

Factors Influencing Mobile Payment Adoption Utilizing Extended UTAUT with a Case Study: Public Transportation Trans Jatim Buses

Rio Kharismawan¹, Edwin Pramana², Yosi Kristian³

Institut Sains dan Teknologi Terpadu Surabaya, Surabaya, East Java, Indonesia

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✉ Corresponding Author

Rio Kharismawan,

Institut Sains dan Teknologi

Terpadu Surabaya,

riokharismawan@gmail.com

ABSTRACT

Mobile payment is widely used across sectors, but its adoption in Bus Trans Jatim remains low, with only 18% of passengers using it monthly in 2024. This study explores factors influencing users' behavioral intention to adopt mobile payment by extending the UTAUT model, incorporating performance expectancy, effort expectancy, social influence, trust, and external factors like network externalities and promotional activities, with education and location as moderating variables. Using a quantitative approach and 432 valid responses collected via online questionnaires, data were analyzed through SEM with AMOS 22. The results show that five out of six variables significantly affect behavioral intention, except for promotional activities. Furthermore, education and location did not significantly moderate the relationships. This research contributes to technology adoption theory and offers practical guidance for transport providers to prioritize performance, ease of use, social influence, and trust in promoting mobile payment usage.

INTRODUCTION

The rapid growth of mobile device usage has significantly transformed daily life, particularly in the way financial transactions are conducted. One notable development is the widespread adoption of mobile payments across various industries [1], which involve performing financial activities through mobile devices [2][3]. As a modern financial innovation, mobile payments have reshaped consumer behavior, especially in emerging markets [4], although further research is needed to fully understand the patterns of adoption and user behavior [5]. In particular, mobile payment offers an alternative transaction method via mobile networks [8], using technologies such as SMS, Near Field Communication (NFC), and QR codes [1]. These systems emphasize convenience, accessibility, and security, making them widely accessible and enabling the emergence of new, inclusive business models [1][9]. In practice, mobile payments are also designed to be user-friendly, typically requiring only the input of the transaction amount and confirmation via a PIN or fingerprint scan [10].

In the context of public transportation, especially Bus Rapid Transit (BRT) systems, mobile payment technologies have attracted growing academic attention due to their potential to improve service efficiency and user experience [6]. In East Java, Trans Jatim has adopted mobile payment systems to support non-cash transactions. However, adoption remains limited; according to the 2024 financial report, only 18% of the 342,000 monthly passengers used mobile payments. This indicates the need to further investigate the factors influencing user

acceptance in this setting. Although many studies have explored mobile payment adoption globally, research specifically focusing on public transportation in Indonesia is still scarce [7].

To address this gap, the present study analyzes the determinants of mobile payment adoption among Bus Trans Jatim users using the Unified Theory of Acceptance and Use of Technology (UTAUT). The model is extended by incorporating additional variables such as trust, perceived security, network externality, and promotional activities, along with moderating factors including education and location. Data were collected via online surveys and analyzed using Structural Equation Modeling (SEM). The findings are expected to offer both theoretical contributions to mobile payment adoption literature and practical insights to support the development of effective digital payment strategies within Indonesia's public transportation sector.

The UTAUT, developed by [11], is a comprehensive model that integrates elements from eight major technology adoption theories: TRA, TAM, MM, TPB, Combined TAM and TPB, MPTU, IDT, and SCT. UTAUT has shown stronger explanatory power than individual models, explaining up to 70% of the variance in user behavior [11]. Figure 1 illustrates the UTAUT Model.

