

Does JASTIP as Facilitating Condition Affect the E-Marketplace Adoption in Developing Region?

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Abstract

E-marketplaces are expanding in developing regions but face barriers related to logistics costs and infrastructure. JASTIP, an informal proxy shopping service, has emerged as a potential solution to improve accessibility. This study examines the influence of perceived cost, social influence, hedonic motivation, and facilitating conditions on e-marketplace adoption using a modified UTAUT model analyzed through PLS-SEM with data from 185 respondents in West Papua. The findings show that hedonic motivation and social influence significantly increase user intention, perceived cost directly affects usage behavior, and facilitating conditions strengthen intention but do not directly influence usage. These results emphasize the role of JASTIP in reducing costs and improving accessibility. This study recommends improving JASTIP access and infrastructure, implementing flexible pricing policies, and promoting community-based marketing to enhance e-marketplace adoption in developing regions.

Keywords: developing region, e-marketplace, JASTIP, PLS-SEM, UTAUT

1 Introduction

Digital transformation has opened up significant opportunities for communities to access products and services through e-marketplace platforms such as Tokopedia, Shopee, and Lazada. However, despite the national increase in internet penetration and e-commerce usage, the reality on the ground shows that not all regions enjoy equal access, particularly in developing areas such as Papua. Infrastructure gaps, limited payment methods, and high logistical costs are real challenges that hinder full participation of communities in these regions within the digital ecosystem [1].

One organically emerging solution to these limitations is the practice of jasa titip (JASTIP), or proxy shopping services. In this context, JASTIP serves as an alternative logistics pathway that helps consumers in West Papua obtain products from e-marketplaces at more affordable costs [2]. Consumers place orders and send them to a JASTIP intermediary address in major cities such as Jakarta or Surabaya. From there, JASTIP operators collectively ship the goods to local JASTIP agents in Manokwari, typically via sea or air transportation. The items are temporarily stored by the local JASTIP until they are collected directly by consumers. This system not only reduces shipping costs per item but also overcomes delivery limitations from sellers to eastern Indonesian regions, positioning JASTIP as an informal yet crucial solution in enabling e-commerce access in developing areas like West Papua.

Unfortunately, despite the strategic role of JASTIP in expanding access to digital services, academic literature on e-marketplace adoption has seldom addressed such informal mechanisms. Most prior studies have focused on conventional factors such as perceived cost [3], social influence [4], and hedonic motivation [5], while neglecting contextual elements like JASTIP as part of the facilitating conditions within technology adoption models [6]. This indicates a significant gap in our understanding of e-marketplace adoption dynamics in regions facing logistical and digital infrastructure limitations. Handayani et al. also emphasized that socio-economic conditions and infrastructure significantly influence the transition process from conventional to digital shopping [2]. In other words, local and informal aspects remain underexplored in the theoretical frameworks used in previous studies.

Accordingly, this study aims to fill the literature gap regarding informal digital inclusion through the JASTIP practice in West Papua—a topic that has received limited academic attention [2].

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The UTAUT model used in this study is extended by incorporating perceived cost as an additional variable and positioning JASTIP as a form of community-based facilitating condition [6]. Moreover, age is used as a moderating variable to examine differences in influence across demographic groups. This strategy provides a more contextual approach to understanding the dynamics of technology adoption in areas with limited digital access.

The main contribution of this research is to expand the scope of the UTAUT model by integrating dimensions of informal social facilitation and introducing Importance-Performance Map Analysis (IPMA) as a tool for mapping intervention priorities. Practically, the results of this study are expected to be utilized by policymakers, community actors, and digital platform providers in designing more inclusive and locally tailored digital literacy and technology adoption programs. Thus, this research not only contributes to academic discourse but also offers concrete solutions for regions facing high structural barriers.

2 Literature Review

2.1. Unified Theory of Acceptance and Use of Technology in E-Marketplace Adoption

The main theoretical framework used in this study is the Unified Theory of Acceptance and Use of Technology (UTAUT) developed by Venkatesh et al. [6]. This model explains the factors influencing technology adoption through four core constructs: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions. However, in this study, only Social Influence and Facilitating Conditions are used, as they are more relevant to the context of e-marketplace adoption with JASTIP as the facilitating condition [7].

UTAUT has been applied in various studies to understand the factors influencing technology adoption, including in the context of e-marketplaces [7]. However, previous research has rarely addressed the role of JASTIP in supporting e-marketplace adoption, especially in regions with limited digital infrastructure, such as West Papua. Therefore, this study fills that gap by highlighting JASTIP as a facilitating factor in the adoption of e-marketplaces.

2.2. JASTIP as a Facilitating Condition

JASTIP is a service that allows individuals or groups to purchase goods on behalf of consumers who do not have direct access to certain products. In the context of e-marketplaces, JASTIP plays an important role in overcoming geographical barriers, high shipping costs, and limitations in direct delivery to eastern regions of Indonesia, such as West Papua. From the UTAUT perspective, JASTIP can be categorized as a Facilitating Condition external factors that ease the adoption of technology [6].

In Manokwari, JASTIP serves as an alternative logistics mechanism that allows consumers to obtain goods from e-marketplaces at more affordable costs. Through this mechanism, consumers place orders to an intermediary address in major cities such as Jakarta or Surabaya. The goods are then collectively shipped by JASTIP operators to the destination city via sea or air freight and temporarily stored by local JASTIP agents until collected by the end consumer. This mechanism not only helps reduce the shipping cost per unit but also builds trust in online transactions by minimizing fraud risks. Therefore, in this study, JASTIP is positioned as a relevant facilitating condition supporting e-marketplace adoption, especially in developing regions facing logistical challenges like West Papua.

