Usage Intention

2.2.5 Social Influence Effects

In the context of Pay Later services, social influence includes recommendations from family, friends, colleagues, and social media that shape individual adoption decisions. Several studies demonstrate that social influence significantly and positively influences usage intention, such as in BNPL service research where social influence proves to influence usage intention (Mohd Thas Thaker, Mohd Thas Thaker, Khaliq, Allah Pitchay, & Iqbal Hussain, 2022; Penney et al., 2021; Raj et al., 2024). When users are influenced by people around them, they are more inclined to use the service. The following hypotheses were proposed:
H11: Social Influence positively influences Continued Usage Intention
H12: Social Influence has an indirect effect on Continued Usage Behavior

2.2.6 Price Value Effects

Price value is the cognitive trade-off that customers make between the monetary cost of utilizing an application and its perceived advantages. Regarding Pay Later services, price value encompasses the perceived economic benefit relative to service costs, including interest rates, fees, and potential savings from promotional offers. Several studies have shown that price significantly influences behavioral intentions. In research on fintech services, price value influences continued usage intention (Kilani et al., 2023). When users feel that a service provides good value for money, they are more inclined to use it (Mohd Thas Thaker et al., 2022; Penney et al., 2021). Based on this understanding, the following hypotheses were proposed:

H13: Price Value positively influences Continued Usage Intention

H14: Price Value has an indirect effect on Continued Usage Behavior

2.2.7 Hedonic Motivation Effects

Hedonic motivation refers to the fun or pleasure derived from using technology. In Pay Later services, hedonic motivation encompasses the enjoyment, satisfaction, and positive emotional experiences users derive from the convenience and flexibility of deferred payment options. Several studies have demonstrated that hedonic motivation influences behavioral intention. In fintech service research, hedonic motivation influences continued usage intention (Ferreira Barbosa et al., 2022; Kilani et al., 2023; Mohd Thas Thaker et al., 2022). When users feel that technology is enjoyable or entertaining, they are more inclined to use it. Therefore, the following hypotheses are proposed:

H15: Hedonic Motivation positively influences Continued Usage Intention

H16: Hedonic Motivation has an indirect effect on Continued Usage Behavior

2.2.8 Perceived Benefits Effects

The perceived benefits variable refers to the subjective assessment of the positive outcomes or advantages that users expect to gain from using a service. In Pay Later services, the perceived benefits include payment flexibility, improved purchasing power, convenience, promotional advantages, and enhanced financial management capabilities. Studies related to BNPL services show that perceived benefits significantly influence behavioral intention, finding that perceived benefits positively enhance customers' intention to use financial services (Raj et al., 2024). This supports the hypothesis that the greater the benefits users perceive from a technology or service, the greater their intention to use it. The following hypotheses were tested:

H17: Perceived Benefits positively influence Continued Usage Intention

H18: Perceived Benefits have an indirect effect on Continued Usage Behavior

2.2.9 Perceived Risk Effects

Perceived risk represents users' subjective assessment of the potential negative consequences that may arise from using a service. In Pay Later services, perceived risk encompasses data security concerns, financial risks from high interest rates, overdue payment penalties, potential debt accumulation, and negative effects on credit scores. Studies related to BNPL services show that perceived risk significantly influences behavioral intention, finding that perceived risk negatively affects customers' intention to use financial services (Raj et al., 2024). This supports the hypothesis that the higher the risk users perceive from technology or service, the lower their intention to use it will be. The following hypotheses were proposed:

H19: Perceived Risk negatively influences Continued Usage Intention

H20: Perceived Risk has an indirect effect on Continued Usage Behavior

2.2.10 Habit Effects

Habit is defined as the extent to which people tend to automatically perform behaviors because of their learning. In Pay Later services, habit encompasses the automatic tendency to use the service based on previous positive experiences and established usage patterns. Several studies have demonstrated that supportive conditions positively impact continued usage intentions and behavior. Research on fintech services shows that habit influences continued usage intention and behavior (Kilani et al., 2023). Additionally, BNPL research has demonstrated that habit has a positive influence on usage intention (Raj et al., 2024). Research on mobile payment platforms consistently shows that habit is a strong

predictor of behavioral intention, with repeated usage and familiarity with technology significantly influencing users' intention to continue using services (de Blanes Sebastián, Antonovica, & Guede, 2023). The following hypotheses were tested:
H21: Habit positively influences Continued Usage Intention
H22: Habit positively influences Continued Usage Behavior

2.2.11 Behavioral Intention Effect
Continued usage intention shows a user's goal to continue using a service in the future, whereas continued usage behavior reflects the actual use of the service. According to several studies, including those on mobile banking, behavioral intention and actual usage behavior are strongly positively correlated (Farzin, Sadeghi, Yahyayi Kharkeshi, Ruholahpur, & Fattahi, 2021). User intention is an important predictor of technology adoption and its sustained use. User intention affects use behavior, according to a BNPL study, and fintech service research also reveals how continuing usage intention affects continued usage behavior (Raj et al., 2024). Based on this theoretical foundation, the final hypothesis is formulated as follows:
H23: Continued Usage Intention positively influences Continued Usage Behavior

3. Research Methodology
This study used quantitative methods and cross-sectional data to achieve its objectives. This study aims to examine the relationship between variables, and a structural equation model is used to explain the key factors that influence the continued usage behavior of BNPL Services in E-Commerce Platforms, both direct and indirect effects. In this study, Smart PLS was used to process the research data.

