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Understanding Ride-Hailing Adoption Among Generation Z in Malang: An Integrated TPB-TAM Framework

Amalia Romadhona Ghiffari Putri[1], Vertic Eridani Budi Darmawan[1*], Chen Yuh Wen[2]
[1)] Department of Mechanical and Industrial Engineering, Universitas Negeri Malang
Jl. Semarang 5 Malang 65145, Indonesia
[2)] Department of Accounting Information, Da-Yeh University
No.168, University Rd., Dacun, Changhua 51591, Taiwan (R.O.C.).
Email: vertic.eridani.ft@um.ac.id[1*]
*Corresponding author

Abstract: This study examines the factors influencing the choice of ride-hailing modes among Generation Z (15-29 years old) in Malang City, given their dominance as the largest user group of ride-hailing services in Indonesia. The analysis will combine the Theory of Planned Behavior (TPB) and the Technology Acceptance Model (TAM) to understand the key drivers behind their decisions to use ride-hailing services. The study surveyed 406 respondents through purposive sampling, focusing on residents of Malang who actively use ride-hailing services such as Grab, Gojek, Maxim, or inDrive. SEM was used to explain the relationships among variables, whereas MGA-PLS was applied to analyze differences by gender and vehicle ownership. Results also show that Ease of Use (KPN) significantly influences Usefulness (K) of the ride-hailing service. While both variables also positively influence Attitudes toward ride-hailing, leading to a stronger Intention to choose these services. Furthermore, Attitude (S) and Subjective Norm (NS) appear to be significant predictors of Intention (N), which in turn has a substantial impact on Behavior. The MGA-PLS results indicate that females are more influenced by Ease of Use (KPN) and Usefulness (K), whereas car owners tend to rely more on Ease of Use (KPN) when assessing Usefulness (K). These findings not only strengthen the integrated TPB-TAM framework in the context of secondary cities in Indonesia but also offer practical insights for designing more targeted and inclusive ride-hailing strategies based on user demographics.

Keywords: MGA-PLS, Ride Hailing, PLS-SEM, Technology Acceptance Model, Theory of Planned Behavior.

Introduction

Public transportation in Indonesia remains underutilized, contributing to the country's persistent traffic problems. This issue is one of the most significant challenges for the government, particularly in its efforts to fulfill point 11 of the Sustainable Development Goals (SDGs), which aims to build sustainable cities and communities. Research indicates that common issues in public transportation include safety, flexibility, accessibility, and public perception [1].

The rise of ride-hailing services enables users to connect with drivers via online technologies. The public seems to view this as a solution to the limitations they encounter with public transportation [2]. The phenomenon of ride-hailing in Indonesia began with Go-Jek and was quickly followed by other services, including Grab, Maxim, and inDrive, with increasing demand every year [3]. It expresses the growing preference for ride-hailing services and reflects changes in travel behavior among Indonesian citizens. The polling conducted in several high-mobility cities indicates that the proportion of Generation Z users among all ride-hailing service users reached 46.4% [2]. This proportion is even higher in cities with significant student populations, such as Malang, which has the highest number of residents aged between 15 and 29 years in the province of East Java, at 22.5% [4]. This specific generation grew up during a period of significant advancements in IT and digital technology, which led to a society where the use of IT in daily life had a profound impact [5].

User motivations necessitate a more in-depth analysis to comprehend the factors influencing ride-hailing usage in Indonesia. A few of these studies have integrated the Theory of Planned Behavior and the Technology Acceptance Model to investigate how Attitudes, Subjective Norms, Perceived Usefulness, and Ease of Use influence intentions to and behaviors of riding hailed rides [6]. Other studies examine socio-demographic factors, including age, gender, income, and vehicle ownership, to assess behavioral differences among groups [6, 7, 8].

Structural Equation Modeling (SEM) is a valuable tool for analyzing complex relationships between observed and latent variables, incorporating factor analysis, path analysis, and regression [7,9]. Multi-Group Analysis (MGA), when used within SEM, enables comparisons across socio-demographic groups, highlighting significant behavioral differences based on these factors [9]. By examining the factors influencing ride-hailing adoption using the combination of TPB, TAM, and socio-demographic factors, the findings provide insights into the preferences of Generation Z in Malang. These findings can support the government's commitment to developing sustainable cities and communities, as outlined in SDG 11.

Methods

Literature review

Ride-hailing refers to transportation services integrated with app-based technologies that enable users to have the option for flexible travel using smartphone applications [2]. Since its establishment in Indonesia in 2014, Go-Jek has grown from a few hundred motorbike taxis to operating in more than 158 cities by 2018. It has also begun offering services in countries such as Singapore, Vietnam, and India [10]. Other platforms operating under this mode of transportation in Indonesia include Grab, Maxim, and inDrive, which offer users convenience, accessibility, and real-time tracking via mobile applications. Ride-hailing services have reshaped travel behavior, either substituting traditional transportation modes or complementing them [11]. The availability of app-based transportation alternatives has influenced user preferences and mobility patterns, particularly among Generation Z, who are more inclined toward flexibility and ease of use [2].

