

Article

Modeling the Modal Shift towards a More Sustainable Transport by Stated Preference in Riyadh, Saudi Arabia

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Abstract: The need to gain a comprehensive understanding of road travelers' choice of mode and their perceptions of using sustainable urban mobility modes have evolved to shape the form of future transport planning and policymaking. To combat the concern of growing traffic congestion in Riyadh City, the government of Saudi Arabia designed and introduced a sustainable public transport project named "Riyadh Metro". This study explores the potential commuters' perception towards the Metro services and the factors that limit their propensity to use Metro and understand the tradeoffs that the individuals make when they are faced with a combination of mode characteristics (e.g., travel time, price, walking time). The stated preferences experiment was conducted on a sample from the Riyadh neighborhood by structured interviews. A discrete choice model based on binary logistic regression has been developed. The coefficient of travel attribute: travel time, fuel cost, Metro fare, and walking time was found to be statistically significant with a different effect on mode choice. The elasticity of the coefficient showed that an increase in the fuel price by 10% would increase the metro ridership by 5.3% and reduce car dependency. Decreasing the walking time by 5 min to the metro station will increase the metro ridership by 22%. Furthermore, the study revealed that implementing a 1 SAR/hour parking charge will decrease car dependency by 14%. Increase Metro fare by 10% will decrease Metro ridership by 6.9%. The socioeconomic factors coefficient shows a marginal effect on the choice decision of passengers.

Keywords: Riyadh metro; mass transit; stated preferences; sustainable mode of transport



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1. Introduction

The capital city of Saudi Arabia, Riyadh is one of the fastest-growing cities in the world, with rapid growth in the population of 8.4 million in 2018 [1]. The gradual economic boom of the last two decades has led to a significant increase in motorized traffic outgrowing the capacity of the city's road network [2]. According to Ar-Riyadh Development Authority (ADA), more than 92% of daily trips are made by private cars, only to increase road congestion [3]. The growing car use is not favorable to the global sustainable goals of reduced energy consumption and improved air quality [4]. Moreover, road congestion causes increased travel time and road safety issues, socio-economic problems, and Green House Gas emissions (GHG) [5]. Road transportation alone is responsible for 14% of global GHG emissions in 2015 per se and the demand for transportation sector energy consumption is expected to increase by 300% in 2050 [6]. The negative impacts impair the quality of urban life and mobility to the city dwellers, thereby, making the transport system unsustainable [7]. Introducing public transport is considered as a remedial measure of limiting car users and solo trips in Riyadh City. To combat such multidimensional transport-related issues the authority has commissioned a new public transport system

comprising six Metro lines complemented with bus networks in 2012. However, most of the dwellers in Riyadh had no prior experience of using public transport and are mostly accustomed to using their private cars for daily commuting [8,9]. In a study, Al-Fouzan reports that higher family income, improved economic factors, and modernization, state-sponsored fuel subsidy, and urban sprawl have contributed to shaping the lifestyle of Saudi families relying more on private vehicles than other modes [4,10]. Lower fuel price, comfort, privacy, and socio-cultural aspects kept the demand for using cars for city trips steady in Riyadh [4].

Aldalbahi and Walker considered Riyadh as a unique case study for both a rapidly moving microcosm trend in transportation, facing significant traffic congestion, and growing transportation demand due to the high rate of urbanization and auto-dependency [11]. Growing transportation demands in Riyadh urban areas makes it vital to introduce major public transportation as a sustainable solution to reduce traffic congestion, especially, with the current trend, it is estimated that 90% of total roads will be overloaded and congested by 2021 [11].

Excessive single occupancy vehicle use leads to adverse social and economic effect costs from reduced air quality, congestion, decreased urban livability [12]. Therefore, Transportation planning policies in congested metropolitan areas often seek to create a more effective, attractive, and sustainable transit service to compete with the single-occupant automobile. The policy goal is to attract travelers away from their private cars toward transit use; yet, various case studies conducted on cities with traffic congestion demonstrate that it is possible to reduce car dependence even in affluent societies with high levels of car ownership if the transit services are designed to meet public expectation [13].

This study attempts to analyze the modal choice shifting from private car to Metro in light of the Metro service attributes of Riyadh City. New Riyadh Metro should attract car users and not “Captive riders”. The above goal can be achieved by investigating how people react to a set of travel attribute factors that contribute to the commuter’s choice across different socioeconomic characteristics of the population upon planning the metro system services scheme. The city dwellers in Riyadh is heavily dependent on the use of private cars for their daily commute [3]. The proposed Riyadh Metro is supposed to attract the car mode commuters that constitute 85% of trips in Riyadh. To archive the goal of sustainable transportation there is a need to test the commuter’s preferences towards the new proposed metro service. The information on mode choice would help plan and operate the metro service better by knowing the extent of modal shift in terms of travel attributes. The study will provide an initial assessment to test various combinations of policies to reduce car usage such as parking price, congestion price, and road toll and increase metro ridership.

