

# Enhancing ride-hailing adoption: understanding factors influencing ride-hailing user attitudes and reuse intention

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## ABSTRACT

Ride-hailing applications (RHA) have emerged as a revolutionary force in the transportation landscape, offering convenient and on-demand mobility solutions, thus gaining widespread popularity in the transportation sector. However, concerns arise as many RHA startups find it difficult to survive in Indonesia, and even big RHA startups are still at risk. RHA must preserve user reuse intent in order to ensure service continuation. Based on the innovation diffusion theory (IDT), the unified theory of acceptance and use of technology (UTAUT), and additional factors, this study examines 11 variables and their impact on consumer attitudes and reuse intention in a model of ride-hailing service adoption. An online survey was utilized to gather data from various demographic backgrounds, and managed to gather data from 240 respondents. Analysis was conducted using partial least squares structural equation modeling (PLS-SEM) to assess the correlations between the variables. The findings revealed that perceived usefulness, perceived ease of use, perceived risk, compatibility, and personal innovation significantly influenced consumer attitudes. Additionally, it was shown that the attitude variable and customer reuse intention were positively and significantly correlated. Based on this outcome, recommendations were made to RHA providers to improve user attitudes and intentions to reuse.

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## 1. INTRODUCTION

The advancement of information technology, particularly the internet, continues to reshape daily life, including transportation. Ride-hailing applications (RHA) have experienced rapid global growth, especially in Southeast Asia [1]. RHA services are defined as online platforms that connect passengers with local drivers using private vehicles for commercial purposes [2]. Gojek, Grab, Maxim, and inDrive are several prominent RHA operating in Indonesia. In 2020, the market value of RHA in Indonesia reached USD 3.63 billion and is projected to continue growing [3]. This growth is driven by the benefits offered by RHA services, such as saving time and money, convenience, avoiding parking issues, and reducing accident risks [4]. Considering the substantial market value they generate, RHA services play an important role in supporting the welfare of Indonesian society.

Concerns emerge, however, as many startup RHA providers struggle to survive and grow in Indonesia. According to Maybank, the Indonesian RHA industry is undergoing consolidation, with fewer new providers entering the market. Consequently, Grab and Gojek have become the dominant players [5].

More critically, even major RHA providers face risks, as demonstrated by Uber’s failure to survive in Indonesia, which ultimately led to the sale of its assets to Grab in 2018 [6]. With fewer new entrants, the potential failure of Grab or Gojek would have significant implications for the national industry and economy. Therefore, ensuring service continuity requires RHA providers to maintain users’ repurchase intention—the desire of users to continue using the service in the future [7]. A positive user attitude significantly increases the likelihood of continued usage [8].

These conditions have motivated researchers to investigate the factors influencing user satisfaction and repurchase intention in RHA services [8]–[16]. Although previous studies have examined various determinants of user attitudes and satisfaction, most include only four to seven variables [8], [10], [12]–[16]. The limited number of variables may omit important potential factors. To address this gap, the present study identifies 11 factors that may influence Indonesian users’ attitudes and reuse intentions and proposes targeted strategies for RHA providers based on the most influential determinants. Drawing from study by Elnadi and Gheith [9], this study integrates the innovation diffusion theory (IDT), a modified unified theory of acceptance and use of technology (UTAUT), and several additional variables. Given the extensive range of factors examined, this research provides valuable insights for academics and practitioners in Indonesia’s RHA industry. For clarity and structure, this paper is organized as follows: section 1 presents the introduction, section 2 discusses the method, section 3 provides the results and discussion, and section 4 presents the conclusion of the paper.

