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A Multinomial Logit Model for Urban Transportation Mode Choice in Nasiriyah City

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Abstract:

Analyzing mode choice is essential for transportation planning, especially in urban areas where commuting significantly affects peak-hour congestion. The travel behavior of city residents regarding their transportation mode choices is crucial, as it impacts the overall efficiency of movement within the city. The multinomial logit (MNL) model is a valuable tool for estimating mode shares when travelers are presented with multiple travel options. This research investigates mode choice in Nasiriyah by applying the MNL model to identify factors that affect transportation preferences within the community. The model incorporates twelve explanatory variables that have not been previously examined in the urban context of Nasiriyah. These variables include income, age, household size, travel distance, travel time, travel cost, road conditions, availability of taxis, availability of public transportation, land use density, cultural characteristics, and safety concerns. The results revealed that private vehicle ownership is the preferred mode of transportation, closely followed by taxi services, indicating a strong inclination toward private vehicles due to their flexibility and convenience. In contrast, public transportation options, such as buses, ranked third due to inadequate service attractiveness stemming from limited geographic coverage and passenger comfort. Non-motorized modes, such as motorcycles and bicycles, received lower preference due to challenging weather conditions and insufficient infrastructure. Additionally, the results indicate that the choice of transportation modes in Nasiriyah City is shaped by various factors, including economic conditions, travel impedances, infrastructure quality, service availability, land development patterns, and safety considerations. This underscores the immediate need to improve public transportation services, as well as infrastructure for pedestrians and cyclists. The model was trained and tested using specific datasets, ultimately achieving an F1-Score of 85.3% on the testing dataset.

1. Introduction

Understanding travel behaviors and mode choices is vital for effective transportation planning, especially as cities encounter rising congestion and environmental issues [1]. Analyzing mode choice, which involves how individuals determine their preferred mode of transportation, offers crucial insights that shape transportation policy and infrastructure planning. [2],[3]. A robust method for analyzing mode choice is the Multinomial Logit (MNL) model, a statistical technique that considers the impact of multiple factors on transportation decisions. Several studies have emphasized the significance of socio-demographic, economic, and environmental factors in determining transportation preferences. As noted by Ben-Akiva and Lerman[4], The MNL model enables researchers to analyze the likelihood of an individual choosing a specific mode of transportation by taking into account the utility derived from each option compared to the available alternatives. Furthermore, the model can include variables like income levels, travel time, and the availability of transport options, all of which greatly influence individuals' decisions. [5].

In urban settings, the availability and reliability of public transit systems frequently impact the choice of transportation mode. Recent studies highlight that accessibility and travel costs are significant factors influencing mode selection. For instance, research conducted by Hensher et al. [6] found that increased public transport fares may discourage usage, whereas enhancements in service quality and shorter travel times can boost ridership. This highlights the necessity for public transportation systems that are both affordable and efficient. Additionally, the growth in private vehicle ownership, driven by urbanization and economic development, presents further challenges for urban mobility. As noted by Miller et al. [7], the growing dependence on private vehicles leads to road congestion and elevated emissions, which has shifted policy emphasis toward encouraging sustainable transportation modes. The MNL model supports this analysis by helping to understand how individual preferences change in response to variations in economic conditions and urban policies. Factors such as income, age, car ownership, household composition, and gender play a significant role in shaping these choices. [8], [9]. Bhat and Guo [10] examined how land use and travel time affect mode choice in urban commuting. They employed the MNL model to analyze data from a metropolitan area in the United States. Their findings indicated that denser urban development and shorter travel times notably heightened the chances of selecting public transport over private vehicles. This underscores the essential role of urban planning in promoting sustainable transportation options. Hensher and Greene [11] investigated how sociodemographic characteristics influence public transport use in Australia. Using the Multinomial Logit (MNL) model, they examined factors like income, age, and household size. The study revealed that younger people and those with higher incomes were more inclined to use public transit, whereas individuals from larger households were more dependent on private cars. These results highlight the importance of designing transportation policies tailored to different demographic segments.