3.1 Data Collection and Participants
The population is the total number of people, events, or interesting things from which researchers draw conclusions based on the sample statistics (Sekaran & Bougie, 2017). In this study, the population consisted of all Indonesian nationals who had used or were actively utilizing the chosen BNPL e-commerce service. A sample is defined as a selected subset of the population. Researching a large population requires a significant amount of time, money, and effort (Sekaran & Bougie, 2017). Due to these limitations, this study only used a small sample for analysis, assuming that this small sample could be used to generalize the population. Purposive and non-probability sampling methods were employed in this study. Respondents who have used or are actively using the chosen BNPL e-commerce service will receive questionnaires from the researchers using purposive sampling. In Indonesia, online questionnaires were distributed through social media platforms such as WhatsApp, X, and Instagram to collect data.

This study employs the inverse square root sampling approach, which evaluates the probability ratio of the path coefficient to the standard error, ensuring that it exceeds the critical value of the statistical test at a specified significance level. The common power level in a study is 80%, and the significance level is 5% (Hair, Hult, Ringle, & Sarstedt, 2022). This study used a minimum path coefficient (Pmin) of 0.118. Therefore, this method yields the minimum sample size using the following formula:

$$n_{min} > \left(\frac{2.486}{|P_{min}|}\right)^2$$
$$n_{min} > \left(\frac{2.486}{|0.118|}\right)^2$$
$$n_{min} > 443.852$$

Based on the above sample calculation, the minimum sample size for this study was 444. In this study, an online questionnaire was distributed from January to April 2025, and 450 responses were obtained.

3.2 Development of Scale
The two main components of the online survey were latent construct items and demographic questions. Eight questions on gender, age, generation, occupation, residence, net income, last level of education,

and frequency of use of BNPL e-commerce services were included in the demographic section (Table 1).

Table 1. Profile of Respondents(N=450)

Variable	Category	Count	Percentage
Gender	Male	192	42.7%
	Female	258	57.3%
Age	< 20 years	20	4.4%
	20-29 years	247	54.9%
	30-39 years	163	36.2%
	40-49 years	15	3.3%
	50-59 years	5	1.1%
Generation	X Generation (1965-1980)	20	4.4%
	Y Generation/Millennial (1981-1996)	230	51.1%
	Z Generation (1997-2012)	200	44.4%
Last level of education	Elementary / Junior High School	10	2.2%
	High School	216	48.0%
	Diploma I/II/III	15	3.3%
	Diploma IV/S1	204	45.3%
	S2/Magister	5	1.1%
Occupation	Student	136	30.0%
	Private Sector Employees	108	24.0%
	Civil Servants	94	20.9%
	Lectures/Teachers	18	4.0%
	TNI/POLRI	15	3.3%
	Others	79	17.6%
Domicile	Sumatera	60	13.3%
	Banten	30	6.7%
	DKI Jakarta	59	13.1%
	Jawa Barat	65	14.4%
	Jawa Tengah	36	8.0%
	Daerah Istimewa Yogyakarta	23	5.1%
	Jawa Timur	45	10.0%
	Bali	6	1.3%
	Nusa Tenggara	12	2.7%
	Kalimantan	30	6.7%
	Sulawesi	30	6.7%
	Gorontalo	6	1.3%
	Maluku	12	2.7%
	Papua	36	8.0%
Net Income	< Rp1.000.000	121	26.9%
	Rp1.000.000 - Rp5.000.000	148	32.9%
	Rp5.000.001 - Rp10.000.000	141	31.3%
	Rp10.000.001 - Rp15.000.000	14	3.1%
	Rp15.000.001 - Rp20.000.000	10	2.2%
	≥ Rp20.000.001	16	3.6%
	1-3 times	59	13.1%

Variable	Category	Count	Percentage
Frequencies of selected BNPL e-commerce service Usage	4-6 times	283	62.9%
	7-9 times	63	14.0%
	More than 9 times	45	10.0%

Source: Processed data by SmartPLS (2025)

Data will be collected using an online questionnaire from January to April 2025. Social media platforms such as WhatsApp, X (formerly Twitter), and Instagram were used to distribute the questionnaires.

3.3 Technique of Statistical Analysis

SmartPLS software was used to analyze the data using Partial Least Squares Structural Equation Modeling (PLS-SEM). PLS-SEM was chosen as the analytical approach because of its capacity to handle complicated models, limited sample sizes, and multicollinearity difficulties. This variance-based approach is ideal for studying the factors influencing the continuous use behavior of specific BNPL e-commerce services because it focuses on optimizing the explained variance of endogenous latent variables and is especially appropriate for predictive research goals.

The PLS-SEM research included a thorough assessment of the structural and measurement models. The outer model assessment included several validity and reliability tests. The inner model evaluation focused on assessing the explanatory and predictive capabilities of the proposed model. Hypothesis testing was conducted using path analysis, examining both direct and indirect relationships between the constructs. The comprehensive analytical approach ensured a robust evaluation of the proposed theoretical model, offering reliable insights into the factors influencing the continuous usage intention and behavior of the selected BNPL e-commerce service among Indonesian customers. The multistage validation process enhanced the credibility and generalizability of the research findings, supporting evidence-based conclusions regarding the adoption and continued usage of Buy Now Pay Later services in the Indonesian market.

