The Role of Social Influence and Security Risk in Shaping Intention to Use Ride-Hailing in West Papua: A Theory of Planned Behavior Perspective

Dewi Aulia Nurhayati Maswatu[1]*, Dedi I. Inan[2], Ratna Juita[3], Muhammad Indra[4]
Department of Informatics[1], [2], [3],[4]
University of Papua
Manokwari, Papua Barat, Indonesia
202165022@student.unipa.ac.id[1], d.inan@unipa.ac.id[2], r.juita@unipa.ac.id[3], m.indra@unipa.ac.id[4]

***Abstract*— This study explores the adoption of ride-hailing services in West Papua, a developing region in Indonesia, where concerns about service performance and security risks influence user decisions. Guided by the Theory of Planned Behavior (TPB), the research examines how service performance, social influence, and perceived security risks affect users' behavioral intention and actual usage. A total of 158 valid responses were collected through a quantitative survey, and data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). Findings reveal that service effectiveness and social influence significantly influence behavioral intention, while efficiency and certainty do not. Additionally, certainty, effectiveness, and behavioral intention strongly affect user behavior. The model demonstrates moderate explanatory power with R^2 values of 0.561 for behavioral intention and 0.600 for user behavior. These results suggest that enhancing perceived service effectiveness and leveraging social influence can encourage adoption in regions with limited digital infrastructure. The study contributes to understanding technology acceptance in underdeveloped areas and offers practical insights for ride-hailing providers aiming to improve user trust and engagement.**

Keywords*— *Service Performance, User Intention, Ride-hailing, User Behavior, Theory of Planned Behavior

I. INTRODUCTION

The rapid development of digital technology has significantly transformed various sectors, including transportation. One key innovation resulting from this transformation is ride-hailing—an application-based system that allows users to request transport services via mobile devices [1]. These platforms offer benefits such as improved accessibility, time efficiency, convenience, and personalized transportation options [2].

In Indonesia, digitalization has supported the expansion of several ride-hailing platforms, including Maxim, which began operating in 2018. Maxim provides a broad range of services—passenger transport (Maxim Bike), goods delivery, food and shopping, cleaning, and cargo transport [3]. Its competitive pricing and wide service coverage make it particularly attractive in areas with limited access to conventional transportation [4].

However, the adoption of ride-hailing in developing regions like West Papua faces challenges such as negative perceptions of service quality, inaccurate driver tracking, and security concerns [3]. These issues are compounded by infrastructural limitations and low digital literacy. Such obstacles are even more pronounced in 3T regions (frontier, outermost, and underdeveloped), where limited infrastructure, low technological readiness, and strong local norms create unique barriers to adoption [5].

To date, most previous studies have concentrated on platforms like Gojek and Grab within densely populated urban settings [1] [6]. This focus has led to a significant gap in the literature concerning the adoption of similar services in regions like Papua. The factors influencing adoption in such areas may differ substantially due to infrastructure limitations, low digital literacy, and distinct social norms [5]. Moreover, many of these studies have overlooked local contextual influences such as trust, perceived usefulness, and perceived risk that are central to users' decision-making processes. In addition, ride-hailing platforms like Maxim have received limited academic attention, despite possessing characteristics that may be more aligned with the needs of local communities. Unlike Gojek or Grab, Maxim tends to penetrate underserved areas more effectively due to its simpler service mechanisms and more affordable pricing, making it a practical option in regions where conventional transportation is scarce. Therefore, research that specifically explores the adoption of Maxim in underdeveloped regions is urgently needed to provide a more accurate understanding of digital service adoption in such contexts.

This study addresses the research gap by examining how five external factors namely service certainty, efficiency, effectivity, social influence, and security risk influence individuals' behavioral intention to use Maxim in West Papua. These factors were selected based on their relevance to the social and infrastructural conditions commonly found in developing regions, which differ substantially from those in urban areas.

The study employs Ajzen's Theory of Planned Behavior

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(TPB) as its theoretical foundation. TPB has been extensively used in studies on technology adoption to explain how attitudes, subjective norms, and perceived behavioral control influence both intention and actual behavior [7]. However, its application in geographically marginalized regions remains limited, despite the fact that environmental constraints and cultural dynamics may significantly shape user behavior. By applying TPB within the context of West Papua, this research seeks to enhance theoretical insights into the adoption of digital transportation services and to support the development of policies that are responsive to the needs of underserved communities.