Miller and Wu [12] investigated how economic factors and personal attitudes influence transportation mode choices in a rapidly urbanizing area. By employing a hybrid MNL model, they analyzed variables such as income, travel expenses, and environmental attitudes. Their findings indicated that individuals with significant environmental concerns were more inclined to choose sustainable transportation options, like cycling and public transit, especially when costs were reduced. This highlights the importance of incorporating environmental factors into transportation planning. Hensher and Mulley [13] investigated how service quality and fare structures affect public transport ridership in Sydney. They utilized a mixed MNL model to consider individual preferences and perceptions. Their findings showed that increases in service frequency and fare reductions significantly boosted public transport usage. This study emphasizes that successful public transport systems need to focus on both affordability and quality to draw in riders. Zhou and Sinha [14] studied the relationship between socio-demographic factors, travel behavior, and mode preferences using a nested MNL model in a major metropolitan area. They found that education level, employment status, and travel distance significantly predict mode selection. The authors emphasized that understanding these variables is crucial for developing policies that promote sustainable transportation options, highlighting the complex influence of socio-demographic, economic, and environmental factors on transportation mode choice At the same time, Sonia et al. [15] analyzed transportation mode selection in Malang City using the multinomial logistic method. Their findings revealed that 11% of participants use private vehicles for commuting, while 88% prefer public transport, and 9% utilize online ride-hailing services, highlighting diverse urban mobility preferences. Ali et al. [16] utilized multinomial logit models to study travel mode selection in urban areas, revealing that socio-demographic factors significantly influence transportation preferences. They discovered that individuals with higher incomes are more likely to use motorized transport, which in turn decreases the use of non-motorized and public transport options. Ghosh and Nagaraj [17] performed a study employing a Multinomial Logit model to analyze mode choice behavior among low and low-middle income households in Bengaluru. Their findings showed that higher travel costs significantly reduce the likelihood of using buses, while shorter travel times increase the preference for the metro. Hao [18] employs a multiple logit model to explore travel mode preferences among residents of Hangzhou, focusing on private cars, public transportation, and non-motorized vehicles. The study considers factors such as gender, age, income, and travel purpose to gain a deeper understanding of mode selection. The results reveal that men are more likely to use private cars for their trips, and that a higher monthly income increases the probability of traveling by private car. Herath et al. [19] apply the Multinomial Logit (MNL) model to examine mode choice variability among commuters, highlighting factors such as age, occupation, trip distance, in-vehicle travel time, and travel cost. Their findings emphasize the complex relationship between socio-demographic and economic factors in shaping transportation preferences across urban environments.

Most studies on urban trip mode choice have focused on Europe, America, and Southeast Asia, with limited attention to Africa [20-24]. Also, in Iraq, there is a dearth of research specifically addressing this context; the limited studies available indicate that commuters tend to prefer private transport modes [25]-[27].

The literature above highlight the diversity in transportation mode usage, noting that some groups prefer public transport while higher-income individuals are increasingly moving away from non-motorized options in favor of private vehicles. In response to these trends, many municipalities are striving to create a balanced mode choice and promote sustainable transportation alternatives, with some aiming to have 30% of commuters utilize sustainable modes for urban travel.. Additionally, 36 cities in developed countries have committed to ensuring at least 15% of intra urban trips are made by bicycle by 2020 through the Charter of Brussels [28]. This objective reflects the desire of policymakers to encourage a shift towards more sustainable transportation modes. This shift is likely driven by a shared belief that reliance on private transport does not contribute to a sustainable urban transport ecosystem [29]. Private cars have negative impacts, including reliance on non-renewable fuels, pollution, noise, and traffic congestion. Consequently, factors that encourage users to continue using public transportation include the cleanliness and comfort of the vehicles, quality service from staff, and punctuality. Users who recommend the service to others and express overall satisfaction are indicators of loyalty to a specific mode of transportation [30]. The engagement of service users in public transportation is anticipated to effectively alleviate traffic congestion on roadways, with public transportation being assessed based on travel time, cost, and waiting time.

Recently, Nasiriyah, the city being studied, has experienced a significant rise in the number of vehicles, particularly since 2003, along with an increase in daily activities and trip rates. Concurrently, the lack of job opportunities has pushed many citizens to adopt taxi drivers, aided by availability of medium quality and affordable vehicles. These factors have led to greater reliance on private transportation with students an important segment of the community also favoring this mode. However, the inability to develop and improve infrastructure due to high capital cost, coupled with the surge in vehicle numbers has resulted in severe traffic congestion, accidents and air pollution. To address these issue, analyzing mode choice and the factors influencing it is essential.

This study aim to analysis and develop a model choice model for trips in city of Nasiriyah that can be used to simulate the travel behavior and mode choice preferences of individuals. Additionally, the research seeks to identify the key factors that influence the transportation mode choice mad by individualsin Nassiriyah.

The paper is organized into five main sections as follows: Section II outlines the study area and provides a brief literature review that establishes the context for the research, along with details on sample size implementation, which serves as the base for developing the mode choice model which discussed in Section III. Section III is divided into three stages: the first stage focuses on constructing the choice model using a multinomial logit model, the second stage addresses model calibration and the third stage evaluates model validation. Section IV presents a discussion of the results. Finally, Section VI summarizes the key conclusions.

2. Methodology

The multinomial logit model (MNL) was chosen for its flexibility in analyzing mode choice data where alternatives are not hierarchically ordered, reflecting the urban transportation context in Nasiriyah. However, a limitation of this model is its assumption of independence of irrelevant alternatives (IIA), which may impact prediction accuracy. The methodology for analyzing mode choice in Nasiriyah involves data collection and model building. Data were gathered through a comprehensive travel survey conducted in Nasiriyah, Iraq, utilizing online questionnaires and personal interviews with car users, who are crucial to this study. The questionnaire featured clear and straightforward questions designed to elicit accurate responses. To ensure adequate statistical power and representation of the urban population, the sample size for both the online survey and face-to-face interviews was determined using statistical formulas.