Understanding user adoption of technology-based services such as ride-hailing often involves applying behavioral frameworks, notably the Theory of Planned Behavior (TPB) and the Technology Acceptance Model (TAM). TPB consists of three main variables: attitude, subjective norms, and perceived behavioral control, all of which influence intention [12]. Attitude refers to an individual's positive or negative evaluation of using ride-hailing services. Subjective norms relate to perceived social pressure, while perceived behavioral control reflects the individual's perception of the ease or difficulty in using the service [12,13]. Meanwhile, TAM focuses on Ease of Use and Usefulness. Ease of use is the degree to which a person believes that using the technology will be effortless, while usefulness refers to the belief that the technology will improve task performance [14].

Studies combining TPB and TAM have produced valuable insights. Sedhigi, et.al. [6] found that Ease of use significantly influenced Usefulness, and both variables positively affected attitude toward ride-hailing. Similarly, Haldar and Goel [16] confirmed the positive relationship between Ease of Usefulness, and attitude. Javid et al. [15], using TPB, found that attitude, subjective norms, and perceived behavioral control significantly affected intention; however, the strength of these relationships varied by country. For example, in India, perceived behavioral control had no significant effect on intention, suggesting that cultural or contextual moderating factors may be at play [10, 15, 16]. Based on these findings, this study formulates hypotheses that Attitude, Subjective Norms, Perceived Behavioral Control, Ease of Use, and Usefulness directly or indirectly influence Behavioral Intention.

Recent studies suggest that socio-demographic factors can moderate the relationships within TPB and TAM. Ardi et al. [2] showed that gender and vehicle ownership influence the strength of relationships between attitude, perceived behavioral control, and intention. For instance, male and female users may differ in their perceptions of control over online transportation, while individuals who own private vehicles may perceive ride-hailing services as less applicable [16]. These findings underscore the importance of incorporating such moderating variables into the analysis.
In Indonesia, where private vehicle ownership is high, especially among urban residents, such factors are highly relevant [3]. Moreover, previous research has rarely addressed the Behavior of Generation Z in secondary urban cities, where mobility patterns may diverge from those in metropolitan areas. This study seeks to fill these gaps by integrating TPB and TAM while considering gender and vehicle ownership as moderators, as shown in Figure 1 as the research framework. Using Structural Equation Modelling (SEM) and Multi-Group Analysis (MGA), the study aims to examine both direct and moderated effects of behavioral determinants on ride-hailing intention. The hypotheses are based on established relationships found in earlier studies and contextualized for the specific setting of Malang City.

SEM is a statistical approach to analyzing the relationships between variables [8, 12]. It involves the measurement model and the structural model, which can be approached using different methods, such as

CB-SEM and PLS-SEM. PLS-SEM is especially suitable for exploratory research and when the assumptions of CB-SEM are not met [12]. This approach examines model validity and reliability, checks predictive relevance and model fit, and tests hypotheses via bootstrapping. Furthermore, MGA-PLS enables the comparison of model effects across groups to assess whether moderation variables influence relationships differently [13].

