Influencer and Live Tracking Impact on Transjakarta Use with Angkot Satisfaction as Moderation

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Abstract

This study explores the influence of social media influencers and the live tracking feature in Google Maps on the intention to use Transjakarta public transportation, with satisfaction from conventional public transportation (angkot) as a moderating factor in South Jakarta. This research aims to understand how digital tools and influencer campaigns shape public transportation choices, particularly in the shift from angkot to Transjakarta. Using a quantitative approach, data was collected from a survey targeting residents who regularly use both angkot and Transjakarta while actively engaging with digital platforms. The analysis reveals that endorsements from influencers and the availability of live tracking information significantly increase users' interest in Transjakarta. Young users, in particular, show greater responsiveness to real-time updates and digital engagement. Satisfaction with angkot moderates this relationship, with users who are less satisfied with angkot showing a stronger preference for switching to Transjakarta. These findings highlight the growing role of social media and live tracking technology in promoting public transport use and suggest that transportation policy should incorporate digital marketing and technological advancements to drive higher adoption rates. This study underscores the importance of modernizing public transportation through strategic integration with digital tools to meet evolving commuter needs, improve user experience, and ultimately foster a more sustainable urban transport environment.

Keyword: influencer; live tracking; transjakarta; conventional angkot; usage intention; user satisfaction

1. Introduction

Public transportation is a crucial element in supporting urban mobility, particularly in large cities such as Jakarta, which is known for its traffic congestion and high levels of air pollution. According to data from the Central Statistics Agency (BPS), the population of Jakarta in 2023 reached approximately 11 million, with an estimated 3.5 million private vehicles operating on the roads daily, consisting of around 13 million motorcycles and 3.3 million cars in the Greater Jakarta area (BPS, 2023). This vehicle density contributes significantly to traffic congestion and the high emissions that affect Jakarta's air quality.

In efforts to reduce congestion and curb pollution levels, the Provincial Government of DKI Jakarta has strengthened public transportation services, one of which is Transjakarta.

Transjakarta, launched in 2004, now has 13 main corridors with hundreds of supporting routes that cover most of Jakarta and its surrounding areas. According to the Jakarta Transportation Department's report, in 2023, the average daily ridership of Transjakarta reached over 1 million passengers. This service offers several advantages, such as more affordable fares, dedicated bus lanes that allow faster travel times, and more regular schedules compared to conventional angkot (minivans).

With these advantages, the use of conventional angkot has gradually decreased, particularly in areas like South Jakarta. The decline in the use of conventional angkot is due to its lower route flexibility and limited availability compared to Transjakarta. However, angkot remains reliable, especially in residential areas that are not yet fully accessible by Transjakarta routes. Based on a preliminary survey conducted with 30 respondents in South Jakarta who use public transportation, approximately 25% of them still frequently use conventional angkot, while 75% have shifted to using Transjakarta, especially on more integrated routes. The main reasons cited by respondents who chose Transjakarta were route flexibility (35%), availability in residential areas (40%), and low cost (25%). Meanwhile, the primary reasons for continuing to use conventional angkot were its proximity to their residences and the lack of familiarity with Transjakarta.

In addition, the influence of digitalization and social media also plays a role in shaping public behavior regarding transportation choices. Social media influencers with a large following and strong credibility can influence user decisions, including transportation choices. A study by Casaló, Flavián, & Ibáñez-Sánchez (2020) showed that promotions conducted by influencers could increase awareness and interest in more modern transportation services, such as Transjakarta. In pre-research, 70% of respondents indicated that they were influenced by content on social media, particularly in choosing more comfortable and efficient public transportation.

Beyond social media influence, technological advancements, such as live tracking features in digital transportation apps like Google Maps (Gmaps), have also contributed to making it easier for people to monitor the real-time location of Transjakarta buses. This feature allows users to know the estimated arrival time of buses, which ultimately increases comfort and trust in using the service. According to research by Peng & Huang (2020), the adoption of live tracking technology can increase user trust in public transportation by 30%. In pre-research, 80% of respondents stated that they felt more comfortable using Transjakarta due to the live tracking feature, compared to angkot, which does not have a fixed schedule and is difficult to predict.

However, despite continuous innovation and expansion of Transjakarta's network, conventional angkot remains relevant for some segments of society. A study by Agyemang & Turner (2019) showed that in developing countries like Indonesia, traditional public transportation such as angkot is still the preferred choice in areas that have not yet been fully integrated with modern transportation. This is also supported by pre-research survey results, which showed that 60% of respondents who use angkot consider this mode of transport more flexible and accessible compared to Transjakarta.

Transjakarta continues to expand its network and collaborates with digital transportation apps to provide live tracking features and facilitate access to information for users. A study by Ardiansyah & Firmansyah (2021) mentioned that the use of Transjakarta increased by 15%

after integration with digital map applications, as users found it easier to plan their trips and monitor bus arrival times. With the development of technology and ongoing promotions, public perceptions are gradually shifting from conventional angkot to more structured transportation services like Transjakarta. Nevertheless, significant challenges remain, particularly in areas like South Jakarta, where transportation infrastructure is not yet fully integrated.