## 2. METHOD

### 2.1. Conceptual model

This research employs the IDT, the modified UTAUT, and several additional variables, as illustrated in Figure 1. UTAUT comprises four key factors influencing user attitudes: performance expectancy, effort expectancy, social influence, and facilitating conditions. Performance expectancy/perceived usefulness (PU) refers to the degree to which an individual believes that using a particular system will be beneficial. Effort expectancy/perceived ease of use (PEOU) reflects the extent to which an individual perceives a technology as easy to use. Social influence (SI) refers to the extent to which a person adjusts their attitudes or behaviors based on pressure or expectations from essential others, while facilitating conditions (FC) describe the degree to which an individual believes that the organizational and technical infrastructures necessary to support system use are available. When consumers perceive strong facilitating conditions, they are more inclined to use the technology [17].

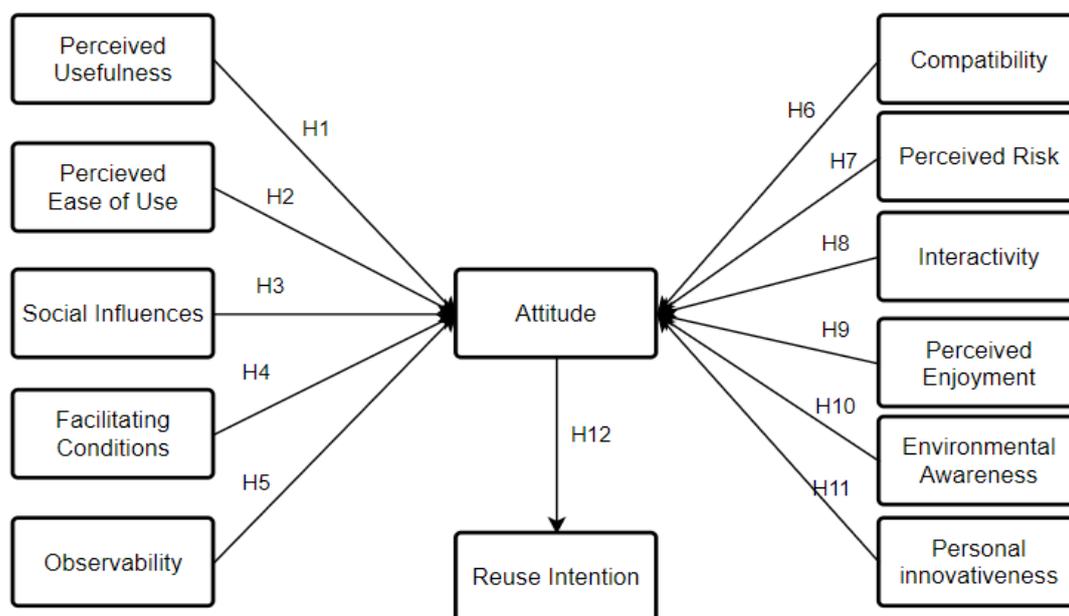


Figure 1. Conceptual model

In previous RHA studies, PU has been identified as a significant predictor of user attitudes and intentions toward using RHA services [8], [12], [13]. Therefore, this study proposes that the more users believe RHA services simplify their daily activities, the more favorable their attitudes will be. PEOU has also been shown to significantly predict attitudes and intentions toward RHA [8], [14], although [12] found it insignificant. Accordingly, this study examines PEOU more closely to determine its influence on user attitudes. SI has similarly demonstrated a significant impact on RHA user attitudes [12], [14], suggesting that the more positively significant others perceive RHA, the more positively users themselves will perceive it. Finally, the significance of FC has been emphasized by Soares *et al.* [15], supporting the argument that users will hold positive attitudes toward RHA when they have the necessary support to use the service. Based on these considerations, the following hypotheses are proposed:

*H1: Perceived usefulness (PU) will have a significant positive impact on consumer attitudes towards RHA.*

*H2: Perceived ease of use (PEOU) will have a significant positive impact on consumer attitudes towards RHA.*

*H3: Social influences (SI) will have a significant positive impact on consumer attitudes towards RHA.*

*H4: Facilitating conditions (FC) will have a significant positive impact on consumer attitudes towards RHA.*