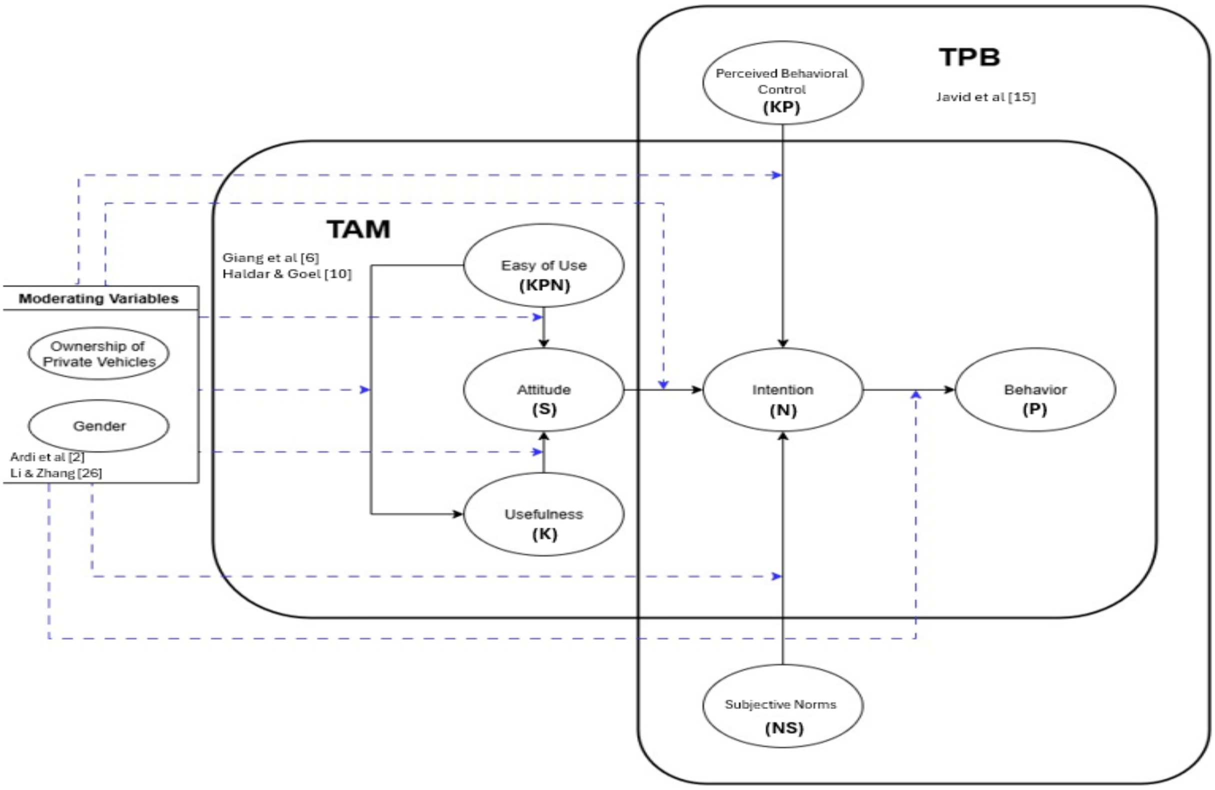

Figure 1. Research framework

The study employs a quantitative method to investigate the factors influencing the intention to use ride-hailing transportation services among Generation Z in Malang City. Data will be collected through a pre-tested questionnaire to ensure validity and reliability, and adjustments will be made as necessary. Descriptive statistics will summarize sample characteristics, while the inferential analysis of Structural Equation Modeling (SEM) will test the conceptual model connecting variables to determine whether the relationship is direct or indirect [19]. Either CB-SEM, in the case of normal data distribution, or PLS-SEM, when the data are non-normal, will be applied, depending on the data distribution. Later, a multi-group analysis will be conducted using AMOS for CB-SEM and SmartPLS 3.0 for PLS-SEM to compare model effects across groups.

This research focuses on the Generation Z ride-hailing users of Malang City, Indonesia. Questionnaires will be distributed online using WhatsApp and Instagram. The questionnaires include socio-demographic questions and statements in the form of a Likert scale (1-5) about latent variables. Respondents will be selected through purposive sampling with the following criteria: aged 15-29 years and currently using one of the ride-hailing services such as Gojek, Grab, Maxim, or InDrive [16, 17, 18]. Using the Slovin formula, a minimum sample of 400 respondents with a 0.05 margin of error must be selected from a population of 190,670 Generation Z individuals in Malang City [4]. This study uses independent variables, such as Perceived Ease of Use, Subjective Norms, and Perceived Behavioral Control; mediator variables, namely Perceived Usefulness, Attitude, and Intention to Choose Online Transportation Mode; and a dependent variable, Behavior in Choosing Online Transportation Mode, together with moderator variables of gender and vehicle ownership, to test the group differences. Descriptive statistics are also used to have a better understanding of the socio-demographic characteristics [11]. The description of the respondents' socio-demographic characteristics is shown in Table 1. The latent variables and their indicators in this study are a combination of TPB and TAM. The use of these variables and their indicators is based on various theories, previous relevant studies, and the researcher's rational thinking. The description of the latent variables used in this study is shown in Table 2.

Table 1. Socio-demographic characteristics variable

No	Socio-demographic characteristics	Description
1.	Gender	1. Male 2. Female
2.	Age	1. 15-19 Years Old 2. 20- 24 Years Old 3. 25- 29 Years Old
3.	Private Vehicle Ownership	1. Yes 2. No
4.	Occupation	1. Junior High School Students 2. Senior High School Students 3. Diploma Students (D1-D4) 4. Bachelor's Degree Students (S1) 5. Postgraduate Students (S2/S3) 6. Job Seeker 7. Part-Time Worker 8. Full-Time Workers 9. Entrepreneurs 10. Housewife

Table 2. Research Latent Variables

Latent variables	Indicator
Usefulness	Ride-hailing services are very useful for my daily activities. (K1) Ride-hailing services make my trips more efficient. (K2) Ride-hailing improve the quality of my travels. (K3) Ride-hailing services help me save time and reduce travel costs. (K4)
Ease of use	Ride-hailing is easy to use. (KPN1) It is easy to understand messages from ride-hailing applications. (KPN2) Making payments for ride-hailing services is simple. (KPN3) It is easy to book ride-hailing services through my smartphone. (KPN4)
Subjective norms	My friends/family recommend using ride-hailing services. (NS1) My friends/family who use ride-hailing services believe I should use them as well. (NS2) Overall, my social environment encourages me to use ride-hailing services. (NS3) I am influenced by my social environment to use ride-hailing services. (NS4)
Perceived behavioral control	I have resources, knowledge, and skills needed for these services. (KP1) I am capable of using ride-hailing services. (KP2)
Attitude	I enjoy using ride-hailing services. (S1) I feel safe using ride-hailing services. (S2) I believe ride-hailing services availability makes this mode very flexible. (S3)
Intention	I intend to use ride-hailing services as my transportation choice in my daily life. (N1) I intend to use ride-hailing services more. (N2) I intend to continue using ride-hailing. (N3) I intend to recommend ride-hailing services to my friends/family. (N4) I intend to continue choosing ride-hailing services over other modes. (N5)
Ride-hailing choice behavior	Ride-hailing services are a mode of transportation I often use. (P1) I prefer ride-hailing services over other options. (P2)