Based on this background, this study aims to analyze the influence of social media influencers and live tracking features in the Gmaps app on the increased use of Transjakarta, with the decreased use of angkot as a moderating variable in the South Jakarta area. This research is important because it can provide a deeper understanding of how social and technological factors work together to shape public behavior in choosing transportation modes. The results of this study are also expected to serve as a foundation for policy decision-making that supports the improvement of public transportation services in Jakarta, while also reducing dependence on less efficient conventional transportation. Based on this, the researcher is interested in conducting the study entitled "The Influence of Social Media Influencers and Live Tracking Features in Google Maps on the Interest in Using Transjakarta with Satisfaction in Using Conventional Angkot as a Moderating Variable in the South Jakarta Area."

2. Literature Review

2.1 Influencer

In recent years, the role of influencers in digital marketing has become an increasingly interesting topic for both researchers and practitioners. Influencers have the ability to influence consumer behavior through the content they share on social media platforms. They are often viewed as more personal and authentic marketers compared to traditional advertisements. Boerman (2020) explains that influencers can build strong emotional connections with their followers, which ultimately enhances marketing effectiveness. Followers tend to trust recommendations from influencers they follow, as the interaction feels "personal" and is trusted more than conventional ads.

Lou and Yuan (2019) introduced the influencer engagement theory, which asserts that audience engagement with influencer content plays a crucial role in shaping consumer behavioral intentions. They found that the more actively an audience engages with influencer content, such as through comments or sharing content, the stronger the influence the influencer can exert. This suggests that the effectiveness of an influencer is not only determined by the number of followers but also by the quality of interactions between the influencer and their audience.

Another study by De Veirman, Hudders, and Nelson (2021) emphasizes the importance of credibility and authenticity in influencer effectiveness. They highlight that influencers who appear overly commercial or frequently promote products that are irrelevant to their image tend to lose the trust of their followers. Conversely, influencers who remain consistent with their image and promote relevant products are more effective in shaping consumer purchase decisions.

2.2 Live Tracking

The use of live tracking features in digital mapping applications, such as Google Maps, has become a crucial aspect in the transformation of public transportation systems, particularly

in large cities like Jakarta. This feature enables users to track the real-time location of vehicles, providing significant benefits to both public transportation users and service providers. According to Santoso (2020), live tracking technology has changed the way people access transportation information. Users can now see the real-time position of vehicles such as buses and trains, helping them plan their journeys more efficiently. Santoso emphasizes that in large cities like Jakarta, the integration of live tracking can enhance user trust and comfort, particularly in reducing uncertainty regarding the arrival times of public transport vehicles.

A study by Putra and Ramadhan (2021) found that the live tracking feature encourages users to prefer public transportation options, such as Transjakarta or Commuter Line, over private vehicles. They noted that by being able to see the real-time position of buses, users feel more comfortable and informed, which reduces their reluctance to switch from private cars to public transport. The use of digital transportation apps supporting live tracking has also seen a significant increase due to the convenience they offer.

2.3 Transjakarta

In the past five years, experts in Indonesia have extensively discussed the development and challenges of public transportation, particularly in large cities like Jakarta. Sutomo (2019) highlights the importance of modernizing public transportation amid the rapid urban population growth. He argues that public transportation must meet the mobility needs of society efficiently, safely, and comfortably. According to Sutomo, the greatest challenge is integrating various modes of transportation, such as buses, trains, and other mass transit systems, into one interconnected system that will help reduce congestion and air pollution in large cities.

Transjakarta, according to Rasyid and Pratiwi (2020), is a bus rapid transit (BRT) public transportation system designed to enhance urban mobility efficiency in Jakarta, launched in 2004. Transjakarta features dedicated lanes called busways, aimed at reducing traffic congestion and shortening passenger travel time. Meanwhile, according to Fahmi (2019), Transjakarta is one of the modern, efficient, and affordable public transportation solutions, focusing on reducing carbon emissions and enhancing user comfort. This system is also integrated with other modes of transport to expand accessibility in the Greater Jakarta area (Jabodetabek).

2.4 Conventional Angkot

According to Nugroho (2019), angkot, or commonly known as "angkutan kota" (city transportation), is a conventional public transport mode operating in urban areas of Indonesia. Angkots are still commonly found in Jakarta with dozens of routes they serve. Angkot has a fixed route but is not bound by a strict schedule like buses or trains, which is why it is often considered flexible by passengers. According to Nugroho, angkot serves as a public transport mode that operates on short routes, which are often not accessible by buses or other public transportation modes. Nugroho also states that the main advantage of angkot lies in its flexibility, as it can pick up and drop off passengers almost anywhere along its route. However, Nugroho also highlights several weaknesses of angkot, including the lack of strict regulations regarding safety standards, the often poorly maintained condition of the vehicles, and the absence of a fixed operational schedule.

Meanwhile, Sugiyanto (2020) mentions that angkots are generally small in size with limited passenger capacity and serve as the primary alternative for lower-middle-class

communities. Sugiyanto (2020) also states that angkot plays an important role in urban mobility, but with increasing demands for efficiency and comfort, angkot must adapt to technological trends and service quality improvements. Although angkot remains an important transportation mode, challenges such as a lack of comfort, overcrowding, and the absence of real-time route tracking facilities make it less competitive compared to modern public transport modes like Transjakarta.