IDT explains societal acceptance of new ideas and technologies through factors such as relative advantage, compatibility, complexity, trialability, and observability [18]. Performance expectancy (UTAUT) aligns with relative advantage (IDT), while effort expectancy (UTAUT) aligns with complexity (IDT) [10]. Trialability is excluded in this study, as RHA is an established service, leaving compatibility and observability as the relevant constructs. Observability (OBS) refers to the degree to which the outcomes of an innovation are visible to others [18]. When individuals recognize clear benefits from a technology, they are more likely to adopt it quickly [18]. Compatibility (COM) reflects the degree to which a service aligns with users' values and needs [18]. Higher compatibility reduces uncertainty and increases adoption rates [9]. Prior RHA studies have shown that OBS significantly influences user attitudes [11], while COM has also demonstrated a significant effect [19]. Therefore, this study posits that the more compatible ride-hailing apps are with users' needs and the more visible their benefits, the more positively users will view them. The hypotheses are as follows:

*H5: Observability (OBS) will have a significant positive impact on consumer attitudes towards RHA.*

*H6: Compatibility (COM) will have a significant positive impact on consumer attitudes towards RHA.*

This study also incorporates additional variables. Perceived risk (PR) refers to the uncertainty or fear individuals experience when using a new service [16]. RHA users may perceive risks such as unsafe drivers, mobile payment issues, failure to secure a ride, or long waiting times [13]. Interactivity (INT) refers to the effectiveness with which the platform responds to the user [20], as reflected in user control, app responsiveness, and two-way communication [9]. Perceived enjoyment (PE) measures the extent to which individuals derive pleasure from using a system, regardless of functional outcomes [21]. For ride-hailing services, greater enjoyment can foster more positive user attitudes. Environmental awareness (EA) reflects an individual's understanding of environmental issues and their concern for the impact of their behavior [12]. Personal innovativeness (PI) captures the tendency of individuals with innovative thinking to more readily adopt new technologies [7]. Given that RHA apps frequently introduce new features, PI remains relevant even in post-adoption contexts [7].

Previous RHA studies show that PR often exerts a significant negative influence on adoption decisions [4], [8], while INT positively affects user attitudes [9]. PE has been found to influence satisfaction and continued usage intention [7] significantly. EA has been associated with positive attitudes toward RHA [12], although [9] reported nonsignificant results. Similarly, PI has been found to influence attitudes and reuse intentions [7] positively [16], but study [22] reported otherwise. Based on this evidence, the following hypotheses are proposed:

*H7: Perceived risk (PR) will have a significant negative impact on consumer attitudes towards RHA.*

*H8: Interactivity (INT) will have a significant positive impact on consumer attitudes towards RHA.*

*H9: Perceived enjoyment (PE) will have a significant positive impact on consumer attitudes towards RHA.*

*H10: Environmental awareness (EA) will have a significant positive impact on consumer attitudes towards RHA.*

*H11: Personal innovativeness (PI) will have a significant positive impact on consumer attitudes towards RHA.*

The relationship between attitude and intention has been examined across multiple theoretical frameworks, including the theory of reasoned action (TRA), the theory of planned behavior (TPB), the technology acceptance model (TAM), and UTAUT 1 and UTAUT 2. These frameworks consistently highlight attitude as a key predictor of behavioral intention. In this study, attitude (ATT) reflects users' satisfaction or dissatisfaction with RHA. Previous RHA studies have found ATT to influence reuse intentions positively [8], [13], [9]. Accordingly, the final hypothesis is proposed:

*H12: Attitude (ATT) will have a significant positive impact on user reuse intention towards RHA.*

## 2.2. Research instrument

The research employed an internet-based questionnaire distributed to individuals who use ride-hailing services in Indonesia. The questionnaire was developed based on the IDT, UTAUT, and additional variables. In total, 44 items were constructed to measure the 13 variables included in this study. Simple and clear language was used to ensure that the statements were easily understood by respondents, including those unfamiliar with technical terminology. A widely used 5-point Likert scale was applied, providing clear and intuitive response options [23]. Data collection was conducted through social media platforms from March 3, 2024, to April 21, 2024. Following methodological recommendations, a minimum sample size of 200 respondents is required for SEM analysis [24]; therefore, this research targeted at least 200 participants.