4. Results and Discussion

4.1 Model of Measurement

The outer model represents a measurement model that describes the relationship between each indicator and its latent variable, thereby explaining the link between the latent variables and their indicators. Four primary tests were used to evaluate the outer model and guarantee the quality of the measurement. Indicator reliability was first assessed using outer loadings, where values greater than 0.70 indicated a significant correlation between the indicators and constructs. Second, Composite Reliability (values > 0.7 indicate strong reliability) and Cronbach's alpha (values of 0.60 to 0.70 are acceptable, not surpassing 0.95) were used to assess internal consistency dependability. Finally, the average variation extracted (AVE) was used to test the convergent validity. Values greater than 0.5 indicate that the structure can account for more than half of the variation in the indicators. Third, three methods are used to test discriminant validity: the Fornell-Larcker criterion, which requires that the square root of the AVE for each construct be greater than the correlations between that construct and other constructs; Cross Loading, which requires that loading on the relevant construct be higher than other constructs; and the Heterotrait-Monotrait Ratio (HTMT) with values < 0.85.

Table 2. Indicator reliability, internal consistency reliability, and convergent validity findings

Variables	Indicator	Outer Loadings	Cronbach's Alpha	Composite Reliability	AVE
Effort Expectancy	EE1	0.843	0.865	0.908	0.712
	EE2	0.846			
	EE3	0.859			
	EE4	0.826			
	PE1	0.829	0.854	0.902	0.696

Variables	Indicator	Outer Loadings	Cronbach's Alpha	Composite Reliability	AVE
Performance Expectancy	PE2	0.826			
	PE3	0.843			
	PE4	0.839			
Trust	TR1	0.813	0.927	0.941	0.695
	TR2	0.852			
	TR3	0.811			
	TR4	0.829			
	TR5	0.859			
	TR6	0.834			
	TR7	0.836			
Social Influence	SI1	0.832	0.899	0.922	0.664
	SI2	0.808			
	SI3	0.808			
	SI4	0.807			
	SI5	0.813			
	SI6	0.822			
Hedonic Motivation	HM1	0.810	0.799	0.882	0.713
	HM2	0.855			
	HM3	0.868			
Facilitating Condition	FC1	0.843	0.859	0.904	0.702
	FC2	0.838			
	FC3	0.836			
	FC4	0.835			
Habit	HB1	0.857	0.866	0.909	0.714
	HB2	0.844			
	HB3	0.855			
	HB4	0.823			
Price Value	PV1	0.843	0.855	0.902	0.697
	PV2	0.829			
	PV3	0.821			
	PV4	0.846			
Perceived Risk	PR1	0.836	0.866	0.908	0.713
	PR2	0.856			
	PR3	0.840			
	PR4	0.845			
Perceived Benefits	PB1	0.846	0.818	0.892	0.733
	PB2	0.867			
	PB3	0.856			
Continuous Use Intention	CUI1	0.831	0.850	0.899	0.690
	CUI2	0.820			
	CUI3	0.832			
	CUI4	0.839			
Continuous Use Behavior	CUB1	0.878	0.816	0.891	0.731
	CUB2	0.844			

Variables	Indicator	Outer Loadings	Cronbach's Alpha	Composite Reliability	AVE
	CUB3	0.843			

Source: Processed data by SmartPLS (2025)

According to the findings of the outer model testing, all the study's structures satisfied the necessary validity and reliability requirements. All 50 indicators had outer loading values over 0.70, according to the indicator reliability tests, demonstrating significant correlations between the indicators and their corresponding constructs. Good internal consistency among indicators within each construct is indicated by values within acceptable ranges (above 0.70 and below 0.95), as determined by internal consistency reliability testing using Cronbach's Alpha and Composite Reliability. Convergent validity is satisfied when the average variation extracted (AVE) values for all variables are more than 0.50, indicating that constructs can account for more than half of the variation of their indicators. The Fornell-Larcker Criterion, which shows that the square root of the AVE for each construct is greater than its correlations with other constructs, cross-loading results that indicate each indicator has higher loadings on its intended construct, and HTMT values below 0.85 are three testing techniques that confirm discriminant validity. These thorough testing findings attest to the measurement model's compliance with the methodological requirements for additional analysis.

