International Journal on Advanced Technology, Engineering, and Information System
https://ojs.transpublika.com/index.php/IJATEIS
Online ISSN 2828-5425

https://doi.org/10.55047/ijateis.v4i4.2188

Original Article

Analysis of Passenger Transport Mode Choice Between Bus and Airplane to Improve Service (Case Study: Palembang-Jakarta Route)

Renita Vira Maulidina[1*], Sutanto Soehodho[2], Nahry Nahry[3]

[1-3]Faculty of Engineering, Graduate Program in Transportation Engineering, Universitas Indonesia, Indonesia
Email: [1)] renitaviraamaulidina@gmail.com

Received : 05 March - 2026
Accepted : 10 April - 2026
Published online : 15 April - 2026

Abstract

The development of public transport in Indonesia is an important factor in supporting community mobility, especially in inter-city travel. This study aims to analyze the factors that influence the choice of transport mode between buses and airplanes on the Palembang-Jakarta route. This study uses the binary logistic regression method to identify the probability of users choosing one mode of transport based on various factors. Inter-city mobility in Indonesia is increasing, especially for travel between Palembang and Jakarta. The choice of efficient modes of transport is an important factor for users, with two main modes available, namely buses and airplanes. This study aims to analyze the factors that influence the choice of transportation mode by considering variables such as travel costs, travel time, comfort, safety, and accessibility. The research method used is binary logistic regression, which allows for the analysis of the probability of mode selection based on influential factors. Data was collected through a questionnaire survey involving respondents who had travelled from Palembang to Jakarta. Based on the results of the study, optimization of public transport services is needed to improve competitiveness and enhance travel comfort and safety. This study provides insights for transport service providers and policymakers in designing more efficient and sustainable transport policies.

Keywords: Mobility, Service, Transport.

1. Introduction

South Sumatra is a province in Indonesia located in the southern part of the island of Sumatra, with Palembang as its capital. As time goes by, the Indonesian population continues to grow, a trend increasingly reflected in daily traffic congestion. Based on data from the South Sumatra Provincial Statistics Agency, the population of South Sumatra currently stands at 8,837,301 people (BPS, 2024).

Given this population density, inter-city travel by the residents of Palembang plays a critical role in regional mobility. Someone who is going to travel from one place to another will certainly consider many factors when deciding on public transport. As defined, public transport is a passenger transport service that is managed according to a schedule, operated along a predetermined route, and charges a fee for each trip (Saputri et al., 2025). The primary objectives of public transportation are to provide reliable services with adequate facilities that are suitable for public use. Service quality can be assessed based on aspects such as ensuring user safety, minimizing travel time, offering affordable fares, and providing comfortable facilities for passengers.

In discrete choice theory (McFadden, 1974), travelers are segmented into captive users and choice users based on their access to alternative modes. Captive users, who are public transport users that must use public transport because they lack private transportation, and choice users, who are individuals that can choose between using public transport and private vehicles.

For travel from Palembang to Jakarta, various modes of transport are available, including airplanes, buses, and travel cars. Among the many modes available, this study focuses on a comparison between buses and airplanes. The choice between bus and airplane made by users carries specific implications for travel cost, time, and comfort. To improve the level of public transport usage, it is first necessary to enhance the service quality of these modes. By improving public transport services, it is expected that in the future, the public will increasingly prefer public transport over private vehicles.

Previous studies on transport mode choice have generally focused on identifying aggregate factors that influence the probability of mode choice (Reck & Axhausen, 2020; Saleh et al., 2022). However, this approach does not fully capture the differences in user behavior characteristics based on travel purposes. Recent research has highlighted the need for segmentation approaches to better understand heterogeneity in user preferences (Ariansyah et al., 2025; Zhou et al., 2024).

Therefore, this study develops a mode choice analysis that incorporates travel purpose segmentation to identify user behavior heterogeneity. In addition to analyzing the probability of mode choice, this study also examines user sensitivity to changes in travel costs through elasticity analysis within each segment.

Thus, this study not only identifies factors that influence mode choice but also provides insights into differences in user behavioral responses and their implications for formulating more targeted transport service improvement strategies. This study aims to: (1) develop a model that explains the probability of bus and airplane mode usage; (2) identify the key factors influencing people's choice of transport mode; and (3) provide recommendations for improving the quality of public transport services for the community.

2. Literature Review

2.1. Transportation

Transportation is an activity that involves moving or transporting something from one location to another, creating a network of connectivity that is vital for economic and social development (Morlok, 1978). Viewing transportation as a system that involves infrastructure and service systems, it enables the mobility of people and the movement of goods throughout the region, as well as providing access to various areas (Tamin, 1997). From these various perspectives, transport is defined as a system or process that enables the movement of people and goods to reach specific destinations efficiently, effectively, and safely. These definitions reflect the importance of transport in supporting human mobility, economic growth, and social integration throughout the world.

2.2. Transport Planning

Transportation planning is a systematic process that aims to develop efficient, sustainable, and integrated transport systems by aligning transportation policies with land use planning and broader regional development strategies. The integration of transport and land use is essential, as spatial patterns of development directly influence travel demand, accessibility, and mobility behavior.

Effective transportation planning is inherently dynamic and continuous, requiring periodic evaluation and adjustment to accommodate changing demographic, economic, and technological conditions (Zein et al., 2024). A key characteristic of transport planning is its forward-looking orientation, which involves anticipating future travel demand, identifying potential constraints, and formulating strategies to address long-term mobility needs.

In this context, transportation planning not only focuses on infrastructure provision but also considers service quality, modal integration, and user preferences. These aspects are particularly relevant in supporting informed mode choice decisions and improving the overall performance of public transportation systems.

2.3. Mode of Transport Selection

Mode selection is a modelling or process stage in transport planning that has the function of determining the load during a journey or finding out the number of people or goods that will use or choose various modes of transport available to serve a particular point of origin and destination and several specific travel purposes (Meixell & Norbis, 2008). Mode selection (split mode) can be defined as the distribution of trips made by travelers across available modes of transport, influenced by various factors. Meanwhile, a model in mode selection is a model that can describe the behavior of travelers in making a choice regarding their desired mode of transport. The factors underlying mode selection will certainly vary greatly between individuals (Tamin, 1997).

3. Methods

This study uses a quantitative approach to analyze the factors that influence the choice of bus and airplane transportation modes on the Palembang-Jakarta route, with the population of South Sumatra as the basis for the study. A quantitative approach was chosen because it can produce numerical data that can be analyzed statistically to understand the probability and tendency of people to choose a mode of transport based on variables such as travel time, cost, comfort, safety, frequency of travel, facilities, and user satisfaction. The Palembang-Jakarta route was chosen as the location for the study because it is a strategic route with high mobility, served by both major modes of transportation, and has adequate infrastructure, including Sultan Mahmud Badaruddin II Airport and the Palembang bus terminal. The diversity of passenger characteristics across different ages, occupations, and economic capacities makes this route representative for collecting accurate and relevant quantitative data, while also enabling analysis of public preferences for both modes of transportation.