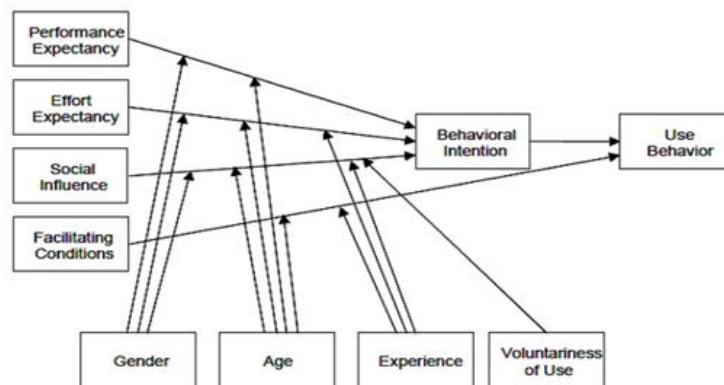


Figure 1. The UTAUT Model

According to [11], empirical testing confirmed that only four core factors significantly influence user behavior: performance expectancy, effort expectancy, social influence, and facilitating conditions. In addition, the UTAUT model includes four moderating variables: gender, age, voluntariness of use, and experience which can strengthen or weaken the relationship between these core factors and user behavior [12].

UTAUT has been widely applied to predict mobile payment adoption [11], with performance expectancy (PE) shown to be a key factor, as users view mobile payment as faster and more convenient [24][3]. Effort expectancy (EE) is also important, especially for new users seeking easy-to-use systems [27][6]. In public transport, simplifying digital systems supports the shift from cash to digital. Social influence (SI) also impacts adoption through encouragement from peers or family [15][3], while reliable infrastructure helps reduce hesitation [11]. Building on UTAUT, [1] added constructs from the Mobile Acceptance Theory (MAT)—including perceived benefits, trust, and security—with trust shown to strengthen perceived usefulness, ease of use, and user confidence [6][11].

Several studies have extended the UTAUT model. [2] introduced Trust and Network Externality, while [3] retained the original UTAUT constructs. [18] applied the model to analyze adoption among Indonesia's Gen Z during the COVID-19 pandemic. Moderating variables such as Gender, Age, Experience, and Income were explored by [14], while [15] included Perceived Security, Promotional Activities, and Education. [16] used Age and Income as segmentation proxies, and [5][4] examined predictors like Hedonic Motivation. Lastly, [17] offered a comprehensive model combining UTAUT with additional external variables

including Privacy, Convertibility, and Financial Costs, giving a broader understanding of user intentions in adopting mobile payments.

As technology and social dynamics continue to evolve, the UTAUT model has been further developed and tested across various sectors through the integration of additional variables. This study builds on that progress by presenting a series of hypotheses.

Performance Expectancy (PE) refers to an individual's belief that using a technology will enhance task completion and performance [1][30]. Previous studies consistently show that PE has a significant impact on Behavioral Intention (BI) to adopt mobile payments [3][1]. H1: PE directly, positively, and significantly influences BI. Effort Expectancy (EE) in the UTAUT model refers to users' perception of how easy a system is to use [1]. A simpler system increases the likelihood of adoption. Several studies confirm EE's significant influence on Behavioral Intention (BI), especially in ICT adoption [17][28], and it is noted as the most dominant factor in public transport using NFC [13]. H2: EE directly, positively, and significantly influences BI. Social Influence (SI) is the extent to which individuals perceive that important others expect them to use a new system [1]. It represents social pressure or encouragement to adopt technology and shapes users' perception of mobile payment usage. Previous studies confirm that SI significantly affects BI in mobile payment adoption [5]. H3: SI directly, positively, and significantly influences BI.

Trust (TR) is users' confidence in the positive outcomes of a technology and belief in the reliability and ethics of service providers. It builds a sense of security and assurance that the system will meet expectations. Trust is a key factor influencing both Behavioral Intention (BI) and PE [1], and it also has a significant direct effect on BI [14]. H4: TR has a direct, positive, and significant influence on BI. Perceived Security (PS) is users' belief that their personal and financial data are protected when using mobile payments, especially from risks like data breaches and financial loss [14]. Studies by [19] and [20] show that PS strongly influences trust in new payment systems, and its absence can lead to user hesitation. PS impacts both BI and Trust by reducing uncertainty in transactions [1]. H5: PS directly, positively, and significantly influences BI. H8: PS has a direct, positive, and significant influence on TR.

