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Factors that influence behavioral intention in m-payment users in Surabaya

Evinka Dindamiatma[1], Siti Rahayu[1], Antonius Budhiman Setyawan[1], Junaid Kajee[2]

[1]*Faculty of Business and Economics, University of Surabaya, Surabaya, Indonesia*
[2]*University for Continuing Education, Krems, Austria*
Corresponding author: Siti Rahayu, s_rahayu@staff.ubaya.ac.id

Abstract. Many aspects of human life have shifted as a result of the rapid advancement of digital technology. Almost every aspect of human life that has been handled traditionally has begun to transition to the digital realm. In the economic field, digital payments using smartphones, also known as m-payments, are one proof of technological advances in the use of digital payments or m-payments. This study aims to analyze the factors that influence the behavioral intentions of m-payment users in Surabaya. The theory used in this study is UTAUT (Unified Theory of Acceptance and Use of Technology) with 6 independent variables (performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habit), 1 mediating variable (behavioral intention), 1 dependent variable (use behavior). Respondents in this study were 150 people who were analyzed using the SEM (Structural Equation Modeling) method of data processing and testing using SmartPLS software. Based on the results of data processing, shows that performance expectations, effort expectations, social influence, facilitating conditions, hedonic motivation, and habits have a positive effect on behavioral intentions. As well as behavioral intentions have a positive effect on usage behavior.

Keywords: m-payment, behavioral intention, UTAUT

Introduction

Many aspects of human life have shifted as a result of the rapid advancement of digital technology. In the economic field, digital payments using smartphones, also known as m-payments, are one proof of technological advances in the use of digital payments or m-payments. Mobile payment is a payment method that utilizes mobile devices such as smartphones and other digital devices to make purchases of goods, services, and bill payments using wireless communication technologies such as QR codes, NFC, and OTP codes (Pal et al., 2019). Mobile payments allow users to transact quickly and easily without the need for physical cash or cards. The technology behind m-payment prioritizes convenience, ease, and cost-effectiveness (Gosal & Linawati, 2018). If your m-payment method is registered with a mobile payment service application, you can use it to make cashless purchases. Users can top up their balance by going directly to retailers, sending money through ATMs, using SMS Banking or Mobile Banking, or similar methods (Yulianto et al., 2015).

Mobile payments utilize smartphones and other digital devices to enable purchases of goods, services, and bill payments through wireless communication technologies such as QR codes, NFC, and OTP codes (Sikri et al., 2019; Stephen et al., 2024). This payment method allows users to transact quickly and easily without the need for physical cash or cards, and its underlying technology prioritizes convenience, ease of use, and cost-effectiveness (Kim et al., 2010; Lerner, 2013). Unlike other digital payment forms that may operate via different interfaces or security protocols, m-payments leverage the ubiquity of mobile devices and diverse connectivity options, making them particularly adaptable to modern consumer lifestyles (Ariyanto, 2017).

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According to Jatmiko (2022), the types of m-payments available in Indonesia today include e-wallet, point of sale (POS), closed-loop mobile payment, carrier payment, and mobile payment applications. The e-wallet type of m-payment has a simple process. Users only need to open the app on their smartphones to do things like pay bills, shop, transfer money, check, and top up their balance. Amidst the current trend of online shopping, 65% of Indonesian customers use e-wallets or digital wallets for transactions. In Indonesia, the government and fintech companies continue to work together to expand the reach of mobile payments, including by providing education to the public on the benefits and usage of e-wallets. This initiative is expected to encourage digital economic growth, optimize transaction transparency, and reduce dependence on cash. The increase in e-wallet users also shows that the campaign implemented by the Indonesian government and startup companies to create a cashless society has been successful. With the increasing use of m-payment services, Indonesia is getting closer to the vision of becoming a less cash-dependent society, simplifying daily transactions, supporting financial inclusion, and driving digital economic growth.

