Investigation of Determining Factors of Intention and Behavior in Using E-Wallet: Extending The UTAUT-2 Model

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Abstract: This research recommends that considering the current global scenario, it would be greatly beneficial for Indonesia to identify more factors of Behavioral intention and slightly explore this construct in case use electronic wallet. Since the factors underlying decision-making of public to use electronic wallets are relatively less studied, this research will contribute in filling that new void. Most existing studies drew from a single theoretical perspective, which exposes an important gap to be filled with additional research. To this end, the study adapted and extended UTAUT-2 model to account for perceived security as well as epistemic value. This research tested the conceptual model using PLS-SEM analysis with 372 respondents through cross-sectional design and survey methodology. The results indicate the majority of the factors, besides effort expectancy and social influence present a statistically significant relationship with behavioral intentions explaining 63.9% variance such insights have important implications for stakeholders in defining strategic actions to enhance the wider adoption and usage of e-wallet technology, particularly within Indonesia.

Keywords: E-Wallet, Extended UTAUT-2, Technology acceptance, Behavioral intention, Consumer behavior

INTRODUCTION

Based on data published by Statista, smartphone usage in Indonesia has increased steadily yearly. Statista (2023) sets the number of smartphone users in Indonesia to a more recent figure, which had risen from 187.62 million in 2022 and is expected to approach almost the 190.03 million marks´ by 2023, with an estimate of reaching this number of 211.21 million during 2028. In this context, digital technology innovation enabled by the increasingly high rates of smartphone penetration globally reveals a conducive environment for effective non-cash payment systems to take off. The banking sector has recognized this potential and recently introduced services enabling them to complete their financial transactions using a mobile device (Al-Adwan et al., 2019). Non-cash payment provides several advantages, such as security, scalability, anonymity, and access to funds (Kim, 2008).

Applications route all cashless payments from and to users (Karjaluoto et al., 2020) and monetization, leading to the rise of e-wallets for money stored or earned through application transfers whenever needed financially (Flavian et al., 2020). In short, this technology offers real-time and secure financial payment (Singh & Srivastava, 2018). The popularity of online services is expanding with digitalization, and electronic payments are now widely trusted and strongly influence consumer behavior, as demonstrated in the cultural shift toward a new lifestyle (Yang et al., 2021). In the present scenario, smartphone users have been able to pay and get paid without using cash or even their debit/credit cards, as it can be done through an e-

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wallet feature on these devices. Like physical wallets, e-wallets are defined as a type of electronic transaction where users can pay without cash (Seetharaman et al., 2017), fulfilling fast and secure transactions (Karim et al., 2020). E-wallet is a type of digital payment tool that enables cashless transactions, which means you can pay your bills and even transfer money from one e-wallet to another without any actual money changing hands. E-wallets add to the consumer experience by their convenience and efficiency (Yuan et al., 2016). The COVID-19 pandemic, as it hit Indonesia in 2020, has led to a massive surge in e-wallet utilization that affects consumer behavior (Eger et al., 2021). Though viewed as a COVID-19 vector many businesses rejected, cash is utilized less often, and e-wallets are now more prevalent to reduce physical contact (Filthy Lucre, 2020).

It is a lot more secure and safe way to use an e-wallet than carrying cash. Another study has shown the increment of e-wallet users in Indonesia, which rose by 44% in 2020 due to raised trustability and security system (Cakti, 2021). A few factors attributable to which e-wallets have gained significant usage are convenience, user-friendliness, availability for different promotional offers, and faster/safer transactions. Exploitation tools and drivers for tool-driven promotions; support to promotion offers and purchase bonuses increased protection. Thus, many smartphone users consider it a regular transaction (Che Nawi et al., 2024).

E-wallets have become the most popular and preferred payment method at 81% in Indonesia (East Ventures, 2023). The advent of e-wallets as a payment method has seen virtual accounts and bank transfers – which were de facto in the past – gradually become less in demand. In addition, e-wallets will reign over credit and debit card use in e-commerce (Zaid Kilani et al., 2023). Based on the IDC (2022) report, Indonesia became the most significant e-wallet users by country in SEA 2021, with more than 98.9 million of them. It is predicted that it will rise to exceed around 215.7 million users by 2026. This projection means that Indonesia will still be called the country with the most significant number of e-wallet users in Southeast Asia by 2026. Similarly, the Statista Digital Market Insights (2024) reported that Indonesia had a market volume of digital payment transaction value in Southeast Asia claimed as the top spot (88.42 billion USD) during 2023 with an estimated growth to reach up to nearly twice its current size, which is at approximately 148.13 billion USD by year-end of 2028.