In the model developing phase, mode choice serves as the dependent variabl
e, while twelve independent variables—coded as categorical—were utilized. These variables include income, age, household size, travel distance, travel time, travel cost, road conditions, availability of taxis, public transport access, land use density, cultural attributes, and safety concerns. K-Fold Cross-Validation was applied to enhance the model's accuracy.

2.1 Case Study Description

Nasiriya, the capital of Dhi Qar Province in Iraq, is situated on the lower Euphrates River, approximately 360 km southeast of Baghdad and in close proximity to the archaeological site of Ur. The city is geographically located at 31.3525° N latitude and 46.2472° E longitude. Encompassing an area of approximately 4,149 km2, Nasiriya has experienced rapid land-use changes in recent years, characterized by homogeneous urban expansion. In 2018, the city's population was estimated at 558,000, comprising approximately 58,013 households [31,32]. In Al Nasiriya City, the road network experiences significant traffic congestion during the morning and evening peak hours due to the presence of various destinations, including educational, commercial, and industrial centers [33,34]. Similar to many urban centers in Iraq, Nasiriya's transportation system faces significant challenges, characterized by a heavy reliance on private vehicles and taxis coupled with limited access to organized public transportation services. The bus transportation system in Nasiriyah operates as a private entity rather than a governmental one. The private transport operations within the city are supported by a government agency known as the State Company for Private Transport (SCPT), which is part of the Iraqi Ministry of Transportation. This company maintains a centralized garage for the coordination of 20 transport lines located near the central business district (CBD), the primary destination for much of the city's population. SCPT is also responsible for issuing bus licenses and setting ticket prices. However, there has been no prior planning regarding the spatial distribution of bus routes in the city. Currently, route determination is driven by passenger demand and the financial interests of bus owners, resulting in some neighborhoods having multiple bus routes while others have very few [35]. Analysis of the data presented in the preceding study reveals that some of the districts in the city are not served by the public transportation network. Furthermore, the survey data indicates a total of 108,187 daily trips, of which 22,310 as public trips are made within this study area. Thus, these high traffic volumes contribute to routing issues and accelerate the premature deterioration of roads, leading to accidents and casualties. As a result, the Department of Roads and Highways in the city continuously strives to maintain or reconstruct these roads. However, these efforts often appear to be short-term solutions [36]. Consequently, the frequent maintenance and reconstruction can be viewed as costly processes. Although Al-Nasiriya city witnesses an expansion in construction projects and the potential of planning new infrastructure, little research is dedicated to this area, and the availability of data is rather limited, as referred to by [37-40]. Concurrently, the process of travel demand needs studying and analyzing within the transportation planning process for Nasiriyah City. Naser et al. conducted the first and second stages of the transportation planning process, or travel demand modeling, at Nassiryah City. In the first stage of transportation planning, [41] estimated trip production for 22 traffic zones using a cross-classification model based on critical factors such as household size, income level, and vehicle ownership. Additionally, [42] developed five models using multiple linear regression (MLR) for the sectors of Nasiriyah city. The key predictive variables that contributed to explaining variations in most travel models across these sectors included family size, number of workers, number of students in households, gender, age groups, and household car ownership. It was observed that trip generation behavior was more closely associated with male drivers than female drivers, with males reflecting the social characteristics of the city. [43] used artificial neural network (ANN) technology to simulate trip production, a key aspect of transportation planning. Data was gathered through a home-based interview survey of about 486 households in the central business district (CBD) of Nasiriyah. Key input variables included gender, household size, number of workers, total household individuals, students, monthly income, dwelling area, car ownership, and dwelling ownership, while the output was total trip production. The performance of the ANN model was evaluated using this data, with significant findings indicating its effectiveness in this context. At the second stage, a trip distribution model had been studied and a matrix of trip distribution that could be adopted for enhancing the transportation network [32]. Recently, the topic of research included the third stage of the transportation planning process, which is mode choice modeling.

2.2 Sampal Size Implementation

Preliminary and secondary data have been gathered for data analysis and model development. The preliminary data collection includes population data from the 2010 Census, and population estimates for 2024 derived from previous census data and population growth trends in the study area. According to the most recent census conducted in 2010, the population of Nasiriyah City was 455,700. To estimate the population for the study year of 2024, the following formula for calculating the population growth rate was utilized:

$$P_t = P_0(1+r)^n \qquad (1)$$

Where:
P_t: The populations approximate number in the study area 2024
P_0: Actual number in the latest census 2010
r: Population growth rate
n: Number of years between P_t and P_0

$$n = \frac{z^2 \times P \times (1-P)}{C^2} \qquad (2)$$

Where:
n: Signifies the sample size for an infinite population.
Z: Represents the Z-value (for instance, 1.96 corresponds to a 95% confidence level),
P :Denotes the proportion of individuals choosing a particular option, expressed as a decimal (0.5 is used to calculate the necessary sample size),
c: Indicates the confidence interval expressed as a decimal (for example, .04 equals ±4%), the confidence level is 95%,
The calculation is based on a normal Gaussian distribution. with a 2.5% margin of error, a 95% confidence level, and a 50% response distribution leading to a required sample size for the analysis is 1388 respondents, including general public respondents (office employees, students, and others). The questionnaire covers: trip maker characteristics such as, gender, age, household income, car ownership, family size. Mode characteristics including type of mode, trip cost, waiting time, and duration). The travel modes include private vehicle, Taxi, Buse,motorcycle, biycycle and walk.