2.5 Diffusion of Innovation Theory

The Diffusion of Innovation Theory, introduced by Everett M. Rogers (2003), is one of the most widely used theories to explain how a new innovation or technology spreads and is adopted by society. This theory applies not only to technological products but also to new ideas, practices, or services. According to Rogers, an innovation is an idea, practice, or object that is perceived as new by an individual or group of people. Innovations can take the form of physical products, new technologies, or new ways of doing things.

Rogers divides the innovation adoption process into five stages, known as the "Innovation-Decision Process." The first stage is when an individual becomes aware of the innovation but does not yet have in-depth information or understanding about how it works. The second stage occurs when the individual becomes interested and seeks more information about the innovation. The third stage is when the individual decides whether to accept or reject the innovation. If they decide to accept it, they will try to use it. If they reject it, they will not adopt the innovation. The fourth stage happens after the decision to adopt the innovation, when the individual begins to use it in daily life and experiences the benefits or drawbacks of the innovation. The fifth and final stage is when the individual decides whether to continue using the innovation after further evaluation. If they are satisfied, they will continue using it; if not, they may abandon the innovation.

2.6 Media Richness Theory

The Media Richness Theory, introduced by Richard L. Daft and Robert H. Lengel (1986), is a theory that explains the effectiveness of various types of communication media in conveying information based on their richness. This theory focuses on how different media have varying abilities to effectively communicate complex or ambiguous messages. Media richness refers to a communication medium's ability to address ambiguity and facilitate mutual understanding between the sender and the receiver of the message. The theory suggests that each medium has a certain capacity to transmit rich or complex information. Richer media can address more uncertainty and ambiguity in communication. Daft and Lengel assert that the main objective of communication is to reduce uncertainty and ambiguity. Therefore, richer media are more effective in conveying complex information, while less rich media are suitable for transmitting simple messages.

According to Daft & Lengel (1986), there are four main dimensions that determine the richness of a medium. The first is Feedback Immediacy. Media that allow direct interaction between the sender and the receiver are considered richer. Rapid feedback enables immediate clarification, reducing the potential for misunderstandings. The second dimension is Multiple Cues. Rich media can transmit various types of cues or signals (such as verbal, vocal, or visual cues), which help clarify the meaning of the message. The third is Language Variety. Rich media allow the use of different forms of language, including emotional expression or body language, which helps clarify the intended meaning of the message. Lastly, Personal Focus

refers to media that enable more personalized interaction, where the message can be tailored and made more relevant to the receiver.

3. Material and Method

3.1 Design Study

In this study, the researcher applied a quantitative research method. According to Sugiyono (2018:14), the quantitative method is based on the philosophy of positivism and is used to study specific populations or samples. Sampling is conducted randomly, data are collected using research instruments, and data analysis is carried out statistically. Quantitative research often refers to causal relationships between the variables studied (Sugiyono, 2018). This research adopts an associative research technique, which aims to determine the cause-effect relationship between two or more variables, to explain a particular phenomenon or event (Quantitative and Qualitative Research Methods, 2020).

For primary data collection, the researcher used a survey method with questionnaires as the primary tool. The questionnaire is a written list of questions or statements to be answered by respondents according to given instructions (Sanjaya, 2015:255). In this study, questionnaires were distributed via Google Forms (GF).

Due to research limitations, the accessible population was narrowed down from the general population. The accessible population in this study consists of residents in South Jakarta who actively use the Google Maps application, specifically the live tracking feature, for daily travel using Transjakarta buses and to find angkot (public minibus) routes. The criteria for this population include:

- Residents domiciled in South Jakarta,
- Aged between 18–55 years, as this age group is generally more active in using digital applications,
- Actively using public transportation, particularly Transjakarta and angkot,
- Having access to and the ability to use digital map applications like Google Maps,
- Actively using social media such as Instagram, TikTok, X, and others.

The research sample will be selected using the purposive sampling technique, in which the researcher selects subjects based on specific characteristics relevant to the research objectives. According to Sugiyono (2012), purposive sampling is used when the researcher has knowledge or criteria about the subjects to be chosen. Unlike random sampling, not all individuals have the same chance of being selected; only those meeting the predetermined criteria are chosen. The sample criteria include:

- Individuals who live or work in South Jakarta,
- Actively use social media, particularly those who follow public transportation influencers,
- Actively use Google Maps, especially the live tracking feature,
- Regular users of Transjakarta with angkot as an alternative mode of transportation.

To determine the sample size, the Slovin formula is applied, as described by Sevilla et al. (1993). The Slovin formula is used when detailed information on population variance is unavailable and provides a reliable estimate of the required sample size for social research. The formula is:

$$n = \frac{N}{1 + N(e^2)}$$

Where:

- n = Sample size
- N = Population size
- e = Margin of error (usually between 0.01 and 0.1)

Referring to Katadata (2024), the population of South Jakarta is 2.36 million people. Using a margin of error of 0.1 (10%), the Slovin formula results in an ideal sample size of approximately 100 respondents.