One of the main objectives of this study is to build a discrete mode choice model using the stated preferences method for a business trip in Riyadh considering several travel attributes and socioeconomic variables. Based on the discrete choice model, sensitivity and simulation study would be conducted to test the effect of changes in travel attributes (time, cost, walking time) on the individual choice probability to ride the Metro. However, the scope is limited to the business trip in Riyadh, which constitutes the biggest share of what will have a significant impact on the travel behavior in Riyadh. The study focuses on business trips as nonbusiness travelers are less elastic than business travelers with regard to the transportation attributes (e.g., travel time and frequency of service). This study offers an opportunity to assess people’s sensitivity to various mode choice scenarios with cars and metro service such as travel time, walk time to the metro station, and fuel cost.

The remainder of this paper is structured as: Section 2 provides a detailed literature review about Riyadh Metro and pertinent studies. Section 3 presents a description of the study area and data collection. Section 4 discusses the data description and study methodology; Section 5 highlights results and discussions. Finally, Section 6 summarizes study findings, provides study limitations and outlooks for future research.

2. Literature Review

Each travel mode is dominant in various travel situations due to the difference in travel speed, comfort, and travel cost of each mode. The understanding to what extent travelers' socio-economic, demographic, and trip characteristics affect the choice of individuals travel mode is significant to the analysis of mode choice behavior.

Numerous studies in the literature have investigated the influence of several factors that would affect an individual's travel mode choices. Beirão and Cabral explored the traveler's attitude towards transport and perception of public transport quality among public transport and car users [14]. The study found that individual characteristics and lifestyle, the journey type, and the perceived service performance of each transport mode tend to influence the choice of transport. They suggested that public transport should be designed to meet the required level of service of the customer to encourage them using it. Hartgen maintains that socio-economic attributes and travel attitude are very important to shape travelers' decisions on mode choice [15]. Forward indicated that the individual status and habit along with the quality and supply of alternative modes are influential in mode choice [16]. Travel purpose and personal characteristics are also found to impact travel mode choice [5]. Albalade and Bel identified factors explaining local public transportation of large European cities from both supply and demand sides. The study stated operational cost, income, and city characteristics influence the supply of public transport (PT), whereas travel cost and travel time have a significant impact on the PT demand [17].

Bhat and Srinivasan showed that households with higher income have a propensity to use auto mode [18]. Yang et al. found that due to several advantages, females prefer to choose public transport than males [19]. Affordable ticket fares and saving of travel time are vital to public transit attractiveness [20,21]. Punctuality in the arrival schedule is another influential factor for choosing PT [22]. Unlike cost and other variables, time is considered as a constraint as people cannot increase the time spent on traveling infinitely [23]. Polat mentioned that three key components comprise travel time by public transport; the time taken to walk to the nearest transit station or bus stop, waiting for service, and time spent in the vehicle [23]. Some other studies added that transfer between vehicles or modes is accounted for in the public transport travel time [24,25].

Chauhan et al., studied the efficacy of a multivariate statistical model to predict the probability of non-Metro commuters to shift to the Metro service at Delhi [26]. A binomial logistic model was developed to predict the switch of existing Metro commuters who used to travel on private motor vehicles or busses. They found that 57% of Metro users have switched from personal vehicles or buses. The reason for switching from private vehicles and busses to Metro is attributed to the longer travel time when compared to Metro services. Their study also analyzed the cannibalism effect (i.e., modal shift within the same category) shift from busses to Metro service. In a similar study by Jain et al. Analytical Hierarchy approach to prioritize the different criteria for urban commuters from private vehicles to Metro service in Delhi, India [27]. Based on reliability, comfort, safety, and cost, the public preference was examined for a potential modal shift of passengers to Metro service. The result revealed that safety was the major reason for which commuters wanted to switch to metro service from other available modes. Commuters were willing to pay more for better public transit.

Wang et al. used Binary Logistic Analysis to assess the impact of modal shift from automobiles and busses after a Bus Rapid Transit (BRT) was introduced along six representative corridors in China [28]. The results of the study showed that commuters' demographic, socioeconomic and trip attributes were vital to modal shift to BRT. Ladhi et al. reviewed and assessed modal shift behavior using a discrete choice model due to the introduction of a new metro mass transit [29]. The result of the study revealed several causes of modal shift from personal vehicles and buses to Metro rail service. Excessive road congestion, less travel time, and lower travel fare were found to be the main cause of shifting from personal vehicle to Metro. A similar study conducted in Thessaloniki, Greece attempted to analyze the modal shift of private car users to a newly constructed metro service for a sustainable

mobility solution [30]. Interestingly, through a stated preference survey this study revealed that the car users are not willing to switch to Metro service even after knowing the benefits of using a mode of public transport. However, the existing bus riders would shift to metro service as they think that metro service will benefit them from several aspects.

Sohoni et al., deployed drafting, executing, and testing revealed preference (RP) and stated preference (SP) questionnaire surveys to investigate mode shifting behavior in Mumbai Metro, India [31]. The RP survey was performed on passengers on the newly constructed Metro corridor, while the SP survey was performed on a proposed extension of the Metro line. A Sequential estimation method was adopted to the combined RP and SP dataset to develop an econometric mode choice model. Sixty percent of the respondents from the SP survey were willing to adopt the proposed metro extension for their regular commute. Ding and Yang estimated commuters' mode choice behavior against a raised parking fees [32]. The variability of travel times is considered and analyzed in the stated choice survey conducted among car, bus, and Metro users. The study results concluded that the increment in driving cost would significantly reduce the driving demand, whereas discounted travel fare was unable to drive car commuters shifting to Metro.