II. Theoretical Background

To understand individuals' decisions in adopting ride-hailing services, it is essential to examine various factors that influence their user behavior and behavioral intentions. These factors form the basis for explaining the motivations behind the use of digital transportation platforms such as Maxim.

A. Ride-hailing

Ride-hailing is an app-based transportation service that permits rapid reservations and offers economic possibilities [1]. The development of this service is supported by rapid technological advances. In developing regions, the impact of providing this service increases community mobility and creates jobs for local residents. Maxim is one example of a ride-hailing service, which comes with various features to increase user interest. With an adaptive business model, Maxim's service continues to compete in the ride-hailing market and provides a viable alternative for the community in choosing a transportation service that suits their needs.

B. Theory of Planned Behavior (TPB)

This study uses Ajzen's Theory of planned behavior (TPB) to explain and evaluate individual intentions and behavior [8]. In this study, TPB is used to evaluate the factors that influence Behavioural intention to use and Use Behaviour in the context of ride- hailing services, specifically the Maxim service. This research considers key factors including Certainty, Efficiency, Effectivity as well as Social Influence and Security Risk that play a role in shaping users' intention to adopt ride-hailing services.

C. Ride-hailing Performance

The performance of ride-hailing services is influenced by factors such as certainty, efficiency, and effectiveness. The certainty provided by the service builds user confidence, particularly regarding pick-up timeliness and transparent fare rates [9]. The more reliable a service is, the more likely users are to continue using it. Users also tend to prefer services that are easy to use and offer quick response times [10]. However, obstacles during usage may reduce user interest [11]. Therefore, meeting customer expectations through high service quality is essential to encourage continued usage [9].

D. Social Influence

Social influence shapes user decisions through direct recommendations or indirect exposure to peer behavior. Support from people in the surrounding environment such as family, friends, or positive reviews on social media can significantly motivate individuals to use ride-hailing services. According to a previous study [1], social influence is closely linked to human attitudes and emotions, as it emerges from interactions within the social environment that ultimately affect the adoption of online transportation services.

E. Security Risk

Perceived risks associated with safety and privacy when using ride-hailing services is one factor that raises user concerns. Concerns about safety and misuse of personal data during the trip can reduce user intention in the decision to use the service. A person's understanding of the security of the services they use greatly influences user intentions and behavior [12].

III. Research Methodology

A. Research Model and Hypotheses Development

This study adopts the Theory of Planned Behavior (TPB) as its foundational framework, incorporating the concept of Performance, which is defined through the dimensions of Certainty, Efficiency, and Effectiveness from the perspective of Maxim users. Additionally, external elements like Social Influence and Security Risk are recognized as determinants impacting user behavior. Moreover, Behavioural Intention to Use serves as an intermediary variable linking the independent and dependent factors, ultimately shaping Use Behaviour in the adoption of ride-hailing services in developing nations regions.

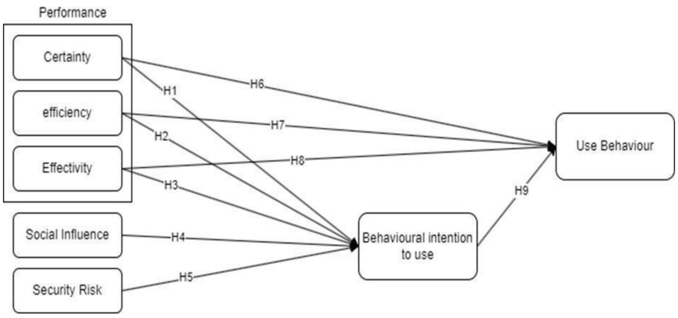

Fig. 1. Research Model

1.) The Impact of Service Certainty on Behavioural Intention to Use and Use Behaviour in Ride-Hailing Services.

The emergence of ride-hailing greatly affects community activities so that users have considerations about the certainty provided by the service. Certainty of service can create a sense of trust to use Maxim services, trust can be conceptualized as a psychological state that certainly motivates a person to accept something specifically based on favorable expectations regarding the intentions and behavior of the other party [13]. Based on this research, researchers try to prove the relationship between Certainty with Behavioural intention to use and Use Behaviour. Therefore this hypothesis was built:

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H1: Certainty about the services provided has a positive influence on behavioral intention to use ride-hailing services.

H6: The level of certainty regarding the quality assurance of ride-hailing services has a significant influence on users' actual use behavior.