The methodology employed in this research utilized PLS-SEM, which was analyzed using SmartPLS 3.0 to examine the factors influencing ride-hailing choices. Accordingly, the PLS-SEM involves two principal evaluations: the outer model was used to evaluate the measurement quality of latent variables, while the inner model was used to test the relationships within the structural model. Bootstrapping was used to test the hypotheses, resampling the dataset to generate subsamples, a beneficial approach particularly in cases of small samples, which enhances the stability of the estimates and the assessment of significance [12]. Grounded on the literature, theories, and previous studies, a conceptual model showing the relationships between exogenous and endogenous latent variables was developed and visualized in a path diagram, as presented in Figure 2.

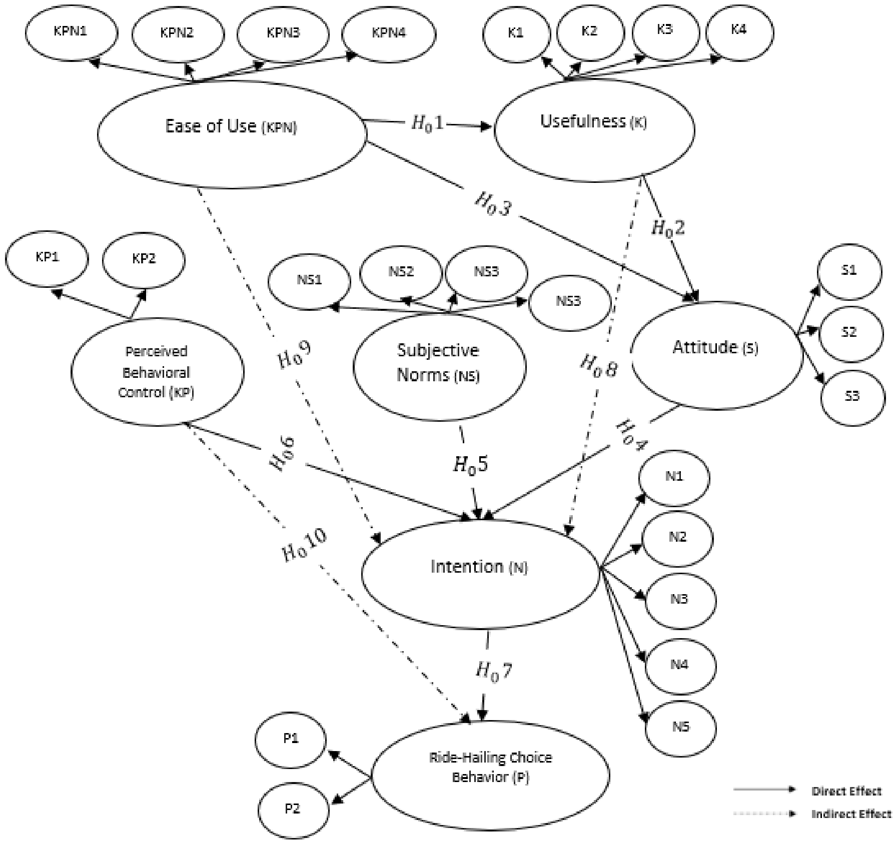

Figure 2. Research Path Diagram

Figure 2 illustrates the direct and indirect relationships among independent, mediator, and dependent variables, forming the following hypotheses:

$H_0 1$: Ease of Use does not have a significant direct effect towards Usefulness.
$H_0 2$: Usefulness does not have a significant direct effect towards Attitude.
$H_0 3$: Ease of Use does not have a significant direct effect towards Attitude.
$H_0 4$: Attitude does not have a significant direct effect towards Intention.
$H_0 5$: Subjective Norms does not have a significant direct effect towards Intention.
$H_0 6$: Perceived Behavioural Control does not have a significant direct effect towards Intention.
$H_0 7$: Intention does not have a significant direct effect towards Ride-Hailing Choice Behaviour.
$H_0 8$: Usefulness does not have a significant indirect effect towards Intention.
$H_0 9$: Ease of Use does not have a significant indirect effect towards Intention.
$H_0 10$: Perceived Behavioural Control does not have a significant indirect effect towards Ride-Hailing Choice Behavior.

Once the path diagram was constructed, this paper tested for convergent validity, discriminant validity, latent variable, and indicator reliability. It also assessed the predictive strength of the structural model across latent constructs by performing tests for multicollinearity and evaluating parameters such as R^2, Q^2, SRMR, and PLS-Predict. P-values were subsequently used for hypothesis testing and later in a Multi-Group Partial Least

Squares analysis to determine demographic factors influencing latent variables, such as gender and vehicle ownership.

Results and Discussions

Instruments Validity and Reliability Test

The validity test in this research demonstrated that the appropriate measurement of each variable was achieved using the Pearson Product-Moment correlation in IBM SPSS 25, with a 5% significance level. Several indicators with an r-value greater than 0.334 were considered valid according to the r-table for a sample size of 35. Reliability is indicated by Cronbach's Alpha, with values over 0.7 considered reliable. The results confirmed that all indicators were valid, with $r > 0.334$, and reliable, as Cronbach's Alpha was higher than 0.7, indicating that the indicators were appropriate for this research.