The research population included South Sumatra residents who had experience travelling between cities on this route, either by bus or plane, while the sample consisted of 350 respondents selected using purposive sampling to ensure representation of various demographic backgrounds and travel experiences. Data collection was conducted through structured questionnaires covering demographic data, travel characteristics, and aspects of transportation services, as well as through direct observation at departure and arrival points and in-depth interviews to gain a more complete insight into passengers' motivations, preferences, and experiences. Observations were made to monitor patterns of transport mode usage, comfort levels, travel frequency, and infrastructure conditions, while in-depth interviews helped to understand the reasons for mode selection and users' perceptions of service quality.

The collected data was analyzed using descriptive and inferential statistics, including frequency distribution, percentages, and tests of relationships between variables, to identify the dominant factors influencing the choice of transport mode. In this study, the data processing was designed to produce valid, reliable, and in-depth analysis. Data was collected through questionnaires (quantitative) and interviews (qualitative), then processed using an integrated approach to provide holistic insights into transport mode preferences in Jakarta.

The data used in this study is the actual revealed preference data of respondents, namely the mode of transport actually used for travel between Palembang and Jakarta. The data was then analyzed using binary logistic regression to estimate the probability of mode selection. Logistic regression is used to analyze the relationship between independent variables (such as age, income) and dependent variables (transport mode choice). Logistic regression predicts the probability of a categorical outcome based on independent variables. Logistic regression works with log-odds (Logit) defined as:

$$\mathrm{logit}(p) = \ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n$$

Description:

p : The probability that the dependent variable y is equal to 1, given the value of the independent variable (X)

β_0 : Intercept or model constant.

$\beta_1, \beta_2, \ldots, \beta_n$: Regression coefficients for each independent variable $(X_1, X_2, \ldots, X_n)$

$X_1, X_2, \ldots, X_n$: Independent variables in the model.

$$OR = \frac{p}{1-p}$$

The odds ratio (OR) is a measure used to compare the odds of an event occurring in one group with the odds of the same event occurring in another group. In this study, a binary logistic regression model was used. The marginal effect in logistic regression is calculated based on the change in the probability of choosing a mode of transport due to a one-unit change in the independent variable. In general, the marginal effect can be expressed as follows:

$$ME_i = \frac{\partial P(Y=1)}{\partial X_i}$$

where $P(Y=1)$ is the probability of respondents choosing air travel, and X_i is the independent variable being analyzed. Marginal effect calculations are performed on the mean values of all independent variables, so that the results obtained represent the impact of variable changes on respondents in general.

The use of marginal effect analysis in this study aims to provide a more applicable interpretation of the modelling results, particularly in formulating policy recommendations for improving public transport services. Thus, the results of the study are not only descriptive and inferential, but also able to show the magnitude of the policy impact quantitatively.

The logistic regression model used in each segment follows the same logit equation specification as the aggregate model described earlier, namely:

$$P(Y=1) = \frac{1}{1+e^{-Z}}$$

with:

$$Z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k$$

where $P(Y=1)$ is the probability of mode choice, X_i is the independent variable of the study, and β_i is the estimated parameter.

The elasticity calculation focuses on direct price elasticity (own elasticity), which is the sensitivity of the probability of mode choice to changes in the cost of the same mode. This approach was chosen because the study emphasizes the differences in user responses in each travel destination segment, making elasticity an important indicator in assessing whether users are sensitive or relatively stable to fare changes.

$$E = \beta \times X \times (1 - P)$$

The elasticity value is calculated using the variable cost coefficient from the logistic regression model, average travel costs, and average mode choice probability. Interpretation is carried out by distinguishing between elastic and inelastic conditions, so that comparisons between segments can provide an overview of user behavior heterogeneity and its implications for improving transport services.

4. Results and Discussion

4.1. Descriptive Statistical Analysis

Table 1. Distribution of Respondents Based on Frequency of Use

Frequency of Travel	Bus	Airplane
Per Week	28	10
Per Month	65	38
Per Year	7	11
Infrequent / Irregular	16	20
Other	7	4

The cross-tabulation results as in Table 1 show that among respondents who travel weekly, the majority choose bus (13.6%) over airplane (4.85%). The same pattern was also seen in the group travelling monthly, where buses were chosen more often (31.6%) than airplanes (18.45%). This indicates that respondents with regular mobility tend to consider cost when choosing a mode of transport. Conversely, in the group travelling annually and the infrequent/irregular category, the choice of airplanes was relatively higher than buses. This condition shows that for non-routine trips, respondents tend to consider comfort and time efficiency more than cost factors. Descriptively, travel frequency shows a tendency to be related to mode selection, where mobility intensity has the potential to influence preferences between buses and planes. These findings were further tested through logistic regression analysis.

Table 2. Distribution of Respondents Based on Income

Income	Bus	Airplane
≤ 5 million	49	25
> 5 million	29	25
No income yet	1	0
Others	44	33

Based on the cross-tabulation results as in Table 2, respondents with an income of ≤ 5 million rupiah per month tended to choose bus over airplane. This pattern shows that for lower income groups, affordability is a major factor in choosing a mode of transport. Conversely, among respondents with an income of > 5 million rupiah, the distribution of mode choice was relatively more balanced between buses and airplanes. This condition indicates that at higher income levels, price sensitivity tends to decrease, making mode choices more flexible.

Descriptively, income level shows a correlation with mode choice decisions, where economic factors play a role in shaping preferences between buses and planes.

Table 3. Distribution of Respondents Based on Purpose of Travel

Purpose of Travel	Bus	Airplane
Work Trip	80	45
Non-Work Trip	43	38

The cross-tabulation results as in Table 3 show that in the work trip segment, respondents preferred bus (38.8%) over airplane (21.85%). Meanwhile, in the non-work trip segment, the distribution of mode selection was relatively more balanced between buses (20.9%) and planes (18.45%). These findings indicate that the purpose of travel is related to the choice of mode of transport, with work trips tending to favor more economical modes, while non-work trips show more flexible preferences. This pattern forms the basis for a separate regression analysis to examine the differences in sensitivity between segments.

4.2. Logistic Regression

The following are the results of logistic regression tests on bus transportation modes.

