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DIGITAL FINANCIAL TRANSFORMATION IN INDONESIA: NON-CASH USAGE VIA MODIFIED UTAUT2 WITH TRUST

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Abstract

Digital payments are transforming the financial landscape in Indonesia, offering fast and efficient services that meet the growing demand for cashless transactions. This study analyzes the factors influencing digital payment adoption using the UTAUT2 model, with the addition of Trust as a critical factor. Cluster analysis was also conducted using the k-prototype algorithm to see their characteristics and perceptions about digital payments. A survey was conducted from June to August 2024, gathering 451 responses from users of digital payment services. The data were analyzed using structural equation modeling to test 13 hypotheses. Of these, 10 hypotheses were accepted, indicating that Effort Expectancy, Performance Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Habit, and Trust significantly influence Behavioral Intention. Social Influence and Facilitating Conditions also directly impacted trust, which further strengthened users' intention to adopt digital payments. However, Price Value did not significantly affect Behavioral Intention, and Habit was not a strong predictor of continued use behavior. Trust emerged as a key factor in driving user engagement and long-term adoption. The study highlights that while convenience and social influence are crucial, trust in digital payment services is essential for sustaining user adoption. Cluster analysis divides respondents into four clusters, where the first, second, and third clusters are from young people with different perceptions about digital payment and the fourth cluster is from mature people who are mostly working as teachers or lecturers. These findings offer valuable insights into promoting digital payment usage and supporting Indonesia's shift towards a digital economy.

Keywords: digital economy, UTAUT2, Behavioral Intention, Use Behavior, Structural Equation Modeling

INTRODUCTION

The development of technology, especially in terms of smartphone use, has opened the door for Indonesian people to carry out digital transactions more easily and efficiently[1]–[6]. These digital transactions cover a wide range of activities, from purchasing goods and services online to paying bills and transferring money between individuals[7][8]. As smartphone usage increases, people are becoming more accustomed to the convenience offered by digital payments[1]. As smartphone usage increases, people are increasingly accustomed to the convenience offered. Thus, digital transactions have become an important aspect of the transformation towards a digital economy in Indonesia because they are considered more effective, practical, and economical. The support of information technology infrastructure that continues to grow, along with encouragement from the government and industry to encourage the adoption of digital payments, has helped accelerate the growth of the digital payment ecosystem in Indonesia by digital payments [9]. In particular, the Covid-19 pandemic that began in March 2020 accelerated the growth of digitalization. The government issued a Large-Scale Social Restrictions (PSBB) policy

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to reduce the impact of the pandemic, encouraging the use of online transactions. The development of digital payment system transactions, including the use of ATMs, EDCs, and Internet Banking, showed a growth trend before and during the Covid-19 pandemic [10].

Bank Indonesia in the 2025 Indonesian Payment System Blueprint stated that the increasing need for financial services meets the principles of a fast, efficient and digital era which is currently disrupting all aspects, including payments [11]. Some digital payment technologies that have been implemented in Indonesia include debit and credit cards, virtual accounts, e-money, digital wallets, and the latest is QRIS (Quick Response Code Indonesian Standard). In 2019, Bank Indonesia released the Blue Print of the Indonesian Payment System (BSPI) 2025. This was done to prepare the payment system infrastructure needed to accelerate the development of an efficient and inclusive digital economy and finance. This initiative will be implemented in stages between 2019 and 2025. As an initial step, QRIS was launched on August 17, 2019 and took effect on January 1, 2020. As of February 2022, the number of merchants using QRIS has reached 15,676,476 merchants[10].

The public response to the use of digital payments has been very good because it can help drive economic progress for MSMEs in Indonesia[12]–[14]. In addition, digital payments are also needed to expand national non-cash payment acceptance more efficiently and strengthen the interconnection of digital ecosystems such as e-commerce, fintech, or banks [9][15]. Digital payments have great potential to accelerate the transformation towards a digital economy in Indonesia [16]–[19].

Despite its many positive impacts, digital payments also have their own challenges. In Asia, digital payment adoption is influenced by factors such as trust, risk perception, social influence, adoption, security, privacy, infrastructure and government policies [20][21]. Then, user perceptions of usefulness, ease of use, social support, and other factors also play an important role in the intention and behavior of using digital payment applications [22]. Previous studies in the context of technology adoption have shown that models such as UTAUT2 can provide valuable insights in understanding the factors that influence user behavior towards a technology, such as m-banking, e-learning, e-wallet, m-payment, QRIS and e-money [5][6][23]–[33].

Understanding the elements that influence adoption only from the viewpoint of the entire population is frequently insufficient when studying the acceptability of digital payment technology. This is because diverse human variables, including socioeconomic situations preferences, technological experience, and demographics, can have varying effects on the degree of technology acceptance. Therefore, user segmentation, which seeks to classify users into specific groups with comparable characteristics[34], can be performed as an additional analysis. There are several techniques commonly used to perform segmentation, such as for customer segmentation using K-means on numerical data [34][35] and cluster analysis using k-prototype because the data used contains numerical and categorical data [36]–[38].

Therefore, this study aims to analyze Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, Habit, Behavioral Intention, Use Behavioral, Trust related to digital payments in Indonesia. Using the UTAUT2 Method (Unified Theory of Acceptance and Use of Technology 2). Then, because this technology is engaged in the sensitive financial sector, of course user trust plays a big role in using technology in this field. Therefore, we also add the Trust factor to the existing UTAUT2 framework. Then a segmentation analysis was carried out on digital payment users using the K-Prototype algorithm. This study will explore the factors that influence user intentions to adopt digital payments as well as the factors that influence the behavior of using digital payments in Indonesian society.

Thus, this study is expected to provide a deeper understanding of the adoption of digital payments in terms of effort expectations, social influence, innovation, government support, trust, and perceived benefits so that it can be a foundation for developing more effective strategies in increasing the use of digital payments in Indonesia.

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METHODS

Unified Theory of Acceptance and Use of Technology (UTAUT)

Unified Theory of Acceptance and Use of Technology (UTAUT), combines eight variables to predict acceptance and use of technology. These variables include performance expectations, effort expectations, social influence, facilitating conditions, behavioral intentions, Use Behavior and moderating factors such as gender, age, experience, and voluntariness[39].

Then, in 2012 UTAUT expanded the model to UTAUT2, by adding three new constructs such as hedonic motivation, price values, and habits. This model is able to explain 74% of the variance in consumer behavioral intentions to use technology, and 52% of the variance in technology use[40].

