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Modeling Tourist Transportation Mode Choice and Trip Chains Through Key Influencing Factors

Indriaty Wulansari [1*], Sumarni Hamid Aly [1], M. Isran Ramli [1], Muralia Hustim [1]

[1] *Department of Civil Engineering, Faculty of Engineering, Universitas Hasanuddin, Gowa, 92171, Indonesia.*

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Abstract

To understand tourist behavior and the factors influencing it, a thorough analysis of transportation mode choice and trip chain is required, especially from the tourists' perspective. Therefore, this study aims to model transportation mode choice and trip chain in the Bira Peninsula, Bulukumba Regency, South Sulawesi. To achieve this, a quantitative method was employed with a sample size of 500 tourists. The study results show that independent variables significantly impact dependent variables, such as individual characteristics, movement characteristics, destination attributes, mode choice attributes, and trip chains. Several indicators showed a significant influence for transportation mode choice with a confidence level of over 85%. These indicators include age, income, origin location, destination location, number of visits, group size, flexibility, facilities, ease of access, activity type, cost, distance, time, and safety. Similarly, the analysis identified several key indicators affecting the trip chain, with a significance level above 85%. These indicators include age, income, origin, destination location, estimated arrival time, number of visits, flexibility, and destination attraction. Other indicators include facilities, ease of access, trip purpose, activity type, travel time, distance from the city center to the tourist destination, cost, distance, time, and safety. Two significant indicators found as differentiators from previous research are flexibility and type of activity. The study demonstrated high accuracy for the mode choice model and the trip chain model, with validity rates of 98.40% and 97.65%, respectively. The findings indicate that the model accurately captures the factors influencing transportation mode choice and trip chains, making it a valuable reference for future explorations to improve transportation systems' efficiency and comfort.

Keywords: Mode Selection; Trip Chain; Individual Characteristics; Movement Characteristics; Destination Attributes.

1. Introduction

The growth of the tourism sector has transformed social, economic, cultural, and environmental aspects of life. Specifically, local tourism has created job opportunities and contributed to national income growth [1, 2]. However, the success of tourism as a driver of regional development heavily depends on the availability of accessible and efficient transportation infrastructure. In general, infrastructure is crucial in facilitating smooth mobility, making it a primary requirement for regional tourism growth [3, 4]. As the foundation of the tourism industry, transportation plays a vital role in the expansion and sustainability of tourism. Therefore, ensuring adequate infrastructure to support tourist mobility is essential for a seamless travel experience. To achieve this goal, local governments must prioritize the availability of reliable road transportation services, which are critical to building a comprehensive tourism transportation system [5, 6].

One of the tourist destinations in Indonesia with remarkable potential is the Bira Peninsula, located in Bontobahari District, Bulukumba Regency, South Sulawesi, Indonesia. This destination is accessible by private or public transportation

* Corresponding author: indriaty.wulansari@gmail.com; wulansarii21d@student.unhas.ac.id

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from Makassar City. The peninsula is approximately 250 kilometers from the city, with a travel time of about 3 hours and 30 minutes. Spanning around 10 kilometers in length and 5 kilometers in width, the Bira Peninsula is renowned for its stunning white sandy beaches, crystal-clear seawater, and pristine natural scenery. This area is home to several significant tourist attractions, including the zero point of Sulawesi, a monument at the southernmost tip of the Bira Peninsula that symbolizes the southernmost point of Sulawesi Island. Additionally, visitors can explore the Bira Terrace, a 50-meter-high observation deck offering beautiful views of the open sea and activities at Bira Harbor. Meanwhile, the Bira Glass Bridge, a 50-meter-long structure standing 10 meters above the sea, provides a unique and fascinating experience. Despite its attractions, previous research indicates a relatively low annual growth in room occupancy compared to the increasing number of visitors, potentially leading to a decline in overall occupancy rates [7]. Another study reveals that 35% of tourists were satisfied with the quality and variety of food, while 44% felt personally safe. High satisfaction was reported regarding accommodation prices and historical and cultural sites. However, only 33% considered shopping facilities adequate. Additionally, 41% expressed high satisfaction with environmental quality and security, and 37% reported overall satisfaction with their experiences [8]. The specific location map considered in this study is shown in Figure 1.

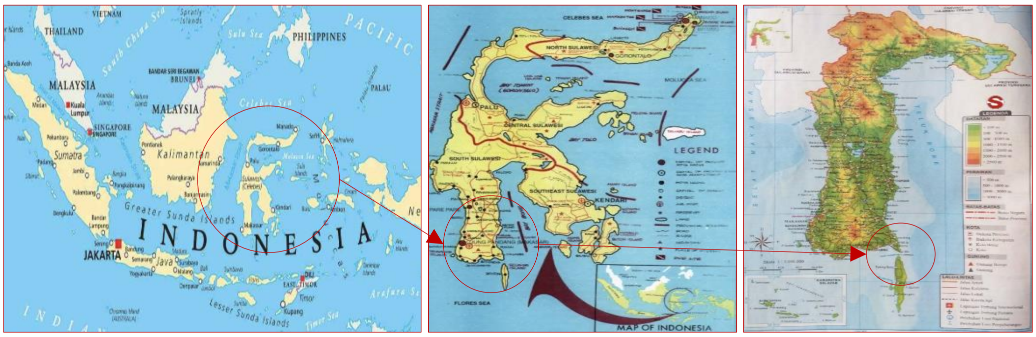


Figure 1. Research location (Bira Peninsula, located in Bontobahari District, Bulukumba Regency, South Sulawesi, Indonesia)

Previous research on tourist transportation modes has been conducted in various countries, exploring factors influencing tourists' preferences and decision-making in selecting transportation modes [9]. Studies on trip chains have introduced innovative methods that link tourist characteristics with travel attributes, connecting travel time and costs to the trip chain [10]. Other research highlights that understanding the final decision-making process in tourist behaviour is crucial to identifying what influences tourists' choices. This process is essential for planning, developing appropriate tourism marketing strategies, preparing infrastructure, managing traffic and accessibility, and ensuring environmental management. Coordinated planning is expected to help achieve a match between market expectations and the tourism products being developed. Tourists travel behavior, mode planning, and monitoring related to accessibility and mobility control measures to and within tourism destinations also serve as a guideline for developing tourism regulations for destinations with multiple attractions [11].