Network Externality (NX) is the concept that a product's value grows as more people use it. In mobile payments, greater user adoption enhances perceived value and trust. A large user base and wide merchant acceptance significantly encourage Behavioral Intention (BI) to adopt the technology [2][23]. H6: NX directly, positively, and significantly influences BI. Promotional Activities (PA) include monetary and non-monetary efforts like discounts and cashback to promote mobile payment adoption. Research shows these campaigns effectively attract younger users and positively influence Behavioral Intention (BI), though their impact is still underexplored [15]. H7: PA directly, positively, and significantly influences BI.

This study examines the moderating roles of Education and Location in influencing the strength of relationships between key variables. While some studies recognize the importance of such moderators, research on Education in the mobile payment context remains limited. [21], cited in [15], found that Education significantly moderates the relationship between Perceived Security and BI, highlighting the role of user understanding in adoption. Although evidence is still developing, Education may enhance or weaken the effect of other variables on BI. Based on this, seven additional hypotheses (H9A–H9G) are proposed to assess Education's moderating role across all main constructs.

Meanwhile, no prior studies have explored Location as a moderator in mobile payment adoption. In this study, Location refers to the user's geographic or regional setting. Understanding its influence may offer insights into how social and regional differences affect technology use. Therefore, another set of seven hypotheses (H10A–H10G) is proposed to evaluate how Location moderates the relationship between core variables and Behavioural Intention.

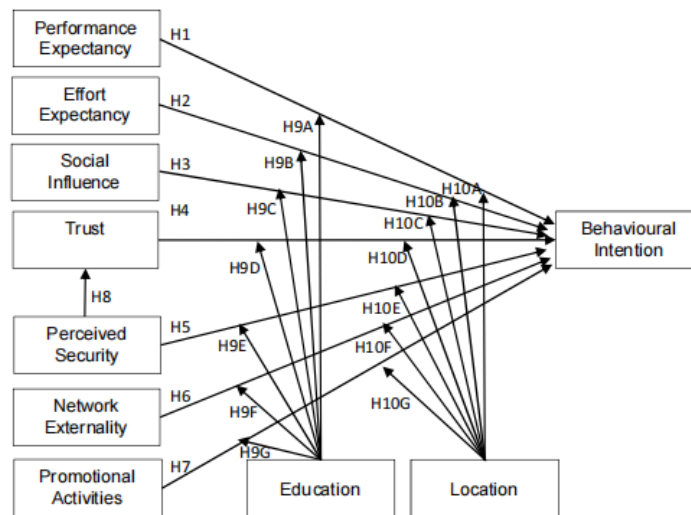


Figure 2. Research Model

Figure 2 shows this study builds on the original UTAUT model by [11], using its four primary constructs: Performance Expectancy, Effort Expectancy, Social Influence, and Behavioral Intention. The model is further expanded by adding external variables, Trust, Perceived Security, Network Externality, and Promotional Activities, based on prior research. The study also explores the relationship between Perceived Security and Trust, and examines the moderating roles of Education and Location. The aim is to identify which factors significantly influence users' intention to adopt mobile payment, with all hypotheses illustrated in the research model.

METHOD

This study applies a quantitative approach using Structural Equation Modeling (SEM) and a survey method. Respondents are mobile payment users of the Bus Trans Jatim system in East Java, selected through judgmental sampling to ensure they are regular users with relevant experience. A minimum sample size of 400 was required to meet a 5% margin of error and a 95% confidence level [22]. Data were collected via Google Forms, with responses stored in Excel. Survey items were adapted from previous studies and measured on a five-point Likert scale, along with additional demographic questions (gender, age, education, travel origin, type, and experience of mobile payment use). The research process included four stages:

- Stage 1: Research Proposal Development.
The Research Proposal Development stage in this study consists of key steps aimed at building the theoretical foundation and analytical framework. These steps include conducting a literature review, developing the research model, formulating hypotheses, and designing the questionnaire. The literature review summarizes relevant theories and prior studies on mobile payment adoption in public transportation, particularly in the context of the Trans Jatim Bus service, to identify influential variables. Based on the review, a research model is developed to illustrate the relationships between variables, focusing on key factors that influence users' interest in adopting mobile payment. The hypotheses are then formulated to empirically test these relationships, grounded in theory and previous findings. Finally, a questionnaire is constructed as the primary data collection tool, with indicators aligned to the variables in the research model to systematically measure each influencing factor.
- Stage 2: Research Data Gathering.
The purpose of the Research Data Gathering stage is to collect the data needed to analyze the factors influencing the adoption of Mobile Payment on the Trans Jatim Bus service. Data was collected through an online questionnaire using Google Forms, which was shared with

passengers via brochures. This method was chosen because it is efficient and can reach many respondents without limitations of time or location. The questionnaire was developed based on the research model and designed to explore users' experiences and perceptions of Mobile Payment. Respondents were selected using judgmental sampling to ensure they were active Trans Jatim users with relevant experience. After collection, the data was downloaded and checked to avoid duplicates or incomplete entries. Finally, the data was analyzed using SPSS to test validity, reliability, and the relationships between variables as defined in the research hypotheses.

- Stage 3: Respondent Profile Development.

The Respondent Profile Development stage aims to describe the characteristics of respondents based on the collected data. The analysis is conducted using a descriptive approach with statistical frequency distribution techniques to understand the distribution patterns and relationships between the variables studied.

- Stage 4: SEM Analysis

This study uses Structural Equation Modeling (SEM) to examine the relationships between variables in the research model. SEM was selected because it can analyze both direct and indirect relationships between variables at the same time. The analysis was performed using AMOS software, which helps create and test the model visually and statistically. The first step was to draw the research model as a path diagram in AMOS, including exogenous and endogenous variables along with their indicators. These indicators were based on validated findings from previous literature. Once the model was set, hypothesis testing was conducted to see whether the relationships between variables were statistically significant. Hypotheses with significant results were accepted, while those without significance were rejected. Finally, the results of the analysis were compiled into a research report that includes key findings, data interpretation, and implications for both theory development and practical applications.

RESULT AND DISCUSSION

In this study, a total of 661 survey responses were successfully collected. Prior to further analysis, the dataset underwent an initial screening process to identify any missing values and outlier responses that were either incomplete or showed abnormal patterns. As a result of this process, 229 responses were found to contain missing data or were identified as statistical outliers. These entries were removed from the dataset to ensure the validity and reliability of the subsequent analysis. After the data cleaning stage, 432 valid responses remained, which still met the minimum required sample size for conducting Structural Equation Modeling (SEM). This refined dataset ensures a solid foundation for drawing accurate and meaningful conclusions from the research. The respondent demographics are presented in Table 1.

Table 1. Respondent Demographics

Characteristics	Description	Frequency	Percentage
Gender	Male	266	61,6 %
	Female	166	38,4 %
Age	17-25 Year	195	59,7 %
	26-35 Year	133	25 %
	36-50 Year	84	12,3 %
	> 50 Year	20	3 %
Education	Non-Bachelor	152	35,2 %
	Bachelor	280	64,8 %
Travel Origin	Sidoarjo	113	26,2 %
	Surabaya	154	35,6 %

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	Mojokerto	67	15,5	%
	Gresik	69	16	%
	Lamongan	18	4,2	%
	Bangkalan	2	0,5	%
	Others	9	2,1	%
Type of Mobile Payment	QRIS	328	76	%
	GoPay	83	19	%
	OVO	59	14	%
	DANA	80	19	%
	ShopeePay	60	14	%
	Link Aja	14	3	%
	AstraPay	7	2	%
	e-Money	42	10	%
	Tab Cash	23	5	%
	Flazz	26	6	%
	BRIZZ	11	3	%
	KHARISMA	17	4	%
	KCI	5	1	%
	Others Payment	27	6	%
Expereince with Mobile Payment	1-2 Year	237	54,9	%
	3-4 Year	91	21,1	%
	5-6 Year	72	16,7	%
	7-8 Year	19	4,3	%
	9-10 Year	13	3	%

