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AN ANALYSIS OF THE FACTORS CONTRIBUTING TO THE FAILURE OF RIDE-HAILING ADOPTION IN DEVELOPING REGIONS THROUGH THE LENS OF THE DIFFUSION OF INNOVATION MODEL: A CASE STUDY OF OKE-JEK IN MANOKWARI REGENCY

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Abstract

This study analyzes the use of the Oke-Jek platform as a ride-hailing service in developing regions. The objective of the study is to identify the factors that hinder the adoption of Oke-Jek as a ride-hailing service in such areas. Currently, the utilization of Oke-Jek remains limited, particularly in regions like West Papua, leading to a research gap regarding the adoption of this service in the area. This study employs the Diffusion of Innovation Theory as its conceptual framework. Data were collected through a Google Forms-based questionnaire, with a total of 112 respondents. Data analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM). The main findings indicate that the proposed model demonstrates good reliability and validity, with an R^2 value of 0.628, meaning that Behavioral Intention to Use explains 62% of the variance in the use of Oke-Jek. Furthermore, the results confirm that Compatibility, Relative Advantage, and Complexity are significant factors influencing the adoption of Oke-Jek among respondents. The implications of this research support the development of ride-hailing services in developing regions. These findings can be used to design effective strategies for increasing the adoption of Oke-Jek in West Papua. In addition to providing theoretical insights, this study also offers strategies for the evaluation and optimization of ride-hailing services.

***Keywords**: Developing Regions, Diffusion of Innovation, Partial Least Squares Structural Equation Modeling, Ride-hailing, Technology adoption*

I. INTRODUCTION

Transportation plays a vital role in daily life, and technological advancements have driven innovation within the industry. Ride-hailing services have emerged as a modern transportation solution, offering greater convenience and efficiency compared to traditional options. In Indonesia, these services have grown rapidly, making significant contributions to the economy while providing benefits such as ease of access, transparency, and enhanced safety for users [1]. Moreover, ride-hailing creates employment opportunities and improves transportation accessibility. In developing regions such as Papua—particularly Manokwari—ride-hailing services are gaining popularity, despite the population's previous reliance on conventional modes of transport. The growing use of smartphones and internet access has facilitated the adoption of these services, providing flexible mobility solutions and contributing to local economic development.

Oke-Jek, which has been operating in Manokwari since 2015 under PT. Okejek Kreasi Indonesia, offers a range of app-based transportation services, including passenger transport, goods delivery, and food delivery [2]. In addition to serving as an alternative mode of transportation, Oke-Jek also creates job opportunities and supports small businesses in distributing their products. However, ride-hailing services in developing areas face several challenges, such as misalignment with local customs where people are more accustomed to traditional transportation. Limited access to technology and low levels of digital literacy also present barriers to adoption.

Previous studies have examined the adoption of ride-hailing services from various perspectives. [3] explored Gojek's diversification strategy, which succeeded due to its strong foundation in technology and innovation. [4] assessed Uber's

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adoption by integrating the Diffusion of Innovation Theory with the Technology Acceptance Model (TAM), highlighting that relative advantage, compatibility, and social influence are key drivers of adoption. However, most prior research has focused more on the drivers of adoption than on the barriers, especially in developing regions. According to the Diffusion of Innovation Theory, the decision to adopt an innovation is influenced by five factors: relative advantage, compatibility, complexity, trialability, and observability [5], [6].

Given the importance of a comprehensive understanding of the adoption process, recent studies have also begun to explore users' psychological factors, including behavioral intention to use ride-hailing services. Research on usage intention continues to evolve ([4]; [3]; [7]. Ride-hailing is defined as an app-based mobility service facilitated by information and communication technology (ICT) [7]. This service differs from conventional transportation in that it is mediated by technology, which shapes user perceptions. Behavioral intention to use refers to an individual's tendency to adopt an innovation in the future, influenced by external factors [8]. Understanding these factors is crucial for Oke-Jek to avoid the failure of service adoption.