Table 3. HTMT

VAR	CUB	CUI	EE	FC	HB	HM	PB	PE	PR	PV	SI
CUI	0.80										
EE	0.78	0.77									
FC	0.80	0.77	0.76								
HB	0.82	0.79	0.79	0.82							
HM	0.79	0.81	0.75	0.77	0.80						
PB	0.76	0.74	0.77	0.75	0.76	0.72					
PE	0.83	0.80	0.77	0.80	0.81	0.83	0.78				
PR	0.80	0.75	0.76	0.79	0.77	0.76	0.76	0.77			
PV	0.84	0.82	0.80	0.82	0.81	0.84	0.78	0.84	0.81		
SI	0.81	0.77	0.78	0.79	0.77	0.78	0.76	0.80	0.78	0.82	
TR	0.74	0.71	0.72	0.71	0.69	0.73	0.72	0.76	0.72	0.74	0.75

Source: Processed data by SmartPLS (2025)

Table 4. Fornell-Larcker Criterion

VAR	CUB	CUI	EE	FC	HB	HM	PB	PE	PR	PV	SI	TR
CUB	**0.86**											
CUI	0.67	**0.83**										
EE	0.65	0.66	**0.84**									
FC	0.67	0.66	0.66	**0.84**								
HB	0.69	0.68	0.68	0.71	**0.85**							
HM	0.64	0.67	0.63	0.64	0.67	**0.84**						
PB	0.62	0.62	0.65	0.63	0.64	0.58	**0.86**					
PE	0.69	0.68	0.66	0.69	0.69	0.68	0.66	**0.83**				
PR	-0.67	-0.65	-0.66	-0.69	-0.67	-0.63	-0.64	-0.67	**0.84**			
PV	0.70	0.70	0.69	0.70	0.70	0.69	0.65	0.72	-0.69	**0.83**		
SI	0.69	0.67	0.69	0.70	0.68	0.66	0.65	0.70	-0.69	0.72	**0.82**	
TR	0.65	0.64	0.65	0.63	0.62	0.63	0.63	0.68	-0.64	0.66	0.69	**0.83**

Source: Processed data by SmartPLS (2025)

5. *Structural Model*

PLS-SEM's inner model describes the structural connections between the research model's latent variables, or "constructs." Its main objectives are to estimate path coefficients and assess the importance and strength of the links among constructs (Hair et al., 2022).

4.2.1 R^2 (Coefficient of Determination)

R^2 is the percentage of endogenous latent variable variation that can be accounted for by the model's exogenous latent variables. The squared correlation between the actual and anticipated values of a certain endogenous structure is known as R-squared, which represents the model's predictive capacity. The total impact of external latent variables on the endogenous latent variable is represented by the R-squared. R^2 values range from 0 to 1, with higher values indicating better model performance in explaining the variance of the dependent variable (Hair et al., 2022).

Table 5. R- Square

Variable	R-square	R-square adjusted
CUB	0.583	0.581
CUI	0.633	0.624
PE	0.546	0.544

Source: Processed data by SmartPLS (2025)

Based on the results, the R^2 values for the related exogenous constructs showed moderate correlations, with values of approximately 0.5. The highest R-squared value was observed for the CUI variable (0.633), indicating that the model explained 63.3% of the variance in continuous use intention.

4.2.2 F^2 (Effect Size)

F^2 is an effect size measure that indicates the magnitude of the influence of independent variables on dependent variables. This testing method aims to assess the strength of the influence of independent variables on dependent variables and to determine which variables contribute most significantly to the model (Hair et al., 2022).

Table 6. F- Square

Ha	Path	f-square	Effect
H1	Facilitating Condition - Continuous Use Intention	0.005	Small
H2	Facilitating Condition - Continuous Use Behavior	0.076	Medium
H3	Performance Expectancy - Continuous Use Intention	0.010	Small
H5	Effort Expectancy - Performance Expectancy	0.184	Large
H6	Effort Expectancy - Continuous Use Intention	0.008	Small
H8	Trust - Performance Expectancy	0.238	Large
H9	Trust- Continuous Use Intention	0.005	Small
H11	Social Influence - Continuous Use Intention	0.006	Small
H13	Price Value - Continuous Use Intention	0.016	Small
H15	Hedonic Motivation - Continuous Use Intention	0.024	Medium
H17	Perceived Benefit - Continuous Use Intention	0.024	Medium
H19	Perceived Risk - Continuous Use Intention	0.003	Small
H21	Habit - Continuous Use Intention	0.015	Small
H22	Habit - Continuous Use Behavior	0.090	Medium
H23	Continuous Use Intention - Continuous Use Behavior	0.095	Medium

Source: Processed data by SmartPLS (2025)

The effect size determination criteria indicate that F^2 values between 0.15-0.35 represent medium effects, while values between 0.02-0.15 represent small effects. Effects below 0.02 were considered negligible. The results revealed that the largest effects were observed for Trust and Effort Expectancy on Performance Expectancy, both demonstrating medium effect sizes.

4.2.3 Q² (Predictive Relevance)

Q² is calculated using predictions generated by the model and comparing them with actual values. A positive Q² value indicates that the model's prediction error is lower than a naïve benchmark, suggesting that the model possesses predictive capability (Hair et al., 2022).

Table 7. Q- Square Predict

VAR	$Q^2_{predict}$
CUB	0.585
CUI	0.618
PE	0.541

Source: Processed data by SmartPLS (2025)

The results demonstrate that the CUB variable has a Q² value of 0.585, indicating that the model possesses a good predictive capability in explaining continuous use behavior. Furthermore, the Q² value for CUI was 0.618, signifying the model's predictive capability in explaining users' intention to use the system continuously. Meanwhile, the Q² value for PE of 0.541 also indicates that the model can predict performance expectancy with reasonable accuracy. All Q² prediction values were positive, demonstrating that the research model has predictive relevance and good predictive relevance for endogenous constructs.