3. Development model

3.1 Building Model Choice modeling Using Multinomial Logit Model(MNL)

Modeling is a critical component of the decision-making process. It involves the methods, whether quantitative or qualitative, that enable us to study and understand the underlying relationships that drive decision-making [25]. The choice of transportation mode is probably one of the most crucial fundamental models in transportation planning. (MNL) is a powerful tool for mode choice analysis that helps understand how individuals make choices among various transportation options. The MNL model is based on the utility function framework and analyzes how explanatory variables influence multiple dependent variables [45]. It assumes that individuals prefer transportation modes that provide the highest utility. The model calculates the probability of choosing each mode as the ratio of its utility to the total utility of all considered modes. Utility reflects the attractiveness of a transportation option, influenced by travel characteristics and individual traits. This allows for the creation of a utility function that ranks alternatives and identifies the mode with the highest utility, which can be expressed as a linear combination of the factors affecting choice [46].

$$U_{ij} = \beta_0 + \beta_1 x_{1ij} + \beta_2 x_{2ij} + \cdots + \beta_{\Pi} x_{n_i j} \qquad (3)$$

Where:
U_{ij} is utility function.
X_{nij} are the attributes of alternative i for individual j
β_n are the parameters to be estimated.
These utility equations, with the specified parameter values, are used to calculate the attractiveness or utility of each transportation mode option. The model then leverages these utility values to estimate the probabilities of individuals choosing the different modes of transportation. To prepare the data for input into software for analysis, it needs to be organized the varables as table 1. As well as categorized based on the requirements of the study. This involves dividing the data into appropriate categories and coding the information accordingly as table2 .

Table 1. *Nomenclature*

Abbrevision	Explantory Variables
U	Utility Function
TD	Travel Distance
TT	Travel Time
TC	Travel Cost
Road CO	Road Condition
H.H	Household Size
Car OW.	Car Ownership
SCON	Safety Concern
LD	land use Density
BOW	Bicycle Ownership
AVT	Avaibility of Taxi
PUTAV	Public Transport Availability
POL	Pollution Level

Table 2. *Description of explantory variables*

Variable Name	Category	Coding Scheme
Income	Socio-Demographic	1 – Low, 2 – Medium, 3 – High
Age	Socio-Demographic	Continuous (years)
TC	Travel Characteristics	Continuous (number)
H.H	Household Characteristics	Continuous (number)
Car Ow.	Household Characteristics	0 – No, 1 – Yes
TD	Travel Characteristics	Continuous (km)
TT	Travel Characteristics	Continuous (minutes)
Road Con.	Infrastructure and Service Quality	1 – Poor, 2 – Fair, 3 – Good
Public Transport Availability	Infrastructure and Service Quality	0 – Low, 1 – Medium, 2 – High
Cultural Attitudes	Cultural and Contextual Factors	1 – Negative, 2 – Neutral, 3 – Positive
Safety Concerns	Cultural and Contextual Factors	0 - Low Concern, 1 – High Concern
Pollution Levels	Environmental Factors	1 – Low, 2 – Moderate, 3 - High

Building upon the (MNL) model framework, the researchers have derived the utility functions for the different modes of travel under consideration and independent variables as table above. Thus, is given below:

$$U(privatcar) = \beta_0 - \beta_1(Incom) - \beta_2(TT) + \beta_3(TD) + \beta_4(TC) + \beta_5(Car\ OW.) + \beta_6(Road.CO)$$

$$U(Taxi) = \beta_0 - \beta_1(Incom) - \beta_2(TT) + \beta_3(TD) + \beta_4(TC) + \beta_5(AVT) + \beta_6(Road\ .CO)$$

$$U(Bus) = \beta_0 - \beta_1(Incom) - \beta_2(TT) + \beta_3(TD) + \beta_4(TC) + \beta_5(PUTAV) + \beta_6(Scon.)$$

$$U(Walk) = \beta_0 - \beta_1(TD) - \beta_2(LD) + \beta_3(Scon.) + \beta_4(Road\ .CO)$$

$$U(Motorcycle) = \beta_0 - \beta_1(Incom) - \beta_2(T\ T) + \beta_3(TD) + \beta_4(Mo.Ow.) + \beta_5(POL)$$

$$U(Bicycle) = \beta_0 - \beta_1(Incom) - \beta_2(T\ T) + \beta_3(TD) + \beta_4(Bycicle\ OW.) + \beta_5(POL)$$