K-Prototypes

Categorical data is commonly used in clustering and other data mining applications. However, the standard approach of turning categorical data into numerical ones doesn't always yield useful outcomes [36]. To handle mixed data types, the K-prototypes algorithm combines the k-means and k-modes algorithms. Because real-world data is mixed-type objects, K-prototypes are more practically useful [37]. The k-prototype method's main algorithm is to determine the separation between data objects and group centers by calculating the distance. Results from the k-prototype approach are suitable for small and medium-sized data sets. However, because of the significant computational cost involved, it is unable to handle mixed data sets on a large scale (millions of occurrences) [38].

Proposed Method

The trust variable, which was initially not included in the UTAUT and UTAUT2 models, has now been added to evaluate its influence on customer behavioral intentions. Previous studies have revealed that knowledge-based trust and innovation attributes influence attitudes toward digital payments [41][42]. The findings of these studies indicate that both trust and innovativeness have a significant impact on the adoption of mobile banking services[43] adding trust variable in FinTech adoption among Islamic and conventional banking users with moderating effect on Education level in Pakistan the results show that when consumers perceive FinTech services as safe and efficient for digital financial transactions, they tend to believe in its long-term benefits[44] as shown in Figure 1.

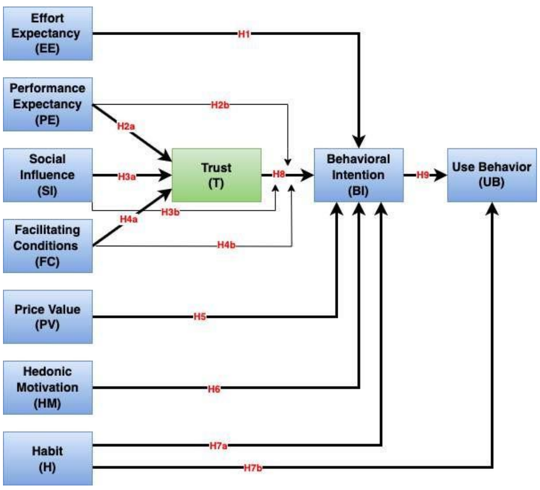

Figure 1 *Research framework*

Extending the UTAUT2 model by adding the trust factor, confirming that trust is a major predictor, the results show that trust was found to be highly significant in the use of mobile banking among consumers in Lebanon and the UK. Built an extended model by adding risk and trust in the use of mobile money services and found that trust has a significant influence on users' Behavioral Intention to adopt mobile money in Ghana [42]. Extended the UTAUT2 model by adding the trust factor to e-wallet adoption where the results found that trust has the most expected effect on continuance usage intention in e-wallet adoption in Jordan[41].

Effort Expectancy (EE)

Effort Expectancy is a major predictor of technology acceptance, defined as the extent to which using a system is perceived as easy or difficult [39]. Assessing perceptions of Effort Expectancy in using biometric payment systems is crucial, as expectations related to Effort Expectancy significantly influence the decision to adopt the system in the payment and checkout process [45]. Several previous studies have investigated the direct relationship between Effort Expectancy and consumer intention to adopt digital payment technology[45]. To ensure alignment, the following hypotheses are proposed:

H1: Effort Expectancy influences Behavioral Intention

Performance Expectancy (PE)

Performance Expectancy is defined as the extent to which individuals feel that a system can improve their work performance[39]. Individual attitudes, which are an important aspect and are seen as personal characteristics that influence the tendency to adopt technology, are expected to be affected by PE[46]. Performance Expectancy is significantly related to user intention towards FinTech services, reflecting the belief that adopting FinTech can increase productivity and simplify financial activities, even though these services are still relatively new in many countries and mainly focus on increasing the efficiency and security of business transactions[47], [48]. To ensure alignment, the following hypotheses are proposed:

H2a: Performance Expectancy influences Trust.

H2b: Performance Expectancy influences Behavioral Intention through Trust

Social Influence (SI)

Social Influence refers to the extent to which an individual's decision to use a system is influenced by the people around them[39]. Social Influence reflects how environmental factors, such as opinions from friends, relatives, and users influence user behavior[42]. Social influence has been shown to have a significant impact on behavioral intentions in digital payment adoption [42], [43]. By referring to the literature on the adoption of online and mobile services, this analysis is simplified to create a situation that supports the acceptance of new services and technologies [49], [50]. To ensure alignment, the following hypotheses are proposed:

H3a: Social Influence affects Trust

H3b: Social Influence Influences Behavioral Intention through Trust

Facilitating Conditions (FC)

Facilitating Conditions is defined as the level of confidence a person has in the company's technical infrastructure support that fully supports the use of technology to improve their performance[39]. The Facilitating Conditions variable indicates that technology adoption will increase if barriers in the technological or organizational environment can be overcome or minimized[51]. In addition, the likelihood of technology adoption tends to increase when individuals perceive facilitating conditions, such as chat features or online service guides, as helpful [52]. Several studies have explored the positive impact of facilitating conditions on usage intentions and behavior in the acceptance of technology-based systems[53], [54]. To ensure alignment, the following hypotheses are proposed:

H4a: Facilitating Conditions influences Trust

H4b: Facilitating Conditions influences Behavioral Intention through Trust

Price Value (PV)

Price Value is how users assess the cost-effectiveness of using digital payment technology [55]. The UTAUT2 model explains that the decision to use technology is influenced by Price Value which refers to the comparison between the perceived benefits and the monetary costs involved in using the technology[56]. This preconception arises from consumers' belief that technology is often perceived as expensive, including subscription, device, and internet costs, which increase the total cost of the application[57]. In the study of digital payment systems, price/value includes

perceived price and initial estimates of value, which often have a negative impact on initial adoption [58][59]. To ensure alignment, the following hypotheses are proposed:
H5: Price Value influences Behavioral Intention.

Hedonic Motivation (HM)

Hedonic Motivation relates to the pleasure and satisfaction felt from using technology [40]. In mobile banking, Hedonic Motivation (HM) encompasses user happiness and satisfaction that aligns with their lifestyle, with pleasure and enjoyment reinforcing the benefits and added value of the technology [59][60]. Hedonic motivation aims to provide satisfaction and pleasure to users through experiences with new systems, prioritizing aspects of personal pleasure and emotional satisfaction obtained from the technology [61]. Hedonic Motivation is assessed as the way users perceive biometric payment systems as an engaging and satisfying technology, which enriches their payment experiences and goals securely [25]. To ensure alignment, the following hypotheses are proposed:
H6: Hedonic Motivation influences Behavioral Intention

Habit (H)

Habit is an action pattern that is formed automatically and repeatedly without requiring active awareness [40]. The main factor that influences the sustainability of mobile application usage is habit [62]. Studies reveal that habits play a crucial role in shaping usage behavior, with various studies emphasizing their impact on users' intentions and actual actions [25][41][47]. Previous research recommends incorporating habits into the UTAUT2 model by assuming that habits are defined as the extent to which technology use becomes part of daily routines and plays an important role in influencing users' intentions and behavior towards technology [41]. To ensure alignment, the following hypotheses are proposed:
H7a: Habit influences Behavioral Intention.
H7b: Habit influences Use Behavioral.