Data Adequacy and Normality Test

The data adequacy test ensures the sample size is sufficient for accurate and reliable results. Using the Slovin formula with a 5% margin of error, the minimum required sample size for Generation Z users of online transportation services, aged 15–29, was calculated as 399 respondents. This study collected data from 406 respondents, confirming that the data adequacy requirement was met.

PLS-SEM, a non-parametric statistical method, accommodates non-normal data distributions through bootstrapping, unlike Covariance-Based SEM (CB-SEM) [12]. To assess data distribution, Skewness and Kurtosis metrics were analyzed using SmartPLS 3.0. Skewness evaluates data asymmetry, with values beyond ±1 indicating skewed distributions. Kurtosis, on the other hand, assesses the shape of the distribution, where values exceeding +1 indicate peaked distributions and values below -1 indicate flat distributions. Most indicators, including K1, K2, K3, K4, NS1, NS2, NS3, NS4, S1, S2, N3, N4, N5, P1, and P2, displayed Skewness and Kurtosis values within the normal range, suggesting a symmetrical distribution around the mean. However, indicators like KPN1, KPN2, KPN3, KPN4, KP1, KP2, S3, N1, and N2 showed non-normal distributions with Skewness values exceeding ±1 and abnormal Kurtosis values. These findings validate the use of PLS-SEM for this study, given its robustness against non-normal data.

Respondents Characteristics

The data for this study were collected using a questionnaire distributed via Google Forms on WhatsApp and Instagram in July 2024. A total of 406 respondents participated, exceeding the minimum sample size of 400 required to represent the population. The socio-demographic characteristics of the respondents are presented in Table 3.

Table 3. Respondents characteristics

Variables		Frequency	Percentage (%)
Gender	Female	285	70.2
	MaIe	121	29.8
Age	15-19 Years Old	106	26.1
	20-24 Years Old	185	45.6
	25-29 Years Old	115	28.3
Private vehicle ownership	Yes	297	73.2
	No	109	26.8
Occupation	Junior High School students	22	5.4
	Senior High School students	60	14.8
	Diploma students (D1-D4)	23	5.7
	Bachelor's degree students (S1)	137	33.7
	Postgraduate students (S2/S3)	5	1.2
	Job seeker	19	4.7
	Part-time worker	22	5.4
	Full-time workers	83	20,4
	Entrepreneurs	35	8.6
	Housewife	0	0.0

The results showed that ride-hailing users of Generation Z in Malang City were predominantly female respondents (70.2%), aged between 20 and 24 years (45.6%), and most had a private vehicle (73.2%), with the majority being students or full-time employees. Out of 406 respondents, the distribution is as follows: 26.1% are between 15 and 19 years old, 28.3% are between 25 and 29 years old, and the rest are between 20 and 24 years old. Vehicle ownership is significant, with 297 respondents owning private vehicles. Educationally, 33.7% are Bachelor's level students, followed by 5.7% Diploma students, 1.2% postgraduates, 5.4% junior high school students, and 14.8% senior high school students. Additionally, 20.4% are full-time workers, indicating that undergraduate students and full-time workers are the largest respondent groups [2].

Structural Equation Modelling - Partial Least Squares

The study employs Structural Equation Modeling with Partial Least Squares (PLS-SEM) to analyze relationships among latent variables, uncovering patterns and structures that cannot be directly observed. This method, applied to data from 406 respondents, tests hypotheses and addresses research objectives using SmartPLS 3.0 software. The analysis begins with the evaluation of the outer model, where convergent validity is assessed through outer loading values. Indicators with outer loading values above 0.70 are considered to have strong correlations with their respective latent variables [20]. The outer loading evaluation of this research, as presented in Figure 3, shows that all indicators exceeded the 0.70 threshold, demonstrating strong correlations with the latent variables they represent.

Another test to conduct on outer model analysis involves assessing discriminant validity. Discriminant validity indicates that each construct in the model must correlate more highly with its respective indicators than with those of any other construct. This phenomenon will prevent problems in multicollinearity and thus distinguish the constructs that were measured. The Fornell-Larcker Criterion requires the square root of the variance extracted for a construct to be higher than its correlations with any other latent variables. In this study, all constructs meet this criterion: their Fornell-Larcker Criterion values are greater than their correlations with other constructs, as shown in Table 4.

Table 4. Discriminant Validity Test

	K	KP	KPN	N	NS	P	S
K	0.852						
KP	0.385	0.917					
KPN	0.598	0.537	0.914				
N	0.643	0.291	0.406	0.854			
NS	0.581	0.279	0.358	0.693	0.850		
P	0.613	0.195	0.337	0.787	0.599	0.933	
S	0.633	0.416	0.548	0.642	0.528	0.544	0.860

The reliability testing was conducted using Cronbach's Alpha and Composite Reliability. Cronbach's Alpha provides the lower bound of reliability, while Composite Reliability represents the actual value; as such, both are deemed reliable if their values are equal to or greater than 0.60 [18]. This study demonstrated strong reliability in both the TAM variables and the TPB components, indicating that the measurement instruments provided consistent reflections of respondents' perceptions and behaviors regarding the use of ride-hailing services.