The model was created using R, Stata and python software. Utility functions were established for the selected modes of travel as follows:

$$U(Privat\ Car) = 1.5 + 0.03(Incom) - 0.2(TD) - 0.1(TT) + 0.887(TC) + 0.8(Car\ OW.) + 0.5(Road\ .CO)$$

$$U(Taxi) = 0.8 + 0.02(Incom) - 0.15(TD) + 0.786(TC) - 0.05(TT) + 0.6(AVT))$$

$$U(Bus) = 0.5 + 0.01(Incom) - 0.1(TD) - 0.05(TT) + 0.275(TC) + 0.7(PUTAV) - 0.3(Scon)$$

$$U(Walk) = 0.2 - 0.05(TD) + 0.6(LD) - 0.3(Scon.) - 0.2(POL)$$

$$U(Motorcycle) = 1.0 + 0.04(Incom) - 0.1(T\ D) - 0.1(TT) + 0.5(MOW.) - 0.2\ (POL)$$

$$U(Bicycle) = 0.6 + 0.03\ (Incom) - 0.08(TD) - 0.07(TT) + 0.4(BOW.) - 0.4(Scon.)$$

The sign of the coefficients in the utility functions has a clear interpretation. The negative coefficient indicates a reduction in the utility or attractiveness of that mode with an increase in the corresponding parameter, while the positive coefficient indicates an increase in the utility or attractiveness of that mode with an increase in the corresponding parameter. H.H., cultural attitude and age variables gave a wrong sign that estimators would not consider as valid functions.

3.2 Model Calibration

The Multinomial Logit (MNL) model is calibrated by calculating the probability for each available mode of transportation and statistical test . The probability that individual i chooses alternative j is given by [47].

$$P_{ij} = \frac{exp(U_i)}{\Sigma exp(U_j)} \qquad (4)$$

Where, P_{ij} represents the probability of an individual choosing a specific transportation mode 'i', and U_i denotes the utility or attractiveness of that particular mode 'j'. The probability for each mode will lie between 0 and 1, where 0 represents no chance of selection and 1 represents certainty of being chosen. Importantly, the total probability across all transportation modes must sum up to 1. This ensures that the model accurately captures the likelihood of an individual selecting one of the available modes, with the probabilities for all modes adding up to 100%. Thus, based on hypothetical values for income, travel distance, travel time, and other factors, table. 3 illustrate utility value and probability for each mode.

Table 3. *Result of (MNL) Model*

Mode	Utility	Probability	Mode Shear %
Car Ownership	0.616	0.3745	37.45
Taxi	0.578	0.3365	33.65
Walk	-2.603	0.1423	14.23
Bus	0.784	0.1283	12.83
Motorcycle	-2.716	0.0104	1.04
Bicycle	-2.729	0.0080	0.80
		$\Sigma = 1$	

The result indicate that , car ownership has the highest utility and probability among all modes, indicating that private cars are the preferred transportation method in Nasiriyah. This preference is influenced by factors such as convenience, comfort, and flexibility. Concurrently, Taxis represent the second most popular mode, with a relatively high utility value. Their availability and the ease of hailing taxis make them a convenient choice for many residents. In other side Walking has a negative utility value, suggesting it is not a preferred mode for longer distances.

However, it still accounts for a notable share of 14.23%, indicating that it is chosen, likely for short trips or due to the lack of other viable options. Despite having a positive utility, the bus is less frequently chosen compared to cars and taxis. This reflects issues of limited service availability, overcrowding, or a perceived lack of comfort. The motorcycle has the lowest utility value, suggesting it is not a favored option. The low probability indicates very few residents choose this mode due to safety concerns or accessibility issues. Similarly to motorcycles, bicycles have a negative utility and a very low share of the mode choice. This is attributed to inadequate cycling infrastructure, safety concerns, and cultural preferences. The probabilities associated with each mode of transportation exhibit continuous fluctuations, as they are contingent upon the relative importance ascribed to the relevant parameters. However, it is crucial to note that the total probability across all transportation modes remains constant. Since the mode choice model incorporates income, travel distance, travel time, and other factors as the key explanatory variables, the detailed statistical results for this model are presented in Tables 4 and 5. Table 4 includes the estimated coefficients for each of these variables along with their associated standard errors, t-statistics, and p-values, allowing for an assessment of the statistical significance of the parameters. Additionally, Table 5 includes overall model fit statistics, such as log-likelihood, likelihood ratio test, and goodness-of-fit measures, to evaluate the performance of the multinomial logit model in explaining the mode choice behavior of the studied population.