To support this understanding, the Diffusion of Innovation (DOI) theory provides a relevant framework for explaining how innovations are introduced, disseminated, and ultimately adopted by society. [9] note that the theory was developed by Rogers (2003), who described five stages of adoption: knowledge, persuasion, decision, implementation, and confirmation. Innovation adoption is significantly influenced by core factors. [10] argue that the main determinants are the perceived attributes of the innovation—namely relative advantage, compatibility, complexity, trialability, and observability. This aligns with the current study, which aims to identify the barriers to adopting the Oke-Jek ride-hailing service.

Based on this theoretical framework and the key factors influencing innovation adoption, this study focuses on identifying specific obstacles to the use of Oke-Jek in the local context of Manokwari. In addition to core constructs such as compatibility, relative advantage, and complexity derived from the Diffusion of Innovation theory, this study incorporates additional variables to better reflect the contextual and behavioral nuances of users in developing regions. These include Perceived Financial Cost, which refers to an individual's perception of the cost associated with using a service; Perceived Ubiquity, defined as the perception of service availability anytime and anywhere; and Resistance to Change, which reflects an individual's tendency to reject new or unfamiliar changes. These variables have been adopted in prior studies involving technology adoption in developing markets, where affordability, accessibility, and psychological inertia significantly affect user acceptance. Furthermore, gender and age are included as control variables, acknowledging that demographic factors influence the adoption patterns of digital services. The findings of this study are expected to provide deeper insights for service providers in designing more effective, context-sensitive strategies to enhance Oke-Jek adoption in emerging regions like Manokwari.

II. RESEARCH METHODOLOGY

In this study, the proposed model is shown in Figure 1. The model illustrates the factors and their relationships to the intention to use, such as diffusion of innovation (compatibility, relative advantage, and complexity), perceived financial cost, perceived ubiquity, and resistance to change, as well as age and gender, which determine the intention to use the Oke-Jek ride-hailing platform.

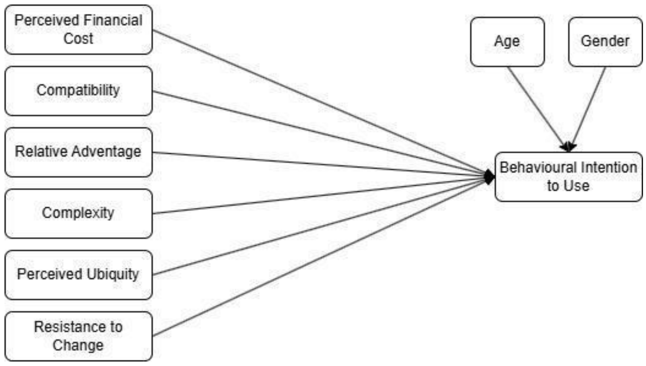

Figure 1. Research Model

This study employs a quantitative research approach. Quantitative research is a methodological approach that uses numerical data or statistics to measure variables and analyze the relationships between them. According to [11], quantitative research describes, investigates, and explains phenomena as they are, drawing conclusions from observable data using numerical analysis. Based on the proposed research model, each factor in this study equally influences the intention to use. The details of the relationships between each factor are as follows:

A. *The Relationship between Perceived Financial Cost and Behavioral Intention to Use*

Perceived Financial Cost refers to an individual's perception of the cost associated with using a service. [12] state that this perception influences the decision to adopt technology-based innovations. Therefore, perceived cost becomes a significant factor in the intention to use the Oke-Jek service. Accordingly, we propose the following hypothesis:
H1: Perceived Financial Cost has a significant influence on Behavioral Intention to Use the Oke-Jek ride-hailing service.