2.) The Impact of Efficiency on Behavioural Intention to Use and Use Behaviour in Ride-Hailing Services.

Ride-hailing services help people to book vehicles and drivers flexibly [14]. Fast pick-ups occur because the application that connects users and drivers will bring together the nearest drivers [15]. Based on the explanation of the ease of using ride-hailing which shows the extent to which a person believes that using this service will help them in their activities, this hypothesis is made:

H2: Efficiency in ride-hailing services has a major influence on Maxim's intention to use.

H7: Perceived time efficiency influences users' propensity to order ride-hailing services.

3.) The Impact of Effectivity on Behavioural Intention to Use and Use Behaviour in Ride-Hailing Services.

Ride-hailing services bring convenience to individuals or communities [16]. The convenience provided by the service to users creates a sense of trust that using technology does not require excessive effort [17]. From study, researchers tried to prove the relationship between Effectivity with Behavioural intention to use and Use Behaviour. Then the hypothesis was built:

H3: The effectiveness of ride-hailing services is significant in choosing to use these services.

H8: Services that have good effectiveness can indirectly influence user behavior in utilizing Maxim services.

4.) The Impact of Social Influence on Behavioural Intention to Use and Use Behaviour in Ride-Hailing Services.

From several factors supporting the use of ride-hailing internally, there are several external considerations that will influence a person to use Maxim services, one of which is social influence which usually comes from family, friends and people around [14]. Individual social interactions can also influence users' feelings about using Maxim services [1]. Thus the researcher hypothesizes the following:

H4: Social influence significantly influences users' intention to use Maxim and recommend it to people nearby.

5.) The Impact of Security Risk on User Intentions in Ride-Hailing Services.

The existence of concerns about the risks felt by users is one of the factors that influence a person's interest in using ride-hailing services [18], individual supporting factors in adopting a service include is security [19], the researcher proposes the following hypothesis:

H5: Perceived security risk affects users' intention to choose to use Maxim ride-hailing service.

6.) The Impact of Behavioural Intention on User Behavior in Ride-Hailing Services.

The last relationship to be examined is the effect of Behavioural intention to use on Use Behaviour later. Individual perceptions of services have an impact on user behavioral and behavior [20], the more users are willing to use online transportation services. With this the following hypothesis is made:

H9: Intention to use ride-hailing services has a positive significant effect on user behavior in using ride-hailing services.

B. Sampel

This study uses a quantitative survey to collect numerical data through questionnaires, which is then analyzed using statistical techniques to assess, interpret, and understand patterns or relationships between variables objectively [21].

The sampling targeted all Maxim service users, regardless of age, gender, or education level. Data were collected through an online questionnaire distributed to potential respondents in the developing area of Manokwari, West Papua. A non-probability sampling technique was employed, based on specific inclusion criteria primarily the participants' willingness to take part in the study. This study employs PLS-SEM, utilizing the G*Power tool for power analysis. By setting an effect size of 0.15, a 5% alpha significance level, and 94% power analysis, with seven predictor variables, the required sample size was 74 respondents [22]. However, from the collected questionnaire responses, 168 respondents participated, and after filtering for completeness, 158 responses were deemed valid for further analysis. The number of valid responses exceeded the minimum sample size determined by G*Power.

This research is conducted online and does not involve any risks that may harm the participants. Participation in this study is voluntary and anonymous. Prior to filling out the questionnaire, respondents are provided with an explanation of the research purpose and informed that the collected data will only be used for academic purposes. Respondents are given the opportunity to read and understand the explanation, and by filling out the questionnaire using a 1-5 rating scale (Strongly Disagree to Strongly Agree), respondents are considered to have given their consent voluntarily. This research was approved by the institutional ethics committee of Universitas Papua. All participant data are kept confidential and used solely for academic purposes. Table I presents the socio-demographic characteristics of the respondents.

TABLE I. DESCRIPTION OF DEMOGRAPHIC RESPONDENTS

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Variables	Category	Frequency	Percentage
Age	<17 Years	20	12,1
	18-30	136	82,4
	31-50	8	4,8
	50 Years	1	0,6
Gender	Male	67	40,6
	Female	98	59,4
Ever Used Maxim	Ever	121	73,3
	Never	44	26,7

C. *Analysis Method*

In research, the PLS-SEM method is applied to evaluate measurement and structural models to test reliability, validity, and the relationships between variables established in the hypothesis. This statistical technique is used to analyze complex associations between latent variables in structural equation modeling [23].