2.3. Perceived Cost, Social Influence, and Hedonic Motivation in E-Marketplace Adoption

Perceived cost is a significant factor in the decision to adopt e-marketplaces. Users often consider various expenses, including product prices, shipping fees, and other additional costs. In developing regions, high costs remain one of the main barriers to using e-marketplaces [8]. However, the presence of JASTIP can reduce this barrier by offering a cheaper and more efficient shipping solution through a collective system [9]. Thus, perceived cost becomes a factor that can influence users' intentions and behaviors in adopting e-marketplaces, particularly with JASTIP as a solution to logistical challenges.

Additionally, social influence also plays a role in users' decisions to adopt technology. Previous studies have shown that recommendations from family, friends, or communities can increase users'

trust in e-marketplaces [10]. When individuals see those around them using JASTIP to shop on e-marketplaces, they are more likely to be encouraged to try the same service. Therefore, in this study, social influence is analyzed as a factor that can enhance e-marketplace adoption through JASTIP as a facilitating condition.

Apart from perceived cost and social influence, hedonic motivation also plays a role in users' decisions to adopt technology. Hedonic motivation refers to the satisfaction and enjoyment users experience when using e-marketplaces. The more enjoyable the shopping experience, the more likely users are to continue using the platform [10]. In this study, hedonic motivation is examined in the context of user experience when using e-marketplaces, with JASTIP providing easier access to products and enhancing transaction convenience.

2.4. The Role of Age in Technology Adoption

In the UTAUT model, age is a moderating variable that can influence the strength of relationships between various factors and the intention or behavior of technology use [6]. Khechine et al. noted that younger users tend to focus more on the practical benefits of technology, while older users are more sensitive to external support conditions [11]. Although the study used constructs such as performance expectancy and facilitating conditions, the general principle of age-based preference differences remains relevant to the variables in this research.

Therefore, in this study, age is positioned as a moderating variable to observe whether the effects of perceived cost, social influence, hedonic motivation, and JASTIP as a facilitating condition on e-marketplace adoption vary across different age groups. This is particularly important in developing regions, where digital literacy and access to technology are often influenced by users' age.

3 Research Method

3.1 Research Model and Hypotheses Development

This research uses a quantitative approach. The quantitative method is an approach that uses numerical data to collect, analyze, and explain the variables being studied objectively [12]. The research framework uses the UTAUT model by considering the variables of hedonic motivation, perceived cost, social influence, and supporting conditions in the context of JASTIP. Behavioural Intention and Use Behaviour act as dependent variables in this study. In addition, the age variable serves as a moderator. [The overall research framework is illustrated in Figure 1.](#)

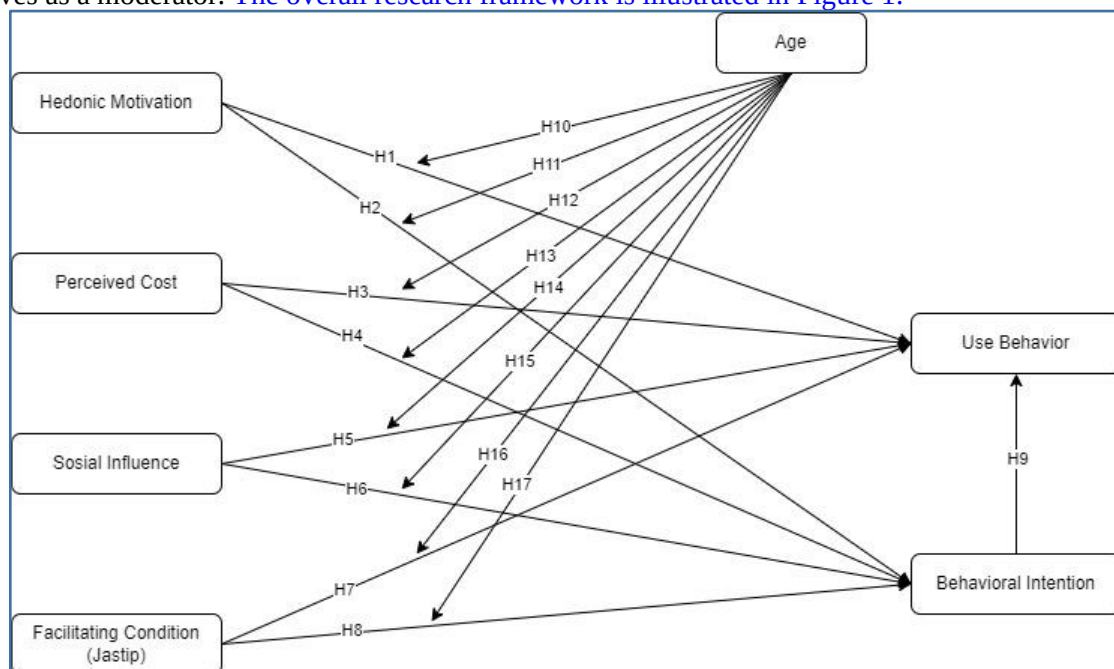


Figure 1 Research model

Based on the research model, the hypothesis in this study is formulated as follows:

Hedonic motivation refers to the user's pleasure or satisfaction when using an e-marketplace. Users who enjoy the experience of shopping with JASTIP tend to have a higher intention to continue using the service. In addition, pleasant experiences can directly drive usage behavior without going through intentions first [13], [14].