B. *The Relationship between Compatibility and Behavioral Intention to Use*

Compatibility reflects the degree to which an innovation aligns with users' needs and lifestyles [6]. The more a service aligns with user habits, the more likely it is to be adopted. Therefore, we propose the following hypothesis:
H2: Compatibility has a significant influence on Behavioral Intention to Use the Oke-Jek ride-hailing service.

C. *The Relationship between Relative Advantage and Behavioral Intention to Use*

Relative Advantage measures the extent to which a service is perceived as more beneficial than existing alternatives [13]. Factors such as cost efficiency, convenience, and accessibility can enhance the adoption of ride-hailing services. Therefore, we propose the following hypothesis:

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H3: Relative Advantage has a significant influence on Behavioral Intention to Use the Oke-Jek ride-hailing service.

D. The Relationship between Complexity and Behavioral Intention to Use

Complexity refers to the degree to which a service is perceived as difficult to use [5]. Highly complex services tend to hinder adoption, especially for users who are less familiar with digital technology. Therefore, we propose the following hypothesis:

H4: Complexity has a significant influence on Behavioral Intention to Use the Oke-Jek ride-hailing service.

E. The Relationship between Perceived Ubiquity and Behavioral Intention to Use

Perceived Ubiquity refers to the perception of service availability anytime and anywhere [14]. High accessibility levels enhance user convenience and the likelihood of service usage. Therefore, we propose the following hypothesis:

H5: Perceived Ubiquity has a significant influence on Behavioral Intention to Use the Oke-Jek ride-hailing service.

F. The Relationship between Resistance to Change and Behavioral Intention to Use

Resistance to Change is an individual's tendency to reject change [15]. In technology adoption, this resistance can be mitigated by improving perceptions of comfort and service availability. Therefore, we propose the following hypothesis:

H6: Resistance to Change has a significant influence on Behavioral Intention to Use the Oke-Jek ride-hailing service.

G. The Relationship between Age and Gender and Behavioral Intention to Use

Demographic factors such as age and gender influence the adoption patterns of digital services [13]. Age may affect ease of technology use, while gender may influence preferences for safety and convenience in ride-hailing services.

This study involved residents of West Papua, with a sample drawn from Oke-Jek users in Manokwari, collected through an online questionnaire. The sample size was determined using Cohen's table to conduct a power analysis, aided by the G*Power application [16], with an effect size of 0.15, a significance level of 5% ($\alpha = 0.05$), and a statistical power of 0.95 [17]. Considering eight predictor variables, the minimum required sample size was 74 respondents.

The questionnaire consisted of two parts: respondents' demographic data, kept confidential, and questions related to their experiences using Oke-Jek. A Likert scale was used to measure respondents' attitudes, opinions, and perceptions of the service [18], with scores ranging from 1 (strongly disagree) to 5 (strongly agree). A purposive sampling technique was applied to ensure that respondents had prior experience using Oke-Jek. Given the large population of West Papua, this technique helped limit the sample size appropriately. During the data collection process, a total of 117 respondents completed the questionnaire, exceeding the required minimum.

Table 1. Respondent Demographics

Category	Item	Total	Percentage
Gender	Male	66	56%
	Female	51	44%
Age	17-25 Years Old	65	56%
	26-34 Years Old	26	22%
	35-43 Years Old	22	19%
	> 44 Years Old	4	3%
Education	Elementary School	1	1%
	Junior High School	7	6%
	Senior High School	72	62%
	S1	25	21%
	S2	2	2%
	S3	1	1%
	D3	8	7%
	No Formal Education	1	1%
Occupation	Student	54	51%
	Housewife	6	6%
	Entrepreneur	7	7%
	PNS	9	8%
	Private Sector Employee	25	24%
	TNI-POLRI	5	5%
Income	< 1 million rupiah	60	51%
	1- 3 million rupiah	35	30%
	4 - 6 million rupiah	14	12%
	> 6 million rupiah	8	7%