Furthermore, like business products in general, although the use of m-payments is growing, the fact is that the development and how a service can become the main choice of consumers is influenced by many factors. When associated with theories related to behavioral intention, researchers assume that behavioral intention in m-payment users in Surabaya is influenced by various factors, such as technological factors, user perceptions and attitudes, security, ease of use, social factors, price, speed and quality of service, and previous user experience. In this study, a survey of m-payment users in Surabaya will be conducted to determine the factors that influence behavioral intention in m-payment users in Surabaya. Surabaya was chosen as the research location based on the fact that Surabaya is the second largest city in Indonesia after Jakarta which has a large population (Sahara & Kristiyanto, 2020). As a metropolitan city, Surabaya has a variety of digital access facilities, such as fast and easy internet access, and a high level of smartphone usage. However, even though these conditions make it possible to use m-payments, there are still some challenges and barriers to the adoption of digital payments. Factors such as varying levels of digital literacy, concerns about transaction security, and people's habit of using cash are some of the obstacles that need to be overcome.

As a reference or reference in this study, researchers conducted a literature review of several previous studies that had similar variables and topics. The first research is conducted by (Gupta & Arora (2020). The purpose of the study was to investigate how the main antecedents of the second model of the Unified Theory of Acceptance and Use of Technology (UTAUT) affect consumer intention to adopt and use mobile payment systems in the Indian National Capital region. Based on the findings of Gupta and Arora's (2020) research, performance expectancy, effort expectancy, facilitating conditions, and habit significantly influence behavioral intention to use mobile payment systems. On the other hand, the results of the study say that social influence and hedonic motivation are weak predictors of behavioral intention.

Another study that serves as a reference for researchers is research conducted by (Hussain et al., 2019). The purpose of the study was to examine the adoption of m-payment for the bottom-of-the-pyramid (BoP) segment in the context of developing countries. The results showed that performance expectancy (H1), effort expectancy (H2), social influence (H3), facilitating conditions (H4), habit (H7), and lifestyle compatibility (H8) had a significant effect on the BoP behavioral intention segment. On the other hand, hypotheses (H5 and H6) linking hedonic motivation and price value with behavioral intention did not receive significant support for adopting m-payments. From these two studies, researchers found that there are limitations and similarities between previous research and the research that researchers conducted. It is important to clarify why this study uses "behavioral intention to use" as the dependent variable rather than measuring actual usage. Although focusing on intention may include

respondents who have never used digital payments, this approach is widely adopted in technology acceptance research. Measuring behavioral intention allows us to capture not only current users but also potential adopters—those who may be influenced by factors such as perceived ease of use, security, and social influence. This is particularly relevant in a context like Surabaya, where digital payment systems are still emerging and consumer experiences vary widely. According to Gupta and Arora's (2020), the social influence factor has no significant effect on behavioral intention. This finding is not in line with the results of previous research conducted by Hussain et al., (2019) that social influence has a significant effect on behavioral intention. Therefore, it is important to further examine the factors that influence Behavioral Intention to use m-payment in Surabaya. This study aims to better understand these factors and find solutions that can increase the acceptance and use of m-payment in Surabaya. The results of this study are expected to provide input for m-payment in Indonesia to improve service quality and meet the needs of users in Surabaya. Based on this explanation, the hypothesis formed is as follows (see Figure 1):

H1: Performance expectancy has a significant positive effect on behavioral intention.
H2: Effort expectancy has a significant positive effect on behavioral intention.
H3: Social influence has a significant positive effect on behavioral intention.
H4: Facilitating conditions have a significant positive effect on behavioral intention.
H5: Hedonic motivation has a significant positive effect on behavioral intention.
H6: Habit has a significant positive effect on behavioral intention.
H7: Behavioral intention has a significant positive effect on use behavior.