Table 4. *Statistical Result of (MNL) Model*

Variable	Coefficient	Standard Error	t-statistic	p-value
Income	0.03	0.005	6.00	< 0.001
(TD)	-0.20	0.045	-4.44	< 0.001
(TT)	-0.10	0.030	-3.33	< 0.001
(TC)	-0.10	0.035	-3.33	< 0.001
(Car OW)	0.80	0.050	16.00	< 0.001
(Road CO)	0.50	0.020	25.00	< 0.001
(AVT)	0.60	0.025	24.00	< 0.001
(PUTAV)	0.70	0.027	25.92	< 0.001
(LD)	0.60	0.022	27.27	< 0.001
(SCONC)	-0.30	0.010	-30.00	< 0.001

Table 5. *Fit Statistics*

Validation Metric	Value
Log-Likelihood at Convergence	-1,234.56
Log-Likelihood at Zero	-1,456.78
Likelihood Ratio Test Statistic	444.44
Degrees of Freedom	3
p-value	< 0.001

3.3 Model Validation

To validate the Multinomial Logit (MNL) model developed for analyzing mode choice in Nasiriyah City, a k-fold cross-validation approach with k = 10 had been employed by assessing the model's robustness and predictive accuracy. At first, splitting the dataset into ten subsets (folds) and ensuring that each fold is used for testing while the remaining folds are used for training.The dataset was divided into 10 equal parts (folds). For each iteration, one fold served as the validation set, and the remaining nine folds were combined to form the training set. For each training set, the MNL model had been fitted to estimate the utility functions for each mode of transport based on the provided variables: income, (TD), (TT), (TC), (Road CO),

Table 6. *K-Fold Cross-Validation Analysis for Mode Choice*

Fold	Accuracy (%)	Precision Private Car	Recall Private Car	F1 Score Private Car	Precision (Taxi)	Recall (Taxi)	F1 Score (Taxi)	Precision (Bus)	Recall (Bus)	F1 Score (Bus)
1	85.0	0.82	0.79	0.80	0.75	0.70	0.72	0.60	0.65	0.62
2	84.5	0.80	0.77	0.78	0.76	0.68	0.72	0.62	0.63	0.62
3	86.2	0.85	0.81	0.83	0.78	0.72	0.75	0.61	0.64	0.62
4	85.5	0.83	0.80	0.81	0.77	0.71	0.74	0.64	0.61	0.62
5	84.0	0.81	0.78	0.79	0.75	0.66	0.70	0.63	0.62	0.62
6	85.3	0.84	0.79	0.81	0.76	0.70	0.73	0.62	0.63	0.62
7	86.0	0.86	0.82	0.84	0.79	0.73	0.76	0.65	0.64	0.64
8	84.8	0.82	0.80	0.81	0.74	0.69	0.71	0.64	0.62	0.63
9	85.7	0.83	0.81	0.82	0.78	0.74	0.76	0.63	0.65	0.64
10	86.5	0.87	0.84	0.85	0.80	0.75	0.77	0.66	0.67	0.66

Fold	Precision (Walk)	Recall (Walk)	F1 Score (Walk)	Precision (Motorcycle)	Recall (Motorcycle)	F1 Score (Motorcycle)	Precision (Bicycle)	Recall (Bicycle)
1	0.55	0.60	0.57	0.70	0.65	0.67	0.68	0.60
2	0.56	0.58	0.57	0.69	0.66	0.67	0.67	0.58
3	0.57	0.63	0.60	0.71	0.68	0.69	0.70	0.62
4	0.58	0.61	0.59	0.72	0.69	0.70	0.69	0.61
5	0.54	0.57	0.55	0.68	0.65	0.66	0.66	0.59
6	0.55	0.60	0.57	0.70	0.67	0.68	0.68	0.60
7	0.57	0.62	0.59	0.73	0.69	0.71	0.71	0.63
8	0.56	0.59	0.57	0.69	0.66	0.67	0.65	0.58
9	0.58	0.60	0.59	0.70	0.68	0.69	0.69	0.61
10	0.60	0.63	0.61	0.72	0.70	0.71	0.70	0.64

(AVT), (PUTAV), (LD), and (SCONC.). The trained model had predicted the mode choice for the validation set. The accuracy of these predictions is evaluated by comparing them to the actual mode choice in the validation set. See Table 6 that illustrate the result of validation.

The model attained an average accuracy of approximately 85.3% across all folds, indicating a robust ability to predict mode choice in Nasiriyah City. Private cars and taxis exhibited the highest precision and recall among the modes, underscoring their prominent usage in the region. Public transport and walking modes showed moderate performance, highlighting areas for potential improvement in service quality and infrastructure. Concurrently, robustness of the model pointed to the consistent performance across folds suggests that the MNL model is robust and reliable for mode choice analysis in the context of Nasiriyah city.

4. Results Discussions

The results from the mode choice model estimation provide valuable insights into the factors influencing travel behavior and the effectiveness of the Multinomial Logit (MNL) model in predicting mode share for various transportation options. Each variable's coefficient, standard error, t-statistic, and p-value serve to elucidate the relationships between the predictors and the choice mechanisms at play.