3.2 Data Analysis

In this study, the author uses the Partial Least Square (PLS) data analysis technique. PLS is a statistical data analysis method that simultaneously analyzes exogenous (independent) and endogenous (dependent) variables (Ghozali and Luthan, 2015:3). PLS follows the Structural Equation Modeling (SEM) approach based on Variance-Based Structural Equation Modeling (VB-SEM). The software chosen for this study is SmartPLS, as it provides multiple pathways in the analysis process, allowing simultaneous testing of independent and dependent variables in a single run. PLS-SEM analysis consists of two main components: the outer model (measurement model) and the inner model (structural model).

The Measurement Outer Model aims to determine the indirect relationships between construct variables (indicators) and latent variables, assessed through validity and reliability tests. Validity testing includes convergent validity, where indicators are deemed valid if the correlation exceeds 0.70; however, for scale development research, values between 0.50 and 0.60 are acceptable (Ghozali and Latan, 2015:10). Discriminant validity examines cross-loading factors to determine the uniqueness of constructs, ensuring that the measurement of one construct is higher compared to others. Reliability testing measures the stability of indicators within variables or constructs using Composite Reliability and Cronbach's Alpha, with reliability values above 0.70 considered acceptable (Ghozali, 2018:45).

The Structural Inner Model identifies relationships between exogenous (independent) and endogenous (dependent) variables, addressing the study's hypotheses. Key tests include Path Coefficients, which determine the strength of relationships between latent variables, and R-Square values, which assess the variation in endogenous variables influenced by exogenous variables. R^2 values are categorized as strong (0.67), moderate (0.33), or weak (0.19). Model fit is evaluated using the Goodness of Fit (GoF), with values ranging between 0–1, where 0.1 indicates a small fit, 0.2 a moderate fit, and 0.36 a large fit. The closer the Normed Fit Index (NFI) is to 1, the better the model.

Finally, Hypothesis Testing is conducted to determine the direct and indirect effects (partial and simultaneous) of exogenous variables on endogenous variables at a 5% significance level (alpha = 0.05). If the significance value of t is less than 0.05, H0 is rejected, and H1 is accepted. Conversely, if the significance value of t is greater than 0.05, H0 is accepted, and H1 is rejected. This hypothesis testing ensures a 5% error rate and a 95% confidence level for conclusions drawn.

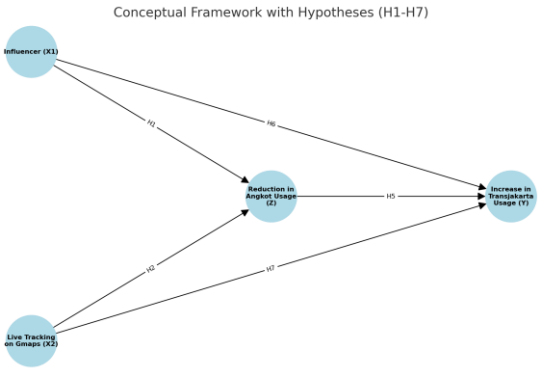

Figure 1. Research Model
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4. Result

4.1 Measurement Model Evaluation (Outer Model)

4.1.1 Indicator Reliability

Outer Loading

The first step in evaluating the outer model involves examining the **outer loading** of the indicators. A high outer loading indicates a strong level of shared variance within the construct. The minimum acceptable value for outer loading is **0.7** (Hair et al., 2022). The results of the outer loading test can be seen in the following table.

Table 1. Outer Loading

	Live Tracking Feature on Google Maps (X2)	Influencer (X1)	Interest in Transjakarta Usage (Y)	Angkot User Satisfaction (Z)
X1.1		0.857		
X1.2		0.774		
X1.3		0.847		
X1.4		0.826		
X1.5		0.871		
X2.1	0.877			
X2.2	0.797			
X2.3	0.842			
X2.4	0.852			
X2.5	0.866			
Y.1			0.861	
Y.2			0.817	
Y.3			0.825	

Y.4			0.849	
Y.5			0.887	
Z.1				0.873
Z.2				0.868
Z.3				0.881
Z.4				0.001
Z.5				0.916

Based on the results of the convergent validity test in the table, it can be observed that there are indicators with outer loading values below 0.7, which therefore need to be eliminated. The following are the outer loading values after elimination:

Table 1.1. Outer Loading

	Live Tracking Feature on Google Maps(X2)	Influencer (X1)	Interest in Transjakarta Usage (Y)	Angkot User Satisfaction (Z)
X1.1		0.857		
X1.2		0.774		
X1.3		0.847		
X1.4		0.826		
X1.5		0.871		
X2.1	0.877			
X2.2	0.797			
X2.3	0.842			
X2.4	0.852			
X2.5	0.866			
Y.1			0.861	
Y.2			0.817	
Y.3			0.825	
Y.4			0.849	
Y.5			0.887	
Z.1				0.874
Z.2				0.868
Z.3				0.882
Z.5				0.916

Based on the results of the convergent validity test in the table, it can be seen that all indicators have an outer loading value ≥ 0.70. Therefore, all indicators in this study can be declared to have met the criteria.