The majority of respondents in this study were male (56%), while female respondents accounted for 44%. In terms of age, most respondents were in the 17–25 age group (56%), followed by those aged 26–34 (22%), 35–43 (19%), and above 44 years old (3%). Regarding educational background, most respondents had completed senior high school (62%), followed by bachelor's degree (S1) holders (21%), diploma (D3) holders (7%), junior high school (6%), and a small percentage with elementary education, master's (S2), doctoral (S3) degrees, or no formal education—each ranging from 1% to 2%. In terms of occupation, the majority were students (51%), followed by private sector employees (24%), civil servants (8%), entrepreneurs (7%), housewives (6%), and military or police personnel (5%). As for monthly income, more than half of the respondents (51%) earned less than 1 million IDR, while 30% earned between 1–3 million, 12% earned 4–6 million, and only 7% earned more than 6 million IDR. These results indicate that the majority of respondents were young individuals still pursuing their education, with limited income.

This study employed the Partial Least Squares-Structural Equation Modeling (PLS-SEM) method to analyze the relationships among research variables. PLS-SEM consists of two main components: the measurement model, used to test the validity and reliability of the constructs, and the structural model, used to test the relationships between latent variables and the proposed hypotheses (Sholiha et al., 2015). The analysis was conducted using SmartPLS 4.0 software.

III. Result and Discussion

A. Measurement Model Evaluation

As previously explained, evaluating the measurement model is the first of two essential stages in SEM-PLS analysis. This stage aims to assess the relationship between indicators and latent variables to ensure data validity and reliability. The process includes testing convergent validity, discriminant

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validity, and reliability, ensuring that the indicators accurately reflect the latent constructs [19]; [20]). The evaluation begins with examining the loading factors (LF), as presented in Table 2. According to Inan et al. (2022), an indicator is considered to have good convergent validity if its outer loading exceeds 0.7. In Table 2, all measurement items have loading factors that meet this criterion, indicating that each construct explains more than 50% of the variance of its indicators. Next, the first reliability assessment criterion involves measuring the reliability of each construct using Cronbach's Alpha (CA) and Composite Reliability (CR). [21] suggest that both CA and CR values should exceed 0.7 to demonstrate good internal consistency. As shown in Table 2, all constructs have CA and CR values above 0.7, indicating strong reliability. The next step in the evaluation involves testing convergent validity using the Average Variance Extracted (AVE) for each measurement item within the constructs. According to [22], a construct is considered valid when its AVE exceeds 0.5. Table 2 shows that all AVE values surpass this threshold, confirming that the constructs demonstrate good convergent validity.

Table 2. Confirmatory test Result

Construct	Statement	Code	LF
Behavioral Intention to Use (BI) CA, CR, AVE = 0.923, 0.951, 0.867 (Tsai et al., 2020)	I intend to use Oke-Jek in the future.	BI1	0.902
	I will use Oke-Jek in my daily life.	BI2	0.950
	I prefer to use Oke-Jek as my mode of transportation..	BI3	0.941
Perceived Financial Cost (PFC) CA, CR, AVE = 0.758, 0.830, 0.621 (Mulyani & Nugraha, 2022)	Using Oke-Jek requires a very high cost.	PFC1	0.745
	To use Oke-Jek as a mode of transportation, I need a smartphone to operate it.	PFC2	0.886
	Using Oke-Jek creates a new financial burden.	PFC3	0.723
Compatibility (CP) CA, CE, AVE = 0.869, 0.920, 0.792 (Ismail, 2016)	I feel that Oke-Jek supports all the work-related needs of its users.	CP1	0.883
	I feel that Oke-Jek meets users' needs according to their jobs.	CP2	0.910
	I feel that Oke-Jek provides easy and quick access for transportation users.	CP3	0.877
Relative Advantage (RA) CA, CE, AVE = 0.931, 0.956, 0.879 (Wulandari et al., 2023)	Oke-Jek services can be accessed anywhere.	RA1	0.944
	Oke-Jek fulfills the needs I am looking for.	RA2	0.945
	An Oke-Jek account can be easily managed.	RA3	0.923
Complexity (CX) CA, CE, AVE = 0.907, 0.935, 0.828 (Redjeki, 2022)	Transportation using Oke-Jek takes more time than conventional transportation.	CX1	0.836
	Transportation using Oke-Jek makes the transportation process more complicated.	CX2	0.918
	Transportation using Oke-Jek requires a longer ordering process.	CX3	0.972
Perceived Ubiquity (PUB) CA, CE, AVE = 0.921, 0.950, 0.864 (Tsai et al., 2020)	Oke-Jek provides me with information anytime and anywhere.	PUB1	0.924
	Oke-Jek provides me with communication and connectivity with the driver anytime and anywhere.	PUB2	0.931
	I will frequently use Oke-Jek as my transportation.	PUB3	0.933
Resistance to Change (RTC) CA, CE, AVE = 0.856, 0.910, 0.772 (Tsai et al., 2020)	I do not want to use Oke-Jek because it has poor service quality	RTC1	0.779
	I do not want to use Oke-Jek because of the uncertainty in trip pricing.	RTC2	0.923
	I do not want Oke-Jek to change the way I interact with others.	RTC3	0.926