This study utilized partial least squares structural equation modelling (PLS-SEM). SEM is an analytical technique used to examine the relationships among multiple variables and is commonly applied in technology adoption research [19]. SEM consists of covariance-based SEM (CB-SEM) and variance-based SEM (PLS-SEM). PLS-SEM was selected due to its suitability for theory development and its capacity to manage models involving numerous constructs and paths [24]. It can also be implemented using widely accessible software such as SmartPLS [25]. Furthermore, hypothesis testing in PLS-SEM was conducted using a two-tailed test at a 95% confidence level.

## 3. RESULTS AND DISCUSSION

### 3.1. Data pre-processing

Prior to conducting the PLS-SEM analysis, data pre-processing was performed to ensure that the dataset was clean, consistent, and ready for analysis. Pre-processing steps included handling missing values, detecting and addressing outliers, and correcting typos, inconsistent labels, or impossible entries (e.g., negative ages). Out of 240 respondents, one outlier was identified and removed, resulting in a final sample size of 239 respondents.

### 3.2. Outer model analysis

Outer model testing in PLS-SEM includes assessments of convergent validity, internal consistency, and discriminant validity. As shown in Table 1, convergent validity was achieved, with all indicator loadings exceeding the minimum threshold of 0.70, leading to the removal of EA2, FC4, PEOU3, and PU4, and all average variance extracted (AVE) values meeting the  $\geq 0.50$  requirement [26]. Internal consistency reliability was confirmed, as both Cronbach's alpha ( $\geq 0.70$ ) and composite reliability ( $\geq 0.60$ ) values fell within acceptable ranges [26]. Discriminant validity, evaluated using the Fornell-Larcker criterion ([https://drive.google.com/file/d/1ZI-wQP1OZ-z7Ct6LMTEnig6BEwIod7J/view?usp=drive\\_link](https://drive.google.com/file/d/1ZI-wQP1OZ-z7Ct6LMTEnig6BEwIod7J/view?usp=drive_link)), was also satisfied, with each construct's square root of AVE exceeding its correlations with other constructs [26], [27].

### 3.3. Inner model analysis

The inner model analysis evaluates the structural model's quality and its ability to address the research objectives. The first step is determining the coefficient of determination ( $R^2$ ), which measures the extent to which the model explains the variance of endogenous variables [28]. In this study, the  $R^2$  value of 0.642 indicates that the model explains 64.2% of the variance in the endogenous constructs, representing a moderate explanatory power [29]. Predictive relevance ( $Q^2$ ), which assesses the model's capability to predict omitted data, yielded a value of 0.591. Since  $Q^2$  is greater than zero, the model demonstrates adequate predictive accuracy [26].

Additionally, the inner model assessment includes effect size ( $f^2$ ) and the variance inflation factor (VIF), as presented in Table 2. COM shows a moderate effect size, whereas PEOU, PI, PR, and PU demonstrate weak effect sizes [30]. All VIF values are below 5, indicating the absence of multicollinearity issues [26]. Further analysis examines the structural relationships among variables. Path coefficients indicate both the direction and magnitude of relationships, with larger absolute values representing stronger effects. A variable is considered statistically significant at the 95% confidence level if its t-value exceeds 1.96 in a two-tailed test [26]. Similarly, a p-value below 0.05 indicates that the relationship is not due to random chance [26].