Based on a review of several previous studies, it was found that the majority of research focuses only on a single aspect, either mode choice modelling or trip chain modelling separately, and tends to use one specific method, such as multiple regression, SEM-PLS (Structural Equation Modeling Partial Least Squares), MNL (Multinomial Logit), MMNL (Mixed Multinomial Logit), MLE, AHP, Amos, or Nested Logit [4, 5, 9, 10, 12-16]. These studies generally do not comprehensively discuss simultaneously integrating mode choice and trip chain models. Moreover, the reliability testing of instruments, such as indicator validity testing and reliability testing, and the detection of multicollinearity symptoms among indicators is often not systematically conducted as an initial step before modeling mode choice and trip chains. To address this gap, the researchers propose a study approach that integrates mode choice and trip chains using two analytical methods, SEM-PLS and MNL. SEM-PLS is used in the initial stage to test the validity and reliability of each indicator, ensuring that the indicators employed effectively explain the constructs being measured and assess multicollinearity among the indicators to avoid bias in subsequent modelling. MNL (Multinomial Logit) is utilized to analyze the significance level of each indicator in influencing mode choice and trip chain decisions and to evaluate the extent to which each indicator contributes significantly to the travel decision-making process. This approach is expected to provide a more comprehensive understanding of the relationship between mode choice and trip chains while ensuring that the research instruments have undergone adequate reliability testing. As a result, this study aims to refine previous models and make a significant contribution to advancing research in the field of transportation [17-19].

Analyzing transportation modes and trip chains serves various purposes, including understanding tourist behavior, improving the quality of tourism products and services, and reorganizing existing policies. Modeling tourists travel behavior is more complex than daily mobility [15, 20]. Therefore, this study aims to identify factors influencing tourists' decisions based on preference analysis to determine significant indicators for mode choice and trip chains. These findings are crucial for future researchers, policymakers, transportation operators, and the tourism industry to enhance services and improve the overall tourist experience. The structure of the article is presented in Figure 2.

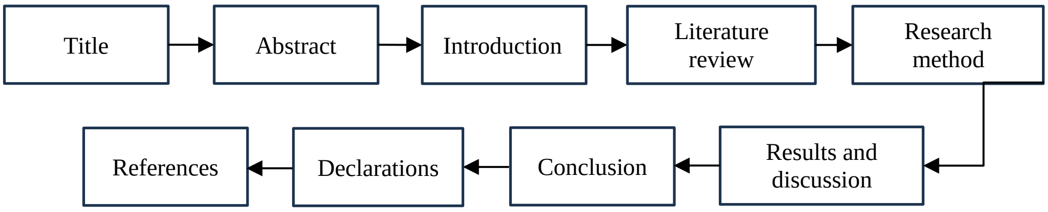


Figure 2. Article Structure

2. Literature Review

2.1. Tourist Characteristics

Understanding tourist characteristics is essential for effective tourism development, as it enables tourism stakeholders to design and deliver products and services tailored to tourists' specific needs and preferences. These characteristics influence tourist behavior at various stages, including planning, execution, and evaluation. In the context of this study, key tourist characteristics include gender, age, education, occupation, marital status, and income [21].

2.2. Movement Characteristics

Movement characteristics encompass all aspects that define mobility, including destination, time, distance, transportation mode, and trip chain patterns. Transportation planners rely on these characteristics to understand movement patterns and design more efficient, effective, and sustainable transportation systems. Based on the discussion, movement characteristics can be used to analyze trip chains [22].

2.3. Destination Attributes

Destination attributes refer to the unique features of a tourist destination that influence a tourist's decision to visit. These attributes can be categorized into two types: physical and non-physical. Physical attributes are elements that can be seen, touched, and directly experienced by tourists, while non-physical attributes are features that exist beyond direct sensory perception. Destination attributes significantly impact tourists' decisions to visit a place. Enhancing destination attributes significantly increases the likelihood of attracting tourists, and developing these attributes is an important factor in boosting the tourism appeal of a destination [23].

2.4. Mode Selection

Tourism-based transportation mode selection involves considerations usually irrelevant to daily travel. Tourists typically consider factors such as income, type of destination, time, cost, distance, and other factors when choosing a transportation mode. By considering these factors, tourists can plan trips that align with their preferences, select the appropriate transportation mode, and ensure sustainable mobility while reducing congestion [24, 25].

2.5. Trip Chain

A trip chain is a term used to describe the series of activities carried out by a tourist during an individual trip. This model can be used to understand tourist behavior and the factors influencing it. Additionally, these activities can be leveraged to develop marketing and promotional strategies for tourism. Several factors can influence the travel chain, including the purpose of the trip, such as leisure, business, or education. Other factors include tourist characteristics, such as age, gender, income, and occupation. Accessibility factors involve the availability of transportation and accommodation, while price factors include transportation tickets, lodging, and attraction costs. Information factors, such as data about travel destinations, accommodation, transportation, and tourist attractions, also influence tourist activities during the trip. Understanding the trip chain can help tourism operators improve the quality of services and products, thus attracting more tourists [5, 10, 26].

3. Research Method

3.1. Research Procedure

Research methodology refers to the methods used to obtain information and data sources for the study. This information varies, including literature such as journals, articles, theses, books, newspapers, and others [27]. The methodology applied in this study is a quantitative method that uses numerical data to answer research questions. Based on the discussion, the quantitative data can be measured and calculated. This study employs two analytical methods: Structural Equation Modeling with Partial Least Squares (SEM-PLS) and Multinomial Logit (MNL). SEM-PLS is a statistical method used to test the relationships between variables, including latent variables and indicators [17-19]. Additionally, the MNL model predicts probabilities across different categories [28, 29]. The flow diagram of the research procedure is shown in Figure 3.

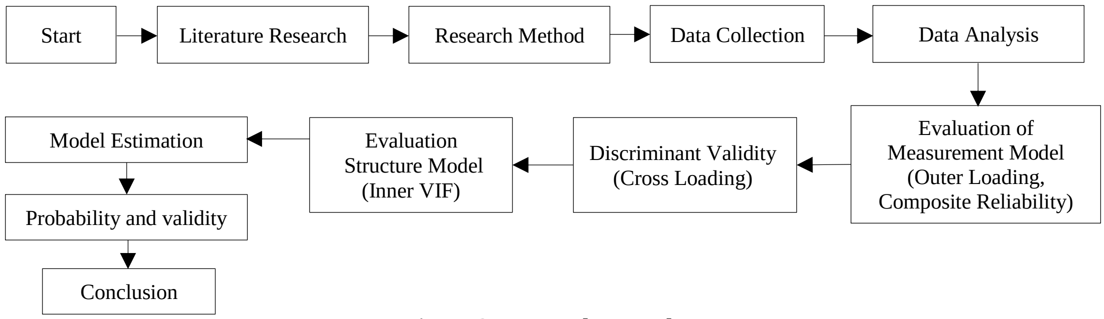


Figure 3. Research procedure

The research process involves several stages, including problem identification and topic selection, formulation of research questions, and objectives. The next stage includes searching for relevant information, choosing the appropriate method, and designing the study. Other stages involve administering a well-designed questionnaire and analyzing the data to ensure validity and reliability. Survey design is crucial to ensure accurate representation in a study [30].