To determine the overall predictive capability of the model, the following formula was applied:

$Q^2 = 1 – (1\text{-}R1^2)(1\text{-}R2^2)…..(1\text{-}Rn^2)$

$Q^2 = 1 – (1\text{-}0.583)(1\text{-}0.633)(1\text{-}0.546)$

$Q^2 = 0.93052$

The Q² value of 0.935 indicates the predictive power of the research model, as it can explain 93.5% of the information in the study.

4.3 Direct Effects Analysis

The hypothesis testing results demonstrate that most variables in the model exhibit significant influence, and their corresponding hypotheses are accepted. Variables including facilitating conditions, performance expectancy, effort expectancy, trust, social influence, hedonic motivation, and habit have been proven to positively influence both continuous use intention and continuous use behavior. This is evidenced by p-values < 0.05 and T-statistics > 1.64. However, three hypotheses were rejected: H1 (facilitating conditions on intention), H17 (perceived benefits), and H19 (perceived risk).

Table 8. Direct Effect Hypothesis

Ha	Path	STD	T Stat	P Values	Path Coef	Result
H1	Facilitating Condition - Continuous Use Intention	0.040	1.881	0.060	0.076	Not Supported
H2	Facilitating Condition - Continuous Use Behavior	0.050	5.375	0.000	0.269	Supported
H3	Performance Expectancy - Continuous Use Intention	0.036	3.001	0.003	0.108	Supported
H5	Effort Expectancy - Performance Expectancy	0.057	6.613	0.000	0.380	Supported
H6	Effort Expectancy - Continuous Use Intention	0.033	2.822	0.005	0.092	Supported
H8	Trust - Performance Expectancy	0.053	8.172	0.000	0.433	Supported

Ha	Path	STD	T Stat	P Values	Path Coef	Result
H9	Trust- Continuous Use Intention	0.032	2.074	0.038	0.066	Supported
H11	Social Influence - Continuous Use Intention	0.039	2.080	0.038	0.082	Supported
H13	Price Value - Continuous Use Intention	0.046	3.026	0.002	0.140	Supported
H15	Hedonic Motivation - Continuous Use Intention	0.045	3.310	0.001	0.150	Supported
H17	Perceived Benefit - Continuous Use Intention	0.031	1.533	0.125	0.048	Not Supported
H19	Perceived Risk - Continuous Use Intention	0.036	1.533	0.125	-0.056	Not Supported
H21	Habit - Continuous Use Intention	0.046	2.746	0.006	0.127	Supported
H22	Habit - Continuous Use Behavior	0.052	5.728	0.000	0.300	Supported
H23	Continuous Use Intention - Continuous Use Behavior	0.052	5.534	0.000	0.291	Supported

Source: Processed data by SmartPLS (2025)

4.3.1 Facilitating Condition's Influence on Continued Usage Intention and Behavior

The research findings indicate that the facilitating conditions' influence on continued usage intention was rejected (p = 0.060, t-stat = 1.881), while its influence on continued usage behavior was accepted (p = 0.000, t-stat = 5.375). This finding differs from Ferreira Barbosa et al. (2022) and Penney et al. (2021) but aligns with Kilani et al. (2023), demonstrating that facilitating conditions do not always influence intention but can directly impact usage behavior (Ferreira Barbosa et al., 2022; Kilani et al., 2023; Penney et al., 2021). In UTAUT2 theory, facilitating conditions refer to an individual's perception of available resources and organizational support (Venkatesh et al., 2012). The results indicate that respondents who used the selected BNPL e-commerce service had high technological familiarity. With 95.55% of respondents being millennials and Gen Z, who are accustomed to digital ecosystems, technological infrastructure is no longer a primary consideration in intention formation, although it remains important for actual behavioral implementation.

4.3.2 Performance Expectancy's Influence on Continued Usage Intention

Performance expectancy positively influenced usage intention (p-value = 0.003, T-stat = 3.001), consistent with Raj et al. (2024) and Ferreira Barbosa et al. (2022). This reflects users' perceptions of benefits such as shopping convenience without immediate payment, payment flexibility, and seamless integration with the Shopee platform (Ferreira Barbosa et al., 2022; Raj et al., 2024). Respondent characteristics, predominantly productive age (91.11% aged 20-39 years) with high education levels and middle-income status (64.22% earning Rp1,000,000-Rp10,000,000), demonstrate their capability to evaluate fintech service benefits effectively, making Pay Later services relevant solutions for enhancing purchasing power and financial flexibility.

4.3.3 Effort Expectancy's Influence on Performance Expectancy and Continued Usage Intention

Effort expectancy significantly influenced both performance expectancy (p-value = 0.000, t-stat = 6.613) and continued usage intention (p-value = 0.005, t-stat = 2.822), aligning with Mohd Thas Thaker et al. (2022) and confirming TAM's theoretical relationship, where ease of use predicts perceived usefulness (Mohd Thas Thaker et al., 2022). The ease of using BNPL e-commerce services, integrated with familiar interfaces, creates positive system benefit perceptions. Respondents from digital generations (95.55% millennials and Gen Z) appreciated easy-to-use systems and considered ease of use a service quality indicator.