H1: Hedonic motivation significantly influences e-marketplace use behavior.

H2: Hedonic motivation significantly influences users' behavioral intention to use the e-marketplace.

Perceived cost refers to the user's assessment of the costs associated with shopping using JASTIP. If the perceived cost is high, users may be reluctant to intend to use the service. Perceived high costs may also directly reduce the frequency of actual use [8].

H3: Perceived cost significantly influences e-marketplace use behavior.

H4: Perceived cost significantly influences users' behavioral intention to use the e-marketplace.

Social influence reflects the extent to which individuals are influenced by others in the decision to use JASTIP. Support or recommendations from the social environment can increase intention and usage behavior [15].

H5: Social influence significantly influences e-marketplace use behavior.

H6: Social influence significantly influences users' behavioral intention to use the e-marketplace.

Supporting conditions, such as the availability of technological infrastructure and technical support, can affect the intention and behavior of using the e-marketplace. Adequate facilities such as JASTIP make it easier for users to access and use the e-marketplace [7].

H7: Facilitating conditions such as JASTIP significantly influence e-marketplace use behavior.

H8: Facilitating conditions such as JASTIP significantly influence users' behavioral intention to adopt the e-marketplace.

Behavioral intention is a key indicator in predicting whether someone will actually use JASTIP. The higher a person's intention, the more likely they are to adopt and use the service [10].

H9: Behavioral intention significantly influences e-marketplace use behavior.

Age can moderate the relationship between the independent variables and the intention and behavior of using JASTIP when shopping. Preferences and responses to technology may differ by age group [6].

H10: Age moderates the relationship between hedonic motivation and use behavior in the adoption of e-marketplaces.

H11: Age moderates the relationship between hedonic motivation and behavioral intention in the adoption of e-marketplaces.

H12: Age moderates the relationship between perceived cost and use behavior in the adoption of e-marketplaces.

H13: Age moderates the relationship between perceived cost and behavioral intention in the adoption of e-marketplaces.

H14: Age moderates the relationship between social influence and use behavior in the adoption of e-marketplaces.

H15: Age moderates the relationship between social influence and behavioral intention in the adoption of e-marketplaces.

H16: Age moderates the relationship between facilitating conditions and use behavior in the adoption of e-marketplaces.

H17: Age moderates the relationship between facilitating conditions and behavioral intention in the adoption of e-marketplaces.

3.2 Research Methodology

This study took a sample of JASTIP users with data collection techniques through distributing online questionnaires. The data obtained were analyzed using the PLS-SEM method which aims to increase the variance of the dependent latent construct. The advantage of PLS-SEM lies in its flexibility with the measurement scale and its ability to handle small samples [16]. In addition,

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descriptive analysis is used to describe the characteristics of the variables before further testing is carried out [17]. The sample size was calculated using G*Power, with an effect size of 0.15, a significance level of 5%, and a power analysis of 94%, resulting in a recommendation of 74 respondents [18]. However, the amount of data collected exceeded the recommendation, totaling 185 respondents.

The research and data collection process was conducted over three months, from October 2024 to December 2024, in Manokwari through an online survey with a total of 185 respondents. Information was collected based on gender, age and education. An explanation can be seen in the following Table 1 below:

Table 1 Respondent demographics

Category	Item	Amount	Percentage
Gender	Male	73	39%
	Female	112	61%
Age	Under 17 Years	11	6%
	18 - 35 Years	158	85%
	36 - 50 Years	16	9%
	Senior High School	90	49%
Last Education	Diploma	21	11%
	Bachelor	63	34%
	Master	3	2%
	etc.	8	4%

4 Result and Analysis

This section presents the results of data analysis and hypothesis testing. The analysis is carried out in two stages: measurement model evaluation and structural model evaluation. The measurement model is examined through validity and reliability testing, while the structural model is analyzed to assess the relationships among the research variables.

4.1 Measurement Model Evaluation

In the outer model analysis, which is the first of two stages of data analysis with the aim of ensuring that the indicators used in the research model can represent latent constructs validly and reliably [19]. There are three criteria in evaluating the outer model, namely convergent validity, discriminant validity, and composite reliability test.

The convergent validity test is used to measure indicators in one construct that are correlated and accurate, which is carried out in two stages, namely checking the loading factor (LF) and average variance extracted (AVE) values. Based on the results in Table 2, all indicators have a loading factor above 0.7 which indicates that the indicator is valid [20]. Convergent validity criteria for AVE > 0.50 which means that more than half (50%) of the indicator variance can be included in the construct [21].

After ensuring the value of the convergent validity test, the next step is to test reliability to determine the extent to which indicators can be trusted in producing consistent measurements [20]. Reliability testing is assessed using composite reliability (CR) and Cronbach's alpha (CA). CA measures the internal consistency of indicators within a construct, while CR provides a more accurate measure of reliability. As shown in Table 2, all constructs have met the reliability criteria with CR and CA values above 0.7 [22], [23]).