4.1.2 Cronbach's Alpha dan Composite Reliability (*Internal Consistency Reliability*)

The next test to be conducted on the outer model is the internal consistency reliability test. This test is performed through the Cronbach's alpha and composite reliability values. Cronbach's alpha describes the correlation of indicators within a construct, while composite reliability examines the variation in outer loading values of the indicator variables. Hair et al. (2022) state that the accepted values for Cronbach's alpha and composite reliability must be greater than 0.6 (Hair et al., 2022).

Table 2. Cronbach's Alpha

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Live Tracking Feature on Google Maps(X2)	0.902	0.903	0.927	0.718
Influencer (X1)	0.892	0.894	0.92	0.699
Interest in Transjakarta Usage (Y)	0.902	0.903	0.928	0.719
Angkot User Satisfaction (Z)	0.908	0.908	0.935	0.783

The test results in the table show that all latent variables meet the reliability test criteria. This is based on the Cronbach's Alpha and Composite Reliability values of all latent variables, which are greater than 0.6. Therefore, all latent variables are declared reliable after fulfilling all measurement criteria.

4.1.3 Validitas Konvergen *(AVE)*

Convergent validity refers to the extent to which a construct is able to measure each of its indicators. The testing of convergent validity can be carried out by evaluating the **Average Variance Extracted (AVE)**. According to Hair et al. (2022), when the AVE value is greater than **0.5**, the construct can explain more than 50% of the variance in its indicators. Based on the Average Variance Extracted (AVE) values, the **Live Tracking Feature on Gmaps (X2)** has an AVE of **0.718**, indicating that the indicators within this construct are sufficiently strong in explaining its variance. The **Influencer (X1)** construct has an AVE of **0.699**, which also meets the convergent validity criteria. The construct for the **Interest in Transjakarta Usage (Y)**, with an AVE of **0.719**, and the construct for the **Angkot User Satisfaction(Z)**, with an AVE of **0.783**, further demonstrate that the variance explained by the indicators within these

constructs is adequate. Overall, these AVE values support the internal consistency and convergent validity of the constructs used in the model.

4.1.4 Discriminant Validity

The evaluation to assess how different one construct is from another in capturing distinct phenomena can be conducted using a **discriminant validity test**. Generally, researchers use several tests for discriminant validity, such as the **Fornell-Larcker criterion**, **cross-loading**, and the **heterotrait-monotrait ratio (HTMT)** (Hair et al., 2022). The first criterion to consider in discriminant validity is the **Fornell-Larcker criterion**, which requires that the **square root of the AVE** of a construct must be greater than its highest correlation value with any other construct. This criterion can be observed in the table to ensure discriminant validity is achieved.

Table 3. Fornell-Larcker criterion

	Live Tracking Feature on Google Maps(X2)	Influencer (X1)	Interest in Transjakarta Usage (Y)	Angkot User Satisfaction (Z)
Live Tracking Feature on Google Maps(X2)	0.847			
Influencer (X1)	0.975	0.836		
Interest in Transjakarta Usage (Y)	0.978	0.975	0.848	
Angkot User Satisfaction (Z)	-0.852	-0.872	-0.874	0.885

Based on the table above, the square root value of the AVE for each construct is not greater than its correlation with other constructs, meaning it does not meet the Fornell-Larcker criterion.

The next criterion that needs to be considered is the cross-loading value. According to this criterion, the outer loading of an indicator on its associated construct must be greater than the cross-loading on other constructs. The loading factor values can be seen in the table.

Table 4. Cross Loading

	Live Tracking Feature on Google Maps(X2)	Influencer (X1)	Interest in Transjakarta Usage (Y)	Angkot User Satisfaction (Z)
X1.1	0.828	0.857	0.829	-0.71
X1.2	0.755	0.774	0.765	-0.678
X1.3	0.852	0.847	0.841	-0.744
X1.4	0.785	0.826	0.781	-0.719
X1.5	0.847	0.871	0.853	-0.787
X2.1	0.877	0.83	0.856	-0.746
X2.2	0.797	0.793	0.758	-0.67
X2.3	0.842	0.825	0.841	-0.735
X2.4	0.852	0.846	0.844	-0.762
X2.5	0.866	0.834	0.839	-0.691

Y.1	0.827	0.84	0.861	-0.745
Y.2	0.789	0.779	0.817	-0.716
Y.3	0.817	0.826	0.825	-0.721
Y.4	0.842	0.816	0.849	-0.721
Y.5	0.869	0.871	0.887	-0.803
Z.1	-0.766	-0.76	-0.78	0.874
Z.2	-0.781	-0.797	-0.785	0.868
Z.3	-0.696	-0.735	-0.739	0.882
Z.5	-0.769	-0.791	-0.79	0.916

Based on the table, it can be stated that the values of each outer loading are not yet higher than the cross loading on other constructs.