4.3.4 Trust's Influence on Performance Expectancy and Continued Usage Intention

Trust significantly influenced both performance expectancy (p = 0.000, t-stat = 8.172) and continued usage intention (p = 0.038, t-stat = 2.074), supporting research on financial technology (fintech) objects (Namahoot & Jantasri, 2023; Shuhaiber et al., 2025). Research using LMS objects also confirms that trust influences the intention to continue using LMS (Sukandi & Ariyanti, 2022). Despite security incidents and 160 OJK complaints in 2024, trust remained significant because respondents were predominantly active Shopee ecosystem users with positive experiences (Aprilia, 2024). Young generations (95.55% millennials and Gen Z) have a higher digital risk tolerance and focus on convenience, while Shopee's strong e-commerce reputation provides a foundation for trust.

4.3.5 Social Influence, Price Value, and Hedonic Motivation Influence on Continued Usage Intention

Social influence (p = 0.038), price value (p = 0.002), and hedonic motivation (p = 0.001) significantly influenced continued usage intention, consistent with research on financial technology (fintech) objects (Mohd Thas Thaker et al., 2022; Raj et al., 2024). Research using Waze as the object also confirms that price value and social influence can influence continued usage behavior (Indrawati, Khairunnisa, & Muthaiyah, 2021). Significant social influence reflects Indonesian collective culture and the characteristics of the young generation (95.55% millennials and Gen Z), where peer recommendations strongly impact technology decisions. Price value significance aligns with respondents' middle-income profile (64.22% earning Rp1,000,000-Rp10,000,000), making 0% installment features and payment flexibility create a high value perception. Hedonic motivation reflects the young generation’s preference for enjoyable experiences beyond functionality.

4.3.6 Perceived Benefits and Perceived Risk Influence on Continued Usage Intention

Both perceived benefits (p = 0.125, t-stat = 1.533) and perceived risk (p = 0.125, t-stat = 1.533) showed no significant influence on continued usage intention, which differs from previous research on pay later (Raj et al., 2024). The non-significance of perceived benefits can be explained through redundancy with performance expectancy, as respondents with high education levels (93.33%) conduct specific evaluations rather than abstract benefit perception. The lack of perceived risk influence indicates that digitally familiar respondents with high-risk tolerance focus on risk mitigation rather than technology avoidance, similar to the findings of Spanish mobile payment research, where regulatory support reduced risk concerns (de Blanes Sebastián et al., 2023).

4.3.7 Habit's Influence on Continued Usage Intention and Behavior

Habit significantly influenced both continued usage intention (p-value = 0.006, t-stat = 2.746) and CB (p-value = 0.000, t-stat = 5.728), with the highest direct influence on behavior, consistent with Kilani et al. (2023) and Raj et al. (2024). Research using Waze as the object confirms that habit is the largest influence on continued usage behavior (Indrawati et al., 2021). Similarly, research using LMS objects states that habit is the largest influence on continued usage behavior variables (Sukandi & Ariyanti, 2022). Habits represent automatic responses formed through repetition in stable contexts. The strong influence indicates that the selected BNPL e-commerce service successfully created repetitive usage patterns among respondents. With 62.89% using the service 4-6 times in six months, users have developed structured habits supported by reward systems and consistent promotions.

4.3.8 Continued Usage Intention's Influence on Behavior

Continued usage intention significantly influences usage behavior (p-value = 0.000, t-stat = 5.534), confirming that intention is a strong predictor of actual behavior, supporting research on finance technology (fintech) objects (Farzin et al., 2021; Raj et al., 2024). This demonstrates that technology behavior prediction models work well in the Indonesian pay-later context. The strong intention-behavior relationship indicates respondent consistency between intention and action, reflecting digital generation characteristics oriented towards technology action and mature financial decision-making among middle-income users.

4.4 Indirect Effects Analysis

This study examined the indirect pathways through which numerous factors influence the continuous use behavior (CUB) of a selected BNPL e-commerce service through continuous use intention (CUI).

Table 9. Indirect Effect Hypothesis

Ha	Path	STD	T Stat	P Values	Path Coef	Result
H2	Facilitating Condition - Continuous Use Behavior through Continuous Use Intention	0.012	1.836	0.066	0.022	Not Supported
H4	Performance Expectancy - Continuous Use Behavior through Continuous Use Intention	0.013	2.411	0.016	0.031	Supported
H6	Effort Expectancy - Continuous Use Intention through Performance Expectancy	0.016	2.557	0.011	0.041	Supported
H7a	Effort Expectancy - Continuous Use Behavior through Continuous Use Intention	0.012	2.286	0.022	0.027	Supported
H7b	Effort Expectancy - Continuous Use Behavior through Performance Expectancy and Continuous Use Intention	0.006	2.151	0.032	0.012	Supported
H9	Trust-Continuous Use Intention through Performance Expectancy	0.017	2.761	0.006	0.047	Supported
H10a	Trust - Continuous Use Behavior through Continuous Use Intention	0.010	1.900	0.058	0.019	Not Supported
H10b	Trust- Continuous Use Behavior through Performance Expectancy and Continuous Use Intention	0.006	2.246	0.025	0.014	Supported
H12	Social Influence - Continuous Use Behavior through Continuous Use Intention	0.013	1.871	0.061	0.024	Not Supported
H14	Price Value - Continuous Use Behavior through Continuous Use Intention	0.017	2.393	0.017	0.041	Supported
H16	Hedonic Motivation - Continuous Use Behavior through Continuous Use Intention	0.015	2.850	0.004	0.044	Supported
H18	Perceived Benefit - Continuous Use Behavior through Continuous Use Intention	0.010	1.423	0.155	0.014	Not Supported
H20	Perceived Risk - Continuous Use Behavior through Continuous Use Intention	0.011	1.412	0.158	-0.016	Not Supported
H22	Habit - Continuous Use Behavior through Continuous Use Intention	0.014	2.675	0.007	0.037	Supported