Table 4. Results of Logistic Regression Analysis for Bus Mode Choice

Variables in the Equation							
		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Travel Time	-0.059	0.028	4.469	1	0.035	0.943
	Cost	-0.324	0.163	3.924	1	0.048	0.723
	Price	-0.579	0.284	4.170	1	0.041	0.560
	Frequency of Use	0.278	0.125	4.918	1	0.027	1.321
	Frequency of Departures	0.592	0.212	7.763	1	0.005	1.807
	Gender	0.789	0.367	4.622	1	0.032	2.200
	Income	-0.084	0.041	4.186	1	0.041	0.919
	Constant	-3.226	1.556	4.296	1	0.038	0.040

Based on the results of logistic regression testing in Table 4, in general, most independent variables have a significant effect on the decision to use bus because they have a significance value (Sig.) < 0.05. This shows that travel time, cost, price, frequency of use, frequency of departure, gender and income have an influence on the probability of someone choosing buses as a mode of transportation.

The travel time variable has a negative and significant effect (B = -0.059; Sig. = 0.035; OR = 0.943). This means that the longer the travel time, the lower the probability of choosing the bus. An odds ratio value of 0.943 indicates that every one-unit increase in travel time will reduce the probability of choosing the bus by 5.7%. This indicates that respondents tend to avoid buses if the travel time is longer.

The cost variable also has a negative and significant effect (B = -0.324; Sig. = 0.048; OR = 0.723). This means that the higher the travel cost, the lower the probability of choosing the bus. Each increase of one unit of cost reduces the probability of choosing the bus by 27.7%. The same applies to the price variable (B = -0.579; Sig. = 0.041; OR = 0.560), which indicates that the higher the price category, the less likely respondents are to choose the bus.

Conversely, frequency of use has a positive and significant effect (B = 0.278; Sig. = 0.027; OR = 1.321). This means that the more often someone uses this mode of transport, the greater the chance of choosing the bus by 32.1%. Similarly, departure frequency (B = 0.592; Sig. =

0.005; OR = 1.807) shows that the better the perception of departure frequency, the greater the chance of choosing the bus by 80.7%.

The gender variable also has a significant effect (B = 0.789; Sig. = 0.032; OR = 2.200). This means that the group coded as 1 is 2.2 times more likely to choose the bus than the reference group. Furthermore, the age of respondents had a negative and significant effect (B = -0.244; Sig. = 0.045; OR = 0.784), which means that the higher the age category, the likelihood of choosing the bus tends to decrease by 21.6%.

The income variable also showed a negative and significant effect (B = -0.084; Sig. = 0.041; OR = 0.919). This means that the higher the respondent's income, the lower the tendency to choose the bus. This indicates that respondents with higher incomes are likely to have other modes of transportation as alternatives.

The constant value of -3.226 indicates that when all independent variables are zero, the base probability of choosing the bus is relatively low. Overall, the model shows that cost, time, individual characteristics, and transport service attributes play an important role in influencing the decision to use the bus. Meanwhile, the following are the results of the logistic regression test on airplane.

Table 5. Results of Logistic Regression Analysis for Airplane Mode Choice

Variables in the Equation							
		B	**S.E.**	**Wald**	**df**	**Sig.**	**Exp(B)**
Step 1[a]	Travel Time	-0.063	0.033	3.600	1	0.058	0.938
	Cost	-0.367	0.187	3.846	1	0.050	0.693
	Price	-0.478	0.330	2.101	1	0.147	0.620
	Frequency of Use	0.276	0.140	3.880	1	0.049	1.318
	Frequency of Departures	0.538	0.254	4.479	1	0.034	1.713
	Gender	0.770	0.423	3.319	1	0.068	2.160
	Income	-0.062	0.048	1.640	1	0.200	0.940
	Constant	-3.226	1.774	3.305	1	0.069	0.040

Based on the results of logistic regression in Table 5, some independent variables show a significant effect on the decision to use Plane (Sig. < 0.05), while several other variables are insignificant or at the threshold of significance. This indicates that not all factors have the same degree of influence in determining respondents' choice of Plane mode.

The travel time variable has a negative coefficient (B = -0.063) with a significance value of 0.058, which is slightly above 0.05. This means that statistically, its influence is at the margin of significance. An odds ratio value of 0.938 indicates that the longer the travel time, the more likely the probability of choosing air travel decreases by 6.2%, although the effect is not very strong statistically.

The cost variable has a negative and significant effect (B = -0.367; Sig. = 0.050; OR = 0.693). This indicates that the higher the travel cost, the lower the probability of choosing to fly by 30.7%. In other words, cost is still an important consideration in choosing to fly. Unlike buses, the price variable for airplanes is not significant (Sig. = 0.147). This means that the price category is not statistically proven to influence the decision to use airplanes in this model.

The frequency of use variable has a positive and significant effect (B = 0.276; Sig. = 0.049; OR = 1.318). This indicates that the more frequently respondents use this mode of transport, the greater the chance of choosing airplanes by 31.8%. Similarly, departure frequency has a positive and significant effect (B = 0.538; Sig. = 0.034; OR = 1.713), which means that the better the perception of departure frequency, the greater the chance of choosing airplanes.

The gender variable has a significance value of 0.068, which is not significant at the 5% level but is close to significant. Meanwhile, the age of respondents has a negative and significant effect (B = -0.300; Sig. = 0.036; OR = 0.741), indicating that the higher the age category, the lower the chance of choosing air travel by 25.9%. This indicates that younger respondents tend to prefer air travel more than older respondents.

The income variable is not significant (Sig. = 0.200), so in this model, income level is not statistically proven to influence the choice of airplane. The constant value of -3.226 with a significance of 0.069 indicates that the base probability of choosing an airplane is relatively low when all independent variables are zero, and the constant is not significant at the 5% level.

It can be concluded that the decision to use airplanes is mainly influenced by cost, frequency of use, frequency of departure, age, private vehicle ownership, number of travel companions, reason for use, and ticket discounts. Ticket discounts and frequency of departure appear to be the strongest determinants in increasing the likelihood of choosing airplanes.

Although logistic regression provides information about the direction and significance of the influence of variables, further analysis is needed to determine the magnitude of the change in the probability of mode selection. Therefore, marginal effect calculations were performed to measure the contribution of each variable to the change in probability.

4.3. Marginal Effect

Based on calculations using the marginal effect formula, the following values were obtained for both modes of transport (bus & airplane constant = -3.226)

$$P = \frac{1}{1 + e^{3.226}}$$
$$e^{3.226} \approx 25.2$$
$$P = \frac{1}{26.2}$$
$$P = 0.038$$

Further, after determining the probability value, the marginal effect formula can be calculated as follows.

$$\begin{aligned} P(1-P) &= 0.038(1-0.038) \\ &= 0.038 \times 0.962 \\ &= 0.036556 = 0.0366 \end{aligned}$$

Table 6 presents the results of the marginal effect test on the choice of bus transportation mode.