Another important criterion to consider in discriminant validity is the heterotrait-monotrait ratio (HTMT). HTMT is the mean of all correlations between indicators across constructs. According to Hair et al. (2022), the maximum acceptable HTMT correlation value is 0.9. An HTMT correlation value greater than 0.9 indicates a lack of discriminant validity.

Table 5. heterotrait monotrait ratio (HTMT)

	Live Tracking Feature on Google Maps(X2)	**Influencer (X1)**	**Interest in Transjakarta Usage (Y)**	**Angkot User Satisfaction (Z)**
Live Tracking Feature on Google Maps (X2)				
Influencer (X1)	0.78			
Interest in Transjakarta Usage (Y)	0.862	0.77		
Angkot User Satisfaction (Z)	0.94	0.967	0.84	

Based on the table above, there is an HTMT correlation value greater than 0.9. This value does not meet the HTMT criteria and has not fulfilled the discriminant validity test.

4.2 Evaluation Inner Model (Structural Model Assessment)

The next evaluation, after the measurement model has been declared valid and reliable, is the Structural Model Assessment, also referred to as inner model evaluation. According to Hair et al. (2022), the structural model assessment is conducted through several tests, including collinearity, significance and relevance of model relationships, Model's Explanatory Power, and Model's Predictive Power, which will be discussed as follows:

4.2.1 Assess the structural model for collinearity issues (VIF)

Collinearity refers to a condition where two or more predictor (independent) variables in a model have a high linear relationship, meaning they are highly correlated with one another. Collinearity testing can be performed by observing the Variance Inflation Factor (VIF) value.

If the VIF value < 5, the model is considered fit and can proceed to the next analysis. The results of the VIF value test can be seen in the following table:

Table 6. VIF

	VIF
X1.1	3.173
X1.2	2.063
X1.3	2.597
X1.4	2.679
X1.5	3.011
X2.1	3.128
X2.2	2.464
X2.3	2.744
X2.4	2.846
X2.5	3.166
Y.1	2.96
Y.2	2.267
Y.3	2.424
Y.4	2.899
Y.5	3.086
Z.1	2.674
Z.2	2.539
Z.3	2.706
Z.5	3.478

It can be seen from the table above that the VIF values between the research variables have met the test threshold of < 5. From the inner model testing, the overall model is considered sufficiently good.

4.2.2 Assess the significance and relevance of the structural model relationships

path coefficient and t-Values

At this stage, the test is conducted by examining the path coefficient and t-values. A path coefficient value close to 1 indicates a strong positive relationship, whereas a value close to 0 indicates a weak relationship within the structural model. Furthermore, the t-value indicates the significance of the relationship between variables at a certain error level. In this study, the researcher uses a 5% significance level, meaning that the t-value must be greater than 1.65 (Hair et al., 2022). The path coefficient values and t-values are presented in the following table.

Table 7. Path Coefficient

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Live Tracking Feature on Google Maps (X2) -> Interest in Transjakarta Usage (Y)	0.551	0.543	0.088	6.243	0

Live Tracking Feature on Google Maps (X2) -> Angkot User Satisfaction (Z)	-0.046	-0.062	0.299	0.155	0.877
Influencer (X1) -> Interest in Transjakarta Usage (Y)	0.352	0.349	0.087	4.074	0
Influencer (X1) -> Angkot User Satisfaction (Z)	-0.826	-0.809	0.253	3.269	0.001
Angkot User Satisfaction (Z) -> Interest in Transjakarta Usage (Y)	-0.098	-0.109	0.055	1.78	0.075

Directly, the Live Tracking Feature on Google Maps has a significant positive effect on the Increase in Transjakarta Usage, with an original sample value of 0.551 and a T-statistic of 6.243, indicating that this feature encourages the use of Transjakarta. However, this feature does not have a significant effect on the Angkot User Satisfaction (O = -0.046, T = 0.155). Influencers also have a significant positive effect on the Interest in Transjakarta Usage (O = 0.352, T = 4.074), but a significant negative effect on the Angkot User Satisfaction (O = -0.826, T = 3.269), indicating that influencer promotions encourage the use of Transjakarta while reducing the use of angkot. Furthermore, the path coefficient values and T-values for the indirect effects are presented in the following table.

Table 8. Indirect Effect

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Live Tracking Feature on Google Maps (X2) -> Angkot User Satisfaction (Z) -> Interest in Transjakarta Usage (Y)	0.005	0.016	0.043	0.105	0.916
Influencer (X1) -> Angkot User Satisfaction (Z) -> Interest in Transjakarta Usage (Y)	0.081	0.081	0.029	2.795	0.005

Indirectly, through Reduction in Angkot Usage as a mediating variable, Influencers have a significant impact on the Increase in Transjakarta Usage, with an original sample value of 0.081 and a T-statistic of 2.795. This indicates that influencers indirectly encourage the use of Transjakarta by reducing dependency on angkot. However, there is no significant influence from the Live Tracking Feature on Google Maps through the reduction in angkot usage on the increase in Transjakarta usage (O = 0.005, T = 0.105).