Source : Smart PLS 4

Once the proposed model meets the criteria for reliability and convergent validity, the next step is to assess discriminant validity. This test is conducted to ensure that each construct is truly distinct from the others within the research model. Discriminant validity can be assessed using the Heterotrait-Monotrait Ratio (HTMT) ([23]; [24]). According to [25], discriminant validity is considered satisfactory if each indicator has an HTMT value of less than 0.90. As shown in Table 3, the HTMT values meet the required threshold. This indicates that each construct is unique and capable of representing its own variable, and it cannot be explained by other constructs within the model.

Table 3. HTMT test Result

	Age	BI	CP	CX	Gender	PFC	PUB	RA	RTC
Age									
BI	0,176								
CP	0,311	0,849							
CX	0,404	0,082	0,249						
Gender	0,150	0,037	0,034	0,092					
PFC	0,511	0,227	0,212	0,485	0,075				
PUB	0,305	0,583	0,757	0,381	0,126	0,260			
RA	0,281	0,697	0,824	0,288	0,120	0,247	0,823		
RTC	0,427	0,357	0,424	0,666	0,041	0,519	0,439	0,454	

Source : Smart PLS 4

B. Structural Model Evaluation

Once the data has been confirmed to be valid and reliable, the next step is to evaluate the structural model. Before proceeding, it is necessary to test for potential collinearity, which ensures that the constructs within the model do not have excessive correlations. Excessive collinearity can lead to insignificant indicators [23]. This test can be conducted using the Variance Inflation Factor (VIF). According to [21], acceptable VIF values fall between 0.2 and 5. As shown in Table 4, all constructs in the model meet this criterion, indicating that multicollinearity is not an issue in this research model.

Table 4. Multicollinearity Test Result

	BI	CP	CX	PFC	PUB	RA	RTC
BI							
CP	2.439						
CX	1.524						
PFC	1.143						
PUB	2.998						
RA	3.445						
RTC	1.681						

Source : Smart PLS 4

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The next test is the coefficient of determination (R-Square), which measures the extent to which independent variables influence the dependent variable [26]. According to [21], an R-Square value of 0.25 is considered weak, 0.50 moderate, and 0.75 strong in terms of predictive power. As presented in Table 5, the R-Square value for Behavioral Intention to Use is 0.629. This means that Behavioral Intention to Use can be substantially explained by Perceived Financial Cost, Compatibility, Relative Advantage, Complexity, Perceived Ubiquity, and Resistance to Change, accounting for 62.9% of the variance.