3.2. Data Collection

This study uses random sampling with a sample size of 500 respondents. This method was chosen to ensure that every tourist has an equal chance of being selected as part of the research sample, thereby increasing the representativeness of the data. The sample is focused on domestic tourists, as this research aims to understand the travel preferences of domestic tourists under various travel conditions. The sample size for SEM-PLS is generally smaller than that required for SEM, as SEM-PLS uses the bootstrapping method to estimate model parameters. Bootstrapping is a statistical method used to estimate population parameters from repeated random samples [17-19]. The sample size required for SEM-PLS typically ranges from 30 to 100 samples. Although the required sample size may vary depending on the characteristics of the research site, it still falls within the recommended sample size criteria [31]. The following criteria are used as guidelines for determining the required sample size for SEM-PLS:

- Chin's (1998) Criteria: This criterion suggests that the minimum sample size for SEM-PLS is 5 times the number of indicators in the construct with the most significant number [32].
- Sarstedt et al. (2017) Criteria: This criterion states that the minimum sample size for SEM-PLS is 30 samples [18, 19].

This study considers the seasonal variation in tourist travel patterns, specifically during peak season when the number of tourists significantly increases during school holiday periods, and off-peak season when tourist visits tend to decrease, such as outside of holiday periods. However, it shows that there are no significant changes in the preferences of domestic tourists in choosing transportation modes and trip chains during these two seasons. Domestic tourists consistently choose private transportation as their primary option, with a single trip chain pattern in peak and off-peak seasons [14]. These findings indicate that seasonal factors do not significantly impact domestic tourists' mode choice and travel structure, where the flexibility of private modes remains the primary consideration across different seasonal conditions.

3.3. Data Analysis

The following variables and indicators are used to analyze the relationship between tourist characteristics, movement characteristics, and destination attributes about mode choice and trip chains. Variable X1 (individual characteristics) has indicators KI1, KI2, KI3, and KI4. Additionally, variable X2 (movement characteristics) has indicators KP1, KP2, KP3, KP4, KP5, KP6, KP7, KP8. Variable X3 (destination attributes) has indicators AD1, AD2, AD3, AD4, AD5, AD6. Furthermore, variable X4 (mode choice attributes) is used specifically for mode choice analysis with indicators MP1, MP2, MP3, MP4, MP5, MP6, MP7, and MP8. Variable X5 (trip chain attributes) is used specifically for trip chain analysis with indicators RP1, RP2, RP3, RP4, RP5, RP6, RP7, and RP8. A review of these variables and indicators is presented in Table 1.

Table 1. Variables and indicators

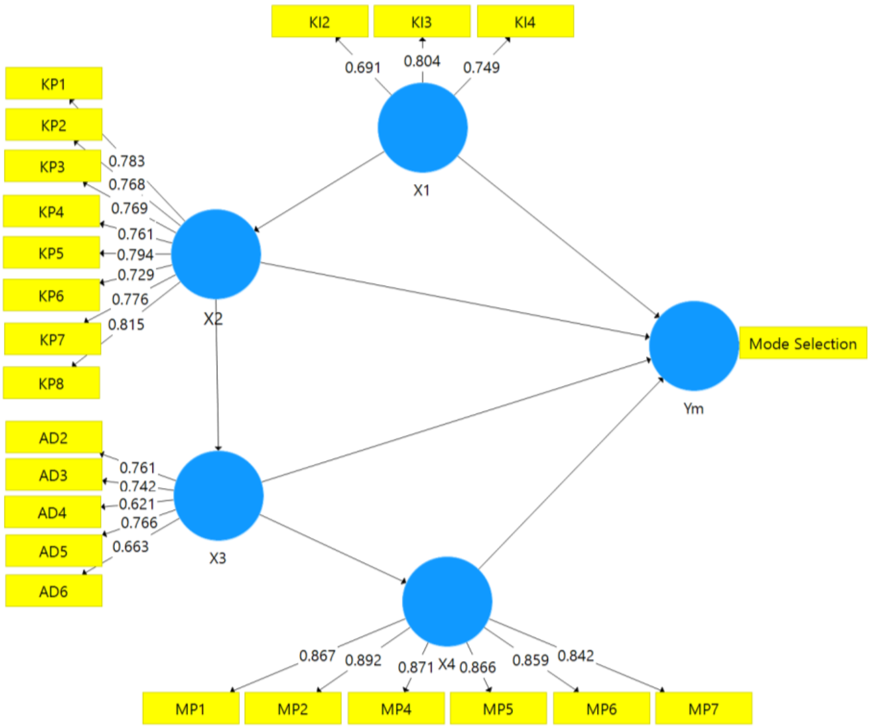
Variable	Indicator
Traveler characteristics	KI1(education level), KI2(age), KI3(employment type), and KI4(income).
Movement characteristics	KP1(origin), KP2(location of tourist destination), KP3(departure time), KP4(estimated arrival time), KP5(length of stay), KP6(number of visits), KP7(number of groups), and KP8(Flexible).
Destination attributes	AD1 (attractiveness of tourist destinations), AD2 (tourist destination facilities), AD3 (ease of accessing tourist destinations), AD4 (purpose of movement), AD5(activity Type), and AD6(tourism information).
Mode choice attributes	MP1(vehicle/sim ownership), MP2(trip length), MP3(distance from city center to DTW), MP4(cost), MP5(distance), MP6(time), MP7(safety), and MP8(weather)Private and public mode
Trip chain attributes	RP1(vehicle/sim ownership), RP2(trip length), RP3(distance from city center to DTW), RP4(cost), RP5(distance), RP6(time), RP7(safety), and RP8(weather)
Mode selection	Private and public mode
Trip chain	Trip chain 1, 2, 3, 4 and trip chain 5