Ashalatha et al. assessed mode choice behavior using a Multinomial Logistic regression model at Thiruvananthapuram city in India [32]. The investigation disclosed that the older age of commuters has a direct repercussion on mode choice as they tend to favor cars more than public transport citing comfort and safety. Increased travel time and cost by public transport caused a shift of passengers to cars and two-wheelers.

Transport planners often need to forecast impacts on travel demand of transport policies, e.g., construction of a new transport alternative, changing public transit fares, or imposing road pricing schemes. In such forecasting of mode choice concepts, stated preference (SP) methods are often used where the individual chooses among different transportation means, which is perceived as a consumer evaluating the available alternatives and selecting the best one [33]. This analysis is rooted in the consumer utility maximization theory as the model choice of traveler is defined through tradeoffs among specific characteristics associated with different modes and that the traveler is willing to maximize his utility [34].

Utility function associated within the alternative is given by:

$$U_i = V_i + \varepsilon_i \quad (1)$$

V_i is the observed utility or representative component of Utility as it is the attribute that reflects the choice.

ε_i is the unobserved utility.

Both are assumed to be additive and independent [35]. The above can be interpreted into a functional form

$$V_i = \beta_{0i} + \beta_{1i} f(x_{1i}) + \beta_{2i} f(x_{2i}) + \beta_{3i} f(x_{3i}) + \dots + \beta_{ki} f(x_{ki}) \quad (2)$$

where β_{0i} represent the unobserved utility called "Alternative specific constant.

β_{1i} -weight of the parameter associated with attribute (x_1) for an alternative I, assuming that component ε_i is identically distributed.

The probability of choosing a mode can be expressed through the logit model given in equation [36]

$$P_{ki} = \frac{\exp(V_{ki})}{\sum_{j \in C_k} \exp(V_{kj})} \quad (3)$$

where, P_{ki} is the probability of k to take mode i, and V_{ki} is the observed component of the utility function of mode i by k as a function of socioeconomic and characteristics of the mode.

Stated preference (SP) has become the principal method in transportation planning; the stated preferences of travel mode takes one of the appropriate data collection methods, e.g., ranking-based, rating-based, or choice-based [37]. The service attribute for the trans-

portation mode may include trip-related factors: travel cost, travel time, vehicle-related attributes such as comfort, accessibility, and punctuality; these terms perception vary among modes, for instance [38].

Stated preference techniques have advantages over revealed preference methods, which are based on actual choices, on the ability to make more than one transportation choice and can be presented with tradeoffs rather than dominated choices and learn the importance that people devote on each attribute based on the choices they make [39]. One of the advantages of stated preference is to collect data with as little bias as possible [40].

Also, SP gained popularity, according to Ortuza and Willumsen, due to its ability to [41]:

- Deal with situations when a new alternative is introduced with no background knowledge about how people would react.
- Determine the separate effects of two variables on the consumer's choice provided.
- Observe the variability in choices and the variables can be controlled
- Deal with sensitivity and elasticity when it is more important than forecasting the substantial mobility level.
- Demonstrate cost-effectiveness.

The base of the SP experiment carried out in cases where the desire is to assess the consequences of a new policy or new technology, such as high-speed transit, is by investigating the reaction to a hypothetical situation. However, in SP, at least three characteristics for each alternative should be present for respondent evaluation bearing in mind that these characteristics should appear realistically by asking the decision-maker to choose among different alternatives, the analyst gathers information about the relationship between the varying attribute level of the transportation mode and the choice that the decision-maker takes based on tradeoffs on these attributes [42].

It is worth noting that these characteristics should appear realistically, furthest, the varying attribute level of the transportation mode, and the choice that the decision-maker takes based on tradeoffs on these attributes [35]. Hensher highlighted the ambiguity faced by the researchers in defining the public perception of some travel attributes that are associated with public transport, apart from travel cost, travel time, safety, level of comfort, and convenience [35]. Safety, for instance, could mean personal assault, but for others, it may mean the vulnerability of train derailment; however, the sources of the estimated parameter are taken from past studies and pilot surveys [35].

In defining the attribute level based on RP, Hensher et al. recommend two methods: first: assign a percentage from the attribute level reported by the decision-maker (e.g., -10% – $+10\%$), second: treat every decision-maker in the associated segment or range of attribute levels [35]. However, the attribute level range can be derived by a focus group or initial survey in a careful way that needs to be factual [35]. Habibian and Kermanshah studied the car commuters' change to public transportation by stated preferences when transportation demand management measures are hypothetically applied; they have modeled the commuter's choice in logit binary and concluded that parking cost, transit access by walk, and fuel cost are highly correlated with commuters' choice mode [43].