Table 4. Multicollinearity Test Result

	R-square adjusted	Description
BI	0.628	Sedang

Source : Smart PLS 4

The evaluation of the structural model is continued by performing a path coefficient test. According to [21], a hypothesis is considered accepted if the p-value is less than 5% and the t-statistic exceeds 1.96. Out of the 8 hypotheses proposed, 3 were accepted and 5 were rejected—specifically, H1, H5, H6, H7, and H8—as their p-values exceeded 5% and their t-statistics were below 1.96. The hypothesis testing results are presented in Table 6, which shows which hypotheses were supported and which were not.

Table 5. Hypothesis Test Result

Hypothesis	Variables	T statistics	P values	Description
H1	Perceived financial cost → Behavioural Intention to use	1.171	0.121	Rejected
H2	Compatibility → Behavioural Intention to use	6.096	0.000	Accepted
H3	Relative advantage → Behavioural intention to use	2.178	0.015	Accepted
H4	Complexity → Behavioural intention to use	2.440	0.007	Accepted
H5	Perceived ubiquity → Behavioural intention to use	0.193	0.424	Rejected
H6	Resistance to change → Behavioural intention to use	0.881	0.189	Rejected

Source : Smart PLS 4

Based on the hypothesis testing results in Table 6, H1 was rejected because the p-value exceeded 0.05 (0.121), and the t-statistic was below 1.96 (1.171). This indicates that Perceived Financial Cost does not have a significant influence on Behavioral Intention to Use. This finding contradicts the statement by [12], which asserts that perceived financial cost serves as an indicator to measure a person's trust regarding the expenses required to use a system. H2 was accepted as the p-value was less than 0.05 (0.000) and the t-statistic exceeded 1.96 (6.096). This indicates that Compatibility has a significant effect on Behavioral Intention to Use. This supports the statement by [6], which explains that the higher the compatibility, the more likely an innovation will be adopted by users.

H3 was accepted with a p-value below 0.05 (0.015) and a t-statistic above 1.96 (2.178). This shows that Perceived Ubiquity significantly influences Behavioral Intention to Use. This aligns with the statement by [13], which identifies relative advantage as one of the attributes of innovation that measures the extent to which an innovation benefits its users. H4 was accepted since the p-value was less than 0.05 (0.007) and the t-statistic was higher than 1.96 (2.440). This indicates that Complexity significantly influences Behavioral Intention to Use. This is consistent with [5], who defined complexity as the level of difficulty in adopting an innovation—the harder it is to understand and use, the less likely it is to be adopted.

H5 was rejected because the p-value was greater than 0.05 (0.424) and the t-statistic was below 1.96 (0.193). This means that Perceived Ubiquity does not significantly affect Behavioral Intention to Use, which contradicts the statement by [14] that the greater the accessibility of technology anytime and anywhere, the more convenience and flexibility it provides to users. H6 was rejected due to a p-value greater than 0.05 (0.189) and a t-statistic below 1.96 (0.881). This implies that Resistance to Change does not significantly influence Behavioral Intention to Use. This contradicts [15] claim that resistance to change, as an individual characteristic, reflects a general tendency to avoid or oppose change.

Next, the hypothesis testing continued by adding control variables, namely gender and age. Table 7 shows that gender consists of two categories: male and female. Meanwhile, age was grouped into two categories: 17–25 years old and above 26 years old. Previously, the age variable included two additional categories—35–43 years old and above 44 years old—but both were merged into the "above 26 years old" category due to the small number of respondents in those age groups.

Table 6. Addition of Gender and Age Control Variables

	Variable	Category			
		Male	Female	< 25 Years Old	> 26 Years Old
H1	PFC → BI	Rejected	Rejected	Rejected	Rejected
H2	CP → BI	Accepted	Accepted	Accepted	Accepted
H3	RA → BI	Accepted	Rejected	Rejected	Rejected
H4	CX → BI	Accepted	Rejected	Rejected	Rejected
H5	PUB → BI	Rejected	Rejected	Rejected	Rejected
H6	RTC → BI	Rejected	Rejected	Rejected	Rejected

Source : Smart PLS 4

The hypothesis testing based on gender shows that for male respondents, three hypotheses were accepted, namely H2, H3, and H4, while three hypotheses were rejected, namely H1, H5, and H6. For female respondents, only one hypothesis was accepted, H2, and five hypotheses were rejected: H1, H3, H4, H5, and H6.