4. Results and Discussion

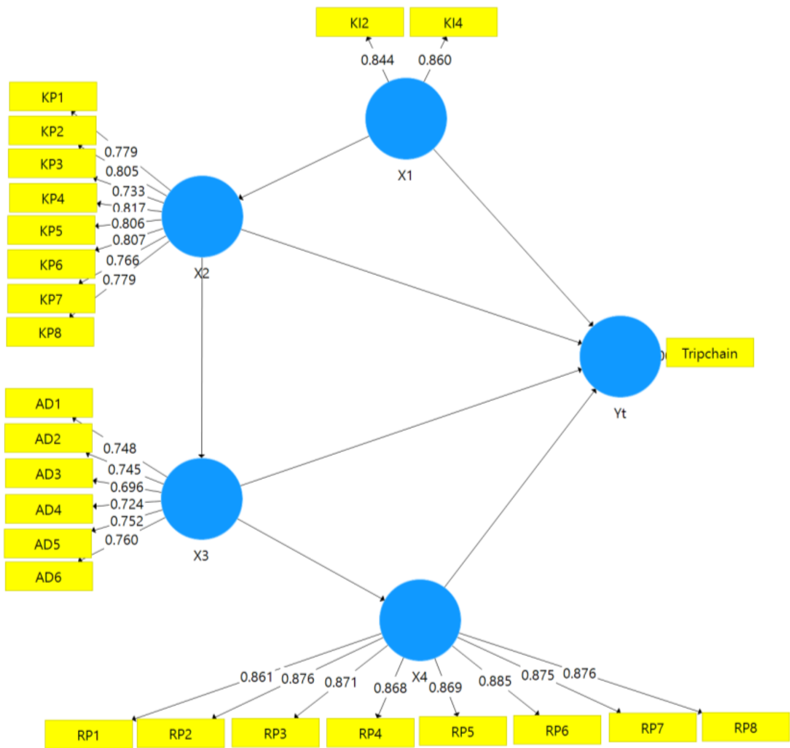
4.1. Evaluation of Measurement

4.1.1. Outer Loading

During the application of Partial Least Squares (PLS) path analysis in Structural Equation Modeling (SEM), the concept of outer loading plays a crucial role in assessing the measurement model. Outer loading, or factor loading, represents the strength of the relationship between a specific observed variable (indicator) and the underlying latent variable (construct) in the reflective measurement model. These variables serve as regression coefficients, measuring the extent to which each indicator contributes to explaining the measured construct [17-19]. The results of the factor loading test are shown in Figure 4.



(a) Mode selection (valid indicators)



(b) Trip chain (valid indicators)

Figure 4. Factor loading test results were valid indicators for a. Mode selection and b—trip chain

During the study, outer loading also contributed to evaluating discriminant validity. Each indicator loads the intended construct more than other constructs in the model. This process ensures that the indicator measures the designated construct and does not overlap with other indicators. Figure 3 shows some indicators that have invalid outer loading (loading < 0.5). These indicators include KI1, AD1, MP3, and MP8 in mode choice and KI1 and KI3 in the trip chain. These values differ from previous studies, indicating that factors such as education level influence tourists' decisions about mode and trip chain [10, 20]. Indicators such as flexibility, ease of access, and other abstract indicators are measured using the Likert Scale (1-5). For example, for flexibility, if the average score given by respondents is 4 out of 5, this score can reflect a high level of flexibility. The same applies to ease of access; if the average score given by respondents is 4 out of 5, ease of access is met according to the perception of most respondents. This approach allows for quantifying abstract variables, providing an objective basis for analyzing tourists' preferences regarding various aspects of travel. Indicators such as flexibility (travel based on needs) and the type of activity (reasons for individual travel, such as recreation combined with family visits or other combinations) are new in this study. These indicators have been tested for validity and reliability, but other researchers have not used them according to their operational definitions.

4.1.2. Composite Reliability

Composite reliability, or construct reliability, is a measure of internal consistency within a set of items used to assess a single underlying construct in a study. This reliability evaluates the extent to which these items are correlated with one another. High composite reliability indicates that the items consistently capture the intended construct, while low values raise concerns about inconsistency or redundancy among the items. This reliability assessment is similar to Cronbach's alpha but is considered a more substantial measure, especially for more minor scales or data that are not normally distributed [18, 19]. Based on this statement, a review of the analysis results is shown in Tables 2 and 3.

Table 2. Mode selection reliability test

Variable	Cronbach's Alpha	rho_A	Composite Reliability
X1 (KI)	0.615	0.632	0.793
X2 (KP)	0.905	0.907	0.923
X3 (AD)	0.757	0.766	0.837
X4 (MP)	0.934	0.937	0.947

Table 3. Trip chain reliability test

Variable	Cronbach's Alpha	rho_A	Composite Reliability
X1 (KI)	0.624	0.625	0.842
X2 (KP)	0.912	0.914	0.929
X3 (AD)	0.833	0.835	0.877
X4 (RP)	0.955	0.956	0.962

Tables 2 and 3 show that all indicators within each variable have met the reliability test criteria. Additionally, all variables within the construct have adequate or high reliability levels, indicating that the measurement instrument or construct used is reliable in assessing the intended variables [19].

4.2. Discriminant Validity Cross Loading

Cross-loading is a term used in SEM to describe a situation where an indicator measuring a construct significantly correlates with another construct. In PLS-SEM, cross-loading is used as a measure of discriminant validity. A construct demonstrates good discriminant validity when its indicators show higher correlations with the same construct than other constructs. The generally accepted threshold for cross loading is 0.3 or higher. When the loading value is lower than 0.3, the indicator is said to measure two constructs simultaneously, which can cause issues in interpreting the research results [17-19]. The results of this evaluation are presented in Tables 4 and 5.

Table 4. Cross loading matrix for mode selection

	X1 (KI)	X2 (KP)	X3 (AD)	X4 (MP)
AD2	0.037	0.285	0.761	0.319
AD3	0.006	0.239	0.742	0.297
AD4	-0.090	0.173	0.621	0.222
AD5	-0.018	0.253	0.766	0.342
AD6	-0.055	0.220	0.663	0.304
KI2	0.691	0.196	-0.039	0.192
KI3	0.804	0.272	0.004	0.278
KI4	0.749	0.200	-0.035	0.233
KP1	0.230	0.783	0.236	0.548
KP2	0.285	0.768	0.256	0.564
KP3	0.180	0.769	0.259	0.537
KP4	0.215	0.761	0.297	0.595
KP5	0.248	0.794	0.250	0.543
KP6	0.247	0.729	0.277	0.588
KP7	0.244	0.776	0.201	0.585
KP8	0.220	0.815	0.352	0.605
MP1	0.331	0.607	0.346	0.867
MP2	0.254	0.654	0.346	0.892
MP4	0.277	0.693	0.416	0.871
MP5	0.239	0.616	0.378	0.866
MP6	0.300	0.679	0.316	0.859
MP7	0.255	0.583	0.371	0.842

Table 5. Cross loading matrix for trip chain

	X1 (KI)	X2 (KP)	X3 (AD)	X4 (MP)
AD1	0.031	0.385	0.748	0.427
AD2	0.008	0.442	0.745	0.419
AD3	-0.050	0.308	0.696	0.368
AD4	-0.006	0.359	0.724	0.366
AD5	0.074	0.385	0.752	0.400
AD6	0.012	0.387	0.760	0.379
KI2	0.844	0.282	0.048	0.338
KI4	0.860	0.298	-0.017	0.341
KP1	0.263	0.779	0.405	0.565
KP2	0.271	0.805	0.402	0.610
KP3	0.268	0.733	0.362	0.564
KP4	0.264	0.817	0.469	0.637
KP5	0.318	0.806	0.410	0.607
KP6	0.293	0.807	0.366	0.593
KP7	0.190	0.766	0.408	0.561
KP8	0.272	0.779	0.412	0.605
RP1	0.365	0.629	0.468	0.861
RP2	0.333	0.685	0.493	0.876
RP3	0.362	0.665	0.445	0.871
RP4	0.348	0.657	0.437	0.868
RP5	0.339	0.651	0.477	0.869
RP6	0.324	0.694	0.471	0.885
RP7	0.334	0.649	0.468	0.875
RP8	0.375	0.632	0.467	0.876

Based on Table 4, indicators such as KI, KP, AD, and MP have the highest loading on their respective constructs. No indicator has a higher cross-loading on another construct, thus ensuring discriminant validity. The indicators in this table are valid and strongly related to their primary constructs. There are no significant violations of discriminant validity. Constructs X1 (KI), X2 (KP), X3 (AD), and X4 (MP) can be considered reliable and valid [19].