Table 2 Test results of CA, CR, AVE, and LF

Construct	Statement Item	Code	LF
Hedonic Motivation (HM) [3] CA, CR, AVE = 0.743, 0.774, 0.664	I feel satisfied using JASTIP when shopping online because of the limited products in Papua.	HM1	0.705
	I am a loyal JASTIP user and will not switch to other services (courier services) when shopping online.	HM2	0.898
	I feel like it would be difficult to shop online without using a JASTIP.	HM3	0.830
Perceived Cost	I believe that using JASTIP will save you money on shipping	PC1	0.817

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Construct	Statement Item	Code	LF
(PC)	costs when shopping online.		
[9]			
CA, CR, AVE = 0.773, 0.773, 0.688	I found it easy to communicate with the JASTIP agent for the purpose of tracking the status of the item delivery.	PC2	0.847
	I have an internet connection to use JASTIP when shopping online.	PC3	0.824
Social Influence (SI)	I use JASTIP when shopping online because of recommendations from friends and family.	SI1	0.828
[6]			
CA, CR, AVE = 0.756, 0.760, 0.672	People in my neighborhood prefer JASTIP because it's fast and you can get products from outside Papua.	SI2	0.796
	I use JASTIP because people I consider important also use it.	SI3	0.834
Facilitating Condition (FC)	I have a cell phone that supports online shopping and using JASTIP.	FC1	0.843
[10]			
CA, CR, AVE = 0.842, 0.842, 0.760	I feel that JASTIP makes the online shopping process easier to get items from outside Papua.	FC2	0.899
	I feel that JASTIP services make it easier to access products from outside Papua.	FC3	0.872
Use Behaviour (UB)	I use JASTIP very often when shopping online.	UB1	0.910
[24]			
CA, CR, AVE = 0.899, 0.901, 0.833	JASTIP is my first choice for online shopping.	UB2	0.927
	JASTIP has become an important part of my online shopping activities.	UB3	0.900
Behavioural Intention (BI)	I intend to use JASTIP for online shopping in the future.	BI1	0.830
[10]			
CA, CR, AVE = 0.808, 0.811, 0.723	I prefer to shop online and use JASTIP because I can buy products from outside Papua.	BI2	0.857
	I will use JASTIP more often to reduce shipping costs when shopping online.	BI3	0.863

In addition to convergent validity, it is important to ensure discriminant validity whose purpose is to ensure that the constructs used are different and do not overlap in research [25]. The results of the discriminant validity analysis use the Heterotrait-Monotrait Ratio (HTMT) method are shown in table 3. There are two standards for measuring HTMT, namely above 0.85 [26] or exceeding 0.90 [25]. In the test, it was found that one of the variables, BI3, had an HTMT value above the standard. This result indicates that there is multicollinearity that can reduce discriminant validity. Therefore, in accordance with the recommendations in the literature, one of the statements in the construct needs to be deleted. However, the removal of this indicator has no impact on the convergent validity that has been tested previously.

Table 3 Discriminant validity test results

	BI	FC	HM	PC	SI	UB
BI						
FC	0,898					
HM	0,837	0,806				
PC	0,793	0,840	0,880			
SI	0,898	0,841	0,845	0,828		
UB	0,832	0,708	0,816	0,784	0,711	

The results of the discriminant validity analysis using HTMT are shown in Table 3, which shows that all correlation values between constructs are below the 0.90 threshold, so the discriminant

validity in this model can be said to be met. In this study, the HTMT method is considered more accurate than the Fornell-Larcker method in assessing discriminant validity, especially in complex models [25]. If the HTMT value of a variable pair exceeds 0.90, then there is a possibility that the two constructs are not really different, which can reduce the accuracy of the research results.

Other recent research results support the use of HTMT in construct validation stating that HTMT can provide a more sensitive evaluation of discriminant validity than other conventional methods [27]. In addition, other studies also confirm that HTMT values below 0.85 indicate stronger discriminant validity [28]. Therefore, considering the analysis results in the table, it can be concluded that this research model has met the necessary discriminant validity requirements.

4.2 Structural Model Evaluation

Inner model is a test to analyze between one variable and another after measuring constructs that can be observed with several indicators, such as the Variance Inflation Factor (VIF) to test the hypothesis and the coefficient of determination (R-square). This test analyzes the relationship between one variable and another [29].

VIF is used to detect multicollinearity between variables. A high VIF value indicates a high correlation between the independent variables which can cause difficulty in interpreting the regression results [20]. Based on Table 4, the VIF value for each variable is in the range of 2.166 to 2.675, which means there is no multicollinearity in the model. The VIF value below 3.3 indicates that there is no high correlation between the independent variables, so it can be used for further analysis [30]. Further testing by conducting hypothesis testing is evidenced in Table 5 by evaluating the T-statistic and P-value values generated through bootstrapping calculations [14]. The hypothesis will be accepted if the T-statistic exceeds 1.96 and the P-value is below 0.05 [19].

Table 4 VIF test result

	BI	FC	HM	PC	SI	UB
BI						2.440
FC	2.325					2.675
HM	2.166					2.252
PC	2.362					2.367
SI	2.209					2.384
UB						

Table 5 Hypotesis test result

Hypothesis	Variables	T Statistics	P Values	Description
H1	BI → UB	2,932	0,003	Accepted
H2	FC → BI	4,167	0,000	Accepted
H3	FC → UB	0,517	0,605	Rejected
H4	HM → BI	1,997	0,046	Accepted
H5	HM → UB	3,069	0,002	Accepted
H6	PC → BI	0,544	0,587	Rejected
H7	PC → UB	2,755	0,006	Accepted
H8	SI → BI	3,219	0,001	Accepted
H9	SI → UB	0,191	0,848	Rejected

The next indicator of the coefficient of determination (R-square) is a measure that shows how much the independent variables in the model can explain the variability of the dependent variable. R² values ≥ 0.75 are considered strong, 0.50-0.74 moderate, and ≤ 0.49 weak [20].