4.2.3 *Assess the model's explanatory power*

R-Square Values

The third step in evaluating the structural model involves assessing the explanatory power of the model. The explanatory power of a model relates to its ability to fit the existing

data by measuring the strength of associations demonstrated in the PLS path model. The most commonly used measure to evaluate the explanatory power of a structural model is the coefficient of determination (R^2). The R-square value or coefficient of determination is used to evaluate the strength of the structural model. A higher R-square value indicates a better predictive model for the proposed research model. The results of the analysis for the R-Square values are presented in the table.

Table 9. R-Square

	R-square	R-square adjusted
Interest in Transjakarta Usage (Y)	0.968	0.967
Angkot User Satisfaction (Z)	0.76	0.755

The table above shows the R-square values for two variables: Interest in Transjakarta Usage (Y) and Angkot User Satisfaction (Z). The R-square value for Interest in Transjakarta Usage (Y) is 0.968, indicating that the independent variables account for 96.8% of the variation in the Interest in Transjakarta Usage, while the remaining 3.2% is influenced by other factors outside the model. Angkot User Satisfaction (Z) has an R-square value of 0.76, meaning that 76% of the variation in the Angkot User Satisfaction is explained by the independent variables, with the remaining 24% influenced by external factors.

Effect Size Value

Furthermore, the next test required at the Assess the model's explanatory power stage is to examine the effect size or f^2 value. The evaluation of effect size is conducted by observing the f^2 value to determine the magnitude of the influence of exogenous variables on endogenous variables within a model. The guidelines for assessing f^2 are that values of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively (Hair et al., 2022). The f-square values for each construct are presented in the table below.

Table 10. Effect Size

	Interest in Transjakarta Usage (Y)	Angkot User Satisfaction (Z)
Live Tracking Feature on Google Maps (X2)	0.475	0
Influencer (X1)	0.17	0.143
Angkot User Satisfaction (Z)	0.072	

Based on the analysis results, the Live Tracking Feature on Google Maps (X2) has a positive influence of 0.475 on the Interest in Transjakarta Usage (Y). This indicates that the feature helps users monitor bus positions in real-time, thereby enhancing their interest and convenience in using Transjakarta services. Additionally, Influencer (X1) also has an effect on the Interest in Transjakarta Usage (Y) with an influence value of 0.17 and on the Angkot User Satisfaction (Z) with a value of 0.143, indicating the role of influencers in promoting the use of modern public transportation such as Transjakarta. Overall, the Angkot User Satisfaction (Z) also impacts the Interest in Transjakarta Usage (Y) with an influence value of 0.072, demonstrating a transition of users from angkot to Transjakarta.

4.2.4 Assess the model's predictive power

Predictive Relevance (Q^2)

For the path model in this study to be useful for managerial decision-making, the model must generate findings that can be generalized. Producing generalizable findings requires assessing whether the research results are not only applicable to the data used during the calculation process but can also be applied to other datasets (Hair et al., 2022). The assessment of predictive power can be performed by examining the predictive relevance (Q^2) value. The higher the resulting Q^2 value, the better the research outcomes and the stronger the model in predicting results using different sample data. The results of the Q^2 test are presented in the following table:

Table 11. Q-Square

	SSO	SSE	Q^2 (=1-SSE/SSO)
Live Tracking Feature on Google Maps (X2)	500	500	0
Influencer (X1)	500	500	0
Interest in Transjakarta Usage (Y)	500	162.885	0.674
Angkot User Satisfaction (Z)	400	169.322	0.577

Based on the Q^2 calculation results, the research model has a Q^2 value of 0.674 (>0) for the variable Increase in Transjakarta Usage (Y) and 0.577 (>0) for the variable Decrease in Angkot Usage (Z). These values indicate that the model has good predictive relevance for both variables, while the variables Live Tracking Feature on Gmaps (X2) and Influencer (X1) do not possess predictive relevance ($Q^2 = 0$).

4.3 Hypothesis Testing

1. **Live Tracking Feature on Gmaps (X2) → Interest in Transjakarta Usage (Y)**
   The path coefficient of 0.551 with a p-value of 0.000 indicates that the Live Tracking Feature on Gmaps has a positive and significant effect on the Interest in Transjakarta Usage. This means that the more effective the live tracking feature on Gmaps is, the greater the interest of users in using Transjakarta, as it becomes easier for them to determine the vehicle's position and schedule.
2. **Live Tracking Feature on Gmaps (X2) → Angkot User Satisfaction (Z)**
   The path coefficient of -0.046 and a p-value of 0.877 shows that the Live Tracking Feature on Gmaps does not have a significant effect on the Angkot User Satisfaction.

This weak and insignificant effect indicates that the presence of the feature does not influence users' decisions to shift from angkot to other modes of transportation.

3. **Influencer (X1) → Interest in Transjakarta Usage (Y)**
   With a path coefficient of 0.352 and a p-value of 0.000, the results show that influencers have a positive and significant effect on the interest in Transjakarta usage. This means that promotions or endorsements from influencers encourage more people to use Transjakarta, strengthening the effectiveness of influencers in shaping transportation preferences.
4. **Influencer (X1) → Angkot User Satisfaction (Z)**
   The path coefficient of -0.826 with a p-value of 0.001 indicates that influencers have a negative and significant effect on Angkot user satisfaction. This means that promotions by influencers tend to reduce public interest in using angkot. This demonstrates that influencers can encourage users to shift to other modes of transportation, such as Transjakarta.
5. **Angkot User Satisfaction (Z) → Interest in Transjakarta Usage (Y)**
   The path coefficient of -0.098 and a p-value of 0.075 indicates that the Angkot user satisfaction usage does not have a significant effect on the interest in Transjakarta usage. In other words, although angkot usage decreases, it does not automatically lead to an increase in Transjakarta usage directly.