In recent years, e-wallet usage in Indonesia has been growing substantially fast as evidenced by the significant growth of e-wallet market size in Indonesia between 2018 to 2023 (Redseer, 2019). E-wallet users are rising due to growing smartphone penetration. One of the most apparent is e-wallets, which we, as Indonesians, actually seem to learn pretty quickly as more and more of us turn towards an online lifestyle. Interesting to note is the high usage of e-wallets for such transactions in Indonesia. According to data from Ipsos (2020), 40% of Indonesians use their e-wallets more than once a week. This also indicates how people in Indonesia are moving to adapt to using e-wallets for transaction purposes.

Although Indonesia emerged as the top market in Southeast Asia for the number of e-wallet users in 2021, penetration is not at its highest. In 2021, Indonesia's adoption rate was 83.5%, ranked fifth in Southeast Asia behind Thailand (94%), Vietnam (93%), Malaysia (86.5%), and Philippines (84.5%) (Statista, 2022). The data, it said, sheds light on the extent to which e-wallets are making inroads into

Southeast Asia. Additionally, Indonesia is no longer the country with the highest expected penetration of e-wallet usage in Southeast Asia between 2020 and 2025. Based on figures from the Asian Banker (2021), Indonesia is ranked third worldwide for growth in e-wallet penetration at 50.9% over this timeframe. On the other hand, Indonesia is expected to be the country with the most users of e-wallets in Southeast Asia come 2026, even as it experiences considerable growth in penetration, but not at nearly such a rapid rate from its relatively low starting point between 2020 and 2025.

In addition, Statista Digital Market Insights (2024), Indonesia is one of the countries with lower stage penetration for digital payment in Southeast Asia, 2023–2028 compared to Malaysia. This is an important data point as higher the digital payment penetration greater will be the number of Digital natives that are acclimatized and accustomed to carrying and using e-wallets. This phenomenon will be well worth exploring in future work. Hence, this study aims to investigate the influential factors on behavioral intentions and e-wallet usage among Indonesian users. Identifying these factors can serve as a sturdy footing to frame well-thought-out and practical strategies to bolster an ecosystem of e-wallet transactions in Indonesia.

In parallel, insight into determinants related to behavioral intentions and the use of e-wallets in Indonesia can be beneficial to understanding different aspects of e-commerce sites, which are influenced by individual characteristics and payment systems. Nevertheless, the elements determining the recognition of persons using e-wallets are doubtful (Che Nawi et al., 2024). Thus, we hypothesized that this phenomenon needs to be empirically confirmed in Indonesia. In short, this provides a new model. The research contributes to the extant literature on e-wallets as it addresses what influences user behavioral intentions and actual usage behavior. This research would benefit the academic literature on e-wallet adoption and usage in Indonesia and propose a policy recommendation that could enhance the use of an effective digital payment system.

This study employs the unified theory of acceptance and use of technology 2 (UTAUT-2). The original method is perfect when focusing on the attitudes towards technology use. It has been used frequently in empirical work regarding UTAUT-2 (Naeem, 2021; Sitar-Taut & Mican, 2021; Yeoh & Chin, 2022). This model is appropriate for examining consumer behavioral intention on digital payment system usage (Azman Ong et al., 2023). As e-wallets have become common in Indonesia, the habit variable is directly linked to the use behavior variable, reflecting e-wallet usage behavior. Habit, the other element of UTAUT-2, affects use behavior both directly and indirectly via behavioral intention (Macedo, 2017).

Incorporating habit into UTAUT-2 emphasizes intention as the main mechanism of behavior (Venkatesh et al., 2012). These common habits through e-wallet usage then enabled more people to obtain familiarity throughout it, and certainly, as many used these for online shopping, bill paying, or money transfer. This study also includes the hedonic motivation variable from UTAUT-2 (Venkatesh et al., 2012). Hedonic motivation, defined as the pleasure or enjoyment experienced from using technology, affects intention regarding the use of technology and actual behavior (Brown & Venkatesh, 2005). This strongly predicts the acceptance of self-service technologies (Farah et al., 2018).