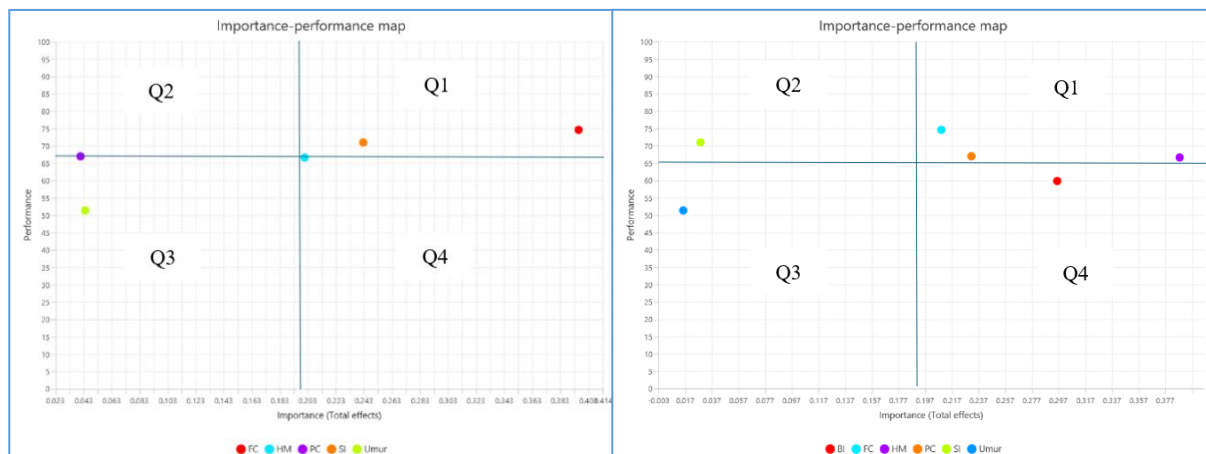
Table 6 R-Square Test Results

Variable	R-square	Adjusted R-square	Category
BI	0,590	0,581	Moderate
UB	0,597	0,585	Moderate

From Table 6, the R^2 value for the Behavioral Intention (BI) variable is 0.590, indicating that 59.0% of the variability in BI is explained by Facilitating Conditions (FC), Hedonic Motivation (HM), Perceived Cost (PC), and Social Influence (SI), while the remaining 41.0% is likely influenced by other factors such as user trust, regulations, and prior shopping experience. For Use Behavior (UB), the R^2 value is 0.597, meaning that 59.7% of the variability in UB is explained by BI, while the remaining 40.3% may be influenced by other factors such as user habits, service quality, and e-marketplace loyalty programs. The higher the R-square (R^2) value, the greater the model's ability to explain the dependent variable. Therefore, the factors in this study play a significant role in influencing behavioral intention and user behavior in using e-marketplaces.

4.3 IPMA

Importance-Performance Map Analysis (IPMA) is a technique in PLS-SEM that expands the results of structural model analysis by considering the performance of each variable against the target variable. IPMA helps in determining which variables have the greatest influence and areas that need to be improved to maximize user satisfaction [20].



In the IPMA analysis, Graph 1 shows the relationship between Behavioral Intention and factors such as Facilitating Conditions (Red), Hedonic Motivation (Blue), Perceived Cost (Purple), Social Influence (Orange), and Age (Green). This graph helps identify factors that have high importance but still have low performance, so these factors need to be improved in order to increase user intention in the JASTIP service. Meanwhile, Graph 2 shows the relationship between Use Behavior and the same factors, but with a focus on how these factors affect user behavior in using the grooming service. If a factor has high importance but low performance in both graphs, then it is a top priority to improve in order to have a greater impact on the use of the grooming service.

Based on both graphs, the factor that needs to be improved in Behavioral Intention is Facilitating Conditions, because the ease of accessing and using JASTIP services has a major influence on user intentions. In addition, Hedonic Motivation is also an important factor because of the pleasure aspect of using the service and can increase users' intention to use it.

Meanwhile, from Use Behavior, the factors that need to be improved are Facilitating Conditions if users still experience problems in using the grooming service, and Hedonic Motivation if the user experience in using the application is still less than optimal. In addition, if the Social Influence factor

has low importance but low performance, then this factor is not a top priority in increasing the use of grooming services.

Table 7 IPMA table

UB			BI	
	Performance	Total Effects	Performance	Total Effect
BI	59,852	0,316		
FC	74,600	0,169	74,600	0,379
HM	66,625	0,342	66,625	0,187
PC	66,971	0,246	66,971	0,045
SI	70,962	0,101	70,962	0,268

Based on Table 7, the HM variable has the largest influence on UB (0.342) compared to other variables, indicating that pleasant experiences when shopping using JASTIP services are instrumental in encouraging users to actually make transactions. While BI also plays a significant role on UB (0.316), its performance is still lower than other variables, indicating that although users' intentions are high, external factors may still hinder the actual implementation of using a grooming service. In influencing BI, FC has the highest total effect (0.379), indicating that ease of access and supporting facilities largely determine whether users have the intention to use the e-marketplace. SI also has a moderately strong effect (0.268) on BI, indicating that social factors, including recommendations from friends or family, can play a role in increasing user intentions. In contrast, PC showed the lowest total effect on BI (0.045), indicating that in the context of developing regions, users' perceived cost is not the main factor hindering their intention to use a JASTIP service.

4.4 Moderation

Moderation is a concept in statistical analysis that explains how the relationship between the independent variable and the dependent variable can change depending on the value of the moderator variable. According to [20], the moderating effect can be enhancing, weakening, or even reversing the relationship (reversing effect) between the independent and dependent variables.