Construct validity in this study was tested using Factor Analysis to ensure that each indicator demonstrated both convergent and discriminant validity, following [25], with thresholds of eigenvalue ≥ 1 and factor loading ≥ 0.40 . Most indicators met these criteria; however, indicators for Perceived Security overlapped with those for Trust, failing to show clear discriminant validity. Due to lower factor loadings, Perceived Security was removed to preserve model clarity. A follow-up factor analysis confirmed that all remaining indicators met validity criteria and were correctly grouped under their respective constructs, as shown in Table 2. Thus, the final factor structure is valid for further analysis. Validity Test

Table 2. Validity Test

Indicator	The Factor Loadings of Variable						
	Social Influence	Trust	Performance Expectancy	Behavioral Intention	Effort Expectancy	Promotional Activities	Network Externalities
SI2	0,802						
SI3	0,787						
SI1	0,767						
SI4	0,751						
TR3		0,765					
TR2		0,762					
TR4		0,730					
TR1		0,706					
PE4			0,771				
PE3			0,735				
PE2			0,728				

PE1	0,726			
BI2		0,823		
BI3		0,811		
BI1		0,801		
EE1			0,833	
EE2			0,832	
EE3			0,814	
PA2				0,824
PA1				0,813
PA3				0,779
NE3				0,812
NE1				0,807
NE2				0,764

After completing the construct validity test, a reliability test was conducted using Cronbach's Alpha, specifically the Alpha Coefficient. The testing was carried out in stages, with reliability assessed based on the grouping of each indicator according to its corresponding latent variable. Consistent with standards used in many previous studies, a Cronbach's Alpha value of 0.70 was set as the minimum acceptable threshold for reliability[29]. The results of the reliability test for each group of indicators by latent variable are presented in Table 3.

Table 3. Reliability Test Results with Alpha Coefficient

Latent Variable	Indicators	Alpha Coefficient	Reliability Status
Effort Expectancy	EE1, EE2, EE3	0,870	Good
Performance Expectancy	PE1, PE2, PE3, PE4	0,895	Good
Social Influence	SI1, SI2, SI3, SI4	0886	Good
Trust	TR1, TR2, TR3, TR4	0,893	Good
Promotional Activities	PA1, PA2, PA3	0,877	Good
Network Externalities	NE1, NE2, NE3	0,850	Good
Behavioural Intention	BI1, BI2, BI3	0,911	Excellent