Past research suggest that is a statistically significant determining factor on the behavioral intentions to adopt digital payment systems (Chaudhary et al., 2019; Singh & Srivastava, 2018) and epistemic value (Balapour et al., 2020; Berraies et al., 2017). Azman Ong et al. (2023) also rarely examined the moderating effects using the UTAUT-2 model. This research will try to break the limitation did by proving that UTAUT-2 variables from hedonic motivation, perceived security, and epistemic value have an effect on behavioral intention and use behavior in using e-wallet among Indonesian people. It also estimates the impact of each on behavior. The novelty of this research lies in applying the UTAUT-2 framework to analyze e-wallet usage in Indonesia, a relatively new context. This research explores the utilization of e-wallets in emerging markets (Indonesia). The study makes a significant contribution to the literature on e-wallets by investigating behavioral intention and use behavior.

The structure of this research paper is outlined as follows. The initial section provides an overview of the background and context of the study. The second section elaborates on the research methodologies, data collection procedures, and data analysis techniques. The third section conveys the results and discussion. Finally, the last section presents the conclusions, implications, and limitations of this research.

METHODS

Sampling and Data Collection

The study is descriptive research, which falls under conclusive research, as the aim was to provide comprehensive descriptions and examine market functions in detail (Malhotra, 2019). The research used a cross-sectional study to collect data from the population sample at one point. It also reveals the relationship among variables during that specific period (Malhotra, 2019). Data for the study was collected through the survey research method using a structured questionnaire with relevant questions distributed and filled in by the targeted respondents (Malhotra, 2019). Surveys are essential to such research since they provide a standard and non-biased method for collecting information from a wide range of individuals in social science and behavioral studies (Ruel et al., 2016).

The sample size in this study was determined according to the method recommended by Hair et al. (2021). The research, however, achieved a sample size of 372 participants, which is a strength in this case. This study used non-probability sampling to gather the sample since its selection is based on subjective criteria rather than random selection from a known probability (Babin & Zikmund, 2015). This purposeful approach was adopted because a complete list of the target population does not exist, making conducting probability sampling unfeasible. Participants' criteria in the sample are that they have reached 18 years old, are domiciled in Indonesia, use an e-wallet as the primary tool for daily transactions, and have at least one year of history using an e-wallet account and maintaining their e-wallet.

Questionnaire Formulation and Scale Development

A questionnaire is a set of questions organized to obtain facts from the respondents (Malhotra, 2019). Online surveys can be broad and disseminated quickly. This is one of the most essential steps to doing your research, and this will define what you want to measure. This study operationalized 38 indicators across 10 variables (Davis, 1989; Karjaluoto et al., 2021; Musa et al., 2015; Patil et al., 2020; Venkatesh et al., 2012; Zaid Kilani et al., 2023). Similarly, this study's online questionnaire gave respondents a Likert scale (Malhotra, 2019). Used in social science literature, this scale assesses attitudes or beliefs on a 7-point Likert scale with responses varying from "strongly disagree" (1) to "strongly agree" (7) (Ruel et al., 2016). Using a seven-point Likert scale adds to validity and reduces ambiguity in measurement (Churchill & Peter, 1984; Finstad, 2010), making it suitable for this study.

Common Method Bias

In survey research, a threat to the validity of questions arises from Common Method Bias (CMB) that can confound associations between constructs under study (Gansser & Reich, 2021). CMB is also reported to be a common concern with survey methodologies, and remedies can help address the potential of bias (MacKenzie & Podsakoff, 2012; Podsakoff et al., 2003). In response to this, the researchers included features that would help resolve logistical issues and reduce apprehension among respondents due to anonymity in data collection (Gansser & Reich, 2021) and additionally iteratively adapted question wording and context to ensure clarity, pre-testing with e-wallet experts before minimizing respondent confusion as per best practice. The researchers finally performed a Harman single-factor test (Kaiser, 1974) to see if CMB was a clear concern. Finally, the results show that CMB explains only 37.996% of the variation, which is captured as a latent construct that violates MacKenzie and Podsakoff (2012) criteria and is less than the threshold rule of thumb value, i.e., below 50 %, so it shows its trivial percentage. It suggests that CMB is not a major concern in this study, although the variance associated with CMB was very small.