Table 6. Results of Marginal Effect Test for Bus and Airplane Mode Choice

Variables	ME_{BUS} (k x 0.036)	$ME_{AIRPLANE}$ (0.038 k x 0.036)
Travel Time	-0.0022	-0.0023
Cost	-0.0119	-0.0134
Price	-0.0212	-0.0175
Frequency of Use	+0.0102	+0.0101
Frequency of Departures	+0.0217	+0.0197
Gender	+0.0289	+0.0282
Respondent Age	-0.0089	-0.0110
Income	-0.0031	-0.0023
Private Vehicle	+0.0231	+0.0217
Luggage	+0.0160	+0.0165
Travel Companions	+0.0119	+0.0141

Variables	ME_{BUS} (k x 0.036)	$ME_{AIRPLANE}$ (0.038 k x 0.036)
Reasons for Use	+0.0161	+0.0191
Bus Driver Characteristics	-0.0168	-0.0240
Ticket Discounts	+0.0268	+0.0329

In general, the marginal effect coefficient indicates the direction of influence on the probability of mode choice. Variables with negative values decrease the probability of mode choice, while positive values increase the probability. The magnitude of the number indicates how sensitive the probability is to a one-unit change in the variable. For the travel time variable, both modes show a very small negative effect (Bus = -0.0022; Airplane = -0.0023). This means that an increase in travel time slightly reduces the probability of choosing both modes, but the impact is relatively weak. This indicates that time is not the most dominant factor in respondents' decisions compared to other factors.

The cost and price variables both have a negative effect on both modes. However, cost is more sensitive for airplane (-0.0134) than bus (-0.0119), while price is more sensitive for buses (-0.0212) than airplanes (-0.0175). This shows that respondents tend to be more sensitive to price changes in bus services, while changes in operating costs have a greater impact on the choice of airplanes. In terms of frequency, both frequency of use and frequency of departure have a positive effect on both modes. The effect of departure frequency is relatively greater on buses (+0.0217) than on airplanes (+0.0197), indicating that more frequent schedules are a stronger attraction for bus users. Meanwhile, frequency of use has an almost equal effect on both modes (around +1%).

Demographic variables show interesting results. Gender has the largest positive effect on both modes (Bus = +0.0289; Airplane = +0.0282), making it one of the most dominant variables. This means that there is a significant tendency for certain gender groups to determine their choice of mode of transport. Meanwhile, the age of respondents has a negative effect on both modes, with a greater impact on airplanes (-0.0110) than buses (-0.0089), indicating that as age increases, the tendency to choose airplanes decreases slightly more than buses. The income variable has a small negative effect on both modes and is relatively weak.

In terms of travel characteristics, private vehicles have a significant positive effect on both modes (Bus = +0.0231; Airplane = +0.0217). This indicates that private vehicle ownership does not necessarily reduce the use of public transport, but rather reflects the high mobility of respondents. Luggage, travel companions, and reasons for use also have a positive effect on both modes, with a slightly greater impact on airplanes for the variables of travel companions and reasons for use. This indicates that social factors and travel purposes are more conducive to choosing airplanes over buses.

The service variable shows quite a striking difference. Bus driver characteristics have a negative effect on both modes, but the impact is much greater on airplanes (-0.0240) than on buses (-0.0168). This can be interpreted to mean that the better the bus driver characteristics, the greater the probability of choosing airplanes decreases, so that bus service quality becomes a competitive factor against airplanes. Conversely, ticket discounts have the most significant positive effect on air travel (+0.0329) compared to bus travel (+0.0268). This means that discount or price promotion policies are very strong factors in encouraging a shift in choice to air travel.

It can be concluded that the most dominant variables influencing mode choice are ticket discounts, gender, private vehicles, and departure frequency. Airplanes appear to be more sensitive to price promotions and the quality of competitor services (bus), while buses are more sensitive to price and departure frequency availability. This indicates that strategies to increase the competitiveness of both modes of transport need to focus on price and service factors, with different approaches according to the sensitivity characteristics of each mode.

The aggregate model results provide a general overview of user behavior, but do not fully capture the differences in characteristics based on travel purpose. Therefore, separate logistic regression estimates were performed on work and non-work travel segments to identify variations in the influence of travel attributes between user groups.

4.4. Separate regression for work and non-work

The results of the segmentation test for workers utilizing bus transportation are shown in Table 7.

Table 7. Results of Segmentation Test on Workers for Bus Mode Choice

Variables in the Equation							
		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Travel Time	-0.032	0.033	0.969	1	0.325	0.968
	Cost	-0.067	0.194	0.120	1	0.729	0.935
	Price	-0.484	0.321	2.272	1	0.132	0.616
	Frequency of Use	0.217	0.152	2.055	1	0.152	1.243
	Frequency of Departures	0.350	0.239	2.144	1	0.143	1.420
	Gender	0.586	0.432	1.837	1	0.175	1.796
	Age of Respondents	-0.186	0.142	1.733	1	0.188	0.830
	Income	-0.052	0.049	1.157	1	0.282	0.949
	Private Vehicle	0.560	0.290	3.720	1	0.054	1.751
	Luggage	0.640	0.265	5.858	1	0.016	1.897
	Travel Companions	0.318	0.218	2.114	1	0.146	1.374
	Reasons for Use	0.487	0.266	3.343	1	0.067	1.628
	Bus Driver Characteristics	-0.398	0.265	2.252	1	0.133	0.671
	Ticket Discounts	0.344	0.414	0.689	1	0.406	1.410
	Constant	-3.407	1.861	3.353	1	0.067	0.033

The main variable that is the focus of segmentation, namely cost, has a negative coefficient of -0.067 with a significance value of 0.729 (>0.05). This shows that in the work travel segment, changes in cost do not have a significant effect on the probability of choosing the bus. In other words, users who travel for work tend not to be very sensitive to fare changes. Behaviorally, this can be explained by the fact that work travel is routine and mandatory, so the certainty of reaching the destination is more dominant than price considerations.

The travel time variable also has a negative effect (-0.032) but is not significant (0.325). This indicates that in the context of work travel, additional travel time does not significantly reduce the probability of choosing the bus. This condition may indicate that users have adjusted their travel schedules so that their tolerance for time is relatively greater as long as the mode of transport remains reliable.

Interestingly, the statistically significant variable is luggage (B = 0.640; Sig. = 0.016). The Exp(B) value of 1.897 indicates that respondents with certain luggage characteristics are nearly 1.9 times more likely to choose the bus than those without. This indicates that on work trips, the need to carry items (e.g., work equipment or documents) is an important factor in choosing a mode of transport.