Based on Table 5, after reviewing the cross-loading matrix, all indicators show high values with the constructs they are intended to measure. This result indicates that these indicators have high loading on the constructs they are meant to measure. Overall, the cross-loading analysis suggests that the measurement instruments used in this study have adequate convergent validity [19].

4.3. Evaluation Structure Inner VIF (Multikolinear)

The Variance Inflation Factor (VIF) measures the extent to which the variance of the estimated regression coefficients increases compared to when the independent variables are orthogonal and linearly uncorrelated. Higher values indicate a higher correlation between the independent variables. Additionally, a VIF value greater than 5 is used as an indication of multicollinearity. In this case, the analysis results show that all indicators used have values less than 5. It can be concluded that all indicators (mode choice and trip chain) are free from multicollinearity symptoms. These variables show independence from each other in this structural analysis, which strengthens confidence in the accuracy of the results obtained [17-19].

4.4. Model Estimation

The MNL model is a statistical model used to predict the probability of outcomes for a dependent categorical variable with more than two categories, an extension of the binary logistic regression model [28]. Additionally, the independent variables used in the model include all individual characteristics, movement characteristics, destination attributes, and travel mode attributes for mode choice. These features are also present in the trip chain variables during the study. In total, there are 22 indicators for mode choice and 24 indicators for the trip chain applied. The estimated parameter results for the mode choice model based on the trip chain are shown in Tables 6 to 8.

Table 6. Parameter estimation for the mode selection model

Indicator	Coef.	P > lzl
Age (KI2)	-0.944	0.039***
Type of work (KI3)	-0.049	0.909
Income (KI4)	-1.143	0.012***
Origin (KP1)	1.507	0.003***
Destination Location (KP2)	-0.654	0.143*
Departure Time (KP3)	-0.13	0.777
Estimated Arrival Time (KP4)	0.08	0.854
Length of Stay (KP5)	0.345	0.457
Number of Visits (KP6)	-0.838	0.022***
Group Size (KP7)	-0.65	0.149*
Flexibility (KP8)	1.515	0.075**
Tourist Destination Facilities (AD2)	0.663	0.136*
Ease of Access (AD3)	-0.632	0.150*
Movement Purpose (AD4)	-0.281	0.492
Activity Type (AD5)	1.608	0.089**
Tourism Information (AD6)	0.006	0.989
Vehicle/License Ownership (RP1)	0.013	0.975
Travel Time (RP2)	0.039	0.937
Cost (RP4)	-1.243	0.040***
Distance (RP5)	-1.389	0.010***
Time (RP6)	-0.635	0.150*
Safety (RP7)	-0.943	0.014***
Constant	-2.568	0.501

* Significance Level 85%; ** Significance Level 90%; *** Significance Level 95%.

Table 7. Parameter estimation for trip chain 2 and 3 (trip chain 1 base outcome)

Variable	Trip chain 2		Trip chain 3	
Indicator	**Coef.**	**P > lzl**	**Coef.**	**P > lzl**
Age (KI2)	-0.028	0.898	-0.259	0.486
Income (KI4)	-0.428	0.082**	-0.546	0.147*
Origin (KP1)	0.079	0.772	-0.231	0.958
Destination Location (KP2)	-0.421	0.128*	-0.584	0.109*
Departure Time (KP3)	0.254	0.345	-0.118	0.796
Estimated Arrival Time (KP4)	0.184	0.53	0.902	0.071**
Length of Stay (KP5)	-0.099	0.729	0.073	0.877
Number of Visits (KP6)	0.171	0.527	-0.563	0.225
Group Size (KP7)	-0.251	0.318	0.217	0.612
Flexibility (KP8)	0.487	0.072**	0.92	0.061**
Attractiveness of tourist destinations (AD1)	0.432	0.117*	0.866	0.060**
Tourist Destination Facilities (AD2)	-0.118	0.65	-0.527	0.213
Ease of Access (AD3)	-0.552	0.034***	-0.662	0.103*
Movement Purpose (AD4)	0.402	0.129*	0.365	0.397
Activity Type (AD5)	-0.428	0.125*	-0.57	0.135*
Tourism Information (AD6)	-0.032	0.91	-0.157	0.743
Vehicle Ownership (RP1)	0.164	0.563	-0.383	0.397
Travel Time (RP2)	0.401	0.141*	-1.184	0.023***
Distance from city center to tourist destination (RP3)	0.04	0.888	0.023	0.959
Cost (RP4)	0.419	0.135*	0.562	0.128*
Distance (RP5)	-0.439	0.109*	-0.548	0.139*
Time (RP6)	-0.46	0.089**	-0.591	0.096**
Safety (RP7)	-0.442	0.126*	0.62	0.182
Weather (RP8)	0.257	0.354	0.178	0.714
Constant	0.63	0.678	-6.067	0.978

* Significance Level 85%; **Significance Level 90%; ***Significance Level 95%

Table 8. Parameter estimation for trip chain 4 and 5 (trip chain 1 base outcome)

Variable	Trip chain 4		Trip chain 5	
Indicator	Coef.	P > lzl	Coef.	P > lzl
Age (KI2)	-0.498	0.184	-0.566	0.133*
Income (KI4)	0.469	0.402	0.628	0.177
Origin (KP1)	-1.134	0.033***	0.144	0.754
Destination Location (KP2)	-1.718	0.003***	-0.567	0.196
Departure Time (KP3)	0.099	0.846	-0.372	0.409
Estimated Arrival Time (KP4)	1.357	0.054**	0.077	0.868
Length of Stay (KP5)	0.251	0.68	0.688	0.158
Number of Visits (KP6)	0.904	0.126*	-0.236	0.606
Group Size (KP7)	-0.296	0.558	0.143	0.749
Flexibility (KP8)	0.473	0.355	-0.508	0.143*
Attractiveness of tourist destinations (AD1)	0.591	0.333	0.073	0.872
Tourist Destination Facilities (AD2)	1.451	0.023***	-0.22	0.628
Ease of Access (AD3)	-1.024	0.110*	-0.126	0.775
Movement Purpose (AD4)	-0.629	0.243	0.181	0.671
Activity Type (AD5)	1.001	0.092**	-0.579	0.116*
Tourism Information (AD6)	-0.062	0.922	0.124	0.799
Vehicle Ownership (RP1)	-0.019	0.973	0.195	0.671
Travel Time (RP2)	1.016	0.083**	0.252	0.612
Distance from city center to tourist destination (RP3)	-0.512	0.377	-0.908	0.066**
Cost (RP4)	0.542	0.141*	0.557	0.126*
Distance (RP5)	0.57	0.137*	0.183	0.7
Time (RP6)	0.508	0.371	0.183	0.707
Safety (RP7)	-0.08	0.888	0.036	0.938
Weather (RP8)	-0.368	0.524	-0.33	0.471
Constant	-6.57	0.069	-0.604	0.979