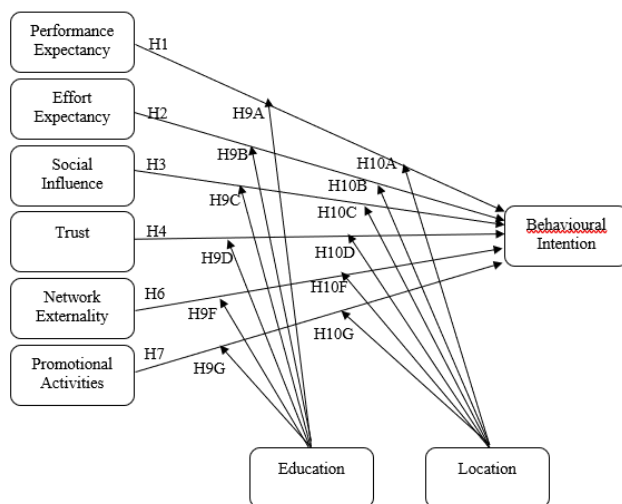


Figure 3. Revised Research Model

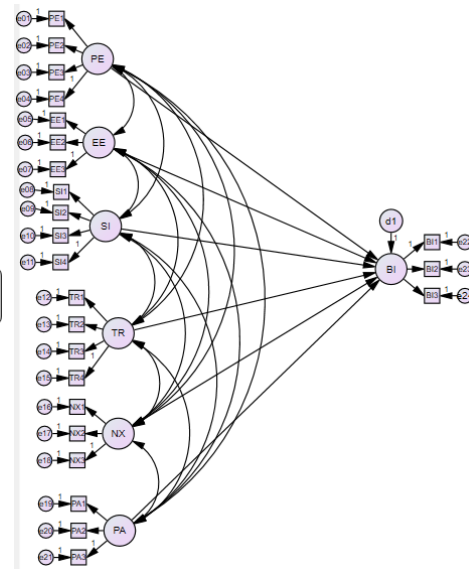


Figure 4. Research Model by AMOS

The removal of the Perceived Security variable led to revisions in the research model and adjustments to the study's hypotheses. While the original model included ten hypotheses, only eight were retained after validity and reliability testing, with H5 and H8 excluded. The updated model is shown in Figure 3. The theoretical framework was tested using AMOS version 22 through the Structural Equation Modeling (SEM) approach, with a visual model presented in Figure 4.

Following model construction, analysis was performed using the dataset processed in SPSS, and the results are summarized in Table 4. The standardized estimates in the table reflect the direction and strength of relationships among variables, while the Magnitude of Effect (MOE) indicates the influence level of each variable within the model.

Table 4. AMOS Hypothesis Calculation

Hipotesis	Regression Path	Estimate	S.E.	C.R.	P	<i>f</i>	E.S.
H1	PE→ BI	0,238	0,082	2,905	0,004	**	0,202
H2	EE→ BI	0,169	0,071	2,392	0,017	*	0,133
H3	SI→ BI	0,210	0,075	2,797	0,005	**	0,163
H4	TR→ BI	0,219	0,083	2,627	0,009	**	0,181
H6	NX→ BI	0,179	0,080	2,233	0,026	*	0,135
H7	PA→ BI	0,129	0,73	1,769	0,77	NS	

In interpreting Table 4, it's important to understand the meaning of the numbers, letters, and symbols used. The term significance is often presented as “Significance,” “Statistical Significance,” or “Probability,” and is denoted by the symbol “p” (p-value). Significance levels are categorized as follows:

- a) “**” for $p < 0.05$ and > 0.01 ;
- b) “***” for $p < 0.01$ and > 0.001 ;
- c) “****” for $p < 0.001$;
- d) “NS” if $p > 0.05$ (not significant).

Additionally, effect size (ES) measures the strength of the relationship between two variables, either in a population or sample. As significance testing alone may have limitations, effect size and shown in Table 5, is crucial to support and strengthen interpretation of results.

Table 5. Size Effect Reference

Value <i>f</i>	Size	Description
$\leq 0,10$	Small	S
$> 0,10$ dan $< 0,4$	Medium	M
$\geq 0,40$	Large	L

Based on the SEM results in Table 4, Performance Expectancy (PE) is the strongest predictor of BI, explaining 23.8% of the variance, showing that perceived usefulness strongly influences adoption. Effort Expectancy (EE) contributes 16.9%, emphasizing the role of ease of use, especially for new users. Social Influence (SI) accounts for 21.0%, highlighting the importance of recommendations and social pressure. Trust (TR) explains 21.9%, reflecting the impact of perceived security and reliability, while Network Externality (NX) contributes 17.9%, indicating that widespread use encourages further adoption. Though Promotional Activities (PA) contribute 12.9%, they have the weakest effect.

However, in hypothesis H7 (PA → BI), the p-value of 0.77 indicates no statistically significant impact of PA on BI, as it exceeds the standard threshold of 0.05. Additionally, eight goodness-of-fit indicators (CMIN/DF, RMR, GFI, AGFI, NFI, IFI, CFI, and RMSEA) confirm that the model fits the data well, as detailed in Table 6.

Table 6. Goodness Of Fit Test Results

N	CMIN/DF	RMR	GFI	AGFI	NFI	IFI	CFI	RMSEA
432	1,701	0,19	0,930	0,909	0,946	0,977	0,977	0,040
Evaluation criteria	< 3	$\rightarrow 0$	$> 0,9$	$> 0,9$	$> 0,9$	$> 0,9$	$> 0,9$	$< 0,08$

This study introduced Education and Location as moderating variables to examine whether they strengthen or weaken the relationships between independent and dependent

variables. The results, detailed in Tables 7 and 8, show that neither variable significantly moderates these relationships, as indicated by pairwise parameter values below 1.96. This suggests that education and geographic location do not play a significant role in influencing how factors like Performance Expectancy, Effort Expectancy, Social Influence, Trust, and Network Externality affect Behavioral Intention to use mobile payments on Bus Trans Jatim.