Trust (T)

Trust is a subjective tendency to believe that an action will be consistent with positive assumptions [44]. Trust is an individual's belief that a system, service, or product will consistently meet their expectations, provide a sense of security, and not disappoint [42]. Trust is a significant predictor of continued usage behavior of mobile payment systems [63]. Trust is also considered to be positively influenced by perceived benefits and satisfaction with technology, which ultimately impacts continued usage behavior [41]. To ensure alignment, the following hypotheses are proposed:
H8: Trust influences Behavioral Intention.

Behavioral Intention (BI)

Behavioral Intention refers to how a user intends or plans to use a technology, and this intention influences the use of the technology [40]. This intention is the starting point that drives the use of a technology [64]. Behavioral intention refers to the extent to which a person deliberately plans the behavior he or she will perform in the future [61]. Several previous studies have shown that Behavioral Intention has an influence on the use of technology [65]–[67]. To ensure alignment, the following hypotheses are proposed:
H9: Behavioral Intention influences Use Behavioral.

Data Analysis

The Partial Least Squares Path Modeling (PLS-SEM) approach was utilized to analyze the research data, and the k-prototype methodology was then applied for clustering analysis. The stages of research analysis carried out consisted of Outer Model Testing, Inner Model Testing, and Cluster Analysis. Outer model testing was carried out to see the validity and reliability of each construct. A number of tests, including Composite Reliability, Average Variance Extracted (AVE), Convergent Validity, and Discriminant Validity, were used to test the outer model. Test-passing constructs will be used for the inner model and cluster analysis testing phases and will be accepted to be valid and reliable. Inner model testing is carried out to evaluate the structural relationship between constructs as seen from the R-square and Q-square predict values, then continued with hypothesis testing which will see what hypotheses are accepted. At the cluster analysis stage, constructs that pass the outer model test will be used as data for analysis using the k-prototype algorithm. The number of clusters will be determined using the elbow method to see the most efficient number of clusters, then an analysis will be carried out on the characteristics of each existing cluster.

RESULT AND DISCUSSIONS

Data Collection

Empirical data were obtained after the questionnaire was distributed, via Google form online and directly with a QR code, in the period from June to August 2024. The total entries received were 451 replies from respondents with experience using digital payments. The analysis presented in Table 1 shows the frequency of user demographic groups to represent various segments and describes gender, education and occupation.

Table 1. Demographic Information

Demographic Information		Frequency	Percentage
Gender	*Man*	194	43.0%
	Woman	257	57.0%
Age	*17-25*	122	27.0%
	26-35	252	55.8%
	36-45	66	14.6%
	>46	11	2.4%
Domicile	*Jabodetabek (Jakarta, Bogor, Depok, Bekasi)*	27	5.98%
	Kalimantan	146	32.37%
	Jawa	126	27.94%
	Sumatera	22	4.88%
	Sulawesi	57	12.64%
	Papua	9	1.99%
	Nusa Tenggara	23	5.10%
	Bali	5	1.11%
	Maluku	20	4.43%
	Kepulauan Riau	16	3.55%
Education	*Senior High School*	87	21.50%
	Diploma D1-D3	44	9.75%
	Bachelor (S1)	227	50.33%
	Master (S2)	63	13.98%
	Doctoral (S3)	30	6.65%
Job	*Students or College Students*	108	23.97%
	Private sector employee	47	10.42%
	BUMN employee	26	5.76%
	Entrepreneur	23	5.11%
	Merchant	20	4.43%
	Farmers or Breeders	8	1.78%
	Teacher or Lecturer	107	23.73%
	Government Employees (PNS)	32	7.10%
	Army or Police	22	4.88%
	Bank employees	27	5.99%
	Medical personnel	31	6.87%

Analysis of demographic data of digital payment service users in Indonesia, as presented in Table 1, reveals several important patterns related to the distribution of gender, age, domicile, education, and occupation in the adoption and use of digital payment technology in Indonesia.

Table 1 shows that 43% of the respondents were male, while 57% were female creating a somewhat imbalanced gender distribution but reflecting female dominance in the use of digital payment services. This may indicate that women may be more active or more likely to adopt this technology than men, which could be relevant to user behavior patterns or preferences in financial technology.

In terms of age, the majority of users are in the 26-35 age range (55.8%), indicating that this age segment is the primary user of digital payment services. This age range typically includes individuals who are already economically established and may be more open to adopting new technologies. The 17-25 age group accounted for 27%, indicating that the younger generation is also an important user group, likely due to their higher technological skills and quick adaptation to digital innovations. In contrast, the 36-45 and above 46 age groups accounted for 14.6% and 2.4% respectively, indicating a significant decline in adoption at older ages. This may be due to a lack of comfort with technology or differences in financial habits between generations.

Geographical distribution shows the dominance of users from Kalimantan (32.37%) and Java (27.94%), while Jabodetabek contributed (5.98%), Sulawesi (12.64%), and Riau Islands 3.55%), indicating that the use of digital payment services is quite evenly distributed outside Java and Kalimantan, although some regions such as Papua (1.99%) and Bali (1.11%) have very small representation. This unevenness may reflect differences in technological infrastructure, internet penetration rates, or service accessibility in various regions.

In terms of education, users of digital payment services in Indonesia show that Bachelor's degree (S1) graduates, which cover 50.33% of the total respondents, indicate that this service is very popular among individuals with higher education. Master's degree (S2) and Doctoral degree (S3) graduates account for 13.98% and 6.65% respectively, indicating that although the proportion is smaller, users with postgraduate education are still a significant segment. On the other hand, high school and Diploma D1-D3 graduates cover 21.50% and 9.75% respectively, indicating that digital payment services are also used by individuals with lower levels of education. Overall, this data shows that digital payment services have a wide reach across various levels of education, but with a higher concentration in those with Bachelor's degrees.