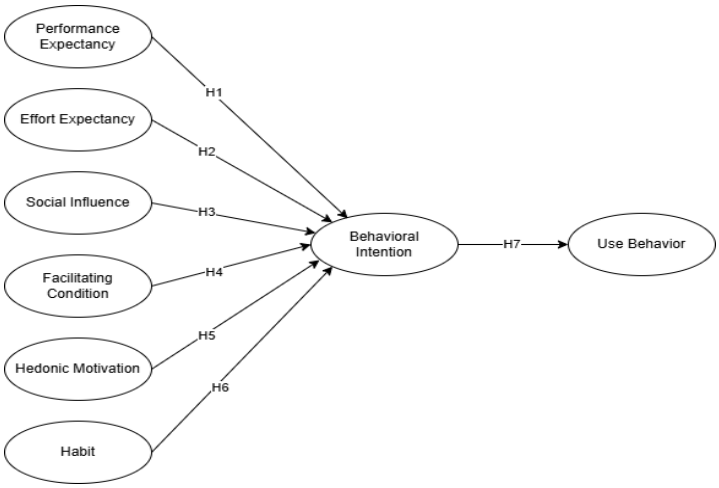

Figure 1. Research Model Source: Gupta and Arora (2020)

Research methodology

Researchers used quantitative methods in this study. This research applies primary data sources. Primary data in this study were obtained from the respondents concerned, namely m-payment users in Surabaya distributed online via google form. Researchers collect through interviews, experiments, direct observation, surveys, and questionnaires. This study uses a Likert scale with intervals of 1-5. Where 1 means Strongly Disagree and 5 means Strongly Agree. Sugiyono, P. D. (2019) states that the Likert scale is used in measuring opinions, attitudes, and perceptions of people or groups of people related to social events and symptoms.

Researchers used the population of m-payment users in Surabaya with a minimum age of 17 years for this study and used m-payment services in the last 3 months. The sampling technique used in this study is purposive sampling which is classified as non-probability sampling. Sugiyono (2013) states that purposive sampling is carried out with certain considerations that allow researchers to obtain samples that best fit the research criteria so that the research results are more relevant and can answer research questions better. The minimum sample size proposed by (Hair et al., 2010) is calculated using the formula:

N = 5 to 10 × the number of indicators in the study

So, the sample in this study has a minimum number of 150 respondents. This study uses the Partial Least Square Structural Equation Modeling (PLS-SEM) analysis technique, a statistical analysis technique used in testing the causality of a model in the form of a structure of many dependent variables by integrating factor analysis and path analysis (Abdillah & Hartono, 2015). SEM analysis using SmartPLS 3 software by evaluating the outer model and inner model.

Findings

The first step is measuring the outer model. From the results of Table 1 and Table 2, it can be seen that each indicator on the research variables has an outer loadings value> 0.70 and the AVE value of each variable> 0.50 so it can be concluded that all indicators have met convergent validity. Table 3 shows that the cross-loading value of each variable indicator has a value greater than the value of other variables, it is stated that it is following the requirements of discriminant validity.

Table 1. Loading Factor

	BI	EE	FC	H	HM	PE	SI	UB
BI1	0.887							
BI2	0.875							
BI3	0.843							
BI4	0.818							
EE1		0.876						
EE2		0.916						
EE3		0.906						
EE4		0.890						
FC1			0.724					
FC2			0.818					
FC3			0.820					
FC4			0.813					
H1				0.851				
H2				0.875				
H3				0.877				
H4				0.807				

	BI	EE	FC	H	HM	PE	SI	UB
HM1					0.925			
HM2					0.936			
HM3					0.863			
PE1						0.843		
PE2						0.798		
PE3						0.705		
PE4						0.774		
SI1							0.907	
SI2							0.885	
SI3							0.860	
UB1								0.754
UB2								0.861
UB3								0.918
UB4								0.828

(Source: Appendix 8)

Table 2. AVE Value

	Average Variance Extracted (AVE)
Behavioral Intention	0.733
Effort Expectancy	0.805
Facilitating Conditions	0.632
Habit	0.728
Hedonic Motivation	0.826
Performance Expectancy	0.611
Social Influence	0.782
Use Behavior	0.709

(Source: Appendix 8)

From the results of Table 1 and Table 2, it can be seen that each indicator on the research variables has an outer loadings value> 0.70 and the AVE value of each variable> 0.50 so it can be concluded that all indicators have met convergent validity. Table 3 shows that the cross-loading value of each variable indicator has a value greater than the value of other variables, it is stated that it is following the requirements of discriminant validity.