The variables of private vehicle (Sig. = 0.054) and reason for use (Sig. = 0.067) were at a marginal level of significance (close to 10%). Private vehicles had a positive coefficient (0.560), indicating that individuals who owned private vehicles still had the opportunity to choose buses, possibly due to considerations of parking cost efficiency or traffic congestion.

Meanwhile, positive reasons for use indicate that certain motivations for choosing a mode of transport are still relevant in the work segment, although their influence is not as strong as the variable of luggage.

Service variables such as bus driver characteristics, departure frequency, and ticket discounts are not significant in this segment. This shows that commuters tend to be less responsive to price promotions or improvements in additional service attributes. Their main focus is likely to be the regularity and certainty of travel. A constant value of -3.407 with a significance of 0.067 indicates that the base probability of choosing the bus for work travel is relatively low when all independent variables are zero, but the constant is not significant at the 5% level.

Overall, the segmentation results show that business travelers have different behavioral characteristics compared to the aggregate model. Cost sensitivity in this segment is very low and insignificant, indicating that business travel is inelastic to fare changes. A more influential factor is functional aspects such as the need to carry goods. These findings support the hypothesis that the purpose of travel influences response patterns to transport attributes, so that fare and service policy approaches should be differentiated between work and non-work segments.

Meanwhile, the results of the segmentation test for non-workers utilizing bus transportation are shown in Table 8.

Table 8. Results of Segmentation Test on Non-Workers for Bus Mode Choice

Variables in the Equation							
		B	**S.E.**	**Wald**	**df**	**Sig.**	**Exp(B)**
Step 1[a]	Travel Time	-0.348	0.235	2.192	1	0.139	0.706
	Cost	-4.702	2.735	2.956	1	0.086	0.009
	Price	-1.392	2.398	0.337	1	0.562	0.249
	Frequency of Use	3.014	1.850	2.654	1	0.103	20.365
	Frequency of Departures	4.017	2.732	2.162	1	0.141	55.561
	Gender	9.285	4.978	3.480	1	0.062	10779.404
	Age of Respondents	-1.240	0.837	2.196	1	0.138	0.289
	Income	-0.435	0.302	2.078	1	0.149	0.647
	Private Vehicle	4.071	2.559	2.530	1	0.112	58.632
	Luggage	-2.313	1.453	2.535	1	0.111	0.099
	Travel Companions	0.914	0.930	0.966	1	0.326	2.494
	Reasons for Use	2.984	2.332	1.637	1	0.201	19.758
	Bus Driver Characteristics	-1.718	1.683	1.042	1	0.307	0.179
	Ticket Discounts	7.067	4.256	2.757	1	0.097	1172.435
	Constant	-22.767	19.174	1.410	1	0.235	0.000

In general, the segmentation results for the non-work group show much larger coefficients (both positive and negative) than the work segment. This indicates that the behavior of non-work users tends to be more volatile and more sensitive to changes in travel attributes. However, most variables are not statistically significant at the 5% level, which is likely due to the smaller sample size or high data variation in this segment.

The main focus of segmentation is the cost variable, which has a very large negative coefficient (-4.702) with a significance value of 0.086. Although not significant at the 5% level, this variable is significant at the 10% level, so it can be said to have a fairly strong practical influence. The Exp(B) value of 0.009 indicates that a drastic increase in cost reduces the likelihood of choosing the bus. This means that non-work users are much more sensitive to fare changes than work trip users. This is in line with transport behavior theory, where non-work trips (tourism, recreation, social visits) are more elastic to price.

The travel time variable has a negative effect (-0.348), but is not significant (0.139). This indicates that although there is a tendency for the probability of choosing the bus to decrease as travel time increases, the effect is not yet statistically significant. For non-work travel, time may be more flexible than for work travel.

Several variables show very large coefficients, such as departure frequency (B = 4.017), frequency of use (B = 3.014), and especially gender (B = 9.285) and ticket discounts (B = 7.067). Although the significance values are in the range of 0.06–0.14 (marginally significant at 10%), the magnitude of the coefficients and odds ratios (Exp(B)) indicates a potentially very strong effect. For example, Exp(B) for ticket discounts of 1172.435 shows that price promotions can drastically increase the likelihood of choosing buses in the non-work segment. This reinforces the finding that non-working users are highly responsive to discounts and price incentives.

In contrast to the working segment, the luggage variable in the non-working segment has a negative coefficient (-2.313), although it is not significant. This may indicate that on non-work trips, carrying certain items may actually reduce the tendency to choose the bus, possibly due to higher comfort preferences.

The very large and negative constant value (-22.767) with a significance of 0.235 indicates that the base probability of choosing the bus in the non-work segment is very low when all independent variables are zero. However, because it is not significant and has a very large standard error, these results need to be interpreted with caution. The magnitude of the coefficients and standard errors for some variables may also indicate possible data issues, such as small sample sizes or quasi-separation in the logistic model.

When compared to the work segment, there are clear differences in behavior. For work trips, the cost variable is insignificant and its effect is small, indicating a relatively inelastic nature. Conversely, for non-work trips, cost has a much greater and marginally significant effect, indicating high sensitivity to fares. Thus, the purpose of the trip is shown to influence the characteristics of user response to transport attributes.

Overall, these segmentation results indicate that fare policies and price promotions would be more effective when applied to the non-work segment, while in the work segment, improvements in functional aspects and service certainty tend to be more relevant than price discount strategies. Table 9 reports the results of the segmentation test for workers who travel by airplane.

Table 9. Results of Segmentation Test on Workers for Airplane Mode Choice

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Travel Time	-0.085	0.043	3.823	1	0.051	0.919
	Cost	-0.473	0.228	4.309	1	0.038	0.623
	Price	-0.493	0.406	1.480	1	0.224	0.611
	Frequency of Use	0.176	0.159	1.212	1	0.271	1.192
	Frequency of Departures	0.817	0.319	6.566	1	0.010	2.263
	Gender	0.486	0.501	0.940	1	0.332	1.626
	Age of Respondents	-0.511	0.190	7.231	1	0.007	0.600
	Income	-0.017	0.059	0.086	1	0.769	0.983
	Private Vehicle	0.575	0.330	3.040	1	0.081	1.777
	Luggage	0.324	0.309	1.101	1	0.294	1.383
	Travel Companions	0.339	0.234	2.096	1	0.148	1.404

Variables in the Equation						
	B	S.E.	Wald	df	Sig.	Exp(B)
Reasons for Use	0.610	0.302	4.078	1	0.043	1.840
Bus Driver Characteristics	-0.532	0.340	2.456	1	0.117	0.587
Ticket Discounts	1.557	0.540	8.316	1	0.004	4.746
Constant	-3.430	2.169	2.502	1	0.114	0.032

In general, the results of this segmentation show that in business travel, the choice of Plane is significantly influenced by cost, frequency of departure, respondent age, reason for use, and ticket discounts. In contrast to the bus segment, which is relatively less sensitive to cost, economic variables play an important role in the Plane segment.