In terms of employment, there is a significant dominance of students (23.97%) and teachers or lecturers (23.73%). This shows that the education sector, both as students and teachers, has high involvement in the use of digital payment services. In addition, the proportion of private sector employees (10.42%), BUMN employees (5.76%), and entrepreneurs (5.11%) is also quite significant. Professions such as farmers or ranchers have a very small representation (1.78%), which may reflect population distribution or survey access. Other professions such as bank employees (5.99%), medical personnel (6.87%), and government employees (7.10%) show that individuals in these sectors are also actively adopting digital technology.

The demographics of digital payment service users in Indonesia show that the dominance of female users and the 26-35 age group reflects a significant adoption trend in this category. Users with higher education, especially Bachelor's graduates, are more likely to use this service, indicating a preference among more educated individuals. Geographically, there is a concentration of users in Kalimantan and Java, while other regions, such as Papua and Bali, show lower participation. In terms of employment, survey respondents are dominated by the education sector, including students and teachers.

Validity and Reliability Testing

The results of the validity analysis from Table 2 show that most indicators have adequate outer loadings values, indicating good construct validity. Indicators for the Behavioral Intention (BI) construct, including BI1 (0.864), BI2 (0.906), and BI3 (0.881), and Effort Expectancy (EE) with EE1 (0.796), EE2 (0.849), and EE3 (0.847), are all above the threshold value of 0.70, indicating that they are valid and represent the construct well as shown in Figure 2.

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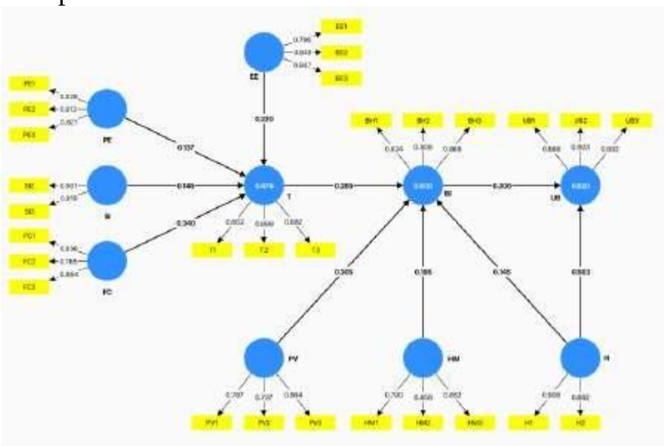


Figure 2 *Validity and reliability testing on structural model*

Table 2. Validity test result

Construct	Outer Loadings	Construct	Outer Loadings
BI1 <- BI	0,864	*PE1 <- PE*	0,829
BI2 <- BI	0,906	*PE2 <- PE*	0,812
BI3 <- BI	0,881	*PE3 <- PE*	0,821
EE1 <- EE	0,796	*PV1 <- PV*	0,792
EE2 <- EE	0,849	*PV2 <- PV*	0,763
EE3 <- EE	0,847	*PV3 <- PV*	0,841
FC1 <- FC	0,836	*SI1 <- SI*	**0,648**
FC2 <- FC	0,785	*SI2 <- SI*	0,863
FC3 <- FC	0,864	*SI3 <- SI*	0,887
H1 <- H	0,874	*T1 <- T*	0,861
H2 <- H	0,853	*T2 <- T*	0,889
H3 <- H	**0,692**	*T3 <- T*	0,882
HM1 <- HM	0,778	*UB1 <- UB*	0,865
HM2 <- HM	0,853	*UB2 <- UB*	0,905
HM3 <- HM	0,866	*UB3 <- UB*	0,880

Likewise, indicators for the Facilitating Conditions (FC) construct such as FC1 (0.836), FC2 (0.785), and FC3 (0.864) and Performance Expectancy (PE) with PE1 (0.829), PE2 (0.812), and PE3 (0.821) show good validity. Perceived Value (PV) also has valid indicators, with PV1 (0.792), PV2 (0.763), and PV3 (0.841). However, there are several indicators that need further attention.

In the Hedonic Motivation (H) construct, the H3 indicator has an outer loading value of 0.692, which is below the 0.70 limit, indicating that this indicator may not be completely valid. For the Social Influence (SI) construct, the SI1 indicator shows a value of 0.648, also below the validity limit, while SI2 (0.863) and SI3 (0.887) are valid. Indicators for Hedonic Motivation (HM) and

Trust (T), with respective values of HM1 (0.778), HM2 (0.853), HM3 (0.866), T1 (0.861), T2 (0.889), and T3 (0.882), and Usage Behavior (UB), with UB1 (0.865), UB2 (0.905), and UB3 (0.880), all show good validity.

Overall, although most indicators show valid outer loadings values, indicators H3 and SI1 require further evaluation to improve the accuracy and reliability of construct measurement in this study.

Table 3. Cronbach’s Alpha, Composite Realibility, and Average Variance Extracted (AVE)

Variables	Cronbach's alpha	Composite reliability (rho_a)	Average variance extracted (AVE)
BI	0,782	0,797	0,695
EE	0,776	0,779	0,691
FC	0,773	0,784	0,688
H	0,753	0,760	0,801
HM	0,779	0,781	0,694
PE	0,759	0,763	0,673
PV	0,718	0,755	0,636
SI	0,793	0,798	0,828
T	0,851	0,851	0,770
UB	0,859	0,860	0,781

Table 3 presents the results of reliability and validity testing for various constructs in the study, including Cronbach's Alpha, Composite Reliability, and Average Variance Extracted (AVE) values. Cronbach's Alpha, which measures the internal consistency of constructs, shows that most constructs have values above 0.70, reflecting good reliability. While the acceptable thresholds for AVE and composite reliability are 0.5 and 0.7[68]. For example, Behavioral Intention (BI) and Usage Behavior (UB) each have a value of 0.859, while Trust (T) also shows a high value of 0.851, indicating very good internal consistency. However, the Perceived Value (PV) construct has a lower value of 0.718, indicating that the internal consistency of this construct is slightly less good than the others.

Composite Reliability, which provides additional insight into internal consistency, showed consistent results with Cronbach's Alpha. All constructs except Performance Expectancy (PE) had Composite Reliability values above 0.70, indicating good reliability. Performance Expectancy (PE) with a value of 0.763, although slightly lower, is still within acceptable limits. Average Variance Extracted (AVE), which measures how well a construct explains the variance of its indicators, also showed good results for most constructs. The AVE value for Behavioral Intention (BI) and Usage Behavior (UB) reached 0.781, reflecting strong convergent validity. Other constructs such as Effort Expectancy (EE) and Hedonic Motivation (HM) had AVE values above 0.69, indicating that they also had good validity. However, Perceived Value (PV) with an AVE of 0.639 indicated that the convergent validity of this construct was slightly lower, although still acceptable.