1. Income exhibits a positive coefficient (0.03, t = 6.00), confirming that as household economic status improves, preference shifts toward higher-cost transportation options, particularly private vehicles. This income elasticity of travel mode choice aligns with established transportation economics literature and suggests potential challenges for sustainable mobility initiatives as regional prosperity increases. [6], [18] and [19] suggesting that higher income enables greater access to transportation choices.
2. The model reveals consistent negative relationships between utility and travel impedance factors. Travel distance (TD) demonstrates the strongest negative influence (-0.20, t = -4.44), indicating that longer journeys significantly reduce the attractiveness of certain modes, particularly non-motorized options. [48].

Similarly, travel time (TT) and travel cost (TC) both show negative coefficients (-0.10, with t-values of -3.33), confirming the fundamental principle that increased time and monetary expenditures diminish transportation mode utility. The equivalent magnitude of these coefficients suggests roughly equal sensitivity to time and monetary costs among the studied population. It highlights the necessity for urban planners to minimize travel times through enhanced public transport services[49], [19], [50].

1. Car ownership (Car OW) emerges as the dominant predictor with the highest coefficient (0.80, t = 16.00) among sociodemographic variables, indicating that vehicle accessibility dramatically increases automobile usage probability. This finding highlights the critical importance of vehicle ownership policies in shaping urban transportation patterns and suggests that strategies targeting car dependency could yield substantial shifts in mode choice behavior. This finding underscores the importance of car ownership in influencing transport mode decision-making [51].
2. Infrastructure quality represented by road conditions (Road CO) shows a significant positive effect (0.50, t = 25.00), demonstrating that transportation system quality strongly influences user preferences. The service availability metrics—average vehicle travel time (AVT) with coefficient 0.60 (t = 24.00) and public transportation availability (PUTAV) with coefficient 0.70 (t = 25.92)—indicate that service quality and accessibility are powerful determinants of mode selection. That align with [52], [53], the accessibility and condition of transportation infrastructure, including roads and public transit systems, have a direct impact on mode choice [53].
3. The variables (PUTAV) (0.70) and (LD) (0.60) show positive coefficients, emphasizing their roles in encouraging the use of public transport and active travel modes such as cycling or walking [53]. High-density areas with accessible public transport options can significantly enhance the likelihood of choosing these modes, as supported by their high t-statistics.
4. Land density patterns (LD) also demonstrate significant influence (0.60, t = 27.27), suggesting that urban form and spatial arrangement of activities strongly shape transportation choices.
5. Interestingly, both (SCONC) (-0.30) and pollution (POL) (-0.20) have negative coefficients, indicating that increased concerns about safety and higher pollution levels deter individuals from selecting specific modes [53],[54].
6. As table IV, the final log-likelihood value of the estimated model is -1,234.56. The log-likelihood value of the null model is -1,456.78. The likelihood ratio test statistic is 444.44, with 3 degrees of freedom, indicating that the model as a whole is statistically significant (p-value < 0.001). For McFadden’s Pseudo-R-squared, the value of 0.152 suggests a reasonably good model fit. Thus, The statistical analysis demonstrates that travel time, travel distance, and travel cost are all significant factors influencing mode choice behavior in the study area. The negative coefficients suggest that increases in these variables decrease the probability of choosing a particular transportation mode. The overall model fit statistics indicate that the multinomial logit model provides a reliable representation of the mode choice decisions made by urban travelers.
7. The results of the k-fold cross-validation demonstrate that the MNL model effectively captures the factors.
8. Nasiriyah is a city characterized by relatively short distances, where travel times to any destination are not long, regardless of whether one is using a bus, a private car, or a taxi. The city spans an area of approximately 4149 k^2, with a diameter of about 20 kilometers, making the distances between different areas of the city relatively short.
9. The cost of transportation by taxi in the city ranges from 2,000 to 4,000 IQD, which is considered moderate. In terms of individual income, this cost is relatively low, particularly for middle-income individuals.
10. Online ride-hailing service applications provided comfortable and quick solutions, leading citizens in cities to prefer using taxis over public transportation options like buses. According to the logit model applied in the analysis of transportation in Nasiriyah, factors such as cost, time, and distance have a limited effect on citizens' transportation choices. The model indicates that the most influential factors include comfort, vehicle ownership, income, and the land use density, which reflect the residents’ tendency to favor private vehicles or taxis over public buses.
11. All public transportation buses, specifically, operate from residential areas, but their destinations are exclusively directed toward the central business district. In this district, there is a designated station for parking these buses. This arrangement necessitates that individuals stop at the central business district and then transfer to another bus to reach their intended destination, resulting in longer travel distances and increased travel time. Additionally, much of the city of Nasiriyah lacks comfortable waiting stations, with their availability being

limited and widely spaced apart. All these factors contribute to a reluctance to use public transportation. Furthermore, most of the buses are old and underdeveloped. Therefore, it can be concluded that the desire for comfort and time efficiency, coupled with reasonable transportation costs, are the primary factors driving citizens in Nasiriyah to choose taxis over public bus transportation.