Table 8 Moderation table

	T statistics	P values	Description
Age x PC → BI	0.542	0.588	Rejected
Age x PC → UB	0.217	0.828	Rejected
Age x FC → BI	0.692	0.489	Rejected
Age x FC → UB	1.226	0.220	Rejected
Age x HM → BI	1.041	0.298	Rejected
Age x HM → UB	0.363	0.717	Rejected
Age x SI → BI	0.503	0.615	Rejected
Age x SI → UB	1.985	0.047	Accepted

The results of the moderation analysis in this study show that age plays a significant role in moderating the relationship between SI and UB, with a p-value of 0.047 (<0.05), which indicates that this moderation effect is statistically significant. However, in other relationships, such as PC → BI/UB, FC → BI/UB, and HM → BI/UB, the moderating effect of age is not significant as it has a p-value above 0.05. Thus, it can be concluded that age only affects the relationship between SI and UB, while in other paths, no meaningful moderating effect was found.

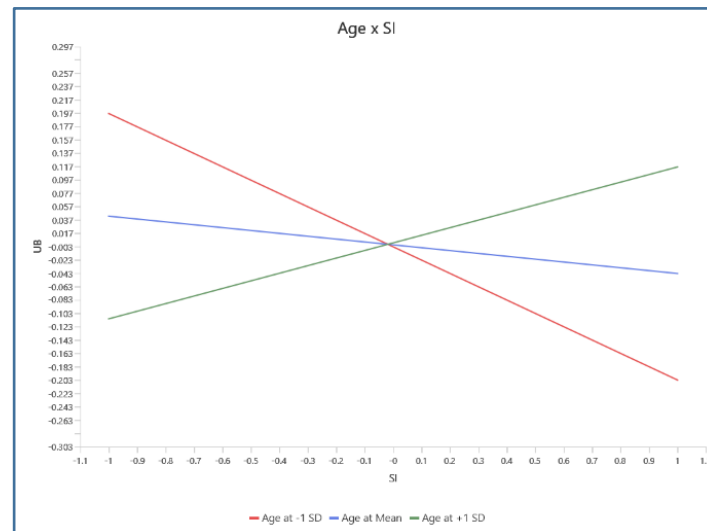


Figure 2 Moderation

In Figure 2, it shows the role of age as a moderating variable in the relationship between Social Influence (SI) and Use Behavior (UB). The three lines represent different ages: younger (red), average (blue), and older (green). The results show that at a younger age, social influence has a negative impact on JASTIP use behavior, possibly because they are more independent in their decisions. Meanwhile, average age shows a neutral relationship, meaning social influence is not a dominant factor. In contrast, at older ages, social influence has a positive impact on usage behavior, suggesting that they are more influenced by social recommendations. Overall, age moderates the relationship between Social Influence and Use Behavior, where older users are more likely to follow social influence in using grooming services [10].

4.5 Result

Based on the hypothesis testing results in Table 5, it was found that H1 and H2 show significant relationships in the research model. In H1, the relationship between Behavioral Intention (BI) and Use Behavior (UB) showed a p-value of 0.003, indicating that users' intention to use JASTIP services when shopping significantly influences their actual usage behavior. This finding is consistent with Venkatesh (2003), who stated that behavioral intention is a primary predictor of technology use. Furthermore, in H2, the relationship between Facilitating Conditions (FC) and BI is also significant with a p-value of 0.000 and a t-statistic of 4.167. This shows that support facilities such as infrastructure, technology, and ease of access play an important role in increasing users' intention to adopt JASTIP-based e-marketplaces. This result aligns with Venkatesh et al. (2012), who emphasized the importance of facilitating conditions in shaping behavioral intentions.

In contrast to H2, hypothesis H3, which examines the direct relationship between FC and UB, shows an insignificant result ($p = 0.605$; $t = 0.517$). This means that although supporting conditions are available, they do not directly encourage actual use behavior of JASTIP services. This result supports the findings of Oliveira et al. (2014), who emphasized that FC plays a greater role in shaping intention rather than directly influencing action. Conversely, in H4, the relationship between Hedonic Motivation (HM) and BI was found to be significant ($p = 0.046$), indicating that users who experience enjoyment and pleasure in using JASTIP tend to have a higher intention to continue using it.

Interestingly, different results were found in H7, where the relationship between Perceived Cost (PC) and UB was significant ($p = 0.006$), indicating that cost perception influences actual decisions to use the service. This means that although cost does not affect initial intention, it remains a crucial factor in the final decision to use. Venkatesh et al. (2012) support this finding by introducing the construct of price value, which considers both benefits and costs in forming usage behavior. Furthermore, in H8, the influence of Social Influence (SI) on BI is also significant ($p = 0.001$), indicating that social support, such as recommendations from friends or family, can increase users' intention to use JASTIP services.

However, in H9, the influence of SI on UB is not significant ($p = 0.848$), meaning that social influence alone is not strong enough to drive actual use of the service. This implies that even though someone receives social encouragement to use JASTIP, it does not necessarily lead to real usage behavior. This finding supports the theory by Venkatesh et al. (2012) that social influence is more relevant in shaping behavioral intention than actual behavior. Overall, these results indicate that in the context of adopting a JASTIP-based e-marketplace, variables such as behavioral intention, facilitating conditions, hedonic motivation, perceived cost, and social influence play varying roles, either directly or indirectly, in users' decisions to use the service.