As shown in Table 3, PU ( $\beta=0.150$ ,  $p=0.026$ ), PEOU ( $\beta=0.178$ ,  $p=0.010$ ), PR ( $\beta= -0.098$ ,  $p=0.010$ ), COM ( $\beta=0.428$ ,  $p<0.001$ ), and PI ( $\beta=0.107$ ,  $p=0.014$ ) all significantly influence attitude. Attitude also significantly affects reuse intention ( $\beta=0.699$ ,  $p<0.001$ ). Conversely, OBS ( $\beta= -0.011$ ,  $p=0.876$ ), PE ( $\beta=0.095$ ,  $p=0.096$ ), FC ( $\beta=0.125$ ,  $p=0.098$ ), SI ( $\beta<0.001$ ,  $p=0.998$ ), INT ( $\beta=-0.091$ ,  $p=0.192$ ), and EA ( $\beta=0.018$ ,  $p=0.726$ ) do not significantly influence attitude. Accordingly, hypotheses H1, H2, H6, H7, H11, and H12 are supported, while H3, H4, H5, H8, H9, and H10 are not supported.

Table 1. Outer model analysis

Variables	Indicator	Loading factor	AVE	Cronbach's alpha	Composite reliability
Attitude	ATT 1	0.768	0.702	0.857	0.861
	ATT 2	0.893			
	ATT 3	0.850			
	ATT 4	0.835			
Compatibility	COM 1	0.758	0.687	0.770	0.777
	COM 2	0.851			
	COM 3	0.873			
Environmental awareness	EA 1	0.820	0.633	0.713	0.722
	EA 2	0.691			
	EA 3	0.751			
	EA 4	0.760			
Facilitating conditions	FC 1	0.792	0.711	0.797	0.798
	FC 2	0.827			
	FC 3	0.837			
	FC 4	0.676			
Interactivity	INT 1	0.805	0.627	0.702	0.703
	INT 2	0.802			
	INT 3	0.768			
Observability	OBS 1	0.840	0.702	0.793	0.829
	OBS 2	0.806			
	OBS 3	0.868			
Perceived enjoyment	PE 1	0.844	0.723	0.810	0.815
	PE 2	0.859			
	PE 3	0.849			
Perceived ease of use	PEOU 1	0.890	0.774	0.853	0.855
	PEOU 2	0.856			
	PEOU 3	0.678			
	PEOU 4	0.833			
Personal innovativeness	PI 1	0.910	0.749	0.832	0.871
	PI 2	0.913			
	PI 3	0.765			
Perceived risk	PR 1	0.888	0.751	0.892	0.953
	PR 2	0.904			
	PR 3	0.833			
	PR 4	0.840			
Perceived usefulness	PU 1	0.792	0.667	0.832	0.833
	PU 2	0.838			
	PU 3	0.810			
	PU 4	0.648			
	PU 5	0.763			
Reuse intention	RI 1	0.894	0.815	0.774	0.779
	RI 2	0.912			
Social influences	SI 1	0.930	0.884	0.869	0.886
	SI 2	0.950			

Table 2. Effect size and VIF values

Variable	Effect size	VIF
COM	0.232	2.191
EA	0.001	1.460
FC	0.015	3.062
INT	0.011	2.182
OBS	0.001	2.617
PE	0.013	1.976
PEOU	0.037	2.502
PI	0.022	1.439
PR	0.025	1.060
PU	0.028	2.295
SI	0.001	1.689
ATT	-	1.000

Table 3. Result of variables influence

Relation	Path ( $\beta$ )	t-value	p-values	Have influence
PU -> ATT	0.150	2.226	0.026	Yes
PEOU -> ATT	0.178	2.568	0.010	Yes
OBS -> ATT	-0.011	0.155	0.876	No
PR -> ATT	-0.098	2.564	0.010	Yes
PE -> ATT	0.095	1.664	0.096	No
FC -> ATT	0.125	1.659	0.098	No
SI -> ATT	-0.000	0.002	0.998	No
INT -> ATT	-0.091	1.302	0.192	No
COM -> ATT	0.428	6.157	0.000	Yes
PI -> ATT	0.107	2.434	0.014	Yes
EA -> ATT	0.018	0.350	0.726	No
ATT -> RI	0.699	16.710	0.000	Yes

### 3.4. Discussion

According to previous findings, variables with strong effects warrant distinct discussions compared to those with weaker influences. Targeted recommendations are provided for the most influential factors, namely perceived usefulness, perceived ease of use, perceived risk, compatibility, personal innovativeness, and attitude, based on their respective loading values. These recommendations are intended to enhance the influence of these variables on both attitude and reuse intention.