IV. Results And Analysis

A. *Measurement Model Evaluation*

Evaluation of the measurement model (outer model) is the first step in the data analysis cycle before proceeding to the evaluation of the structural model (inner model) [24]. In this study, there are criteria used to assess the outer model, namely convergent validity, discriminant validity, and composite reliability [25]. Convergent validity test can be done by checking the factor (outer loading) and average variance extracted (AVE). Where an indicator is considered to have good convergent validity if it meets the standard > 0.7 [24]. AVE is a standard value that each variable must have where the acceptable threshold for AVE is 0.5 or higher [26]. Reliability testing is carried out using two methods, namely Cronbach's alpha (CA) and composite reliability (CR), where the construct is considered reliable if the value of CA and CR is above 0.07. For LF < 0.40, indicators must be removed [27]. All constructs and measurement items are presented in Table II.

TABLE II. Confirmation Variabel Results

Building	Statement	Code	LF
Certainty (C) [13] CA, CR, AVE = 0.851, 0.855, 0.771	I believe that Maxim can be relied upon to deliver me to destination without delay	C1	0.844
	I am satisfied with the timeliness of the service provided by Maxim.	C2	0.911
	I am confident that Maxim is able to handle situations that may cause delays and still deliver services on time.	C3	0.877
Efficiency(E) [14], [28] CA, CR, AVE = 0.816, 0.837, 0.731	I had no difficulty filling in information required to place an order.	E1	0.815
	The driver Maxim arrived at my location according to the estimated arrival time..	E2	0.834
	The routes taken by Maxim drivers always match the estimated time given before the trip.	E3	0.914
Effectivity (EF) [1] CA, CR, AVE = 0.851, 0.855, 0.770	Maxim offers a wide selection of services (maxim *bike*, maxim *car*, maxim *food*) that are adequate for my needs.	EF1	0.862
	I feel comfortable and safe when using Maxim's services for my travel.	EF2	0.911
	I feel comfortable and safe when using Maxim's services for my travel.	EF3	0.858
Social Influence (SI) [1] CA, CR, AVE = 0.865, 0.865, 0.788	Those I trust recommended me to use Maxim's services.	SI1	0.886
	Those who influence my behavior thinks I should use Maxim's services.	SI2	0.907
	I use Maxim's service because some people around me also use it.	SI3	0.870
Security Risk (SR) [29] CA, CR,AVE = 0.878, 1.246, 0.880	Maxim may present hazards that could jeopardize the safety of the user.	SR2	0.897
	Maxim may put me at potential risk of physical threats during the trip.	SR3	0.977
Behavioral Intention to Use (BI) [1] CA, CR, AVE = 0.830, 0.837, 0.747	I feel the need to use Maxim's services in my daily activities.	BI1	0.878
	I plan to use Maxim's services in the near future.	BI2	0.896
	I would recommend using Maxim's services to others based on my intention to use them.	BI3	0.817
Use Behaviour (UB) [30] CA, CR, AVE = 0.851, 0.851, 0.772	I use Maxim's services regularly in my daily activities.	UB1	0.888
	I often use Maxim's services for both long and short trips.	UB2	0.915
	I feel comfortable using Maxim's services for a long time while traveling.	UB3	0.831

In Table II, the majority of indicators have LF values > 0.7 and AVE > 0.5. However, in order for the test to continue, the SR1 indicator was eliminated because it had a non- ideal LF value of 0.434. In addition, two other indicators, E2 and UB1 were also eliminated because they could interfere with the discriminant validity test, but did not affect the validity of the previous test.

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Furthermore, this study conducted a discriminant validity test, to ensure that a variable is different from other similar variables using the Heterotrait-monotrait ratio (HTMT) - Matrix test [31]. In determining the limit value of HTMT, there are two general standards, namely a maximum of 0.85 and 0.9 [14]. Table III shows that all variables have an HTMT value < 0.85. So that the discriminant validity test has been fulfilled through the HTMT test [32].