Overall, the results from Table 3 show that most of the constructs in this study have good reliability and validity, with only a few constructs such as Perceived Value (PV) and Performance Expectancy (PE) requiring further attention to ensure measurement accuracy and consistency.

Table 4. R-square, R-square adjusted, Q-Square

Variables	R-square	Q^2predict
BI	0,600	0,568
T	0,474	0,454
UB	0,620	0,613

Table 4 presents the results of the R-square, adjusted R-square, and Q^2predict analyses for the various constructs in the study. These results provide insight into how well the model explains the variance of the dependent variable and its ability to predict.

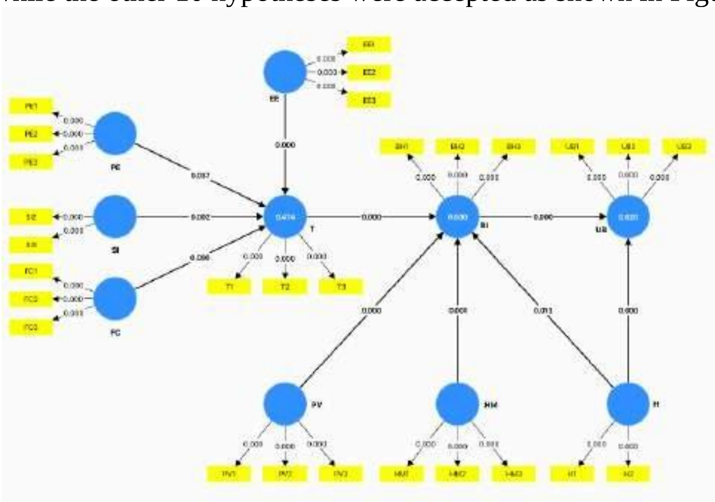
R-square describes the proportion of variance in the dependent variable that can be explained by the independent variables in the model. This value indicates the strength of the model in explaining the variables studied. For example, the Behavioral Intention (BI) construct has an R-square value of 0.648, indicating that the model can explain about 64.8% of the variance of BI. Trust (T) has an R-square value of 0.468, meaning that this model explains 46.8% of the variance of Trust. The most striking is Usage Behavior (UB), with an R-square value of 1.000, indicating that the model fully explains the variance of UB, a very ideal and rare result.

Q^2predict is a predictive measure that shows how well the model predicts the dependent variable. Q^2predict values above 0 indicate that the model has good predictive ability. For Behavioral Intention (BI) and Trust (T), the Q^2predict values are 0.622 and 0.448, respectively, indicating adequate predictive ability, although the value for Trust is lower than BI. Meanwhile, Usage Behavior (UB) has the same Q^2predict value as its R-square, which is 0.622, indicating that the model is very effective in predicting UB variance.

Overall, Table 4 shows that this research model has good predictive and explanatory power for the variables Behavioral Intention and Usage Behavior. Although the R-square and Q^2predict values for Trust are slightly lower, the model still shows adequate predictive ability. The success of the model in explaining and predicting UB variance, with perfect R-square and Q^2predict values, highlights the effectiveness of the model in the context of this variable.

Hypothesis Testing

Hypothesis testing in this study uses statistical methods involving T-statistics and p-values. The critical limits applied are 1.96 for T-statistics, and p-value of 0.05. The test results presented in Table 5 show that out of a total of 13 hypotheses analyzed, 3 of them were rejected based on these criteria, while the other 10 hypotheses were accepted as shown in Figure 3.



low quality picture

Figure 3 *Model testing result*

Table 5. Hypothesis Testing

Hypothesis	Track	Original sample (O)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Note
H1A	EE → BI	0,063	0,023	2,676	0,007	Accepted
H2A	PE → T	0,137	0,066	2,086	0,037	Accepted
H2B	PE → T → BI	0,039	0,023	1,709	0,088	**Rejected**
H3A	SI → T	0,145	0,046	3,167	0,002	Accepted
H3B	SI → T → BI	0,041	0,014	2,895	0,004	Accepted

H4A	FC → T	0,340	0,055	6,155	0,000	Accepted
H4B	FC → T → BI	0,097	0,029	3,402	0,001	Accepted
H5	PV → BI	0,305	0,061	5,001	0,000	Accepted
H6	HM → BI	0,185	0,056	3,271	0,001	Accepted
H7A	H → BI	0,145	0,059	2,478	0,013	Accepted
H7B	H → UB	0,608	0,048	12,703	0,000	Accepted
H8	T → BI	0,285	0,066	4,318	0,000	Accepted
H9	BI → UB	0,306	0,054	5,722	0,000	Accepted

Cluster Analysis

Constructs obtained from the inner model together with respondent data will be used at this stage. First, feature engineering is carried out to reduce data dimensions by aggregating the construct based on the type of existing variables and removing features that are considered unimportant.

Based on the Elbow method technique that has shown in Figure 4, it was found that the most optimal number of clusters is 4. This number of clusters is used as a parameter in the k-prototype algorithm used.

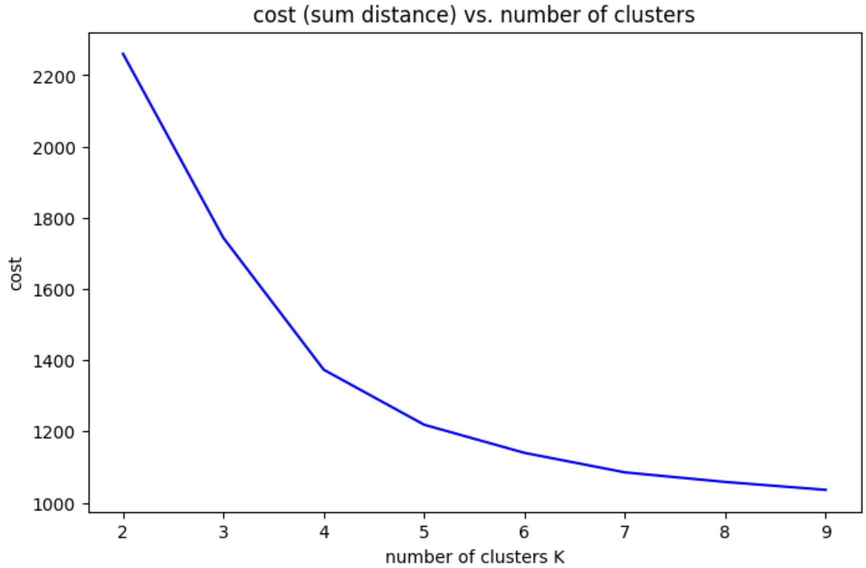


Figure 4 *Elbow Method result*

Discussion

Hypothesis H1 which states that Effort Expectancy (EE) has an effect on Behavioral Intention (BI) shows a T-statistic of 2.319 and a p-value of 0.020. Both of these values meet the limit criteria (T-statistic> 1.96 and p-value <0.05), so this hypothesis is accepted. This finding indicates that ease of use significantly affects user intention to adopt digital payment services, users who consider the technology easy to use tend to have a stronger intention to adopt it. This finding is consistent with research by[53], which found that EE significantly affects BI in the use of QR code-based payment services in Indonesia. In addition, research by [69], shows that EE also has a significant influence on BI, making it a major determinant of the adoption of mobile payment technology in Brazil.