The PLS-SEM analysis continues with the structural model analysis, also known as the inner model, to describe the relationships between latent variables [20]. Collinearity evaluation is critical to ensure unbiased regression results. In general, collinearity represents a high linear relationship between independent variables, leading to distortion in the estimates of parameters and the interpretation of results. The VIF has been used to check for collinearity, where no collinearity issues will be found among the independent variables with a VIF value less than 3 [18]. Therefore, collinearity assessment is an important stage to ensure unbiased and reliable regression results before the structural relationships analysis.

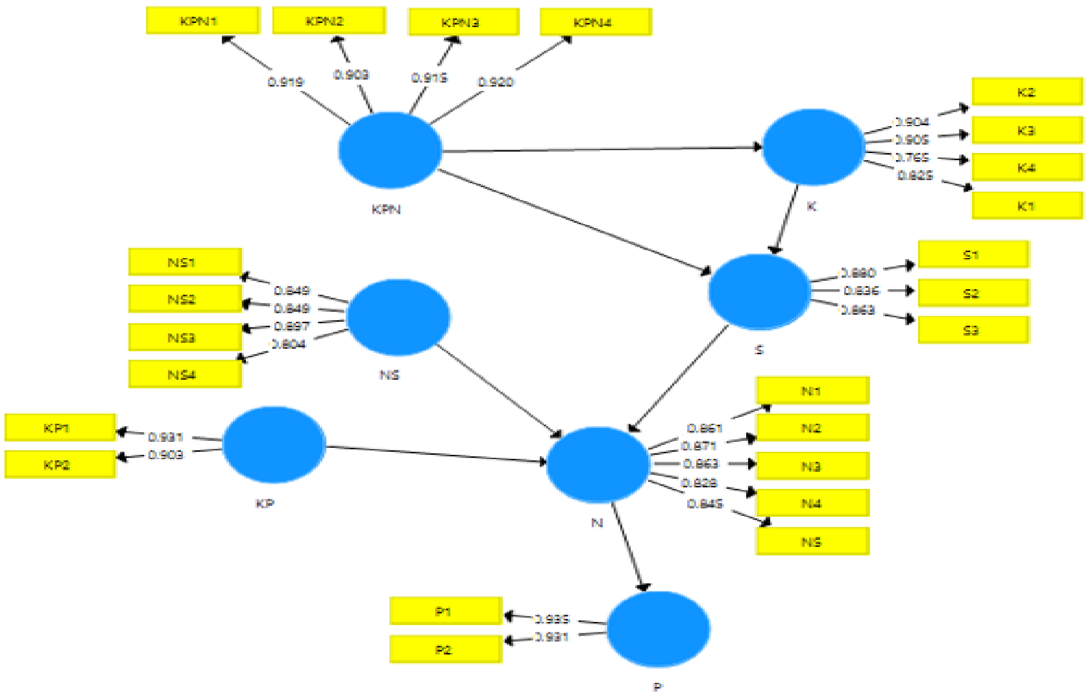

Figure 3. Outer Loading

The collinearity test conducted shows that the two variables KP and NS exhibit VIF values of 1.085 for the variable K. Additionally, when K was tested against KP and NS, the results indicated that K has a VIF value of 1.497 against KP. In contrast, the K against NS value is 1.161, indicating that the K variable does not exhibit moderate collinearity with other independent variables. Similarly, other independent variables, such as KP and NS, also have VIF values < 3. Overall, all variables in this model do not exhibit collinearity issues, allowing for valid interpretation through Structural Equation Modelling [20].

After identifying the collinearity issue within the model, the research continues by evaluating the model using R^2, Q^2, PLS Predict, and SRMR values, as shown in Table 5. The acceptable range for the (R^2) coefficient is between 0 and 1, where R^2 values above 0.19 but below 0.33 are considered weak, values between 0.33 and 0.67 are considered moderate, and values above 0.67 are considered high [18]. In this study, the R^2 for "Usefulness" (K) is 0.357, and for "Attitude" (S) is 0.446, indicating that "Ease of Use" (KPN) explains 35.7% of the variance in K, while KPN and K explain 44.6% of the variance in S, both categorized as moderate. The R^2 for "Intention" (N) is 0.586, and for "Ride Hailing Choice Behavior" (P) is 0.620, indicating that the model explains 58.6% of the variance in N and 62.0% of the variance in P, both of which are categorized as moderate.