Table 7. Pairwise Moderation Value Education

Hypothesis	Effect	Comparison of Non-Undergraduates and Undergraduates		
		Difference in Standardized Estimate (Non-Undergraduates and Undergraduates)	Critical Difference Pairwise Parameter	Statistical Signal
H9A	PE → BI	0,236	-1,724	NS
H9B	EE → BI	-0,101	0,931	NS
H9C	SI → BI	-0,035	0,163	NS
H9D	TR → BI	-0,248	1,707	NS
H9F	NX → BI	0,201	-1,584	NS

Note: Not Significant (NS)

Table 8. Pairwise Moderation Value Location

Hypothesis	Effect	Comparison of Urban and Rural		
		Difference in Standardized Estimate (Urban – Rural)	Critical Difference Pairwise Parameter	Statistical Signal
H10A	PE → BI	-0,257	0	NS
H10B	EE → BI	0,067	0	NS
H10C	SI → BI	-0,041	0	NS
H10D	TR → BI	0,093	0	NS
H10F	NX → BI	-0,065	0	NS

Note: Not Significant (NS)

This study contributes to the theoretical development of the UTAUT by extending its application to mobile payment adoption in public transportation, particularly Bus Trans Jatim. While the original UTAUT model emphasized PE, EE, SI, and BI [11], this research adds TR, NX, and PA as external variables. The findings reveal that PE has the strongest influence on BI, followed by TR, SI, and NX, with EE showing a moderate but significant impact. PA was not statistically significant, suggesting that promotional efforts alone may not drive adoption in public transit, where users prioritize practical factors like convenience and security.

The study also examines Education and Location as moderating variables. However, neither showed a significant effect on the relationships between the core constructs and BI, consistent with [26], indicating that demographic factors may play a limited role in mobile payment adoption for transit users. These results expand the applicability of UTAUT by integrating relevant external and moderating factors, and offer a foundation for future research on topics such as user experience, risk perception, and comfort with technology.

Practically, the study offers actionable insights for increasing mobile payment adoption on Bus Trans Jatim. Key influencing factors PE, TR, SI, NX, and EE can be addressed through strategies such as promoting transaction speed, reducing queues, enabling automatic check-in, and real-time balance tracking. EE can be improved by simplifying app interfaces, providing one-tap payment options, multilingual support, and tutorials. To build TR, strong data protection, transparent privacy policies, and reliable customer service are essential. SI can be enhanced through community outreach, referral programs, and influencer support, while NX can be strengthened by expanding mobile payment functions and offering user rewards. Although PA did not show significant direct impact, it can still serve as a complementary tool

through cashback or peak-hour incentives. Together, these strategies can support user convenience, improve adoption rates, and build long-term loyalty in the transition toward digital payments in public transport.

CONCLUSION AND SUGGESTIONS

This study identifies key factors that significantly influence users' behavioral intention to adopt mobile payment in Bus Trans Jatim services. PE is the strongest predictor, showing that users are more inclined to adopt mobile payments when they perceive clear benefits in efficiency. Other factors TR, SI, NX, and EE also have significant positive effects. However, PA were found to be statistically insignificant, indicating they are not a primary driver of adoption. Additionally, Education and Location did not significantly moderate the relationships between the main variables and behavioural intention.

For future research, incorporating other moderators such as Age is recommended. Different age groups, especially Generation Z, may show varying levels of comfort and familiarity with digital technology. Since Gen Z is often more open to mobile innovation, Age could offer deeper insights and improve model relevance. Expanding the sample to include a more balanced age distribution may also enhance the understanding of adoption behaviour across different demographics in public transportation.

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