Source: Processed data by SmartPLS (2025)

4.4.1 Indirect Effects of Performance Expectancy

Performance Expectancy demonstrated significant indirect effects on CUB through CUI (H4: β=0.031, t=2.411, p=0.016). This finding reflects the rational decision-making behavior of predominantly educated respondents (93.33% with secondary to higher education), who systematically evaluate cost-benefit ratios before adopting financial services. The mediation suggests that perceived performance benefits serve as a crucial filter that translates various motivational factors into actual usage behaviors. This emphasizes the importance of communicating tangible benefits rather than merely technical features or promotional aspects, particularly given respondents' tendency toward systematic evaluation processes in financial decision-making (Mohd Thas Thaker et al., 2022; Penney et al., 2021).

4.4.2 Indirect Effects of Effort Expectancy

Effort Expectancy exhibited complex mediation patterns through multiple pathways: via Performance Expectancy to CUI (H6: β=0.041, t=2.557, p=0.011), directly through CUI (H7a: β=0.027, t=2.286, p=0.022), and through the dual pathway of Performance Expectancy and CUI (H7b: β=0.012, t=2.151, p=0.032). This multi-pathway mediation reflects the cognitive processing typical of digitally savvy users (95.55% of those with good digital habits) who expect seamless user experience. These findings are consistent with Kilani et al. (2023) and suggest that ease of use not only directly influences intention but also enhances perceived performance benefits, creating a reinforcing cycle. This is particularly relevant for the young demographic (predominantly millennials and Gen Z), who do not tolerate complex interfaces or convoluted processes, making user experience optimization crucial for sustained engagement (Kilani et al., 2023; Mohd Thas Thaker et al., 2022; Penney et al., 2021).

4.4.3 Indirect Effects of Trust

Trust demonstrated a distinctive mediation pattern, where indirect effects on CUB were significant only through the dual pathway of Performance Expectancy and CUI (H10b: β=0.014, t=2.246, p=0.025), but not through CUI alone (H10a: p=0.058). Additionally, Trust showed significant indirect effects on CUI through Performance Expectancy (H9: β=0.047, t=2.761, p=0.006). This pattern indicates that trust alone is insufficient to drive continuous behavior among educated users with moderate income levels (64.22% earning Rp1-10 million). Instead, trust must be coupled with tangible performance benefits, reflecting a risk-aware approach to the adoption of financial technology. This finding aligns with Kilani et al. (2023), who noted that the effects of trust are more significant through performance expectancy mediation. This is particularly relevant given the documented security incidents and customer complaints regarding selected BNPL e-commerce services (Aprilia, 2024), suggesting that users require both trust and performance validation before committing to sustained usage (Kilani et al., 2023; Namahoot & Jantasri, 2023; Shuhaiber et al., 2025).

4.4.4 Indirect Effects of Social Influence, Price Value and Hedonic Motivation

Social Influence showed non-significant indirect effects on CUB (H12: p=0.061, t=1.871), indicating that while social pressure may influence initial intention, it has a limited impact on sustained behavior. This aligns with the Theory of Planned Behavior's emphasis on personal evaluation over social pressure for continuous behaviors (Ajzen, 1991), suggesting that actual usage decisions are more influenced by personal and situational factors rather than social expectations (Mohd Thas Thaker et al., 2022; Penney et al., 2021; Raj et al., 2024).

Price Value demonstrated significant mediation effects (H14: β=0.041, t=2.393, p=0.017), indicating that value perception requires cognitive processing through intention formation before being translated into behavior. This reflects the systematic evaluation approach of users who assess cost-benefit ratios before adopting them for sustained use (Kilani et al., 2023; Mohd Thas Thaker et al., 2022; Penney et al., 2021). Hedonic Motivation emerged as the strongest indirect predictor of CUB (H16: β=0.044, t=2.850, p=0.004), highlighting the critical importance of enjoyable user experience. This finding is particularly relevant for the young demographic, who prioritize user experience quality, suggesting that the enjoyment and pleasure derived from using selected BNPL e-commerce services significantly contribute to sustained usage behavior through intention reinforcement (Ferreira Barbosa et al., 2022; Kilani et al., 2023; Mohd Thas Thaker et al., 2022).