Table 3. Cross Loading

	BI	EE	FC	H	HM	PE	SI	UB
BI1	**0,887**	0,508	0,591	0,576	0,628	0,600	0,192	0,539
BI2	**0,875**	0,385	0,595	0,557	0,664	0,591	0,275	0,509
BI3	**0,843**	0,535	0,412	0,629	0,617	0,525	0,227	0,596
BI4	**0,818**	0,360	0,527	0,505	0,552	0,490	0,274	0,557
EE1	0,459	**0,876**	0,302	0,415	0,359	0,478	0,217	0,433
EE2	0,483	**0,916**	0,320	0,509	0,357	0,495	0,228	0,477
EE3	0,399	**0,906**	0,295	0,404	0,284	0,485	0,138	0,360
EE4	0,522	**0,890**	0,387	0,485	0,378	0,493	0,200	0,421
FC1	0,385	0,326	**0,724**	0,234	0,436	0,450	0,191	0,268
FC2	0,498	0,278	**0,818**	0,325	0,526	0,368	0,194	0,353
FC3	0,565	0,388	**0,820**	0,441	0,529	0,457	0,122	0,445
FC4	0,498	0,175	**0,813**	0,276	0,555	0,381	0,207	0,281
H1	0,632	0,516	0,451	**0,851**	0,606	0,533	0,169	0,691
H2	0,587	0,442	0,356	**0,875**	0,507	0,383	0,188	0,615
H3	0,563	0,418	0,317	**0,877**	0,503	0,419	0,384	0,624
H4	0,456	0,336	0,250	**0,807**	0,372	0,290	0,426	0,521
HM1	0,688	0,386	0,593	0,543	**0,925**	0,621	0,122	0,546
HM2	0,653	0,367	0,617	0,568	**0,936**	0,585	0,155	0,539
HM3	0,620	0,299	0,552	0,502	**0,863**	0,543	0,076	0,469
PE1	0,531	0,526	0,463	0,303	0,483	**0,843**	0,070	0,352
PE2	0,523	0,455	0,426	0,321	0,482	**0,798**	0,011	0,325
PE3	0,442	0,283	0,295	0,468	0,445	**0,705**	0,110	0,403
PE4	0,517	0,418	0,420	0,446	0,598	**0,774**	0,044	0,455
SI1	0,285	0,252	0,213	0,349	0,155	0,102	**0,907**	0,270
SI2	0,214	0,137	0,159	0,284	0,046	0,041	**0,885**	0,234
SI3	0,238	0,181	0,205	0,226	0,130	0,040	**0,860**	0,046
UB1	0,469	0,274	0,391	0,422	0,418	0,311	0,208	**0,754**
UB2	0,583	0,441	0,484	0,603	0,538	0,496	0,181	**0,861**
UB3	0,576	0,425	0,370	0,677	0,545	0,444	0,109	**0,918**
UB4	0,530	0,442	0,202	0,720	0,409	0,375	0,224	**0,828**

Table 4. Cronbach's Alpha & Composite Reliability Value

	Cronbach's Alpha	Composite Reliability
Behavioral Intention	0.878	0.916
Effort Expectancy	0.920	0.943
Facilitating Conditions	0.806	0.872
Habit	0.876	0.914
Hedonic Motivation	0.894	0.934
Performance Expectancy	0.786	0.862
Social Influence	0.861	0.915
Use Behavior	0.862	0.907

Table 4 shows that each variable has a Cronbach alpha value> 0.60 and a composite reliability value> 0.70, which means that all variables in this study are reliable. After measuring the outer model, the next step is to measure the inner model. According to Ghozali (2020), the inner model includes the relationship between latent variables or constructs. There are several tests for structural models, one of which is R-Square. The higher the R-Square value, the better the prediction model of the proposed research.