Furthermore, research [43] produced similar findings, where EE influences BI in the context of FinTech adoption among Islamic banking users in Pakistan, showing that users in Pakistan consider FinTech applications easy to use, easy to understand, and convenient for financial transactions. In contrast, research conducted in the study [70] stated that Effort Expectancy has no effect on Behavioral Intention in the case of mobile payment usage in Taiwan.

Hypothesis H2A, which proposes that Performance Expectancy (PE) affects Trust (T), shows a T-statistic of 2.014 and a p-value of 0.044. These values support the acceptance of the hypothesis, indicating that the relationship is statistically significant. This finding implies that users tend to trust digital payment services that are perceived as effective and efficient in meeting their needs, so that the expected performance of the technology contributes to increased trust in the reliability of the service. The results of this study are in line with the findings of previous studies conducted[71] which states that Trust has an influence on Behavioral Intention on the adoption of the OVO e-wallet on Tokopedia. A different thing is shown by [72] where Performance Expectancy does not affect trust in the case of using cashless payments in Thailand.
Hypothesis H2B, which proposes that Performance Expectancy (PE) influences Behavioral Intention (BI) through Trust (T), shows a T-statistic of 1.767 and a p-value of 0.077. These values indicate that the hypothesis is not accepted, because the T-statistic is less than 1.96 and the p-value is greater than 0.05, indicating that the tested relationship is not statistically significant. This finding may be due to the fact that users tend not to consider trust as a major mediator in their decisions. Instead, they focus more on the ease of use and the immediate benefits of the service. The results of this study are consistent with the findings of previous studies conducted in the research [70], [73]which stated that Performance Expectancy influences Behavioral Intention in the case of mobile payment usage in Taiwan and Pakistan. The opposite is found in [74] which states that Performance Expectancy has no effect on Behavioral Intention in the case of Mobile Banking in Indonesia. The absence of Performance Expectancy on Behavioral Intention through Trust is also shown by in the case of cashless payment usage in Thailand.
Hypothesis H3A, which proposes that Social Influence (SI) has an effect on Trust (T), shows a T-statistic of 2.554 and a p-value of 0.011. These values support the acceptance of the hypothesis, indicating that the relationship is statistically significant. This finding indicates that Social Influence significantly affects user trust in digital payment services. Specifically, these results show that recommendations and influences from individuals or close social groups can significantly increase the level of user trust in digital payment services. The results of this study are in line with a study conducted by [72]on the case of cashless payment usage in Thailand. A different thing is shown in [75]where social influence and trust do not influence each other on gen Z in Vietnam, which is more influenced by the practicality of using e-wallet than social influence.
Hypothesis H3B, which proposes that Social Influence (SI) influences Behavioral Intention (BI) through Trust (T), shows a T-statistic value of 2.132 and a p-value of 0.033. These values support the acceptance of the hypothesis, indicating that the tested relationship is statistically significant. This finding suggests that the influence of social groups can strengthen trust in digital payment services, which can then increase users' intention to adopt the service along with increased trust in its reliability. This result is in line with the findings of a study conducted by [58] which states that factors that form trust in users affect the use intention of mobile travel apps in Korea. The opposite was found in the study [58], [70] which stated that Social Influence had no effect on Behavioral Intention in the case of mobile payment usage in Taiwan and Korea. The same thing was also shown in the case of mobile banking usage in Indonesia [74].
Hypothesis H4A, which proposes that Facilitating Conditions (FC) affect Trust (T), shows a T-statistic value of 6.177 and a p-value of 0.000. These values support the acceptance of the hypothesis, indicating that the relationship is highly statistically significant. This finding indicates that the availability of facilities—including technical support, adequate infrastructure, and resources that support the use of services—significantly contributes to increasing user trust in the reliability of digital payment services. The results of this study are consistent with the findings of previous research conducted by [76] also showed that there was no relationship between trust in services and facilitating conditions in using mobile payment services. However, the same study showed that there was no relationship between trust in service providers and facilitating

conditions. This indicates that users prioritize trust in services provided by third parties compared to the third parties themselves.

Hypothesis H4B, which proposes that Facilitating Conditions (FC) affect Behavioral Intention (BI) through Trust (T), shows a T-statistic value of 3.169 and a p-value of 0.002. These values support the acceptance of the hypothesis, indicating that the relationship tested is statistically significant. This finding suggests that the availability of adequate technical support and infrastructure increases user trust in the service, which in turn strengthens their intention to adopt digital payment services. The results of this study support the findings of previous studies in the study [70] which stated that Facilitating Conditions affect Behavioral Intention in the case of mobile payment use in Taiwan. Other results that are in line with the findings of the study [58] which states that factors that form trust in users affect the use intention of mobile travel applications in Korea. A different thing is shown by [71] which states that Facilitating Conditions do not affect Behavioral Intention in the adoption of OVO e-wallet on Tokopedia.

Hypothesis H5, which proposes that Price Value (PV) influences Behavioral Intention (BI), shows a T-statistic value of 1.327 and a p-value of 0.185. Since the T-statistic value is less than 1.96 and the p-value is greater than 0.05, this hypothesis cannot be accepted. This finding indicates that price value does not significantly influence users' behavioral intention to adopt digital payment services. This may be due to users' higher priority on convenience and infrastructure support of the service compared to cost, or there may be differences in price value perceptions that do not significantly impact their decision to adopt digital payment services. This finding is consistent with research by [59] which also found that PV did not have a significant effect on BI in the adoption of peer-to-peer mobile payment platforms in Spain. In contrast, research conducted by[59] showed that PV had a significant effect on BI in the adoption of mobile banking, especially among consumers in the UK. The study attributed this influence to the perception that access to mobile services is associated with low cost or free usage, which reduces the impact of direct costs on usage decisions. A different thing is shown in [77] which shows that Price Value has no effect on Use Intention among accounting students in Bali.