4.4.5 Indirect Effects of Perceived Benefits and Perceived Risk

Both Perceived Benefits (H18: p=0.155, t=1.423) and Perceived Risk (H20: p=0.158, t=1.412) showed non-significant indirect effects. The lack of perceived benefit mediation likely reflects a theoretical overlap with Performance Expectancy, where concrete performance evaluations supersede abstract benefit assessments among technologically savvy users (Raj et al., 2024). The non-significance of Perceived Risk suggests that users may have established sufficient trust levels, though this warrants attention given documented security concerns and OJK's continuous monitoring of security standards and customer data protection (OJK, 2025). These findings indicate that in familiar technology contexts, users rely on more specific and actionable evaluations (Performance Expectancy) rather than abstract assessments (Perceived Benefits), while established trust may diminish the salience of perceived risks in decision-making processes. This is consistent with the UTAUT2 framework, where Performance Expectancy provides a more concrete evaluation than abstract benefit perceptions (Venkatesh et al., 2012). Despite the non-significant effects, attention should be paid to security concerns given reported incidents (Bangsa, 2024; Ibrahim, 2023) (Aprilia, 2024).

These findings extend UTAUT2 by revealing critical mediation pathways in fintech adoption, particularly emphasizing the importance of user experience design that integrates ease of use, performance benefits, and trust-building mechanisms (Farzin et al., 2021; Kilani et al., 2023; Raj et al., 2024). The results suggest that successful fintech platforms must optimize interconnected pathways rather than focusing on isolated factors, with particular attention to hedonic aspects and performance validation for sustained user engagement in the Indonesian fintech environment.

5. Conclusion

5.1 Conclusion

This study provides comprehensive insights into the factors driving the continued use of selected BNPL e-commerce services among Indonesian users, contributing valuable knowledge to both theoretical understanding and practical applications in the fintech industry. Through the analysis of 450 respondents, this study reveals that digital natives, particularly millennials and Gen Z users, demonstrate sophisticated evaluation processes when engaging with digital financial services.

The findings confirm that traditional technology acceptance factors remain relevant in the fintech context, with Performance Expectancy, Effort Expectancy, and trust emerging as critical drivers of continued usage intention. However, the study also revealed important nuances, such as the non-significance of general risk-benefit perceptions among experienced digital users, suggesting that theoretical models may need to be refined for specific contexts and user populations. The dominant role of habit in predicting actual usage behavior underscores the importance of moving beyond initial adoption studies to understand sustained usage patterns. This finding has significant implications for business strategy, suggesting that fintech companies should focus not only on attracting users but also on creating experiences that are integrated into users' daily financial routines.

The complex mediation patterns observed highlight the interconnected nature of user perceptions and behaviors regarding digital financial services. Trust, while important, requires validation through perceived benefits before influencing actual behavior, indicating that trust-building strategies must be coupled with a clear demonstration of value. For the Indonesian fintech industry, these findings provide a roadmap for developing customer-centric services and marketing strategies. The research suggests that while initial adoption may be influenced by social factors and perceived benefits, sustained usage depends more on service quality, ease of use, and habitual use. The limitations of this study, particularly its cross-sectional design and demographic concentration, highlight critical areas for future research. Longitudinal studies and broader demographic representation could enhance the understanding of adoption dynamics and the generalizability of the findings. Overall, this study contributes to the growing body of knowledge on fintech adoption in emerging markets, providing both theoretical insights and practical guidance for stakeholders in the digital financial services ecosystem. As the fintech industry continues to evolve rapidly, understanding user behavior and adoption patterns is becoming increasingly critical for sustainable growth and innovation in the sector.

5.2 Limitation

Despite the novelty of this research in being among the first to comprehensively examine the continued usage behavior of Pay Later services in Indonesia using an extended UTAUT2 model with the unique addition of the trust variable, revealing the dominance of habit over traditional adoption factors, and identifying the theoretical redundancy of perceived risk and perceived benefit constructs in mature digital user contexts, several limitations should be acknowledged. The observation of behavioral changes over time and the establishment of causal linkages are limited by the cross-sectional approach. The sample's high concentration of Gen Z and millennial users (95.55%) may limit its applicability to other age groups. By eliminating the opinions of non-adopters, the study's sole emphasis on current Shopee Pay Later customers may have introduced a selection bias. Social desirability bias may have affected the self-reported statistics. Furthermore, the study's geographic scope was restricted to Indonesia, and its conclusions may not apply to other nations with distinct fintech ecosystems and regulatory frameworks.

5.3 Suggestion

This research extends the applicability of the UTAUT2 model in the Indonesian fintech context, revealing that specific constructs (Performance Expectancy, Trust) are more relevant than general risk-benefit perceptions for experienced digital users. The complex mediation patterns and the dominant role of habit provide insights into trust mechanisms and habitual behavior in digital financial services. For practitioners, the findings suggest prioritizing user experience optimization, continuous cybersecurity investment, and designing engagement strategies that promote routine usage patterns. Social influence strategies work for customer acquisition, whereas service quality drives retention. For regulators, education-focused digital financial literacy initiatives may be more effective than traditional risk-focused approaches for digitally native populations.

Future research should address this study's limitations through longitudinal designs to track behavioral evolution over time and cross-generational studies to understand adoption patterns across various age groups. Given the theoretical redundancy observed, exploring more specific constructs such as Financial Risk Tolerance, Digital Financial Literacy, or Privacy Concerns could provide better discrimination among experienced digital users. Comparative studies across different fintech services and cross-cultural research could enhance our understanding of universal versus context-specific factors. A mixed methods approach combining quantitative findings with qualitative insights into user decision-making processes, particularly around trust formation and habit development, would provide a more comprehensive understanding.

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