* Significance Level 85%; **Significance Level 90%; *** Significance Level 95%

Based on the analysis of Table 6 above, it is stated that a positive coefficient indicates that if a variable's coefficient is positive and significant, the higher the value of that variable, the greater the likelihood of someone choosing rental transportation. Conversely, a negative coefficient means that if a coefficient is negative and significant, the higher the value of that variable, the greater the likelihood of someone choosing private transportation. Age: The negative coefficient indicates that the older a person is, the more likely they are to choose private transportation. Income: The negative coefficient suggests that the higher a person's income, the more likely they are to choose private transportation. This may be because they can afford to purchase and maintain private vehicles. Origin: The positive coefficient indicates that individuals from certain locations (represented by the "Origin" variable) are more likely to choose rental transportation. This could be due to better availability of rental services in those locations or other location-specific factors. Number of Visits: The negative coefficient shows that the more frequently someone travels, the more likely they are to choose private transportation. This may be because owning a private vehicle provides greater flexibility. Flexibility: The positive coefficient indicates that individuals with higher time flexibility are more likely to choose rental transportation. This might be because they are not constrained by public transportation schedules. Cost, the negative coefficient shows that the higher the travel costs, the less likely someone is to choose rental transportation. Distance: The negative coefficient indicates that the greater the travel distance, the less likely someone is to choose rental transportation. Safety: The negative coefficient shows that lower levels of safety reduce the likelihood of someone choosing rental transportation. The significant indicators identified in this study closely align with previous research [14, 33].

This study does not explicitly analyze the impact of particular weather events, and therefore, weather is not categorized based on its type or intensity. The approach is through direct surveys of tourists to understand how they perceive weather influencing their travel decisions. For example, one of the questions in the survey was, "Do you choose your trip chain based on weather?" Respondents were asked to provide answers using a Likert scale ranging from 1 to 5, where 1 indicates that weather has no influence at all, and 5 indicates that weather greatly influences travel decisions. If the survey results show an average score of 4 out of 5, tourists choose their trip chain based on weather factors. This approach provides an insight into tourists' perceptions of weather without requiring technical analysis related to the weather changes. In Table 7 below, several variables, such as income, destination location, flexibility, ease of access, type of activity, travel time, cost, and distance, significantly influence the selection of trip chains 2 and 3. Variables with a p-value of less than 0.05 are considered significant at the 95% confidence level. The indicators found to be significant in this study are in line with previous studies [5, 10]. With trip chain 1 as the base outcome, the estimation parameters are presented in Table 7.

Based on the analysis results in Table 7 above, the results indicate the following ease of access (AD3): Tourists are more likely to choose trip chain 1 over trip chain 2 when ease of access decreases. Income (KI4): Tourists with higher incomes are more likely to choose trip chain 1 over trip chain 2. Flexibility (KP8), tourists tend to choose trip chains 2 and 3 over trip chain 1 when the mode of transportation is more flexible. Attraction of tourism destinations (AD1), tourists are more likely to choose trip chains 2 and 3 over trip chain 1 when the destination attraction is higher. Type of activities (AD5): Tourists with certain types of activities are more likely to choose trip chain 1 over trip chains 2 and 3. For trip chain 3 (compared to trip chain 1), travel time (RP2), tourists are more likely to choose trip chain 1 over trip chain 3 when travel time increases. Income (KI4): Tourists with higher incomes are more likely to choose trip chain 1 over trip chains 2 and 3. Flexibility (KP8): Tourists are more likely to choose trip chains 2 and 3 over trip chain 1 when the mode of transportation is more flexible. Attraction of tourism destinations (AD1), tourists are more likely to choose trip chains 2 and 3 over trip chain 1 when the destination attraction is higher. Travel Duration (RP6): Tourists are more likely to choose trip chain 1 over trip chain 3 when the travel duration is longer.

Here is the interpretation of the parameter estimates in Table 8 for trip chains 4 and 5, with trip chain 1 as the base. Positive coefficients: If a variable has a positive and significant coefficient, it means that the higher the value of that variable, the greater the likelihood of a person choosing the respective trip chain (either trip chain 4 or trip chain 5) compared to trip chain 1. Negative coefficients: Conversely, if a variable has a negative and significant coefficient, it means that the higher the value of that variable, the lower the likelihood of a person choosing the respective trip chain compared to trip chain 1. Age: Tourists are more likely to choose trip chain 1 over trip chains 4 and 5 as age increases. Point of origin, tourists are more likely to choose trip chain 1 over trip chain 4 and 5 if their point of origin is far away. Destination location: Tourists are more likely to choose trip chain 1 over trip chains 4 and 5 if the destination location is farther away. Estimated arrival time: Tourists are more likely to choose trip chain 4 and 5 over trip chain 1 if the estimated arrival time aligns with their plans. Flexibility: Tourists are more likely to choose trip chain 1 over trip chain 5 if flexibility decreases. Facilities, tourists are more likely to choose trip chain 4 over trip chain 1 if the facilities are adequate. Type of activities: Tourists are more likely to choose trip chain 4 over trip chain 1 if there are more types of activities available. Travel time: Tourists are more likely to choose trip chain 4 over trip chain 1 if the travel time is well-managed. Cost and distance, tourists are more likely to choose trip chains 4 and 5 over trip chain 1 if the costs incurred are higher. The constant represents the coefficient value showing the model's intercept. Several variables, such as age, point of origin, destination location, estimated arrival time, number of visits, flexibility, facilities, type of activities, travel time, distance from the city center to the destination, cost, and distance, show a significant influence on the choice of trip chains 4 and 5. Other variables do not show a strong influence. Variables with a p-value less than 0.05 are considered significant at the 95% confidence level. The indicators found to be significant in this study are similar to those in previous research [5, 34].

4.5. Probability Model

Probability in mode choice and trip chain selection refers to the likelihood of individuals or groups choosing a particular type of transportation and trip chain. In this context, research on probability is part of the transportation behavior analysis that can be used by stakeholders, governments, and city planners to understand tourist preferences in designing more effective and efficient transportation systems. The following variables present the probabilities for mode choice and trip chain selection in Figures 5 and 6.