TABLE III. HETEROTRAIT-MONOTRAIT RATIO

	BI	C	E	EF	SI	SR	UB
BI							
C	0.720						
E	0.728	0.879					
EF	0.779	0.835	0.888				
SI	0.808	0.812	0.708	0.743			
SR	0.096	0.086	0.057	0.090	0.087		
UB	0.858	0.668	0.576	0.544	0.643	0.071	

B. *Structural Model Evaluation*

This structural model evaluation aims to analyze the relationships among variables in the research model, including multicollinearity testing using the Variance Inflation Factor (VIF) values and hypothesis testing through T-statistics and P-values [33]. The multicollinearity test is conducted to assess whether there is a high correlation between independent variables in the model. According to [24], VIF values are considered acceptable if they fall between > 0.2 and < 5. Based on Table IV, all VIF values meet these criteria, indicating no multicollinearity issues, and therefore, the regression analysis can proceed with greater accuracy.

TABLE IV. MULTICOLLINEARITY TEST RESULT

	BI	C	E	EF	SI	SR	UB
BI							1.896
C	2.955						2.593
E	2.571						2.603
EF	2.687						2.804
SI	2.134						
SR	1.013						
UB							

Based on the VIF results in Table IV, which indicate that there are no multicollinearity issues among the variables, hypothesis testing can be conducted to evaluate the direct effects between variables [34], [35]. A hypothesis is accepted if the T-statistic value is greater than 1.96 and the P-value is less than 0.05 [36], [17]. According to Table V, out of 9 proposed hypotheses, 5 were accepted and 4 were rejected.

TABLE V. HYPOTHESIS TEST RESULT

Hypothesis	Variables	T-statistics	P values	Description
H1	C → BI	0.256	0.798	Rejected
H2	E → BI	1.565	0.118	Rejected
H3	EF → BI	3.127	0.002	Accepted
H4	SI → BI	4.560	0.000	Accepted
H5	SR → BI	1.395	0.163	Rejected
H6	C → UB	3.297	0.001	Accepted
H7	E → UB	0.064	0.949	Rejected
H8	EF → UB	2.120	0.034	Accepted
H9	BI → UB	10.801	0.000	Accepted

The coefficient of determination (R-Square) is used to see the extent to which the independent variable is able to explain the variation in the dependent variable. If the R- Square value is 0.75, it can be said to be strong, a value of 0.50 is said to be moderate and a value of 0.25 is said to be weak [26]. The higher the R-Square value, the better the model in explaining the effect of the independent variable on the dependent variable.

TABLE VI. R-SQUARE TEST RESULT

	R-square	Description
BI	0.561	Moderate
UB	0.600	Moderate

Based on Table VI above, the value of R^2 owned by Behavioral Intention to Use (BI) is 0.561, which indicates that the level of prediction accuracy in the model is moderate. This also applies to Use Behavior (UB), where the value at R^2 is 0.600, which indicates a moderate level of prediction accuracy.

V. DISCUSSION AND CONCLUSION

The analysis revealed that Certainty did not have a significant effect on Behavioral Intention (H1), as indicated by T = 0.256 and P = 0.798. This suggests that users' sense of assurance about the service does not automatically translate into a clear intention to use it. This finding contradicts the results of , which found a significant positive relationship between the two variables. It indicates that even when users feel confident about the service, this confidence alone may not be sufficient to drive their intention to adopt it. On the other hand, Certainty was found to significantly influence Use Behavior (H6), with T = 3.297 and P = 0.001. This implies that a higher level of perceived certainty about the service may encourage actual use, even if the initial behavioral intention is weak. This finding contradicts the results of [36] and indicates that, in this context, users may choose to use the service based on their perceived reliability, even in the absence of strong prior intentions.

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Hypotheses H2 and H7, which tested the influence of Efficiency on Behavioral Intention and Use Behavior, were both rejected. Efficiency did not significantly affect Behavioral Intention (T = 1.565; P = 0.118) or Use Behavior (T = 0.064; P = 0.949). These results are inconsistent with [14], which emphasized the importance of efficiency. A plausible explanation is that users in underdeveloped regions (3T areas) tend to prioritize service availability and affordability over technical efficiency. Thus, efficiency may not be considered a crucial factor when deciding whether to use the service.

On the other hand, Effectiveness was observed to have a substantial influence on both Behavioral Intention and Use Behavior. Hypotheses H3 (T = 3.127; P = 0.002) and H8 (T = 2.120; P = 0.034) were validated, which is consistent with the results presented in [36] and [37].These results suggest that users' perceptions of the service’s effectiveness such as timely response and ease of use play a vital role in encouraging both their intention and actual usage. When the service is perceived as delivering what users expect, it becomes more appealing for repeated use.