Table 5. Inner Model and PLS-Predict

Indicator	R^2	Q^2	PLS		LM	
			RMSE	MAE	RMSE	MAE
K1	0.357	0.250	0.820	0.637	0.867	0.730
K2			0.717	0.553	0.756	0.613
K3			0.779	0.590	0.845	0.666
K4			0.929	0.713	1.062	0.839
S1	0.446	0.323	0.827	0.598	0.887	0.681
S2			0.783	0.612	0.818	0.648
S3			0.799	0.565	0.819	0.606
N1	0.586	0.421	0.958	0.736	0.960	0.761
N2			0.955	0.733	0.976	0.774
N3			0.923	0.704	0.916	0.715
N4			0.698	0.536	0.722	0.577
N5			0.870	0.690	0.872	0.705
P1	0.620	0.533	0.930	0.721	0.933	0.753
P2			0.950	0.738	0.940	0.756

For the Q^2 values, which range from 0 to 1, indicating the model's predictive relevance, the Q^2 value for "Usefulness" (K) is 0.250, demonstrating that "Ease of Use" (KPN) has predictive relevance for K. Similarly, the

Q^2 value for "Attitude" (S) is 0.323, showing that KPN and K have predictive power for S. The variable "Intention" (N) has a Q^2 value of 0.421, indicating that KPN, K, S, NS, and KP have predictive relevance for this variable. Lastly, the Q^2 for "Ride Hailing Choice Behavior" (P) is 0.533, the highest among all variables, which can be interpreted as the overall model has strong predictive relevance for P [12].

PLS-Predict evaluates a model's predictive ability by comparing it with a linear regression model [21]. The model is considered superior if its RMSE or MAE values are lower than those of the regression model [12]. The results show that the PLS model generally has smaller RMSE and MAE values, indicating moderate predictive accuracy. While a goodness-of-fit model is indicated by an SRMR value of less than 0.08, values in the range of 0.08 to 0.10 are also considered acceptable [20]. The results reveal that both the saturated and estimated SRMR values are below 0.08, with 0.064 for the saturated model and 0.079 for the estimated model. These findings indicate that the constructed model demonstrates a good fit, accurately representing the relationships among the research variables.

The Technology Acceptance Model (TAM) shows that Ease of Use (KPN) positively influences Usefulness (K), which in turn affects Attitude (S) and indirectly impacts Intention (N), leading to Ride-Hailing Choice Behavior (P), which aligns with Sedhigi et al. findings that ease and usefulness influence user attitudes and usage [6]. In the Theory of Planned Behavior (TPB), Attitude (S) and Subjective Norms (NS) positively affect Intention (N), while Perceived Behavioral Control (KP) has no significant effect. This finding supports studies in Pakistan, showing that positive perceptions and social norms strengthen intention [22]. Intention (N) strongly predicts Ride-Hailing Behavior (P), with a correlation of 0.787, confirming its role as a key factor in usage [12]. The hypothesis testing results are presented in Figure 4 and Table 6.

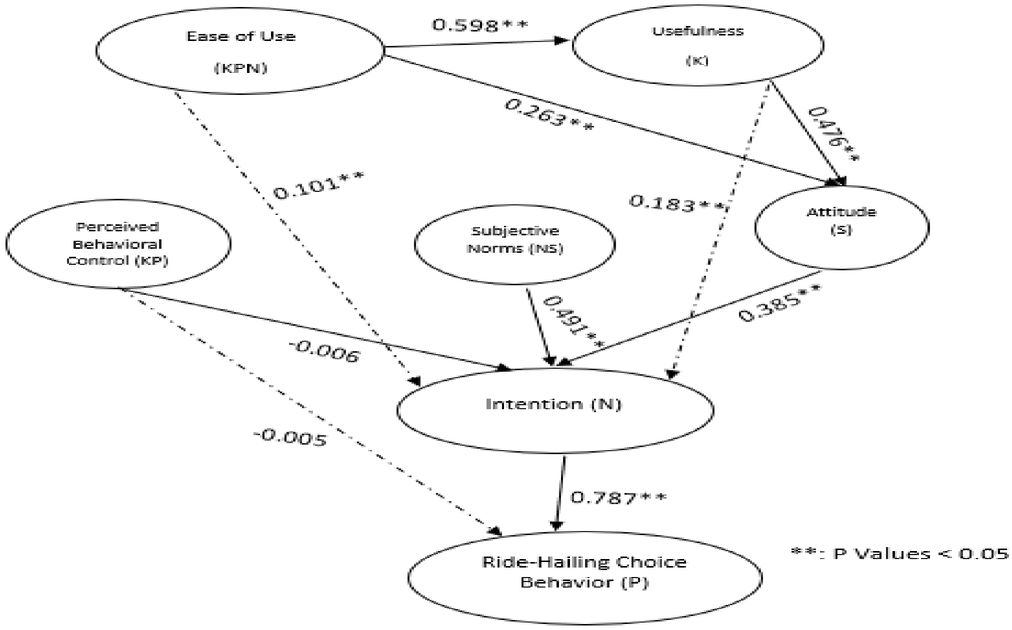

Figure 4 Hypothesis testing

Table 6. Hypothesis testing

Correlation	Correlation Coefficient	P Values	Conclusion
KPN→ K	0.598	0.000	Significant
K→ S	0.476	0.000	Significant
KPN→ S	0.263	0.000	Significant
S→ N	0.385	0.000	Significant
NS→ N	0.491	0.000	Significant
KP→ N	-0.006	0.850	Not significant
N→ P	0.787	0.000	Significant
K→ S→ N	0.183	0.000	Significant
KPN→ S→ N	0.101	0.000	Significant
KP→ N→ P	-0.005	0.850	Not significant

Multi-group Analysis Partial Least Squares

The subsequent analysis employs the Multi-Group Partial Least Squares (MGA-PLS) technique to examine the differences in relationships among variables across various groups. This MGA-PLS analysis aims to identify significant impacts from socio-demographic variables, such as gender and ownership of personal vehicles, on the relationships within the model.