To improve user attitudes, ride-hailing service (RHA) providers should ensure that their platforms are generally well-regarded by users ( $ATT1=0.768$ ;  $ATT2=0.893$ ;  $ATT3=0.850$ ;  $ATT4=0.835$ ). Providers should actively promote key benefits to strengthen positive user perceptions. However, such promotional messages must be supported by consistent and reliable service performance. In the Indonesian market, users often express dissatisfaction in several areas of ride-hailing services, including driver behavior, service delays, and inaccurate fare calculations [31]. Providers are therefore advised to address these shortcomings before highlighting them as selling points or, at a minimum, avoid promoting features that remain prone to complaints. This approach helps prevent misleading marketing, which may undermine customer attitudes and long-term loyalty [32].

To strengthen users' perceptions of usefulness, providers may take two key steps: distribute drivers more evenly to improve access ( $PU1=0.792$ ;  $PU2=0.838$ ;  $PU3=0.810$ ) and refine routing algorithms to ensure the fastest possible trips ( $PU4=0.648$ ;  $PU5=0.763$ ). While map optimization is likely already part of RHA development strategies, redistributing drivers more evenly requires careful trade-off analysis. Deploying drivers to low-demand areas increases operational costs and may result in fewer assignments, potentially reducing driver earnings by up to 8 percent. Such reductions risk triggering strikes and decreasing overall driver availability, which can negatively affect user attitudes [33], [34]. Conversely, concentrating drivers in high-demand areas such as public transit hubs may provoke conflict with traditional transport operators [35]. To minimize these risks, providers could offer targeted incentives for serving low-demand neighborhoods and coordinate with traditional operators by designating shared service zones.

Regarding perceived ease of use, providers can streamline their applications by automating routine tasks, simplifying workflows for new users, and directing users to frequently asked questions when they remain on a page for an extended period ( $PEOU1=0.89$ ,  $PEOU2=0.856$ ,  $PEOU3=0.678$ ,  $PEOU4=0.833$ ). However, excessive automation may reduce user autonomy and obscure system processes, which could undermine trust when limitations later become apparent. Providers should therefore selectively automate low-value tasks, such as assigning a default driver rating when the user does not submit one. More advanced features, such as a one-tap rescheduling option, could be offered after users demonstrate consistent engagement, balancing development costs with enhanced satisfaction.

In terms of compatibility, personalization strategies such as offering multiple vehicle options ( $COM3=0.873$ ), segment-based services ( $COM2=0.851$ ), and customizable features ( $COM1=0.758$ ) require additional considerations. Operating multiple service tiers demands substantial resources related to driver allocation, training, and algorithm adjustments. Segment-based services may also risk perceived discriminatory practices. For example, women-only ride services, although intended to enhance safety, may conflict with anti-discrimination standards in some jurisdictions [36]. While Indonesia does not currently prohibit gender-segregated transportation, offering preferential service levels or pricing to specific demographic groups may attract challenges in the future. Providers must therefore balance the benefits of personalization with operational complexity and ethical concerns.

To reduce perceived risk, providers should communicate terms and conditions clearly, especially regarding personal data use ( $PR2=0.904$ ), strengthen secure payment options ( $PR1=0.888$ ), establish and enforce rigorous vehicle and driver safety standards ( $PR4=0.840$ ), and consistently apply sanctions for driver misconduct ( $PR3=0.833$ ). However, enforcing stricter standards may increase financial burdens for drivers. In Jakarta, approximately 41 percent of drivers resisted mandatory inspections due to cost concerns [37]. Furthermore, because ride-hailing platforms classify drivers as independent partners, their authority to enforce compliance is limited [38]. A balanced approach may include integrating brief e-learning safety modules into driver applications or implementing a tiered penalty system that adjusts ride assignments based on safety records.