Hypothesis H6, which proposes that Hedonic Motivation (HM) influences Behavioral Intention (BI), shows a T-statistic value of 3.910 and a p-value of 0.000. These values support the acceptance of the hypothesis, indicating that the relationship is statistically significant. This finding indicates that Hedonic Motivation significantly influences users' behavioral intention to adopt digital payment services. This result suggests that individuals tend to be more motivated to use technology that provides a pleasant and emotionally satisfying experience, which ultimately increases their intention to continue using digital payment services. The results of this study support the findings of a previous study in [71] which showed that Hedonic Motivation influences Behavioral Intention on the adoption of OVO e-wallet on Tokopedia. In contrast, research [44] showed that HM did not have a significant influence on BI in the adoption of mobile banking in Lebanon and the UK. In addition, research [59] also shows that HM has no significant influence on BI in the adoption of peer-to-peer mobile payment platforms in Spain, indicating that low positive perceptions related to transactions can reduce user motivation to engage in the use of the technology. The same thing is shown in [77] which shows that Price Value has no effect on Use Intention among accounting students in Bali.

Hypothesis H7A, which proposes that Habit (H) has an effect on Behavioral Intention (BI), shows a T-statistic value of 8.007 and a p-value of 0.000. These values support the acceptance of the hypothesis, indicating that the relationship is highly statistically significant. This finding indicates that habits that have been formed in the use of technology play an important role in facilitating adoption and consistency of use, thereby increasing individuals' intention to continue adopting digital payment services. The results of this study strengthen the results reported in previous research by [59] which also reported that H has a significant effect on BI in the adoption of peer-to-peer mobile payment platforms in Spain. In addition, the theory of habits and user behavioral intentions explains that behavior that is carried out repeatedly will form habits, where rational processes and conscious evaluation often no longer influence the behavior [78]. In this context, habits that are formed through repetition of behavior become automatic, thereby reducing the role of rational decisions in the decision-making process. A different thing is mentioned in [58] which states that habit cannot be a factor in predicting the behavioral intention of users in using mobile payments in Korea for Chinese tourists.

Hypothesis H7B, which proposes that Habit (H) influences Use Behavioral (UB), shows a T-statistic value of 0.505 and a p-value of 0.613. These values indicate that this hypothesis cannot be accepted, because the T-statistic is less than 1.96 and the p-value is greater than 0.05, indicating that the relationship being tested is not statistically significant. This finding indicates that habits that have been formed do not always guarantee continued adoption or utilization. This may be due to the influence of external factors, such as technological changes or changes in individual preferences, which can play a more dominant role in influencing the use of digital payments. This study supports the findings revealed in previous studies by [42], [77] which stated that habit influences use behavioral. A different thing is mentioned in [58] which states that habit cannot be a factor in predicting the use intention of users in using mobile payments in Korea for Chinese tourists.

Hypothesis H8, which proposes that Trust (T) influences Behavioral Intention (BI), shows a T-statistic value of 3.596 and a p-value of 0.000. These values support the acceptance of the hypothesis, indicating that the relationship is statistically significant. This finding suggests that the level of trust in the reputation and credibility of service providers influences an individual's intention to engage more intensively and interact with digital payment services. The findings of this study are consistent with the results reported by [44] who in their study on mobile banking adoption in Lebanon and the UK also found that Trust (T) had a significant effect on Behavioral Intention (BI). In the study, trust was considered a major factor influencing behavioral intention to adopt technology. The same thing is also shown in [42] where trust greatly influences behavioral intention in the case of using digital money services in Ghana. Different things were found in [79] where trust did not affect the intention to use mobile wallets in Vietnam. Previous research also shows that there is no influence between trust and behavioral intention in using mobile payment services [80].

Hypothesis H9, which proposes that Behavioral Intention (BI) influences Use Behavior (UB), shows a T-statistics value of 1996.436 and a p-value of 0.000. These values support the acceptance of the hypothesis, indicating that the relationship is highly statistically significant. This finding indicates that a strong intention to use the service has a significant effect on real actions in utilizing the technology consistently and sustainably. The results of this study are consistent with the findings of previous studies conducted on [74] which stated that Behavioral Intention influences Use Behavior in the case of Mobile Banking in Indonesia.

In cluster analysis, clusters are divided into 4 categories. Based on the characteristics of the respondents, the first cluster has a fairly even gender ratio where 51% are women and 49% are men. This cluster is dominated by respondents aged 26-35 years and none are over 45 years old. Based on work, it is also quite even where most are filled by students. The characteristics of this cluster are shown in Figure 5. The second cluster is very much dominated by women (73.9%) compared to men (26.1%) with the least number of domicile variations with 5 domiciles and is mostly filled by students (52.2%) aged 17-25 years (60.9%). The characteristics of this cluster are shown in Figure 6.

The third cluster is still dominated by women (58.5%) compared to men (41.5%) with around 51.1% of respondents aged 17-25 years followed by 36.2% of respondents aged 26-35 years but the difference is not as big as the second cluster. Because many respondents are aged 17-25 years, this cluster is also dominated by students. The characteristics of this cluster are shown in Figure 7. The fourth cluster is still dominated by female respondents (57.1%). Most respondents are aged 26-35 years (68%) followed by respondents aged 36-45 years (19.9%) with the most varied jobs, with the most jobs being teachers or lecturers (35.1%). This can be seen from the number of

Masters and Doctoral graduates in this cluster when compared to other clusters. The characteristics of this cluster are shown in Fig 8.