Table 7. Multi-group Analysis

Correlation	P-Value Based on Gender (Male vs Female)	Significant Differences Between Groups	P-Value Based on Private Vehicle Ownership (Yes vs No)	Significant Differences Between Groups
KPN→ K	0.006	Yes	0,000	Yes
K→ S	0.035	Yes	0,174	No
KPN→ S	0.883	No	0,067	No
S→ N	0.214	No	0,895	No
NS→ N	0.445	No	0,154	No
KP→ N	0.299	No	0,042	Yes
N→ P	0.116	No	0,140	No
K→ S→ N	0.041	Yes	0,398	No
KPN→ S→ N	0.678	No	0,126	No
KP→ N→ P	0.309	No	0,043	Yes

In this study, significant differences were observed in the relationships among socio-demographic groups, as shown in Table 7. It was found that females perceive the ease of use to have a more substantial effect on their perception of usefulness. Additionally, the relationship between "Usefulness" (K) and "Attitude" (S) showed coefficients of 0.592 for females and 0.310 for males, indicating that women's perceptions of the usefulness of online transportation applications have a greater impact on shaping their attitudes compared to men. A similar pattern was found in the indirect effect of Usefulness (K) on the Intention to Choose Online Transportation Mode (N), where the relationship was statistically significant for females but not for males. This finding aligns with the research conducted by Li and Jiang [23], which suggests that gender can act as a moderating variable. However, while Li & Zhang's study found significant gender differences, particularly in the relationships between personal norms and perceived behavioral control in the context of carsharing in China, the current study highlights gender-based differences primarily in the influence of usefulness and attitude [22,24].

Regarding personal vehicle ownership, significant differences were noted in the relationship between "Ease of Use" (KPN) and "Usefulness" (K), with coefficients of 0.623 for vehicle owners and 0.182 for non-owners. These findings suggest that for individuals who own personal vehicles, ease of use plays a more critical role in shaping their perception of the usefulness of online transportation, whereas for non-owners, this relationship is not statistically significant. Furthermore, although a significant difference was found in the direct effect of "Perceived Behavioral Control" (KP) on "Intention to Choose Online Transportation Mode" (N), as well as its indirect effect on "Behavior in Choosing Online Transportation Mode" (P), further analysis revealed that "Perceived Behavioral Control" (KP) does not significantly influence either Intention or Behavior in the overall sample, nor within the subgroups of vehicle owners and non-owners. These findings contrast with those of Li & Zhang (2021), which identified significant moderating effects of personal vehicle ownership on the relationship between perceived behavioral control and the intention to use carsharing in the Chinese context. While their study emphasized the importance of behavioral control among different ownership groups, the present study shows that perceived behavioral control plays no significant role, regardless of vehicle ownership status. The key differentiating factor lies instead in the perception of usefulness, shaped by ease of use [23].

Conclusion

The factors that significantly influence Online Transportation Mode Selection Behavior (P) of Generation Z in Malang City are Usefulness (K), Ease of Use (KPN), Attitude (S), Subjective Norms (NS), and Intention to Choose Online Transportation Mode (N). Perceived Behavioral Control (KP) does not influence Behavior (P) either directly or indirectly. Ease of Use (KPN) has a positive and significant effect on Usefulness (K), which in turn positively influences Attitude (S) towards ride-hailing, and ultimately affects Intention (N) and Behavior (P). This phenomenon preferably occurs through an indirect channel. Besides Attitude (S) and Subjective Norms (NS), which significantly influence Intention (N), Intention (N) has a powerful influence on Behavior (P), thus making it the most critical determinant as far as ride-hailing usage is concerned. Furthermore, MGA-PLS analysis indicates that gender and vehicle ownership moderate these relationships. Females show stronger responses than males in Attitude (S) and Intention (N), driven by perceived Ease of Use (KPN) and Usefulness (K). Other than that, individuals who own personal vehicles are more likely to perceive benefits from online transportation due to the Ease of Use (KPN) compared to individuals without personal vehicles.

These findings address a gap in the integration of TAM and TPB with respect to considering gender and vehicle ownership as moderators in secondary cities of developing countries. The application of PLS-SEM and Multi-Group Analysis also adds to the methodological rigor of studying socio-demographic moderators in intention-to-act research. Urban policymakers and ride-hailing providers could pay attention to the segmented socio-demographics, particularly among female and private vehicle users, focusing on ease of use and usefulness. In addition, the study is limited by its focus on a single city (Malang) and the use of purposive sampling, which risks compromising generalizability, as well as the employment of self-reported survey data, which carries the risk of response bias. Further research could be applied to other urban settings within Indonesia or Southeast Asia, using a longitudinal design to examine changes in behaviors over time and analyze other moderating variables, such as digital literacy and income.

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