Ahern and Tapley conducted a study on the preferences of passengers on interurban rail and bus in Ireland using stated preferences and revealed preferences; in comparing the two methods, they identified limitations in both methods, especially by the limited ability of the respondent to understand the hypothetical situation which can be overcome by generating realistic alternatives [44]. Habibian and Kermanshah studied the car commuters change to public transportation by stated preferences when transportation demand management measures are hypothetically applied; they have modeled the commuter's choice in logit binary and concluded that parking cost, fuel cost, car ownership for car mode, and travel time and transit accessibility for public transits were the influencing factors [43]. The study concluded that parking cost, transit access by walk, and fuel cost are positively correlated with commuters' choice mode. Chakour and El-Geneidy studied the travel mode choice and transit route choice behavior in Montreal, Canada [45]. The study

objectives are two-fold. First, investigate an individual's choice between transit and car mode of transportation for commuting to McGill University. Second, for transit commuters, the decision that influences their decision is to be analyzed. The study considered several variables in the empirical analysis, socio-demographic aspects, age, gender, driving license, employment status, and vehicle ownership. At the travel attribute, travel time, travel time by mode, walking time, initial waiting time, waiting time in transit, a number of transfers, and time of day were accounted for.

A stated preference survey by Gleaves on the rail network in England investigated the importance of various characteristics given by passengers to the rail transportation such as time to access the rail station, headway, and in-vehicle time; the aim was to recommend whether to test the feasibility to build new lines in the future (future trend) [6]. The weights of these parameters were tested in an initial study in 2002. The respondents were faced with hypothetical but realistic value alternatives; each alternative has been described by attributes variation to reflect the people's perception towards these attributes [46]. From a data collection perspective, Antoniou et al. maintain that most studies use stated preference data as obtaining revealed preference data is not always favorable [47]. Furthermore, due to practical reasons, most studies use mixed discrete choice models or logit models for mode choice analyses.

3. Study Area and Data Collection

The increased rate of car use in Riyadh as in other countries, especially in rich developing countries, has major implications in terms of pollution, noise, and congestion problems. Commuters rely more on private cars as a way of transportation, ignoring or due to lack of other alternatives such as public transportation systems [14]. Introducing Riyadh Metro is a major solution as it is expected to form the backbone of the public transport system in Riyadh. Six lines at a total length of 176 km and 85 Metro stations, the Metro network will cover most of the densely populated areas, public facilities, and the educational, commercial, and medical institutions.

The Riyadh Public Transport Network (RPTN) is a multimodal network covering the Riyadh area with connections to both local and international modes of transport (air, rail, and intercity buses). It is developed using transit-oriented development principles and includes a fully integrated public transport service with integrated facilities. The masterplan of RPTN consists of Riyadh Metro, which is composed of rail-based urban transit systems operating along six selected corridors with the highest demand generated from the high density of urban development (Figure 1). The capacity of the project is 1.16 million passengers at the trial operation and is expected to reach 3.6 million passengers per day in 10 years. The Riyadh Metro is expected to reduce car journeys to almost 250,000 trips per day, thereby it will reduce the cities fuel demand by 400,000 L per day [15]. Bus Rapid Transit (BRT) lines which are fully integrated with the Riyadh Metro to provide seamless intermodal service and Community Bus Lines will provide coverage to the parts of the city not covered by Riyadh Metro or the BRT lines. Feeder Buses will ensure the first and last portion of the journey with pick-up or drop-off of passengers at an acceptable walking distance from their door-step.

We have carefully chosen one of the Metro corridors that connect the residential neighborhood to central CBD, where the travel distance is feasible to travel by Metro. The proposed trip's origin would be from any parcel from the neighborhood to a particular Metro station downtown. The proposed trip is set to be along the Metro corridor from Al-Naseem Western to Metro Station 3j1 (line3) to Station 2B2-S1 (line1) the distance 19.323 km (Figure 2).

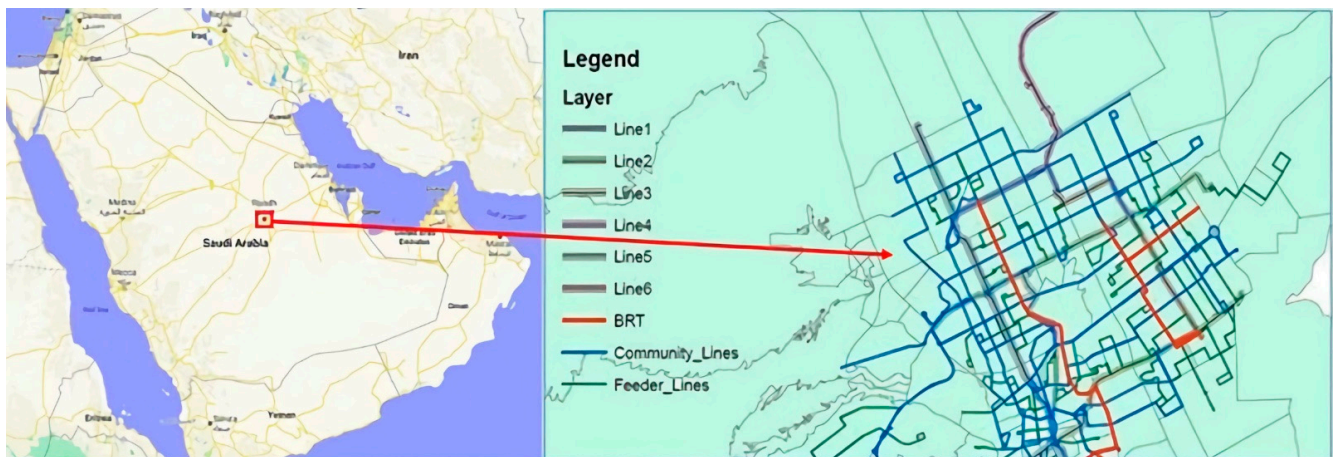


Figure 1. Riyadh Metro Network.