The cost variable has a negative coefficient of -0.473 with a significance of 0.038 (<0.05), which means it is statistically significant. The Exp(B) value of 0.623 indicates that every increase in cost will reduce the probability of choosing air travel by around 37.7% (1 – 0.623). This indicates that even though work travel is mandatory, users still consider fares when choosing air travel, mainly because the price difference between air travel and other modes is usually quite large.

The travel time variable also has a negative effect (-0.085) with a significance value of 0.051, which is marginally significant at the 10% level. This means that the longer the travel time, the less likely people are to choose air travel. This is in line with the characteristics of business travel, which demands time efficiency. One of the most significant variables is departure frequency (B = 0.817; Sig. = 0.010). The Exp(B) value of 2.263 indicates that an increase in departure frequency significantly increases the likelihood of choosing air travel by more than double. This confirms that schedule flexibility is very important for business travelers.

The age of the respondent has a negative and significant effect (B = -0.511; Sig. = 0.007). Exp(B) of 0.600 indicates that as age increases, the probability of choosing air travel decreases. This can be interpreted as younger age groups tending to prefer air travel for business trips compared to older age groups. In addition, the reason for use (B = 0.610; Sig. = 0.043) is also significant, with Exp(B) of 1.840. This shows that specific motivations or purposes in choosing a mode of transport greatly influence the decision to use air travel for business trips.

The variable with the strongest influence is ticket discounts (B = 1.557; Sig. = 0.004). The Exp(B) value of 4.746 indicates that the existence of discounts increases the likelihood of choosing air travel almost fivefold. This shows that even in business travel, discount policies or corporate pricing are very effective in encouraging the selection of air travel. Meanwhile, variables such as income, gender, luggage, and travel companions do not show a significant influence in this segment. This indicates that the decision to travel by air for business is determined more by efficiency and fare policies than by socio-demographic characteristics.

A constant value of -3.430 with a significance of 0.114 indicates that the base probability of choosing air travel is relatively low when all independent variables are zero, but the constant is not significant. It can be concluded that compared to the bus business segment, the air travel business segment shows higher sensitivity to cost, departure frequency, and price promotions. This means that for the business travel market, strategies to increase schedule frequency and discount policies will be more effective in improving the competitiveness of air travel than simply improving other service attributes. Table 10 presents the results of the segmentation test for non-workers who use airplane transportation.

Table 10. Results of Segmentation Test on Non-Workers for Bus Mode Choice

Variables in the Equation							
		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Travel Time	-0.227	0.114	3.934	1	0.047	0.797
	Cost	0.710	0.789	0.811	1	0.368	2.034
	Price	-0.736	1.155	0.406	1	0.524	0.479
	Frequency of Use	1.192	0.610	3.821	1	0.051	3.294
	Frequency of Departures	0.277	0.674	0.169	1	0.681	1.319
	Gender	0.631	1.311	0.232	1	0.630	1.880
	Age of Respondents	0.557	0.512	1.184	1	0.277	1.746
	Income	-0.218	0.144	2.311	1	0.129	0.804
	Private Vehicle	1.866	1.153	2.622	1	0.105	6.465
	Luggage	1.681	1.204	1.951	1	0.162	5.371
	Travel Companions	2.001	1.028	3.792	1	0.051	7.400
	Reasons for Use	1.956	1.449	1.823	1	0.177	7.073
	Bus Driver Characteristics	-1.353	0.747	3.282	1	0.070	0.258
	Ticket Discounts	-2.234	1.552	2.072	1	0.150	0.107
	Constant	-9.054	7.128	1.613	1	0.204	0.000

In general, these results indicate that non-work users' behavior in choosing airplane tends to be more influenced by social factors and travel characteristics than purely economic factors such as cost. Several variables show statistical significance and marginal significance at the 10% level, indicating a certain sensitivity in this group. The travel time variable has a negative coefficient of -0.227 with a significance of 0.047 (<0.05), making it statistically significant. The Exp(B) value of 0.797 indicates that each increase in travel time reduces the probability of choosing an airplane by approximately 20.3%. This means that on non-work trips, although they are more flexible than work trips, time efficiency remains an important consideration in choosing air travel.

In contrast to the work segment, the cost variable in non-work trips is not significant (Sig. = 0.368) and has a positive coefficient (0.710). Although the direction of the effect shows a tendency for the probability of choosing air travel to increase as costs rise, this result is not significant and should be interpreted with caution. This may indicate that for certain non-work trips (e.g., tourism), users are willing to pay more for comfort or a better experience. The frequency of use variable has a positive coefficient (1.192) with a marginal significance of 0.051. The Exp(B) value of 3.294 indicates that respondents who use a particular mode more frequently are approximately 3.3 times more likely to choose air travel. This indicates a habit effect in the choice of non-work modes.

The social variable shows a fairly strong influence. Travel companions have a positive coefficient of 2.001 with a marginal significance of 0.051 and an Exp(B) of 7.400. This means that travelling with friends significantly increases the chance of choosing air travel by almost seven times. This shows that on non-work trips, social factors and group comfort play a significant role. The private vehicle variable also has a large coefficient (1.866) with a significance of 0.105 (marginal at 10%). The Exp(B) value of 6.465 indicates that individuals who own private vehicles still have a high probability of choosing air travel, possibly due to higher mobility and purchasing power.

Interestingly, the bus driver characteristics variable has a negative effect with marginal significance (0.070). The Exp(B) value of 0.258 indicates that improving bus service quality can reduce the likelihood of choosing air travel. This indicates a fairly strong mode substitution in the non-work segment. Conversely, the ticket discount variable has a negative coefficient (-2.234) and is not significant (0.150). This negative direction indicates that in the non-work sample, ticket discounts do not always encourage the choice of airplanes, possibly because recreational travel preferences are more influenced by factors such as experience, flexibility, or other alternative modes of transport.

The constant value of -9.054 with a significance of 0.204 indicates that the base probability of choosing air travel is relatively low when all independent variables are zero, but it is not statistically significant. It can be concluded that compared to the business segment for air travel, the non-business segment shows a different pattern. For work travel, cost and ticket discounts are very significant, while for non-work travel, social factors such as travel companions and usage habits are more dominant. This indicates that Plane marketing strategies for the non-work segment should emphasize group travel experiences and ease of access, while for the work segment, price strategies and increased schedule frequency are more effective.

The difference in coefficients between segments shows that there are variations in user sensitivity to travel attributes, especially cost. To measure this level of response quantitatively, an elasticity analysis was conducted as an indicator of the sensitivity of mode choice probability to changes in travel costs.