5 Conclusion

This study analyzed the effects of hedonic motivation, social influence, perceived cost, and facilitating conditions on the adoption of JASTIP-based e-marketplaces in developing regions. The results indicate that hedonic motivation and social influence significantly increase users' intention to adopt JASTIP services, while perceived cost has a more direct impact on actual usage. Facilitating conditions support intention but show limited direct influence on usage behavior. Age was also found to moderate the relationship between social influence and usage behavior. Theoretically, this study extends the UTAUT framework by including JASTIP as a facilitating condition and considering perceived cost as a factor relevant to regions with limited infrastructure. This provides a clearer understanding of how informal logistics solutions can help increase e-marketplace adoption, particularly in remote areas. Practically, the findings suggest that improving access to JASTIP services, applying flexible pricing strategies, strengthening payment and delivery systems, and promoting community-based marketing can encourage wider adoption. Policymakers and service providers may use these insights to design programs that bridge the digital gap and improve e-marketplace access in developing regions. This research is limited to one region (West Papua) and does not examine other possible factors such as trust or service quality. Future studies are recommended to expand the scope to multiple regions, include other influencing factors, and use combined research methods to gain a more comprehensive view of e-marketplace adoption.

Reference

- [1] A. D. Oktavia, D. I. Inan, R. N. Wurarah, and O. A. Fenetiruma, "Analisis Faktor-faktor Penentu Adopsi E-Wallet di Papua Barat: *Extended UTAUT 2 dan Perceived Risk*," *MALCOM Indones. J. Mach. Learn. Comput. SCI.*, Vol. 4, No. 2, pp. 587–600, 2024, DOI: 10.57152/malcom.v4i2.1277.
- [2] P. W. Handayani, R. A. Nurahmawati, A. A. Pinem, and F. Azzahro, "Switching Intention from Traditional to Online Groceries using the Moderating Effect of Gender in Indonesia," *J. Food Prod. Mark.*, Vol. 00, No. 00, pp. 425–439, 2020, DOI: 10.1080/10454446.2020.1792023.
- [3] Z. Shoheib and E. A. Abu-Shanab, "Adapting the UTAUT2 Model for Social Commerce Context," *Int. J. E-bus. Res.*, Vol. 18, No. 1, pp. 1–20, 2022, DOI: 10.4018/IJEBr.293293.
- [4] A. Gupta, A. Yousaf, and A. Mishra, "How Pre-Adoption Expectancies Shape Post-Adoption Continuance Intentions: An Extended Expectation-Confirmation Model," *Int. J. Inf. Manage.*, Vol. 52, No. April 2019, p. 102094, 2020, DOI: 10.1016/j.ijinfomgt.2020.102094.
- [5] A. A. Alalwan, Y. K. Dwivedi, and N. P. Rana, "Factors Influencing Adoption of Mobile Banking by Jordanian Bank Customers: Extending UTAUT2 with Trust," *Int. J. Inf. Manage.*, Vol. 37, No. 3, pp. 99–110, 2017, DOI: 10.1016/j.ijinfomgt.2017.01.002.
- [6] V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, "User Acceptance of Information Technology: Toward a Unified View," *MIS Q. Manag. Inf. Syst.*, Vol. 27, No. 3, pp. 425–478, 2003, DOI: 10.2307/30036540.
- [7] N. S. Subawa, N. W. Widhiasthini, and C. A. Mimaki, "An Empirical Study of E-Marketplace Acceptance in MSMEs under the Constructs of Effort Expectancy, Social Influence and Facilitating Condition Factors," in *Proceedings of the 2020 The 6th International Conference on E-Business and Applications*, New York, NY, USA: ACM, Feb. 2020, pp. 116–120. DOI: 10.1145/3387263.3387288.
- [8] J.-H. Wu and S.-C. Wang, "What Drives Mobile Commerce?: An Empirical Evaluation of the