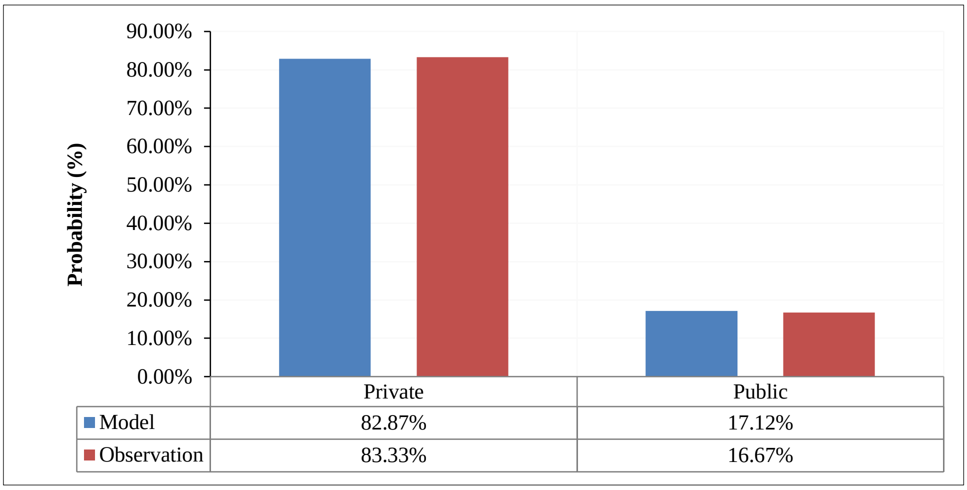


Figure 5. Probability of mode choice

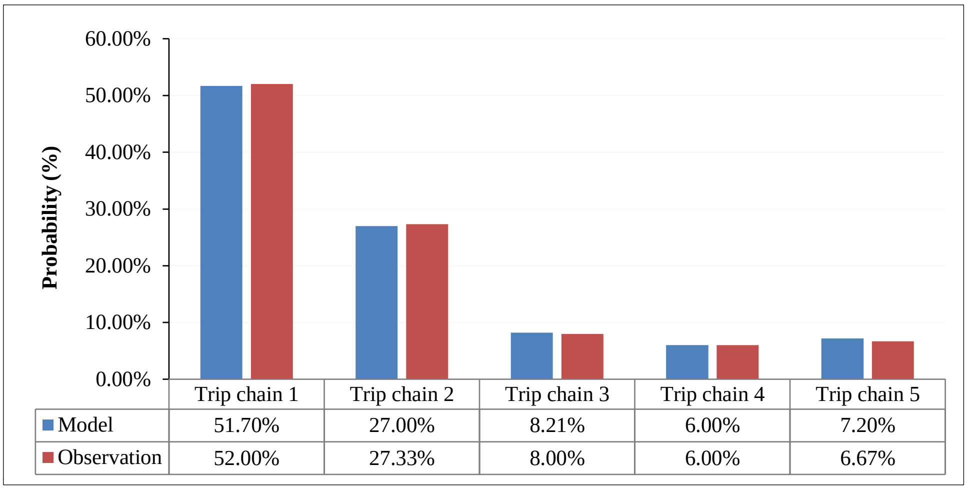


Figure 6. Probability of trip chain 1,2,3,4 and 5

A very high percentage in the private category indicates that the ownership and use of private cars remain dominant, both in model predictions and actual data. Meanwhile, the low percentage in the public category suggests that the use of tourism-based rental cars is still relatively small. Similar findings were discussed in previous studies regarding public transport, which only holds a 14% market share [14], with private transportation being more dominant among professional tourists [35]. Although the percentage remains low, the potential market for tourism-based public cars is still relatively large. Rental service providers can take various steps to increase public interest, such as offering attractive promotions, expanding service coverage, or improving service quality. Other studies stated that public mode choice is more dominant in one popular destination [36]. This differs due to various determining factors such as the demographics and sociology of the area.

This chart compares the predictions (model) with actual data (observation) regarding an event or occurrence, divided into 5 categories called trip chains. The percentage difference between the model and observation is relatively tiny for each trip chain, indicating that the model used accurately predicts the actual events. The model and the observation show that trip chain 1 has the highest percentage, meaning that this stage is the most frequent occurrence. As the trip chain number increases, the percentage decreases, which suggests that the likelihood of an event occurring diminishes in subsequent trip chains. However, there is an increase in percentage at trip chain 5. This differs from previous studies, where the highest probability among the four trip chain options was in trip chain 3, and the lowest was in trip chain 5. The difference is attributed to this study being based on international tourists [19].

4.6. Validity Model

The probability model for mode choice and trip chains using the MNL model method was validated using field survey data. The results show that this model achieved an average validity rate of 98.40% in predicting the probability of mode choice for both private and public (rental) modes based on the composition of trip chains, supported by observational evidence. Following this discussion, the validation rate for trip chains 1, 2, 3, 4, and 5 is 97.65%. This high validity indicates a strong agreement between the model's predictions and the actual observational data. The results of the mode choice model validation are shown in Figure 7.

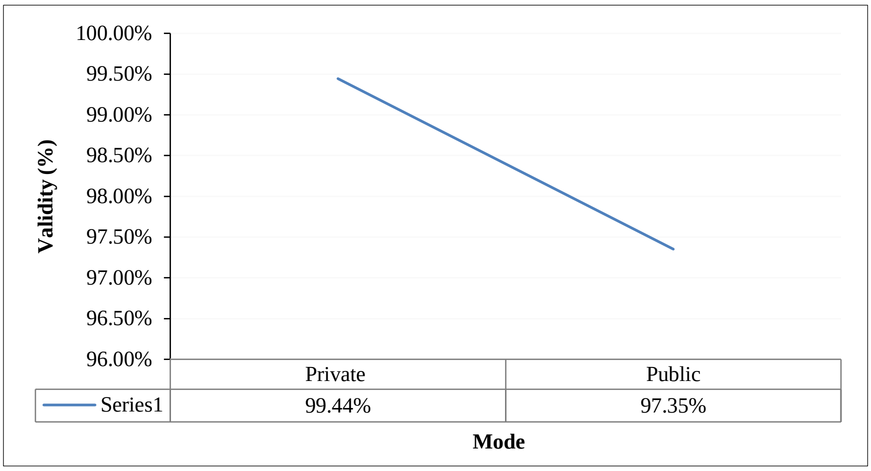


Figure 7. Validity of MNL Model for Mode Choice

The MNL model in Figure 7 shows an excellent accuracy rate in predicting mode choice, with a total validity value of 98.40%. This means that the model can explain approximately 98.40% of the variation in observed mode choices. This indicates that the MNL model is quite effective in capturing the factors that influence a person's decision to select a mode of transportation [20]. The results of the trip chain model validity test are shown in Figure 8.