Table 5. R-Square

	R Square	R Square Adjusted
Behavioral Intention	0.680	**0.667**
Use Behavior	**0.413**	0.409

The R Square value in Table 5 shows the behavioral intention variable of 0.667, which means that the percentage of behavioral intention can be explained by all independent variables by 66.7%, while the remaining 33.3% is influenced by other variables outside the study. For the use behavior variable, the R Square value is 0.413. This value shows that use behavior can be explained by behavioral intention by 41.3% and the remaining 58.7% is explained by other variables not examined in this study.

Hypothesis testing using PLS is done by looking at the t-statistics and P-values. Hypotheses can be declared supported and have a strong significant effect between two variables if the t-statistics value ≥ 1.96 and the P-value value ≤ 0.05. Based on the test results in Table 6, seven hypotheses are supported.

Table 6. Direct Effect

Hypothesis	Original sample	t-statistics (|O/STDEV|)	P-values	Description
H1 (+) PE → BI	0,187	2,429	0,008**	Supported Hypothesis
H2 (+) EE → BI	0,099	2,249	0,012*	Supported Hypothesis
H3 (+) SI → BI	0,087	1,962	0,025*	Supported Hypothesis

H4 (+) FC → BI	0,180	2,047	0,021*	Supported Hypothesis
H5 (+) HM → BI	0,285	3,262	0,001**	Supported Hypothesis
H6 (+) H → BI	0,251	3,241	0,001**	Supported Hypothesis
H7 (+) BI → UB	0,643	13,599	***	Supported Hypothesis

***. Correlation is significant at the p < 0.001 level (2-tailed
**.Correlation is significant at the p < 0.01 level (2-tailed)
*. Correlation is significant at the p < 0.05 level (2-tailed) (Source: Appendix 8)

The first hypothesis states that performance expectancy (PE) has a significant positive effect on behavioral intention (BI) with the results of the t-statistics value 2.429> 1.96, p-values 0.008 <0.05. Thus, H1 is supported, the results of this study are aligned with research conducted by Gupta and Arora (2020) which shows that performance expectancy has a significant positive effect on behavioral intention. So, it can be concluded that positive performance expectations imply that consumers after using the m-payment system feel that the system is knowledgeable and safe, and overall increases their productivity.

The second hypothesis states that there is a significant positive effect between effort expectancy (EE) on behavioral intention (BI) with a t-statistics value of 2.249> 1.96, and p-values 0.012 < 0.05. Thus, H2 is supported. The research results are in line with Damayanti et al. (2021) who found that effort expectancy has a positive effect on behavioral intention. This shows that effort expectancy affects behavioral intention. Effort expectancy refers to how easy the payment process is. Technological advances have made payments faster and easier for customers to understand. So, this explains that the ease of technology such as m-payment will affect people's interest in using it.

The third hypothesis states that there is a significant positive influence between social influence (SI) on behavioral intention (BI) with a t-statistics value of 1.962 < 1.96, p-values 0.025 > 0.05. Thus, H3 is supported. These results are in line with the research of Hussain et al., (2019). So, the results of this hypothesis explain that some of the decisions made by users to use the m-payment system are based on the social environment or people closest to them. In addition, some previous users were active enough to invite others to use m-payment, which will encourage their behavioral intentions to want to use the application and feel that the application will provide benefits to them.

The fourth hypothesis states that there is a positive influence between facilitating conditions (FC) on behavioral intention (BI) with a t-statistics value of 2.047> 1.96 and, p-values of 0.021 <0.05. Thus, H4 is supported, and the results of this study are aligned with (Verkijika, 2018). According to Venkatesh et al. (2012) facilitating conditions are one of the factors that can directly influence behavioral intentions or goals which include the level of trust a person has in resources, organizational support, and technical infrastructure to support system use. The results of this hypothesis explain that facilitating conditions such as available online assistance related to the use of m-payments, and compatible m-payment systems are very influential for m-payment users.

The fifth hypothesis states that there is a positive influence between hedonic motivation (HM) on behavioral intention (BI) with a t-statistics value of 3.262> 1.96 and, p-values of 0.001 <0.05. Thus, H5 is supported. The effect of hedonic motivation on behavioral intention was also found in purchasing airline tickets online through the website (Escobar-Rodríguez & Carvajal-Trujillo, 2014). This shows that the sense of pleasure and comfort obtained by users when using the website makes users want to buy tickets using the same website later.