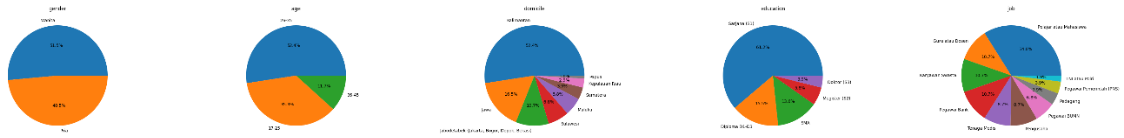


Figure 5 *Cluster 1 characteristics*

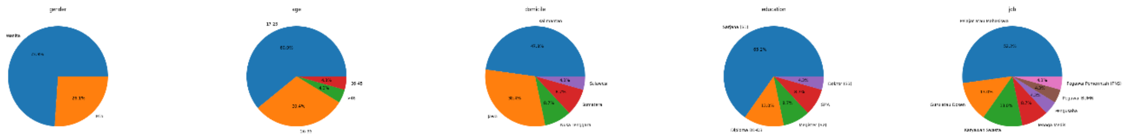


Figure 6 *Cluster 2 characteristics*

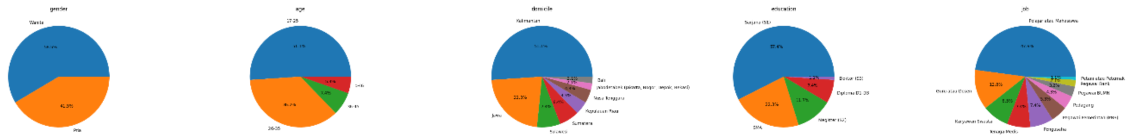


Figure 7 *Cluster 3 characteristics*

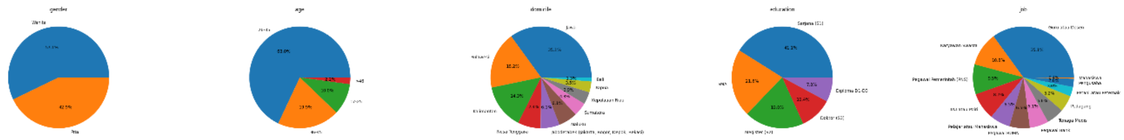


Figure 8 *Cluster 4 characteristics*

If we look at the boxplot of each cluster that shown in Figure 9, it is known that the first cluster tends to be spread on a scale of 4.5-5 for each existing variable. This indicates that for most young people, almost all aspects that exist are very important to influence them in using digital payments. The second cluster, although dominated by young people, tends to rate neutral on a scale of 3 and Performance Expectancy, Effort Expectancy, and Social Influence which are neutral tend to agree on a scale of 3-4. For Habit, neutral tends to disagree on a scale of 2.5-3. The third cluster is also dominated by young people, but they are neutral tend to agree (3-4) to the factors in accepting digital payment technology except for Performance Expectancy and Effort Expectancy which tend to strongly agree (3-5). The fourth cluster, which is filled with adults who are mostly working, tends to strongly agree to the factors in accepting digital payment technology, where most are on a scale of 4-5. From here, this grouping is carried out not only by looking at the characteristics of the respondents but also how the respondents assess the factors that influence the acceptance of digital payment technology.

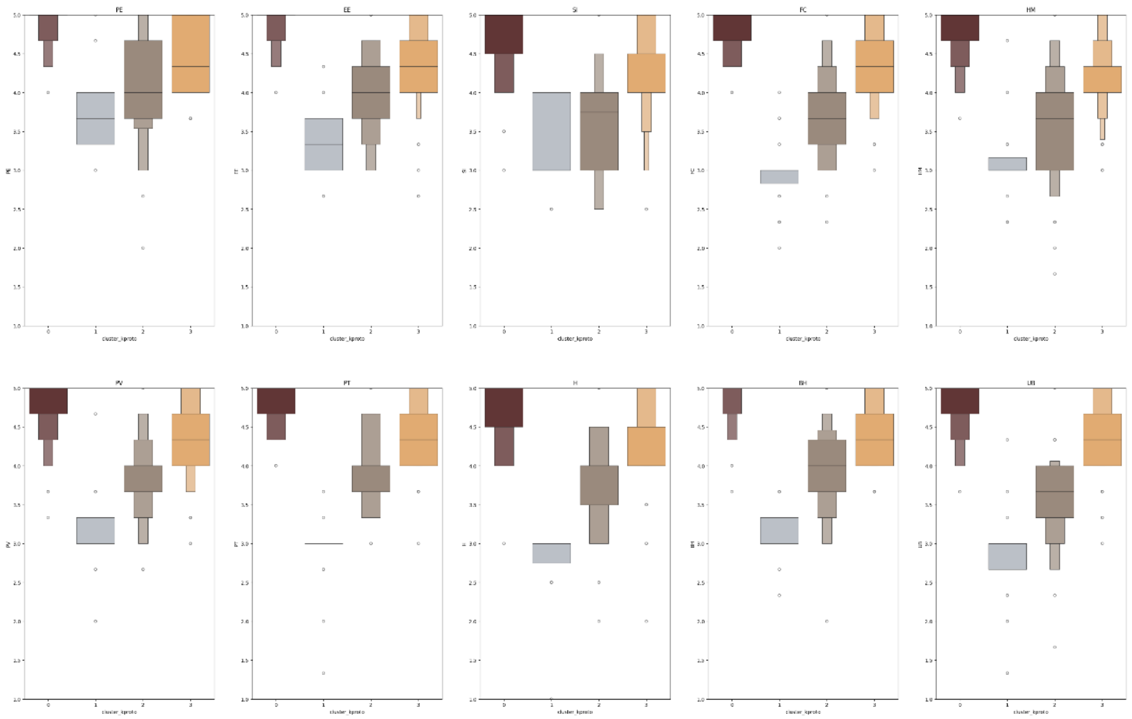


Figure 9 *Cluster assessment of each variable in digital payment technology*

CONCLUSIONS

The study demonstrates that digital payment adoption in Indonesia is significantly influenced by factors such as ease of use (Effort Expectancy), performance expectations, social influence, facilitating conditions, and trust, with Hedonic Motivation and Habit also playing key roles in driving behavioral intention. Of the 13 hypotheses tested, 10 were accepted, confirming the importance of these factors in influencing users' intention to adopt digital payments, while 3 were rejected, showing that Price Value and Habit's effect on actual usage did not significantly impact adoption. Trust was found to be a crucial mediator, enhancing users' confidence in the technology, and Behavioral Intention strongly predicted actual use behavior, indicating the potential for long-term digital payment adoption. Overall, while price considerations were less impactful, users' social networks, enjoyment, and habits greatly contributed to their engagement with digital payments, reinforcing the importance of trust and reliable infrastructure in sustaining the growth of the digital economy in Indonesia. Cluster analysis divides respondents into four clusters based on their demographic characteristics and perceptions of digital payment technology. The first, second, and third clusters are all dominated by young people who are mostly students with different perceptions of digital payment technology. Based on their perceptions of the factors that make them use digital payment technology, the first cluster tends to rate all aspects as very important, the second cluster tends to be neutral, and the third cluster is neutral to important. While the fourth cluster has different characteristics where it is dominated by mature users who are mostly working. The perception of this cluster also assesses that these factors are important in influencing them to use digital payment technology.

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