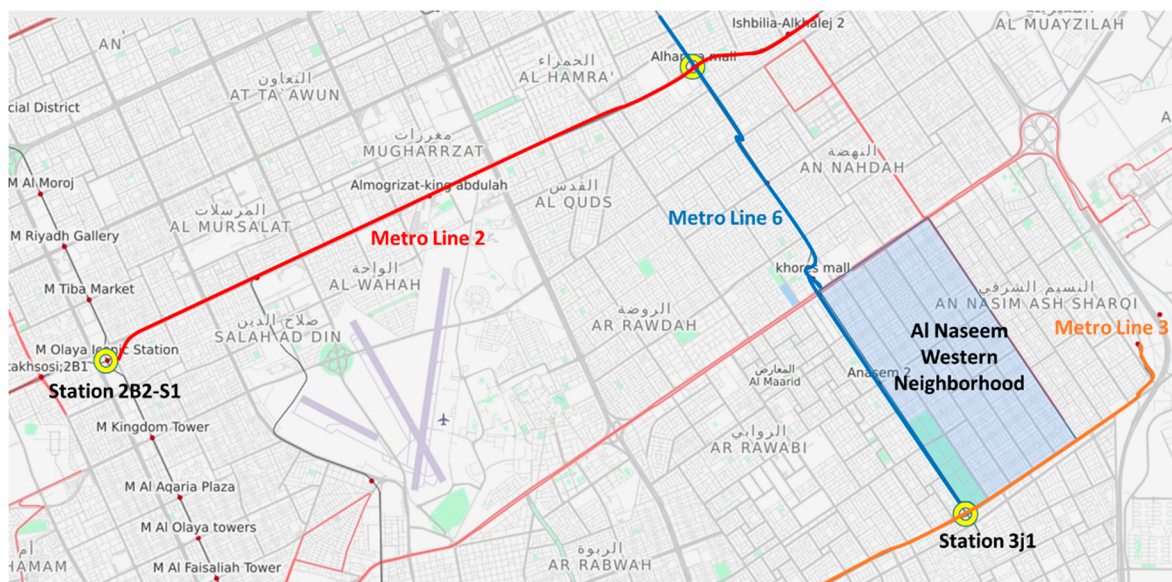


Figure 2. Study Area.

The neighborhood option can be justified by:

- accessibility to Metro lines
- has a demographic feature that conforms to Riyadh demographic
- Maintains heterogeneity in socioeconomic characteristics. Furthermore, this variability of socio-demographic characteristics and contextual effects observed within the sample will significantly affect if such effects are to be included within the model.

The respondent is asked to express his choice preference between the existing transportation choices (e.g., car mode) with the hypothetical one (Riyadh Metro that is not yet in operation). The summary of the demographic feature is shown in Table 1.

Table 1. Al-Naseem Neighborhood Demographics Feature, Source [30].

Locality	Saudi Nationality			Non-Saudi Nationality			Total Population	Ratio
	Male	Female	Total	Male	Female	Total		
Al-Naseem Neighborhoo, Riyadh	68,833	63,129	131,962	14,923	9688	24,611	155,573	0.18
	1,445,968	1,295,087	2,741,056	847,000	532,418	4,379,674	4,120,730	0.50

4. Research Methodology

The attribute influences the individual choice assuming that the sampled individual is aware of the factors that influence his choice decision, which is a crucial issue and can be achieved by conducting a structured interview of focus groups, literature reviews, and expert interviews [35]. The inter-attribute correlation, although the correlation may not be applied statistically but may be reflected in the decision-maker perception of specific combination (e.g., quality and price) or in the application which generates unrealistic combination, the designer should overcome this problem by using different experimental design [35]. From the literature review, the most important attribute that influences transportation choice are taken into consideration. Questionnaire surveys were administered to collect data on stated preferences from different travel modes. The questions had four parts, targeted to the intended user groups. Socioeconomic and travel characteristics of the commuter, quality of travel, modal shifts to Metro services, and travel frequencies were the four major sections, in which there were some sub-sections. Gender, age, profession, nationality, monthly income, car ownership, trip purpose, and trip origin-destination (O-D) are the basic socio-economic and travel characteristics included in the questions, while travel time, travel cost, and waiting time were the variables focused on the quality of travel. The modal split includes travel modes before and after implementing the metro service and the prime reason for mode changes. The average number of work trips per week made by different travel modes describes the travel frequency. Hypothetical scenarios are presented to respondents by the intercept survey. The respondent is briefed on the purpose of the study and the scenarios that are included in the survey beforehand. The participants respond to the general information and then were presented with 12 scenarios in which there are changes in attribute level of Metro (travel time, walking time and fare) and for personal vehicle (fuel price, parking cost, and travel time) and in each scenario they had to tick down his/her preferred mode. Data set results from choice sets is 720 row each row represent one scenario which is analyzed by NOLGIT 6. The general questions related to respondents' social characteristics are analyzed by SPSS. A general framework for choice modeling is shown in Figure 3.