Data Analysis Techniques

A multivariate statistical technique, Structural Equation Modeling (SEM) was used in this study, to test hypothetical relationships between latent constructs – dependent and independent variables (Hair et al., 2021). SEM can be classified into two main types: covariance-based (CB-SEM) and variance-based approaches (PLS-SEM). PLS-SEM was chosen because it has capabilities that the Management display properties better model constructs (Hair, 2011; Henseler, 2010). PLS-SEM is popular in predicting relationships among latent variables for confirmatory and exploratory analyses, especially for complex models (Sitar-Taut & Mican, 2021). Therefore, Smart-PLS software has been enlisted for data analysis. Testing an SEM model with PLS is carried out in two steps: the measurement and structural model assessments (Hair et al., 2021).

During the measurement model phase, we evaluated the validity and reliability of constructs with their indicators. The critical metrics measured included Indicator Loads and Average Variance Explained (AVE), also known as Cronbach's Alpha (CA), and Composite Reliability (CR) (Hair et al., 2021). To assess discriminant validity, first, the Fornell-Larcker Criterion (Fornell & Larcker, 1981) was reviewed, followed by the Heterotrait-Monotrait ratio of the correlations or HTMT criteria (Hair et al., 2021; Henseler et al., 2016). The next stage in structural model evaluation was hypothesis testing. Variance Inflation Factor (multicollinearity among the predictor constructs). Bootstrapping analysis with 5000 resamples was carried out for path coefficients using t-statistic and p-values. Model fit was examined using the Standardized Root Mean Square Residual (SRMR), which reflects remaining discrepancies between correlations (Henseler et al., 2015). The following hypotheses are proposed in this study:

H1. Performance expectancy has a positive relationship with behavioral intention, as is the case of the intention or desire to use e-wallets in Indonesia
H2. Effort expectancy has a positive relationship with behavioral intention, as is the case of the intention or desire to use e-wallets in Indonesia
H3. Social influence has a positive relationship with behavioral intention, as is the case of the intention or desire to use e-wallets in Indonesia
H4. Facilitating conditions have a positive relationship with behavioral intention, as is the case of the intention or desire to use e-wallets in Indonesia
H5a. Habit has a positive relationship with behavioral intention, as is the case of the intention or desire to use e-wallets in Indonesia
H5b. Habit has a positive relationship with use behavior, as is the case of e-wallet usage in Indonesia
H6. Hedonic motivation has a positive relationship with behavioral intention, as is the case of the intention or desire to use e-wallets in Indonesia
H7. Perceived security has a positive relationship with behavioral intention, as is the case of the intention or desire to use e-wallets in Indonesia
H8. Epistemic value has a positive relationship with behavioral intention, as is the case of the intention or desire to use e-wallets in Indonesia
H9. Behavioral intention, as is the case of the intention or desire to use e-wallets in Indonesia, has a positive relationship with use behavior, as is the case of e-wallet usage in Indonesia

RESULTS AND DISCUSSION

Respondents' Demographic Profile

Table 1 shows this research's sample profile (background of the respondents). We initiated online survey recruitment via social media platforms and collected 382 respondents before dropping 10 respondents who failed to meet the inclusion criteria. All respondents were from Indonesia, with a demographic breakdown of 60.5% women and 39.5% men. Respondents spread relatively in six regions: Daerah Khusus Jakarta (24.73%), West Java (18.55%), D.I. Yogyakarta (14.78%), Central Java (13.98%), East Java (9,68%), and other provinces. Thus, in Java, the distribution might signal that more people use e-wallets there because of better internet penetration and higher purchasing power and account holders based out of this geographical area, or it may simply be indicative that this is where merchants are mostly situated.