Regarding personal innovativeness, providers should maintain user interest by introducing features regularly and offering new functionalities for limited trial periods ( $PI2=0.913$ ;  $PI1=0.910$ ;  $PI3=0.765$ ). Nevertheless, excessive feature releases may lead to feature fatigue, where an abundance of options overwhelms users [39]. To avoid this, providers should monitor usage patterns and churn rates after feature launches. This evaluation helps ensure that new functionalities add meaningful value without compromising the stability and usability of core services.

Researchers seeking to extend this study are encouraged to incorporate additional variables such as habit and price value. Habit reflects the extent to which users are accustomed to similar services, while price value represents consumers' evaluation of the benefits of using a technology relative to its costs [21]. Prior studies have shown that habit positively and significantly influences user attitudes toward ride-hailing applications [10], [15]. Future research may also introduce moderator variables such as age, gender, and income, as prior work indicates that demographic factors can significantly influence relationships among constructs in ride-hailing adoption models [4], [9].

**4. CONCLUSION**

This study analyzes the determinants of user attitude, including perceived usefulness, perceived ease of use, social influence, perceived risk, facilitating conditions, perceived enjoyment, compatibility, observability, interactivity, personal innovativeness, and environmental awareness, as well as how attitude drives RHA reuse intention using PLS-SEM. A total of 240 RHA users were surveyed using a structured questionnaire. The validity and reliability of the research model were assessed, and the overall model quality was evaluated using multiple established criteria. Furthermore, the *t*-value, *β*-value, and *p*-value were employed to examine the relationships among the variables.

The findings show that reuse intention is significantly influenced by user attitude, and user attitude is significantly shaped by perceived usefulness, perceived ease of use, perceived risk, compatibility, and personal innovativeness. In contrast, facilitating conditions, perceived enjoyment, interactivity, environmental awareness, observability, and social influence do not significantly influence user attitude. Ride-hailing application providers must ensure that users positively perceive their platforms to encourage repeat usage. Although they should highlight the key benefits of their services, persistent challenges in Indonesia’s RHA market require companies to address core service issues before promoting them. At a minimum, they should avoid advertising features that frequently generate user complaints to prevent misleading marketing. To strengthen user attitudes, providers are advised to segment their customer base and offer tailored services, diverse vehicle options, and personalization features while considering administrative complexity and ethical implications. Providers may also automate low-effort tasks and introduce user-requested features that become accessible as usage increases. Additionally, refining routing algorithms to provide faster trips and distributing drivers more evenly may enhance accessibility, though such strategies must be implemented carefully to avoid unintended adverse outcomes.

Moreover, providers should clearly communicate data policies, secure payment procedures, and safety standards. These standards can be reinforced through integrated e-learning modules for drivers and the implementation of strict penalties for misconduct. To maintain user engagement, providers may introduce new features and offer limited-time trials, but should prioritize feature quality over quantity to ensure that each update contributes meaningful value. For future research, additional moderator variables and new constructs, such as habit and price value, may be incorporated to enrich the findings further.

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**AUTHOR CONTRIBUTIONS STATEMENT**

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C : **C**onceptualization

M : **M**ethodology

So : **S**oftware

Va : **V**alidation

Fo : **F**ormal analysis

I : **I**nvestigation

R : **R**esources

D : **D**ata Curation

O : **O**riginal Draft

E : **E**diting

Vi : **V**isualization

Su : **S**upervision

P : **P**roject administration

Fu : **F**unding acquisition

**CONFLICT OF INTEREST STATEMENT**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## DATA AVAILABILITY

The data that support the findings of this study are available on request from the corresponding author, Mudjahidin. The data, which contain information that could compromise the privacy of research participants, are not publicly available due to certain restrictions.

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