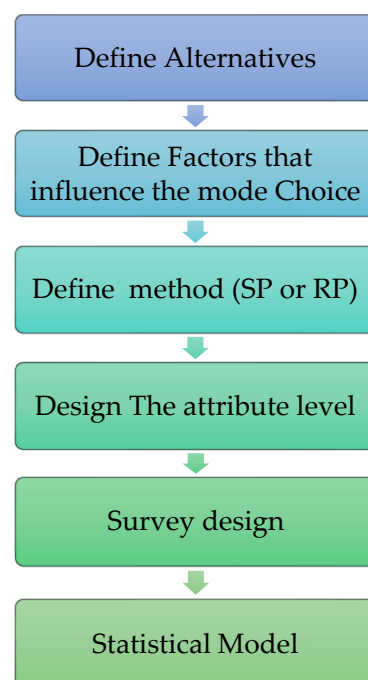


Figure 3. Choice modeling general framework.

4.1. Metro Trip Attribute Level

Geographic Information System (GIS) network analysis facilitates calculating the designated trip attribute; the following considerations have been taken into account and outlined in Table 2.

- The walking distance has been taken from the center of each parcel to the nearest station, the equivalent time of walking has been taken according to international standard (80 m require 1 min)
- The speed of the Metro vehicle is 80 km [48]
- The average stop time at metro station is 90 s/station, including boarding time
- In-vehicle time include the connecting bus in Vehicle time if applicable considering the bus speed 40 km/h

Table 2. Calculation of Travel Attribute.

Description		Metro Route	Private Car
Route Information	Trip Origin	Station (line3) 3j1	Similar Previous Trip
	Destination	Station (line1) 2B2-S1	Naseem Neighborhood
	Distance	19.323 Km	-
Attribute		Fare	One way fuel cost/liter
Attribute Level		5, 8, 12 SAR	1, 2, 3 SAR
Attribute		Time in vehicle variation	Travel time variation due to traffic congestion
Attribute Level		45, 60, 75 min	+25%, +35%, +45%
Attribute		Walking to the nearest stop	Parking cost
Attribute Level		5, 10, 15 min	0, 1.5, 3 SAR/ hr

4.2. Experiment Design

Orthogonal designs produce unbiased parameter estimates and the ability to control statistical problems such as multicollinearity [35,49]. The finite number of alternatives is derived from the study's context. It can be defined through focus groups, in-depth interviews, and secondary data. To reduce the alternatives number, insignificant alternatives may be excluded [35]. The choice analysis flowchart along with associated stages can be found in Figure 4.

A choice experiment is an attribute-based stated preference method, where the respondents are asked to choose their preferred service [50]. Unlike the Contingent Valuation Method (CVM) where the respondents are presented with only a single situation, choice experiments offer several options for the respondents to choose from. Such design by the choice experiment closely resembles the real-world condition and removes the bias associated with the CVM method. There are several options available for choice set generation. All pairs, 2^j block assignment, balanced incomplete block design, and L^{IK} are the few acceptable methods of generating choice set [51]. The number of possible choice sets using the L^{IK} method can be given by the equation

$$C = L^{MA} \quad (4)$$

C is the labeled choice experiment; L is the number of levels; M is the number of alternatives, and A is the number of attributes. All possible treatment combinations of the attributes are enumerated as two modes, two alternatives, and three attributes, resulting in 81 scenarios.

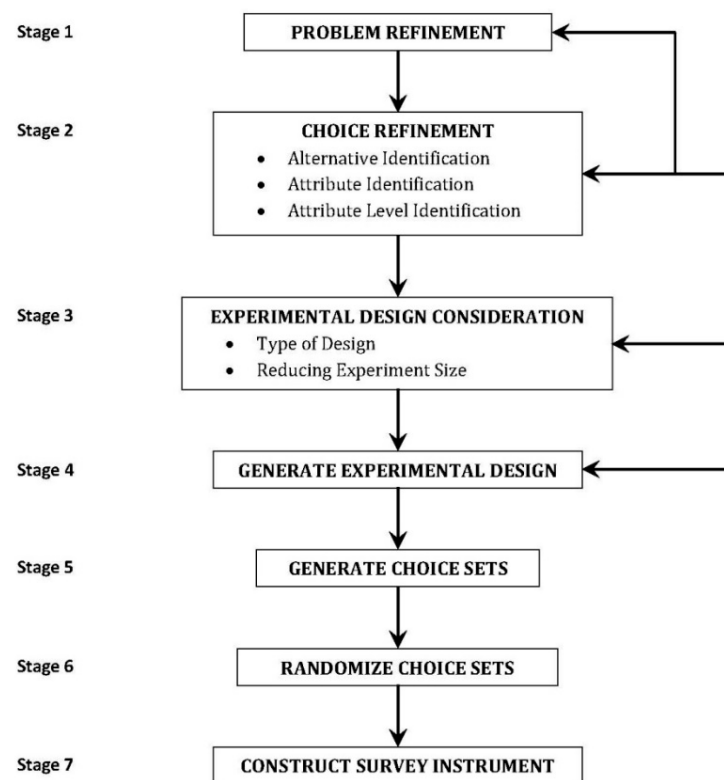


Figure 4. Experimental design for choice analysis [35].