Table 1. Respondents' Profile

Information	Frequency	Percentage
Gender		
Male	147	39.5
Female	225	60.5
Education Level		
No formal education	1	0.27
Primary or secondary education (elementary school, junior high school, senior high school, and vocational school)	87	23.39
Graduated from diploma or vocational education	55	14.78
Graduated from university (Bachelor's, Master's, and Doctorate degrees)	229	61.56
Frequently Used Digital Wallets		
Gopay	115	30.91
ShopeePay	92	24.73
OVO	62	16.67
Dana	82	22.04
LinkAja	19	5.11
Others	2	0.54
Monthly Expenditure Using Digital Wallets		
≤ Rp1.800.000	118	31.72
Rp1.800.001 to Rp3.600.000	121	32.53
Rp3.600.001 to Rp7.200.000	106	28.49
Rp7.200.001 to Rp14.400.000	22	5.91
≥ Rp14.400.001	5	1.34
Province of Residence		
Aceh	1	0.27
Banten	9	2.42
D.I. Yogyakarta	55	14.78
Daerah Khusus Jakarta	92	24.73
Jambi	3	0.81
Jawa Barat	69	18.55
Jawa Tengah	52	13.98
Jawa Timur	36	9.68
Kalimantan Barat	1	0.27
Kalimantan Timur	2	0.54
Kepulauan Bangka Belitung	2	0.54
Kepulauan Riau	1	0.27
Nusa Tenggara Barat	1	0.27
Nusa Tenggara Timur	3	0.81
Papua	1	0.27
Riau	2	0.54
Sulawesi Selatan	4	1.08
Sulawesi Selatan	4	1.08
Sulawesi Tengah	1	0.27
Sulawesi Utara	1	0.27
Sumatera Barat	2	0.54
Sumatera Selatan	2	0.54
Sumatera Utara	28	7.53

Measurement Model Evaluation

In SEM, PLS measurement model analysis is the most crucial step because this ensures that all latent are defined, measured with great precision, and as reliable as possible. Reflective Indicators — All constructs in this research are reflective indicators that measure different aspects of the underlying latent construct (J. F. Hair et al., 2021). Reflective measurement models typically make explicit the expectations that indicator variables should correlate with one another and score on the overall latent construct (J. F. Hair et al., 2021). Expectancy-value theory built the UTAUT-2 framework where, according to Venkatesh et al. (2012), their expectation impacts individuals' technology use as goal-achieving benefits in using the UTAUT Model.

The reflective model of UTAUT-2 should have items that reflect the construct (MacKenzie et al., 2005; Venkatesh et al., 2012). These items, which contrast one another, individually represent different facets of user experience (MacKenzie et al., 2005), thus attesting to the reflective nature of intention to use technology (Hair et al., 2017). While in the reflective measurement model, indicators are said to be reflections of an unobserved construct such that a change in the underlying construct leads to a change in the indicators (MacKenzie et al., 2005), this is not true for formative constructs where we assume that the indicators define the latent construct. The UTAUT-2 model has been well fitting with the reflective model in studies

Indicators for perceived security and epistemic value are also modeled reflectively, aligning with the characteristics of reflective constructs in psychological and behavioral measurements (DeVellis, 2016). In the reflective model, these indicators correlate with those in the UTAUT-2 framework (DeVellis, 2016; Hair, Babin et al., 2019). This agrees with the results of Azman Ong et al. (2023), who backed up a reflective form for perceived security and epistemic value, among which were singled out as the reflective constructs leading to measurement equivalence. In assessing the reflective measurement model, four tests were applied in line with Hair et al. (2021): LF, AVE, CA, and CR values.

Table 2. Loadings, VIF values, Reliability Measures, and Validity Measures

Variable	Indicator	Skewness	Kurtosis	LF	VIF	AVE	CA	CR
Performance Expectancy	PE1	-1.455	3.857	0.805	1.820	0.662	0.830	0.887
	PE2	-1.358	2.427	0.813	1.759			
	PE3	-1.540	4.528	0.805	1.814			
	PE4	-1.176	1.839	0.831	1.864			
Effort Expectancy	EE1	-1.394	2.308	0.813	1.742	0.660	0.829	0.886
	EE2	-1.482	4.205	0.814	1.713			
	EE3	-1.354	2.089	0.826	1.799			
	EE4	-2.113	8.004	0.797	1.794			
Social Influence	SI1	-1.008	0.567	0.854	2.270	0.722	0.870	0.912
	SI2	-1.006	0.641	0.896	2.841			
	SI3	-1.122	1.083	0.896	2.874			
	SI4	-1.483	2.280	0.743	1.533			
Facilitating Conditions	FC1	-1.167	0.315	0.872	2.517	0.716	0.865	0.909
	FC2	-2.108	4.469	0.887	2.696			