4.5. Elasticity Analysis (Own Elasticity)

The following are the results of elasticity calculations for workers who use air transport.

$$E = \beta \times X \times (1 - P)$$
$$E = -0.473 \; x \; 1 \; x \; 0.962$$
$$E = -0.455$$

An elasticity value of -0.455 indicates that demand is inelastic ($|E| < 1$). This means that every 1% increase in cost will reduce the probability of choosing air travel by 0.455%. This indicates that workers are relatively insensitive to changes in airfare prices, possibly because business travel is mandatory, so that time and work requirements are more dominant than cost. The following are the results of elasticity calculations for non-workers who use airplane as travel mode.

$$E = \beta \times X \times (1 - P)$$
$$E = 0.710 \; x \; 1 \; x \; 0.962$$
$$E = 0.683$$

In the non-working segment that uses airplanes, an elasticity value of 0.683 was obtained. In terms of magnitude, this value also indicates inelastic conditions. However, the positive sign indicates an unusual relationship in theory, namely that an increase in costs actually increases the probability of choosing airplanes. These results need to be interpreted with caution because the cost coefficient in the previous model was not statistically significant, so the effect of cost on the choice of airplane in the non-working segment is not strong enough to be used as a basis for policy making. The following are the results of elasticity calculations for workers who use bus as travel mode.

$$E = \beta \times X \times (1 - P)$$
$$E = -0.067 \; x \; 1 \; x \; 0.962$$
$$E = -0.064$$

The results of bus mode for the worker segment, an elasticity value of -0.064 was obtained. This value indicates highly inelastic demand, where a 1% increase in cost only reduces the probability of choosing the bus by 0.064%. This condition indicates that bus-using workers are almost unresponsive to fare changes, possibly due to limited alternative modes of transport or because the bus is the primary choice for commuting. The following are the results of elasticity calculations for non-workers who use bus as transportation mode.

$$E = \beta \times X \times (1 - P)$$
$$E = -4.702 \; x \; 1 \; x \; 0.962$$
$$E = -4.524$$

Meanwhile, in the non-working segment that uses buses, the elasticity value obtained is -4.524. This value indicates highly elastic demand because the absolute value of elasticity is greater than one (E>1). This means that a 1% increase in cost will reduce the probability of choosing buses by 4.524%. This shows that the non-working group is very sensitive to changes in bus fares and tends to switch to other modes of transport when prices increase.

The difference in coefficients between segments shows variations in user sensitivity to travel attributes, particularly cost. To measure this level of response quantitatively, an elasticity analysis was conducted as an indicator of the sensitivity of mode choice probability to changes in travel costs.

4.6. Comparison of Travel Destination Segments

After conducting separate logistic regression estimates and elasticity calculations for each segment, the next step is to compare the sensitivity characteristics of mode choice based on travel purpose. This comparison aims to identify differences in behavior between work and non-work travel segments in response to changes in service attributes, particularly travel costs.

Table 11. Comparison of Travel Destination Segments

Mode	Work segment	Non-Work Segment	Behavioral Characteristics	Service Implications
Bus	Inelastic	Elastic	Work-related travel is relatively insensitive to fares, while non-work-related travel is sensitive to price changes.	Effective pricing strategies in the non-work segment, while increased comfort and punctuality are important for the work segment
Airplane	Tends to be inelastic	Sensitivity is unstable	Plane users in the work segment have high mobility needs, while those in the non-work segment are influenced by promotional factors and service perceptions.	Improved reliability is important for the work segment, while promotion and service differentiation are effective in the non-work segment

The table 11 shows that there are differences in sensitivity characteristics between work and non-work travel segments. In the work segment, both buses and airplanes tend to exhibit inelastic behavior, indicating that mobility needs are more essential. Conversely, in the non-work segment, particularly for buses, higher elasticity levels indicate that users are more responsive to fare changes.

These findings confirm that segmenting travel purposes is important in understanding the heterogeneity of user behavior. Differences in elasticity between segments indicate that service improvement strategies cannot be standardized, but rather need to be tailored to the characteristics of users' travel.

4.7. Service Implications

The results of the elasticity comparison show that user sensitivity characteristics differ based on travel purpose. This finding aligns with previous research demonstrating that traveler segmentation based on trip purpose reveals significant heterogeneity in mode choice behavior and price responsiveness (Yang et al., 2025).

In the work travel segment, users tend to exhibit relatively stable behavior towards cost changes, so that service improvements are more effectively focused on reliability, punctuality, and comfort. This stability can be attributed to habitual behavior and inertia effects commonly observed among commuters, who tend to maintain consistent travel patterns once established (Ortega & Link, 2025). Research by Ortega and Link (2025) found that car commuters exhibit significant inertia, making them less likely to change travel modes despite price interventions. Similarly, work travelers using public transport display lower sensitivity to cost changes as their mode choice is driven more by schedule adherence and reliability than by fare variations (Nala et al., 2024; Qiu et al., 2025).

Conversely, in the non-work travel segment, higher sensitivity to costs indicates that pricing strategies, promotions, and service flexibility have the potential to be more influential in affecting mode choice decisions. This is consistent with findings from Yang et al. (2025), who demonstrated that non-commute trips such as leisure, shopping, social activities exhibit greater responsiveness to fare adjustments and promotional policies. Non-work travelers are more likely to be choice riders who evaluate multiple mode alternatives and make decisions based on perceived value rather than habit (Salazar-Serna et al., 2024).

These findings indicate that improvements in transport services cannot be applied uniformly, but need to be tailored to the characteristics of users' travel needs. This supports the market segmentation approach advocated by recent transportation research, which emphasizes that understanding user value heterogeneity is essential for designing effective retention and service improvement strategies (Yang et al., 2025).

4.8. Policy Simulation (Indicative)

Based on the results of the marginal effect analysis, as part of the discussion of the research results, the indicative policy simulation shows that policies focused on adjusting ticket costs have the potential to have a greater impact on mode choice than policies that only focus on reducing travel time. This finding is corroborated by Hensher et al. (2025), who systematically assessed push and pull transport policy initiatives and found that combined policy interventions particularly those involving fare adjustments produce significantly different elasticity effects compared to stand-alone policies. Their research demonstrated that policies combining fare changes with other measures such as service frequency improvements yield higher behavioral responses than any single policy alone (Hensher et al., 2025).

In addition, improvements in punctuality and service comfort also have the potential to increase the attractiveness of modes of transport. This aligns with Salazar-Serna et al. (2024), who found that in developing country contexts, factors such as safety, comfort, and personal security significantly influence mode choice decisions across different socioeconomic groups. Their agent-based simulations revealed that multifaceted policy approaches addressing diverse user preferences are more effective than single-dimensional interventions (Salazar-Serna et al., 2024).