4.3. Fractional Factorial Design

Minimum treatment combination requirements for main effects only for fractional factorial designs of the variable of non-Linear labeled data is calculated by [35]

$$\begin{aligned}
 C &= (L - 1) AM + 1 \\
 &= (3 - 1) * 2 * 2 + 1 = 9
 \end{aligned}
 \tag{5}$$

4.4. Reducing the Size of Experimental Design

Reducing the choice set can be carried out in different ways:

- Reducing the attribute level: consider the extreme value of the attribute known as end-point design and assuming the linear shape of part-worth utility. In this study, three levels of attributes are considered as the attribute levels have non-linear relation with utility reducing the estimation error.
- Ignoring the interaction between the variables and building the model considering the main effects will reduce the scenario to 12 sets.

SPSS software was used considering the following attribute and attribute levels in Table 3.

The research is based on a structured interview closed-ended questionnaire; the questionnaire consists of the following parts:

- **Part one:** Socioeconomic characteristics of the respondent, (e.g., age, income, education, and employment)
- **Part two:** daily travel pattern (last trip characteristics done by the respondents)
- **Part three:** Stated preferences of two modes (car, Metro) alternatives associated with travel attributes.

Table 3. Choice Set.

Card ID	Car			Metro		
	Travel Time Variability	Fuel Cost/liter	Parking Cost	Travel Time Variability	Walking Time to Station	Parking Cost
1	+25%	3 SAR/L	1.5 SAR	30 min	5 min	12
2	+45%	2 SAR/L	1.5 SAR	40 min	5 min	5
3	+35%	3 SAR/L	1.5 SAR	40 min	10 min	5
4	+25%	2 SAR/L	3 SAR	50 min	10 min	5
5	+35%	1 SAR/L	3 SAR	30 min	15 min	5
6	+25%	1 SAR/L	1.5 SAR	50 min	10 min	8
7	+25%	3 SAR/L	3 SAR	40 min	15 min	8
8	+45%	2 SAR/L	0 SAR	30 min	10 min	8
9	+45%	1 SAR/L	1.5 SAR	50 min	15 min	12
10	+35%	2 SAR/L	1.5 SAR	30 min	15 min	8
11	+45%	3 SAR/L	0 SAR	50 min	15 min	5
12	+35%	3 SAR/L	0 SAR	50 min	5 min	8

4.5. Sampling and Sample Size

McFadden set a rule of thumb that less than 30 responses per alternative produce estimators that cannot be reliably analyzed [52]. Therefore, 60 respondents would be enough for two modes for this study. However, the most commonly cited rule of thumb was proposed by Orme, who suggested the following equation to estimate the sample size required for experiments involving the estimation of main effects only [53].

$$N \geq 500 \cdot L_{\max} / JS \quad (6)$$

L_{\max} is the largest number of levels for any of the attributes,

J is the number of alternatives.

S is the number of choice tasks each respondent faces. Now consider $L = 3$, $J = 2$, $S = 12$

$$N \geq 500 \cdot L_{\max} / JS = 500(3) / 12(2) = 63$$

5. Results and Discussion

5.1. Descriptive Analysis

A computer software (SPSS) was used to carry the descriptive analysis as well as socioeconomic variables analysis. SPSS is a statistical package suitable for analyzing the close-ended questionnaire; for this purpose, numerical coding is required to code the questions as variables; the answers act as variable values. The output package provides a set of graphs and tables with the necessary statistical equations. This section is introductory to measure the effect of a socioeconomic variable on mode choice.

The education level of the sample is shown in the doughnut chart Figure 5a. College graduates account for 48.33%, while high school is 35% of the sample. Figure 5b shows the distribution of work types among the respondents. The age groups in the sample revealed that the age group (25–39) accounts for more than 50% of the sample, as shown in Figure 5c. Car ownership is also an important factor in choice modeling, Figure 5d demonstrates that 58.35% of households own one car, 26.7% two cars, and only 6.7% own more than three cars.

The actual cost and average trip distance reported by the respondent for business trip summarized in descriptive Table 4. with an average distance of 32.08 km and an average cost of 4.68 SAR.