Variable	Indicator	Skewness	Kurtosis	LF	VIF	AVE	CA	CR
	FC3	-1.553	2.172	0.896	2.788			
	FC4	-1.133	0.125	0.717	1.512			
Habit	H1	-1.345	1.837	0.758	1.546	0.665	0.831	0.888
	H2	-1.138	0.669	0.863	2.649			
	H3	-0.910	0.278	0.831	2.411			
	H4	-1.483	2.728	0.805	1.677			
Hedonic Motivation	HM1	-1.182	1.520	0.888	2.154	0.794	0.870	0.920
	HM2	-1.114	1.196	0.915	2.876			
	HM3	-1.200	1.398	0.868	2.253			
Perceived Security	PS1	-1.308	1.875	0.871	2.306	0.796	0.915	0.940
	PS2	-1.099	1.106	0.889	2.903			
	PS3	-1.122	1.226	0.908	3.604			
	PS4	-1.178	1.286	0.901	3.524			
Epistemic Value	EV1	-1.221	1.455	0.850	2.106	0.755	0.838	0.903
	EV2	-1.325	1.759	0.903	2.531			
	EV3	-1.552	3.224	0.853	1.742			
Behavior Intention	BI1	-1.428	3.022	0.868	2.387	0.751	0.890	0.923
	BI2	-1.196	2.160	0.866	2.259			
	BI3	-1.406	2.463	0.887	2.570			
	BI4	-1.668	3.928	0.844	2.231			
User Behavior	UB1	-1.467	2.691	0.888	2.442	0.663	0.829	0.886
	UB2	-1.525	2.772	0.878	2.342			
	UB3	-1.502	1.750	0.696	1.415			
	UB4	-1.976	5.395	0.782	1.674			

Note: LF = Loading Factor; VIF = Variance Inflation factor; AVE = Average Variance Extracted; CA= Cronbach's Alpha; CR = Composite Reliability.