The sixth hypothesis states that there is a positive influence between habit (H) on behavioral intention (BI) with a t-statistics value of 3.241> 1.96 and p-values of 0.001 <0.05. Thus, H6 is supported. Gupta and Arora (2020) conveyed that habit is the strongest influence on the desire to use m-payment in the results of empirical studies that support the influence of habit on the behavioral value of research on the adoption of payments made via smartphones. The current generation is increasingly using smartphones for all purposes, one of which is transactions. Therefore, it can be concluded that currently, the habit of using digital transactions has automatically emerged. This habit will always form the intention to use m-payment repeatedly.

The seventh hypothesis states that there is a positive influence between behavioral intention (BI) on use behavior (UB) with a t-statistics value of 13.599> 1.96 and, p-values of 0.000 <0.05. Thus, H7 is supported. These results are in line with the research of Karyoto et al., (2024) related to the influence of behavioral intention on the use behavior of using the Gojek application that in this study the behavioral intention variable has a significant positive effect on use behavior. Use behavior means a person's behavior in using technology. Theory of Reasoned Action (TRA), the method used to create UTAUT, states that the intention to perform a behavior (behavior) is based on the intention to perform the behavior. Thus, the intention to perform behavior (use behavior) will determine how it is used (Venkatesh et al., 2012).

Conclusions

After testing the entire hypothesis, the results obtained are that the seven hypotheses are supported or acceptable. 2 hypotheses have different results from previous research conducted by Gupta and Arora (2020). The third hypothesis regarding social influence variables on behavioral intention and the fifth hypothesis regarding hedonic motivation on behavioral intention in this study have a positive and significant effect. Research shows that various factors such as convenience, performance expectations, effort expectations, social influence, adequate facilities, and encouraging motivation affect users' intention to use m-payments. Management should understand these factors and adjust educational strategies according to consumer needs and preferences.

In the digital economy, the use of m-payments provides convenience and efficiency for consumers, so companies need to respond to this trend with the right strategies to increase adoption. The first step is to increase digital education and literacy through programs that explain the benefits, usage, and security measures of m-payments. Second, m-payment applications should be designed with a simple and easy-to-use interface so that they can be accessed by various groups. Third, building partnerships with many merchants will expand payment points and increase the practicality of its use. Fourth, companies need to listen to consumer feedback through easily accessible channels to improve services. Finally, continuous innovation, such as integration with other services and improved security features, is important to meet consumer needs and increase trust in m-payments.

Future research on m-payment adoption and usage in Indonesia should include several important aspects to enrich understanding, such as expanding the scope of research areas to cities with different characteristics, including areas with low internet penetration or rural areas, to get a holistic picture of the factors that influence adoption in various geographic and socio-economic contexts. In addition, the analysis of digital literacy needs to be deepened to identify effective educational strategies, involving diverse demographics such as age, education, and technology experience to understand the influence of digital literacy on user behavior. It is also important to examine users' security perceptions of m-payments, including their expectations of protection mechanisms, the effectiveness of security features implemented, and the extent to which users' knowledge of such features affects their confidence in using m-payments.

Theoretical Contribution

This study advances the theoretical understanding of m-payment adoption by validating and extending existing models like the UTAUT framework. Notably, it highlights the significant roles of social influence and hedonic motivation—factors that have been inconsistently reported in previous research. By integrating these variables with traditional determinants such as performance and effort expectancy, the study provides a more nuanced framework that better explains consumer behavior in the context of m-payments, thereby opening new avenues for future academic inquiry in digital payment systems.

Managerial Contribution

For practitioners, the findings offer actionable insights to drive m-payment adoption. The identification of key influencing factors such as digital literacy, interface simplicity, robust security measures, and strategic partnerships provides clear guidance for designing and implementing effective marketing and operational strategies. Managers can leverage these insights to tailor educational programs, enhance user experience, and foster consumer trust, ultimately supporting the shift toward a more efficient, cashless society.

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