This simulation is illustrative and is used as a basis for policy discussion. However, it is important to note that the effectiveness of these policy interventions may vary depending on local contextual factors, including income distribution, availability of alternative modes, and cultural attitudes toward public transport (Salazar-Serna et al., 2024; Qiu et al., 2025). Future policy design should consider integrating multiple intervention types such as fare subsidies combined with frequency improvements and enhanced security) to achieve meaningful modal shifts (Hensher et al., 2025).

5. Conclusion

The results of the study indicate that the choice of transport mode on the Palembang-Jakarta route is significantly influenced by ticket prices, comfort levels, and punctuality, with ticket prices being the most dominant factor. The variables of travel time and frequency of travel did not show a significant influence, meaning that travel decisions are more influenced by economic considerations and service quality. An analysis of travel destination segmentation reveals different behaviors between segments which are business travelers tend to be stable and inelastic to fare changes, while non-business travelers are more sensitive, especially to changes in bus prices. These findings confirm that strategies to improve transport services need to be tailored to the characteristics of users' journeys, including segment-based fare adjustments, improved comfort and facilities, enhanced punctuality, and specific service approaches according to travel destination.

This study has several limitations, including a sample limited to a specific region, the use of a closed questionnaire that did not fully explore the reasons behind respondents' choices, a focus on limited variables, and a short research period that did not reflect seasonal dynamics. Therefore, further research should involve a broader sample, use mixed methods such as interviews or group discussions, include additional variables such as service quality, comfort, safety, and infrastructure conditions, and be conducted over a longer period to capture seasonal variations. In addition, comparing results across different modes of transport or regions will provide a more comprehensive perspective and strengthen the relevance of the findings.

6. References

Ariansyah, K., Dwi Takariani, C. S., Sari, D., Setiawan, A. B., Budhirianto, S., Ardison, Nugroho, A. C., Hidayat, D., & Hikmaturokhman, A. (2025). Transportation accessibility for people with disabilities: Examining preferences for conventional public transport and ride-hailing services in Indonesia. *Case Studies on Transport Policy*, *20*, 101451. https://doi.org/10.1016/j.cstp.2025.101451

BPS. (2024). *Provinsi Sumatera Selatan Dalam Angka 2024*. https://sumsel.bps.go.id/id/publication/2024/02/28/24b0b0a6676d1d095ab88ce2/provinsi-sumatera-selatan-dalam-angka-2024.html

Hensher, D., Wei, E., & Liu, W. (2025). Systematic Assessment of Push and Pull Initiatives in Behavioural Responses Associated with Public Transport Fares, Service Frequency, Car-Related Tolls, Distance-Based Road User Charges, and Parking Charges. *Case Studies on Transport Policy*, *23*, 101656. https://doi.org/10.2139/ssrn.5117118

McFadden, D. (1974). The measurement of urban travel demand. *Journal of Public Economics*, *3*(4), 303–328. https://doi.org/10.1016/0047-2727(74)90003-6

Meixell, M. J., & Norbis, M. (2008). A review of the transportation mode choice and carrier selection literature. *The International Journal of Logistics Management*, *19*(2), 183–211. https://doi.org/10.1108/09574090810895951

Morlok, E. K. (1978). *Introduction to transportation engineering and planning*. McGraw-Hill.

Nala, D. D. O., Hardati, R. N., & Trianti, K. (2024). The Influence of Price, Service Quality, and Promotion on the Decision to Use GrabBike Services in Malang City: (A Study on Students of the Faculty of Administrative Sciences at Islamic University of Malang Who Use Grab Online Transportation). *Journal of International Accounting, Taxation and Information Systems*, *1*(2), 84–94. https://doi.org/10.70865/jiatis.v1i2.55

Ortega, M. F. G., & Link, H. (2025). Mode choice inertia and shock: Three months of almost fare-free public transport in Germany. *Economics of Transportation*, *41*, 100382. https://doi.org/10.1016/j.ecotra.2024.100382

Qiu, G., Li, T., & Guan, T. (2025). Analysing Mode Choice Behaviour in a Multi-modal Commuting System with Customised Bus Services. *Journal of Transport Economics and Policy*, *59*(2), 85–109. https://doi.org/10.3828/jtep.2025.59.2.85

Reck, D. J., & Axhausen, K. W. (2020). How Much of Which Mode? Using Revealed Preference Data to Design Mobility As a Service Plans. *Transportation Research Record: Journal of the Transportation Research Board*, *2674*(7), 494–503. https://doi.org/10.1177/0361198120923667

Salazar-Serna, K., Cadavid, L., & Franco, C. J. (2024). Modeling Urban Transport Choices: Incorporating Sociocultural Aspects. *2024 Winter Simulation Conference (WSC)*, 146–157. https://doi.org/10.1109/WSC63780.2024.10838860

Saleh, S., Apriandy, F., Sugiarto, S., Lulusi, L., & Salmannur, A. (2022). Investigating the determinants of travel mode choice across age classes in Langsa, Indonesia utilizing logit model. *Journal of Applied Engineering Science*, *20*(2), 511–522. https://doi.org/10.5937/jaes0-34044

Saputri, F. A. A., Patriadi, A., & Tjendani, H. T. (2025). VISSIM Modeling and Simulation to Optimize the Performance of the Blimbing Ngoro Three-Way Intersection in Jombang Regency. *INTERNATIONAL JOURNAL ON ADVANCED TECHNOLOGY, ENGINEERING, AND INFORMATION SYSTEM*, *4*(2), 315–328. https://doi.org/10.55047/ijateis.v4i2.1742

Tamin, O. Z. (1997). Public transport demand estimation by calibrating a trip distribution-mode choice (TDMC) model from passenger counts: A case study in Bandung, Indonesia. *Journal of Advanced Transportation*, *31*(1), 5–18. https://doi.org/10.1002/atr.5670310103

Yang, C., Dong, W., Yuan, Q., Cao, R., & Yu, C. (2025). Integrating user values assessment with the augmented RFM model to enhance bus transit systems' market segmentation. *Transport Policy*, *171*, 50–62. https://doi.org/10.1016/j.tranpol.2025.05.028

Zein, F. H., Muhammadun, H., & Marleno, R. (2024). Comparative Analysis of Road Network Simulation Model Performance of Pahlawan Road Area. *International Journal of Social Science and Community Service*, *2*(2), 67–75. https://doi.org/10.70865/ijsscs.v2i2.22

Zhou, Y., Wang, P., Zheng, S., Zhao, M., Lam, W. H. K., Chen, A., Sze, N. N., & Chen, Y. (2024). Modeling dynamic travel mode choices using cumulative prospect theory. *Transportation Research Part A: Policy and Practice*, *179*, 103938. https://doi.org/10.1016/j.tra.2023.103938