Structural Model Evaluation and Hypothesis Testing

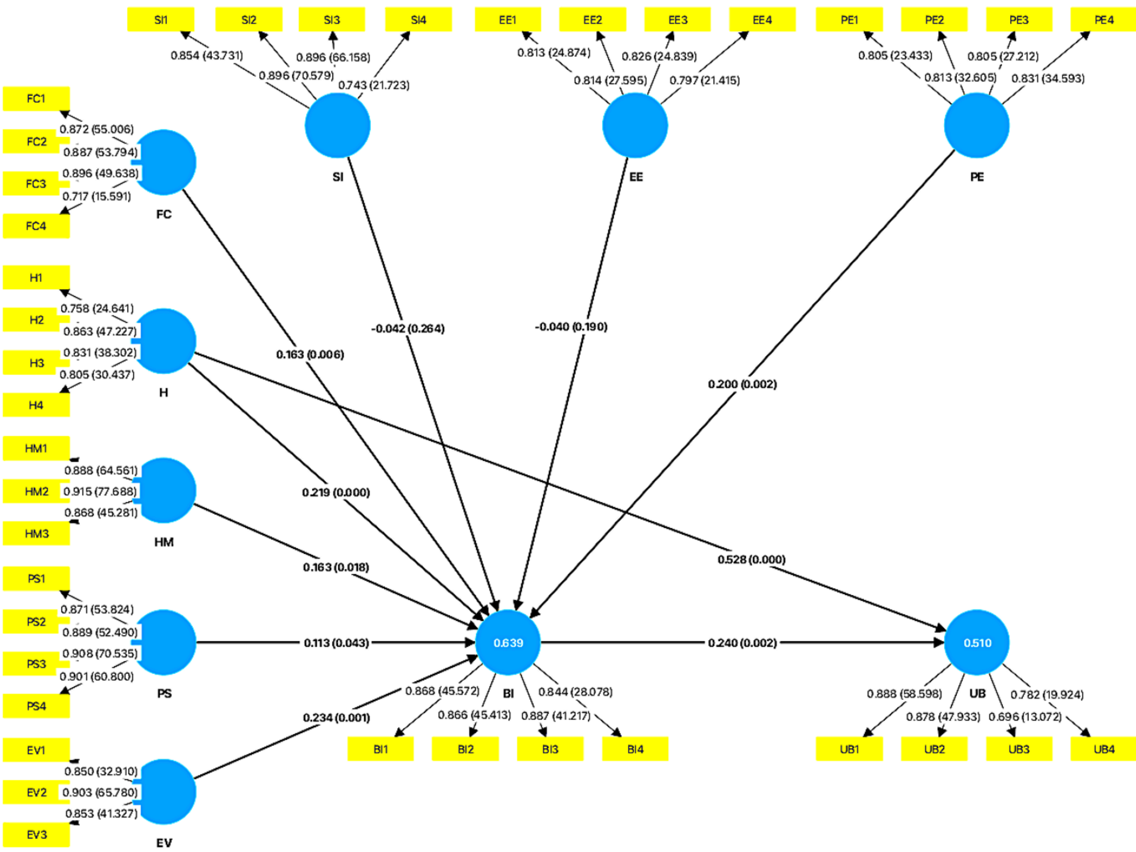
Following the assessment of the measurement model, Hair et al. (2021) recommended consideration of examining the structural model. First, collinearity was examined by using internal VIF values less than 5, showing no severe multicollinearity or performance bias (Hair, Risher, et al., 2019). The model has significant predictive capacity (BI: R^2 = 0.639; UB: R^2 = 0.510). This finding suggests that the eight exogenous variables, that are Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Habit (H), Hedonic Motivation (HM), Perceived Security (PS), and Epistemic Value (EV) contribute to a 63.9% variance in Behavioral Intention. Habit and Behavioral Intention mask over 51% of the variance in Use Behavior, demonstrating the model's substantial explanatory power (Straub et al., 2004). The study presented an SRMR result of 0.066, which indicates good model fit, according to Henseler et al. (2016)

Using a 5000 resample recommended by Hair et al. (2021), path coefficient analysis produced the following results shown in Table 3. However, Effort Expectancy (EE) and Social Influence (SI) did not significantly affect BI. Detailed results and statistical scores of the Partial Least Squares Structural Equation Modeling (PLS-SEM) can be seen in Figure 1.

Table 3. Structural Model and hypothesis Testing

Hypothesis	Path	PC	t-statistics	p-values	Decision
H1	PE → BI	0.200	2.922	0.002**	Supported
H2	EE → BI	-0.040	0.879	0.190	Not Supported
H3	SI → BI	-0.042	0.632	0.264	Not Supported
H4	FC → BI	0.163	2.492	0.006**	Supported
H5	H → BI	0.219	3.608	0.000***	Supported
H6	H → UB	0.528	7.725	0.000***	Supported
H7	HM → BI	0.163	2.087	0.018*	Supported
H8	PS → BI	0.113	1.713	0.043*	Supported
H9	EV → BI	0.234	3.217	0.001***	Supported
H10	BI → UB	0.240	2.942	0.002**	Supported

Note: BI = Behavioral Intention; EE = Effort Expectancy; EV = Epistemic Value; FC = Facilitating Conditions; HA = Habit; HM = Hedonic Motivation; PE = Performance Expectancy; PS = Perceived Security; SI = Social Influence; UB = Use Behavio; PC = Path Coefficients; *p < 0.05; **p < 0.01; ***p < 0.001.



Note: Inner Model = Path Coefficients and p-values; OuterModel = Outer Weights/Loadings and t-values; Constructs: R-Square.

Figure 1. Research Output

Discussion

This study analyzes and evaluates whether the variables in the Unified Theory of Acceptance and Use of Technology 2 (UTAUT-2) framework model, including the hedonic motivation variable and its extended variables such as perceived security and epistemic value, have an effect on behavioral intentions, as is the case of the intention or desire to use e-wallets in Indonesia. The first construct, performance expectancy, positively influences behavioral intention, which, in line with previous research findings, an easy-to-use e-wallet with a fast transaction process can indeed increase performance expectancy and encourage users to continue using it (Azman Ong et al., 2023; Bommer et al., 2022).