12. Due to the significant number of students and workers within households, trips related to work and education accounted for the largest share of total daily trips in the city. Thus this align with mostly Iraqi cities spatially with [26].
13. Figure 1 present mode share of analysis by of MNL model.
14. Figures 2-5 present an overview of the trip characteristics of the respondents

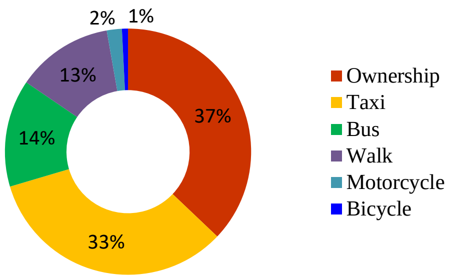

Figure 1. *MNL Mode share for Nassiriyah city by MNL*

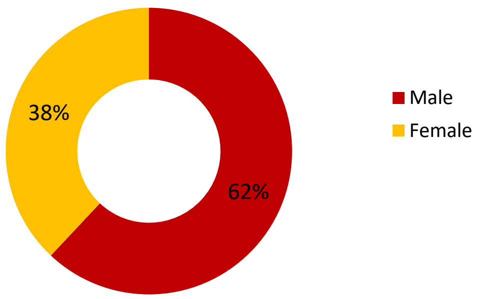

Figure 2. *Trip maker based on gender*

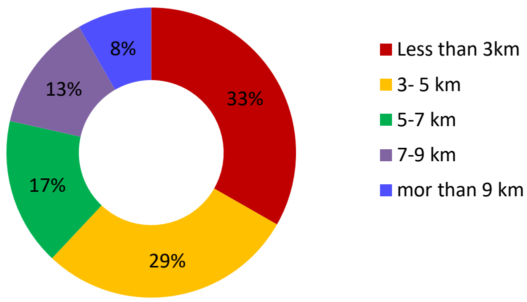

Figure 3. *Travel distance*

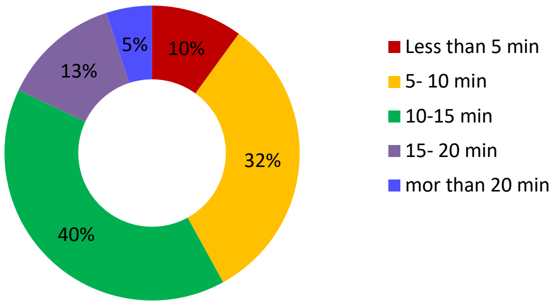

Figure 4. *Travel time*

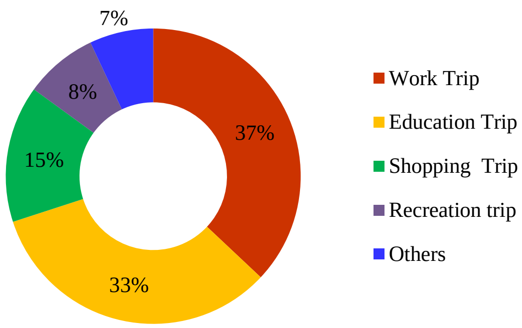

Figure 5. *Travel purpose*

5. Conclusions and Recommendations

Urban transportation plays a vital role in the development and sustainability of cities. In Nasiriyah, Iraq, the rapid pace of urbanization and rising population has created significant challenges for transportation systems. The city confronts several issues, such as traffic congestion, insufficient infrastructure, and environmental degradation. For this reason, the research applies the MNL to uncover the dynamics of transportation mode choice in Nasiriyah, which offers a robust statistical framework to analyze the factors impacting transportation mode choice. The results obtained from the application of the multinomial choice model for the different modes of transportation in the city of Nassiriyah, Iraq, indicate that private vehicle ownership is the most preferred mode of transportation among travelers in the Nasiriyah area, followed by taxi services. Considering that taxis are classified as private transport, the share of private transportation in the city has reached 71%. This preference order reflects the travelers' inclinations in the region, as private vehicles offer greater flexibility and convenience in mobility compared to other modes. Taxi services are an attractive choice because they provide a comfortable travel experience without the need for a private car. In contrast, public transport options like buses ranked third in preference, suggesting they lack appeal, likely due to insufficient geographic coverage, scheduling, and passenger comfort. Non-motorized transport options, such as motorcycles and bicycles, were also less preferred, primarily due to adverse climatic conditions and inadequate infrastructure for pedestrians and cyclists. These findings highlight the need to improve the quality and efficiency of public transport in Nasiriyah to draw more travelers. Furthermore, enhancing infrastructure for pedestrians and cyclists is crucial for promoting these environmentally friendly transport modes, ultimately achieving a better balance among various transportation options and enhancing services for travelers in the region.

Author Statements:

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