In the age category of 17 to 25 years, one hypothesis (H2) was accepted, and five were rejected (H1, H3, H4, H5, and H6). Similarly, for respondents over 26 years old, the results were the same, with only H2 accepted and the remaining hypotheses (H1, H3, H4, H5, and H6) rejected.

The results of hypothesis testing in this study indicate that only a few variables significantly influence the intention to use Oke-Jek in Manokwari, namely Compatibility, Perceived Ubiquity, and Complexity. These findings are consistent with previous studies conducted in urban areas such as Jakarta and Surabaya, which also found that service compatibility with

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user needs and perceptions of service availability play crucial roles in driving digital service adoption [6][13]. However, the results also reveal notable differences, particularly in the variables Perceived Financial Cost and Resistance to Change, which did not have a significant influence in the context of Manokwari. This contradicts findings from more developed urban regions, where cost considerations and resistance to change are often cited as major barriers to technology adoption [12][15]. These differences highlight the importance of local context—such as exposure to technology, digital culture, and public perception of online services—in shaping user behavior. Additionally, the varying results across age and gender categories suggest that adoption strategies in developing regions must be tailored to demographic characteristics. Therefore, this discussion extends the local findings toward a broader understanding that efforts to increase digital service adoption in developing areas must account for local economic, cultural, and technological factors.

IV. CONCLUSION

This study takes a closer look at why the Oke-Jek ride-hailing service has seen limited adoption, using the Diffusion of Innovations Theory as a foundation and expanding it with additional factors like perceived financial cost, perceived ubiquity, and resistance to change. These added variables help paint a fuller picture of the real-world challenges users face when deciding whether to adopt ride-hailing services—especially in developing areas.

The analysis found that 62.9% of users' behavioral intention to use Oke-Jek could be explained by the model's variables, while the rest might be shaped by other factors outside the scope of this study. Of the six variables tested, only compatibility, relative advantage, and complexity had a meaningful impact. This suggests that users are more inclined to use Oke-Jek when the service fits their needs, offers clear benefits, and is easy to understand and operate.

Beyond contributing to theory by extending the Diffusion of Innovation framework, this study also offers practical insights. By including context-specific factors like cost perception and service availability, it provides a more grounded understanding of adoption behavior in areas that are often overlooked in mainstream research. The demographic findings further highlight how strategies must be adapted to different user groups, such as by age and gender.

Ultimately, the insights from Manokwari can serve as a useful reference for ride-hailing providers aiming to grow their presence in other developing regions of Indonesia. The results point to the importance of designing more inclusive, user-friendly, and locally relevant strategies to encourage wider adoption of digital transport services in communities with similar social and technological conditions.

V. SUGGESTION

This study has several limitations. First, it was conducted only in a developing region—Manokwari Regency, West Papua—which may limit the generalizability of the findings to other developing areas with different social and economic contexts. Second, while the R-square value of 62.9% indicates that the proposed independent variables substantially explain behavioral intention to use, there remains 37.1% unexplained variance, suggesting the presence of other influential factors not captured in the current model.

Given these limitations, several suggestions are offered for future research. First, future studies could expand geographically to include other developing regions to determine whether the results remain consistent or whether additional factors emerge. Second, incorporating other variables such as government support, digital infrastructure quality, public transport accessibility, or social influence could provide a more comprehensive analysis. Lastly, employing alternative theoretical models such as the Technology Acceptance Model (TAM) or the Unified Theory of Acceptance and Use of Technology (UTAUT) may provide different perspectives in understanding the barriers to adopting ride-hailing services like Oke-Jek.

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