In contrast, effort expectancy as the second construct does not positively influence behavioral intention. This contrasts with attribution, though it is consistent with the research indicated (Abrahim Sleiman et al., 2023; Liébana-Cabanillas et al., 2017). As stated by Chopdar et al. (2018), users are getting used to smartphones and apps. The growing familiarity with technology due to the internet spreading and even the number of users is another role (Venkatesh, Morris, et al., 2003; Venkatesh & Zhang, 2010). With this in mind, effort expectations may not be necessary, considering that individuals already accustomed to electronic payment technologies might not find e-wallets challenging (Merhi et al., 2019). Likewise, the third construct, social influence, does not positively influence behavioral intention. This suggests that while social networks affect technology adoption, personal financial preferences limit their impact (Merhi et al., 2019). Accepting social influence is voluntary (K. Gupta & Arora, 2020), and individuals are likely to take it only if it aligns with their behavior (Shaw & Sergueeva, 2019; Venkatesh et al., 2003).

The fourth construct, facilitating conditions, indicated a strong positive effect to behavioral intention, and as per the previous studies, this adds to the evidence of technical infrastructure and necessary support that e-wallet consumers seek before adopting (Morosan & DeFranco, 2016; Sivathanu, 2019). The fifth construct, habit, exhibited significant positive effects to both the behavioral intention and use behavior of e-wallets, implying that it will be the leading key to fostering regularity (frequency) in using e-wallets over time amongst users (Gansser & Reich, 2021; A. Gupta & Arora, 2017). The sixth construct, hedonic motivation, indicated the positive impact to behavioral intention that reflects items about fun and reward experience during an interaction with e-wallet services, which expands previous results of continued usage (Alalwan et al., 2018; Handayanto & Ambarwati, 2022). The seventh construct, perceived security, has a positive effect to to behavioral intention, indicating that user confidence in e-wallet transaction security enhances their willingness to use digital payment systems (Balapour et al., 2020; Sivathanu, 2019). Users' perception of learning through e-wallet services increases their behavioral intention to adopt and continue use (Berraies et al., 2017; Hasan, 2022); the eighth construct revealed a significant positive impact, epistemic values.

Finally, the ninth construct, behavioral Intention, had a strong positive influence to use behavior, which ends with an observation that many of the factors leading to intention need to be addressed if broader adoption is the goal (A. Gupta & Arora, 2017; K. P. Gupta et al., 2019; Upadhyay et al., 2022). To sum up, these results give light on how e-wallet adoption and usage in Indonesia are affected by a variety of factors on an individual level toward a more comprehensive explanation that should be taken into account at the user's end for e-wallet providers could enhance their service experience and achieve sustainable uptake among users.

CONCLUSION

As previously described, user-friendly e-wallets can process transactions and deliver high satisfaction with continuous use quickly. Thus, performance expectancy has a significant positive influence on behavioral intention. On the other hand, effort expectancy has no significant impact on behavioral intention, perhaps due to a continuing diminishment of technology durability and commodification. Social influence has either been unsupported. Facilitating conditions also influence behavioral intention, reinforcing the importance of technical infrastructure. Habits significantly affect the behavioral intention and use behavior of an e-wallet. Thus, hedonic motivation, perceived security, and epistemic values all positively affect behavioral intention, suggest enjoyable experiences, security confidence, and knowledge gain are crucial for the continued use of the system. Finally, behavior intention significantly influences use behavior; decision-makers need to focus on intention-related factors to promote e-wallet acceptance. These findings offer insights into e-wallet adoption dynamics in Indonesia, highlighting crucial factors for enhancing user experience and sustaining digital payment technology use.

This study has several limitations and possible directions for future research. The model focuses on drivers of e-wallet use in Indonesia by combining predictors under UTAUT-2, including hedonic motivation, perceived security, and epistemic value. This will also make e-wallet usage more advantageous if researchers based on the proposed UTAUT-2 model add another theory, such as TTF (Task Technology Fit), to elaborate on a wider set of factors explaining intention and behavior toward adopting e-wallets. Additional studies should be conducted to assess these generational variances and complement technology acceptance models with demographic and psychological constructs.

REFERENCES