- Revised Technology Acceptance Model*,” *Inf. Manag.*, Vol. 42, No. 5, pp. 719–729, Jul. 2005, DOI: 10.1016/j.im.2004.07.001.
- [9] K. Al-Saedi, M. Al-Emran, T. Ramayah, and E. Abusham, “Developing a General Extended UTAUT Model for M-Payment Adoption,” *Technol. Soc.*, Vol. 62, No. September 2019, 2020, DOI: 10.1016/j.techsoc.2020.101293.
- [10] V. Venkatesh, J. y. . Thong, and X. Xu, “Consumer Acceptance and use of Information Technology: Extending the Unified Theory of Acceptance and use of Technology by Viswanath Venkatesh, James y.l. Thong, xin xu :: ssrn,” *MIS Q.*, Vol. 36, No. 1, pp. 157–178, 2012, [Online]. Available: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2002388
- [11] H. Khechine, S. Lakhal, D. Pascot, and A. Bytha, “UTAUT Model for Blended Learning: The Role of Gender and Age in the Intention to use Webinars,” *Interdiscip. J. e-Skills Lifelong Learn.*, Vol. 10, pp. 033–052, 2014, DOI: 10.28945/1994.
- [12] J. W. Creswell, *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches*, 4th ed. SAGE Publications, 2014.
- [13] P. K. Chopdar and V. J. Sivakumar, “Understanding Psychological Contract Violation and its Consequences on Mobile Shopping Applications use in a Developing Country Context,” *J. Indian Bus. Res.*, Vol. 10, No. 2, pp. 208–231, Apr. 2018, DOI: 10.1108/JIBR-07-2017-0109.
- [14] N. Huda Mahmud, D. Iskandar Inan, and I. Yusuf, “Development and Evaluation of the Utilization of Augmented Reality to Enhance the Physics Teaching and Learning Process using the Design Science Research Method,” *J. Ris. Sist. Inf. Dan Tek. Inform. (JURASIK)*, Vol. 9, No. 1, pp. 223–234, 2024, [Online]. Available: <https://tunasbangsa.ac.id/ejurnal/index.php/jurasik>
- [15] N. Nurhalimah, “Pengaruh Social Influence terhadap Behavioral Intention Penggunaan Marketplace pada UMKM di Kota Bandung,” *J. Digit. Bisnis, Modal Manusia, Mark. Entrep. Financ. Strateg. Bisnis*, Vol. 1, No. 1, p. 1, Aug. 2021, DOI: 10.32897/dimensi.v1i1.771.
- [16] P. E. Setiawati, D. I. Inan, R. N. Wurahrah, R. Juita, and M. Sanglise, “How the Perceived Enjoyment Effect M-Payment Adoption in West Papua Province: DeLone and McLean Information Systems Success Model,” *JUPI (Jurnal Ilm. Penelit. dan Pembelajaran Inform.)*, Vol. 9, No. 3, pp. 1494–1505, Aug. 2024, DOI: 10.29100/jupi.v9i3.5738.
- [17] I. Samberi, D. I. Inan, R. N. Wurarah, R. Juita, and M. Sanglise, “Analysis of the Adoption Level of Qris in West Papua: The Roles of Self-Efficacy, Personal Innovativeness, and Privacy Concern,” *Jutisi J. Ilm. Tek. Inform. dan Sist. Inf.*, Vol. 13, No. 1, p. 346, 2024, DOI: 10.35889/jutisi.v13i1.1823.
- [18] N. Kock and P. Hadaya, “Minimum Sample Size Estimation in PLS-SEM: The Inverse Square Root and Gamma-Exponential Methods,” *Inf. Syst. J.*, Vol. 28, No. 1, pp. 227–261, 2018, DOI: 10.1111/isj.12131.
- [19] D. I. Inan et al., “Because Follower Experience Matters: The Continuance Intention to Follow Recommendation of the Influencer,” *Hum. Behav. Emerg. Technol.*, Vol. 2022, pp. 1–13, Nov. 2022, DOI: 10.1155/2022/3684192.
- [20] J. F. Hair, G. T. Hult, C. Ringle, and M. Sarstedt, *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)* - Joseph F. Hair, Jr., G. Tomas M. Hult, Christian Ringle, Marko Sarstedt. 2017.
- [21] D. I. Inan et al., “What Motivate Students to Continue using Online Collaborative Tools: Post-Acceptance of Information System Approach,” *Int. J. Emerg. Technol. Learn.*, Vol. 18, No. 09, pp. 49–64, May 2023, DOI: 10.3991/ijet.v18i09.36177.
- [22] P. W. Azizah, D. I. Inan, and M. Sanglise, “Apa yang Memotivasi Seseorang Mengakses Aplikasi Mobile Laporkitong? Perspektif Teori Uses And Gratification (U&G) dengan PLS-SEM,” *J. Ris. Sist. Inf. Dan Tek. Inform. (JURASIK)*, Vol. 9, No. 1, pp. 383–390, 2024, DOI: 10.30645/jurasik.v9i1.745.g720.
- [23] M. Walrave, C. Waeterloos, and K. Ponnet, “Ready or Not for Contact Tracing? Investigating the Adoption Intention of COVID-19 Contact-Tracing Technology using an Extended Unified Theory of Acceptance and use of Technology Model,” *Cyberpsychology, Behav. Soc. Netw.*, Vol. 24, No. 6, pp. 377–383, 2021, DOI: 10.1089/cyber.2020.0483.
- [24] M. Z. Alam, M. R. Hoque, W. Hu, and Z. Barua, “Factors Influencing the Adoption of mHealth Services in a Developing Country: A Patient-Centric Study,” *Int. J. Inf. Manage.*, <http://sistemasi.ftik.unisi.ac.id>

- Vol. 50, No. April 2019, pp. 128–143, 2020, DOI: 10.1016/j.ijinfomgt.2019.04.016.
- [25] J. Henseler, C. M. Ringle, and M. Sarstedt, “A New Criterion for Assessing Discriminant Validity in Variance-based Structural Equation Modeling,” *J. Acad. Mark. Sci.*, Vol. 43, No. 1, pp. 115–135, 2015, DOI: 10.1007/s11747-014-0403-8.
- [26] C. Fornell and D. Larcker, “Structural Equation Models with Unobservable Variables and Measurement Error: Algebra and Statistics. *Journal of marketing research*,” *Adv. Methods Mark. Res.*, Vol. 18, No. 3, pp. 382-388., 1994.
- [27] J. F. Hair, G. T. M. Hult, C. M. Ringle, M. Sarstedt, N. P. Danks, and S. Ray, *Evaluation of Formative Measurement Models*. 2021. DOI: 10.1007/978-3-030-80519-7_5.
- [28] M. Sarstedt, C. M. Ringle, and J. F. Hair, *Handbook of Market Research*, No. July. 2020. DOI: 10.1007/978-3-319-05542-8.
- [29] A. Purwanto and Y. Sudargini, “Partial Least Squares Structural Squation Modeling (PLS-SEM) Analysis for Social and Management Research : A Literature Review,” *J. Ind. Eng. Manag. Res.*, Vol. 2, No. 4, pp. 114–123, 2021.
- [30] J. F. Hair, C. M. Ringle, and M. Sarstedt, “PLS-SEM: Indeed a Silver Bullet,” *J. Mark. Theory Pract.*, Vol. 19, No. 2, pp. 139–152, 2011, DOI: 10.2753/MTP1069-6679190202.