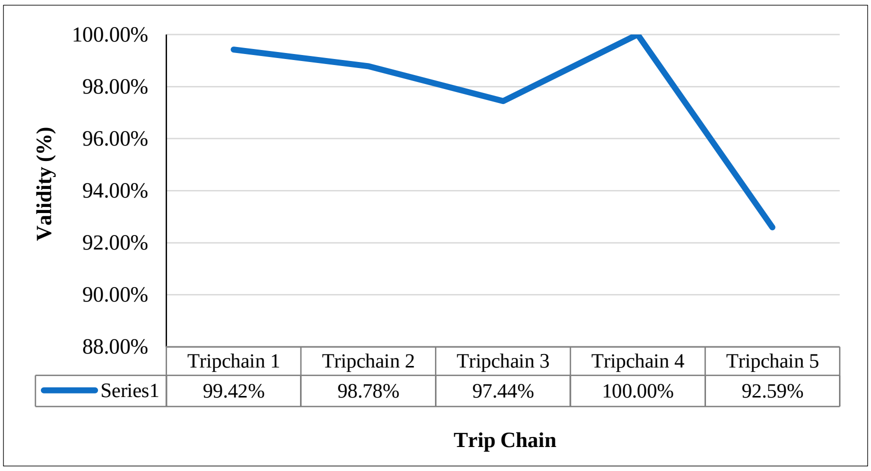


Figure 8. Validity of MNL Model for Trip Chain 1, 2, 3, 4, and 5

Figure 8 focuses on the validity of the model in predicting trip chains. A trip chain refers to the sequence of trips made by an individual. The MNL model also strongly predicts trip chains, with a total validity score of 97.65%. However, there is slight variation in the accuracy levels for each trip chain. Some trip chains show very high validity (close to 100%), while others are slightly lower. Both tables show that the Multinomial Logit (MNL) model used in this study performs well in predicting both mode choice and trip chains [10, 20, 24]. This suggests that the model can help analyze travel behavior and transportation planning.

Comparing the model with similar studies involves referring to indicators with significant influence and the probability of mode choice and trip chain selection. The primary benchmark used is the alignment between the indicators employed in previous models and those adopted in this study. The indicators used in this research encompass factors that have been validated and deemed significant in previous studies, such as age, income, origin of the tourists, destination location, number of visits, group size, estimated arrival time, trip duration, flexibility, facilities, ease of access, cost, distance, time, safety, destination attractions, type of activities, and movement purpose. By using these indicators, this study not only assesses the relevance of variables in the current context but also provides a stronger foundation for evaluating the consistency of the model with previous studies [19]. Furthermore, this approach is expected to broaden the understanding of mode choice and trip chain patterns in various contexts.

5. Conclusion

In conclusion, the measurement results using the SEMPLS method for outer loading indicate that the indicators with an outer loading value > 0.5 for mode choice include age, occupation, income, origin, destination location, departure time, and estimated arrival time. Other indicators include length of stay, number of visits, group size, flexibility, facilities, ease of access to tourist destinations, movement destination, activity type, tourist information, vehicle ownership/driving license, trip length, cost, distance, time, and safety. During the study, the indicators with an outer loading value > 0.5 for trip chain include age, income, origin, destination location, departure time, estimated arrival time, length of stay, number of visits, group size, flexibility, and destination attraction. Other indicators include facilities, ease of access to tourist destinations, movement destinations, activity types, tourist information, vehicle ownership, trip length, distance from the city center to tourist destinations, cost, distance, time, safety, and weather. The results show that a set of indicators, including age, income, origin, destination location, number of visits, group size, flexibility, facilities, ease of access, activity type, cost, distance, time, and safety, significantly influence mode choice, with a significance level of over 85%. Additionally, the indicators that substantially influence trip chains with a significance level of more than 85% include age, income, origin, destination location, estimated arrival time, number of visits, flexibility, and destination attraction. Other indicators include facilities, ease of access to tourist destinations, movement destinations, activity types, trip length, distance from the city center to tourist destinations, cost, distance, time, and safety. Two significant indicators found as differentiators from previous research are flexibility and type of activity. The comparison of mode choice probabilities between observation and model results shows an average validity rate of 98.40%. Additionally, the probabilities for trip chains based on observation and the model reach 97.65%. These results indicate that the model effectively represents the indicators influencing transportation mode choice and trip chains. This study provides a foundation for further investigations to improve the efficiency and comfort of tourism transportation systems.

5.1. Recommendations and Implications

Recommendations and Implications for Infrastructure Development and Service Enhancement

- Infrastructure development to support mobility and accessibility: Encourage cooperation and alliances among regional tourist attractions to achieve synergy and coordinated development. Improving road conditions is essential, as ease of access, distance, and time are significant factors. The construction and improvement of roads connecting various tourist destinations in the Bira Peninsula are vital. The focus should be on road widening, high-quality paving, and street lighting installation to enhance accessibility, especially to remote tourist spots. Safety improvements, such as fire extinguishers and disability access facilities, should also be considered [37].
- Development of transportation modes to improve flexibility and efficiency: Based on factors such as flexibility and time, tourists require flexible, punctual public transportation modes that can reach various locations. Operating shuttle buses or small transport services with routes covering major tourist sites in the Bira Peninsula, especially during peak seasons, should be prioritized. Adaptive schedules, such as increased trip frequency during peak tourist visits, can help reduce waiting times [33].
- Enhancement of tourist facilities and services: Comfortable and strategically placed rest areas are needed to support travel duration and group sizes. Improvements to public transport facilities, such as waiting rooms, should be added to enhance comfort and convenience [38].
- Optimization of costs and accessibility: For cost factors, government subsidies, particularly for domestic tourists, can reduce fares on public transport such as buses. This could make public transport more attractive compared to private modes. As tourists tend to consider both cost and destination appeal, local governments could collaborate with transportation operators to provide integrated tour packages. These packages could include transportation, entrance tickets to tourist destinations, and accommodation at more affordable prices, thereby boosting tourist numbers [39].
- Utilizing technology to improve service: Based on time and estimated arrival factors, the development of apps providing real-time information on transportation schedules, fastest routes, and weather conditions could help tourists plan their trips better. Considering that tourists often travel in groups, an online ticket booking system for transportation would make the process more convenient [34, 37, 40, 41].
- Support for destination and attraction development: To support activities and movement purposes, diversification of tourist activities such as cultural tours, nature tourism, or local festivals should be promoted. Transportation to these activities should be well-planned to ensure easy tourist access [37].

6. Declarations

6.1. Author Contributions

Conceptualization, I.W., S.H.A., M.I.R., and M.H.; methodology, S.H.A., M.I.R., and M.H.; software, I.W.; validation, S.H.A., M.I.R., and M.H.; formal analysis, I.W.; investigation, I.W.; resources, I.W.; data curation, I.W.; writing—original draft preparation, I.W.; writing—review and editing, I.W.; visualization, I.W.; supervision, S.H.A., M.I.R. and M.H.; project administration, I.W.; funding acquisition, I.W. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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6.4. Conflicts of Interest

The authors declare no conflict of interest.

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