4.4 Pengaruh Mediasi

1. **Live Tracking Feature on Gmaps (X2) → Angkot User Satisfaction (Z) → Interest in Transjakarta Usage (Y)**
   With a path coefficient of 0.005 and a p-value of 0.916, the results show that the Live Tracking Feature on Gmaps, through the Angkot user satisfaction, does not have a significant mediating effect on the interest in Transjakarta usage.
2. **Influencer (X1) -> Angkot User Satisfaction (Z) -> Interest in Transjakarta Usage (Y)**
   With a path coefficient of 0.081 and a p-value of 0.005, the results indicate that the effect of influencers on the interest in Transjakarta usage is significantly mediated by the Angkot user satisfaction. This means that the influence of influencers reduces public interest in using angkot, which in turn increases their interest in using Transjakarta.

5. Discussion

This study highlights that the influence of social media influencers and the live tracking feature on the Google Maps application significantly impacts interest in using TransJakarta. The results align with the innovation adoption and media richness theories, which emphasize the role of technology and information in driving behavior change. Influencers play a crucial role in shaping public perception and promoting modern transportation services like TransJakarta through engaging and credible content. This supports findings from previous studies indicating that social influence is instrumental in changing consumer preferences toward new services.

Furthermore, the live tracking feature contributes to increased convenience and trust, reducing uncertainty and improving the user experience. This finding is consistent with

previous research suggesting that real-time tracking systems enhance user satisfaction by providing reliable and accessible information, making public transportation more appealing.

Interestingly, satisfaction with conventional angkot moderates these relationships. Users dissatisfied with angkot services are more inclined to transition to TransJakarta when influenced by social media promotions or supported by the convenience of live tracking. This moderation effect highlights the importance of improving conventional transportation to remain competitive.

Overall, this study provides insights into how social and technological factors complement each other to accelerate shifts toward modern transportation modes, particularly in urban areas with robust infrastructure like South Jakarta. It demonstrates that combining influencer-driven campaigns with technological advancements can effectively drive behavioral changes and support sustainable urban mobility.

6. Conclusion, Implication, and Recommendation

Based on the results of the study on the influence of influencers and the live tracking feature in the Google Maps application on the interest in using TransJakarta, with satisfaction in using conventional public transportation (angkot) as a moderating variable in South Jakarta, the following conclusions are drawn: Influencers have a significant positive effect on the interest in using TransJakarta. The content produced by influencers successfully creates awareness and encourages changes in public behavior toward the use of public transportation. The live tracking feature on Google Maps significantly contributes to increasing user convenience and trust in using TransJakarta. Real-time information about bus arrival schedules reduces uncertainty and waiting times. Satisfaction with the use of conventional angkot moderates the relationship between the influence of influencers and the live tracking feature on the interest in using TransJakarta. When satisfaction with angkot is low, people are more open to switching to TransJakarta. Simultaneously, the influence of influencers and the live tracking feature accelerate the shift from angkot to TransJakarta, particularly in South Jakarta, which has relatively good transportation infrastructure.

Implications of the Study

- Theoretical Implications: This research expands academic insights into how social factors (influencers) and technological factors (live tracking) contribute to changing transportation preferences in the digital era. The findings support innovation adoption theory and media richness theory, which suggest that the presence of rich and reliable information accelerates the adoption of new services.
- Practical Implications:
    - For Transjakarta Management: Strengthen collaboration with influencers to promote public transportation services through digital campaigns and expand the integration of live tracking technology to enhance user experience.
    - For Google Maps: Extend the live tracking feature beyond Transjakarta to include conventional angkot, improving overall transportation efficiency.
    - For the Public: Provide better access to information to support the transition to more efficient and environmentally friendly public transportation.
- Policy Implications: The government can develop regulations that encourage the modernization of conventional angkot, such as equipping them with real-time tracking

systems. Public campaigns involving influencers and technology can be used to reduce dependence on private vehicles.

Recommendations

- For Transjakarta Development: Ensure the accuracy of live tracking features to address complaints related to inconsistent information and develop standalone applications with additional features, such as travel time estimation and optimal route options. Collaboration with influencers should incorporate storytelling strategies in digital campaigns to reach a broader audience and build trust.
- For Conventional Angkot: Angkot needs to adopt digital systems to remain competitive, such as integrating their routes with Google Maps. Providing training for angkot drivers on technology usage and service improvements is also recommended.
- For Future Research: Future studies can expand the geographical scope to include the entirety of Jakarta or other regions to understand broader patterns. Additional variables, such as demographic or economic factors, should also be considered to explore their influence on public transportation interest.

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