Social Influence was also found to significantly affect Behavioral Intention (H4), with T = 4.560 and P = 0.000. This indicates that users’ decisions are highly shaped by recommendations and opinions from their social circles. This result supports [1], which emphasized the strong role of social context in forming intention. In collectivist or community-oriented settings such as Papua, group norms and shared perceptions often outweigh individual reasoning.

Conversely, Security Risk was not found to have a significant effect on Behavioral Intention (H5), as shown by T = 1.395 and P = 0.163. This contrasts with [25], which reported a significant negative relationship. One possible explanation is that users in this region may exhibit a tolerance for perceived risks due to limited alternatives, or they may have normalized low expectations regarding safety. Additionally, users may give greater weight to cost considerations than to potential security concerns.

Finally, Behavioral Intention had a strong and significant effect on Use Behavior (H9), with T = 10.801 and P = 0.000. This confirms that intention is a key predictor of actual usage, aligning with [36]. It also indicates that even in remote or underserved areas (3T), behavioral intention remains a central factor in shaping actual service adoption. This highlights the importance of understanding the factors that influence users' intentions in order to encourage continued use.

In summary, the results indicate that Effectiveness and Social Influence significantly affect users' Behavioral Intention to use Maxim services. Furthermore, Certainty, Effectiveness, and Behavioral Intention are key factors influencing Use Behavior. On the other hand, Certainty, Efficiency, and Security Risk were not found to be significant predictors of Behavioral Intention, and Efficiency also did not notably impact Use Behavior. These findings imply that, within the context of West Papua, the perceived usefulness of the service and social factors play a more crucial role in adopting the service compared to operational efficiency or concerns over safety.

The R-square analysis indicates that the model falls within the moderate prediction category. The Behavioral Intention to Use (BI) had an R^2 value of 0.561, meaning that the tested variables explained 56.1% of the variance in BI, while the remaining 43.9% is attributed to other unexamined factors. Similarly, Use Behavior (UB) had an R^2 value of 0.600, suggesting that 60% of the variance in UB can be explained by the model, particularly through BI, while the remaining 40% is likely influenced by external factors not addressed in this study.

In summary, Certainty, Efficiency, Effectivity, Social Influence, and Security Risk collectively account for 56.1% of the variation in Behavioral Intention, which in turn explains 60% of the variation in Use Behavior. The remaining variance may be shaped by other relevant variables not included in the current research framework.

A. Theoretical Implications

This study explores the influence of internal factors by adopting the Theory of Planned Behavior (TPB) to analyze users' intentions and users behavior toward the adoption of the Maxim ride-hailing service in a developing region affected by the 3T (Frontier, Outermost, and Disadvantaged areas) context, specifically Manokwari, West Papua. The research aims to understand how psychological and social aspects influence users' decisions in utilizing app-based transportation services in areas where infrastructure and technology penetration are still developing.

The findings indicate that perceived service effectiveness and social influence are the key factors driving the adoption of Maxim's ride-hailing service. Perceived service effectiveness relates to reliability, efficiency, and overall service performance, while social influence, including support from friends, family, and the community, enhances users' trust in the platform. Both factors play a crucial role in shaping user confidence, particularly in regions where access to digital transportation solutions is still expanding.

On the other hand, security risk does not significantly impact users' intentions. This finding suggests that users in developing regions prioritize service convenience and efficiency over potential security concerns. Factors such as easy access, affordability, fast service, and vehicle availability play a more significant role in user decision-making. Additionally, users may have a certain level of risk tolerance or perceive that Maxim's security measures are adequate, making security concerns a less critical factor in the adoption of ride-hailing services.

B. Limitations and Future Research Directions

This research provides significant practical implications for understanding the adoption of Maxim ride-hailing services. However, the results of this study still show some limitations that need further attention. This study focused on the use of Maxim services in the developing area of Manokwari, West

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Papua therefore, evaluation with a wider and diverse respondents will be the main focus of further research in the future because the needs of maxim services in other developing areas may be different from maxim services Manokwari. In addition, this study still shows that there are many factors that might contribute especially to the individual's intention to use the service and their attitudes later, this allows the need for consideration of other variables that are more effective in providing an understanding of the use of Maxim ride-hailing services.

Future research could focus on the Maxim driver experience, including aspects of welfare, protection, and income. Understanding drivers' experiences can reveal issues and other unmet needs, which can help with service development. Driver and user perspectives provide a more thorough understanding and help identify gaps and improve service quality. In addition, it can encourage new innovations in services and build a more balanced ecosystem for all parties.

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