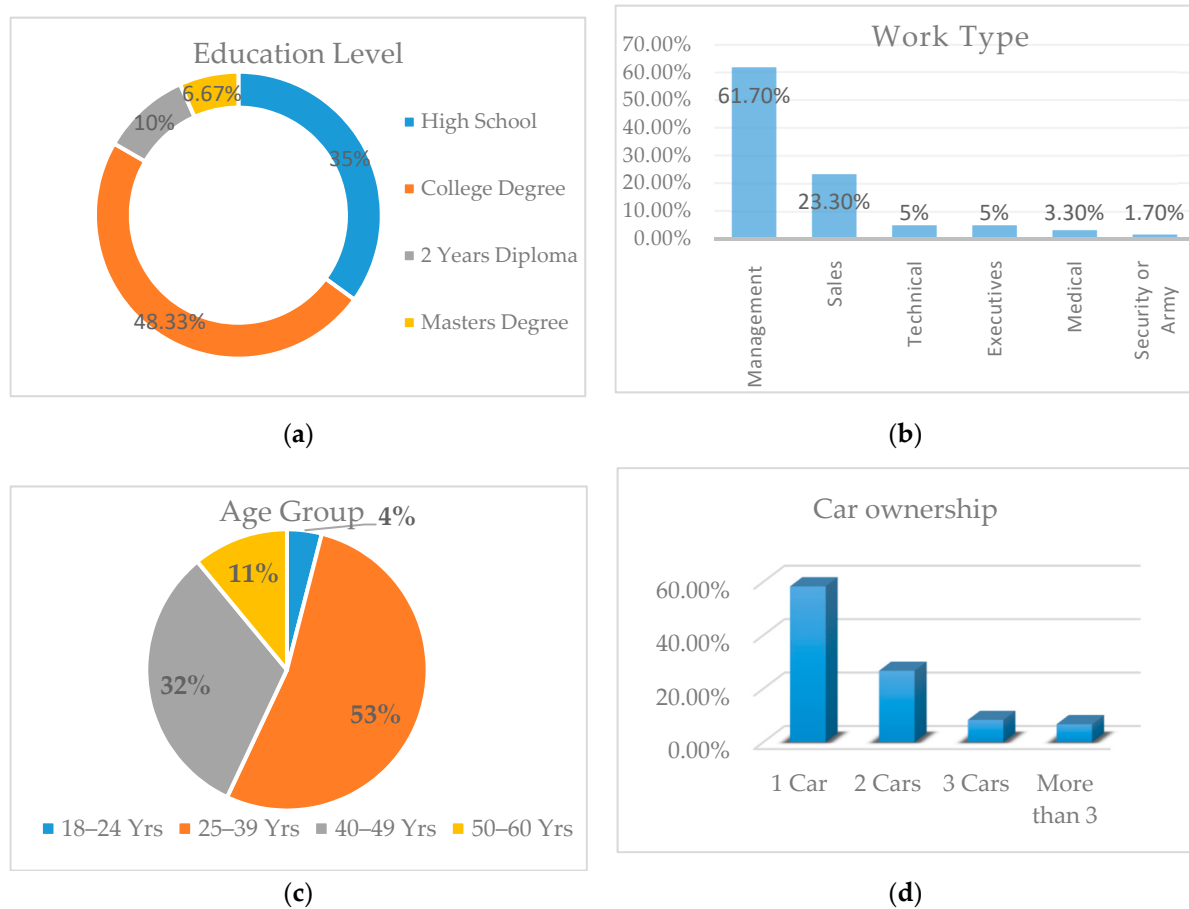


Figure 5. Descriptive statistics of respondent attributes (a) Level of Education (b) Work Type (c) Age group (d) Car ownership.

Table 4. Trip average cost.

	N	Minimum	Maximum	Mean	Std. Deviation
Trip Distance (km)	52	15	80	32.08	8.234
Trip Average Cost (SAR)	57	1	10	4.68	1.490

5.2. Inferential Analysis

The binary choice model is estimated below using SPSS considering the socioeconomic variables (Age, income, car ownership, and nationality). The classification table produced by the SPSS shows that the model was able to explain 63.3% of the variation in the data. The coefficient from the model shows that Nationality has the highest effect; this suggests different behavior between Saudi and non-Saudi regarding the mode choice. The negative sign of Nationality refers to the variable coded 1(Saudi) is less likely to fall in the target group (Metro choice). The income coefficient has a zero value, implying that there is no effect of income on the choice. Age has a small effect on choice, and that can be explained that more than 50% of the sample age falls in the range of (25–39) years. The correlation matrix shows (Table 5) that the correlation between variable, in general, are less than 0.6, which is acceptable in avoiding the multicollinearity in logistic regression.

Table 5. Correlation Matrix.

	CONSTANT	AGE	INCOME	CARNO	NAT
CONSTANT	1.000	−0.521	0.148	−0.713	−0.747
AGE	−0.521	1.000	−0.590	0.206	−0.123
INCOME	0.148	−0.590	1.000	−0.326	0.212
CARNO	−0.713	0.206	−0.326	1.000	0.559
NAT	−0.747	−0.123	0.212	0.559	1.000

5.3. Discrete Choice Model with Travel Attributes

The logit model has common use in modeling the travel choice model [34]. Special computer package NLOGIT 6 was used due to its capability to estimate the choice model based on stated preferences observations. The data set contain 720 observations, where each respondent answers 12 choice sets. To track any data error, descriptive statics is performed, known as “data cleaning,” by examining the mean, minimum, and maximum values of the variable in Table 6.

Table 6. Descriptive Statistics of the Variable.

Variable Values	Mean	Standard Deviation	Minimum	Maximum	Cases
ID	30.5	17.32412	1.0	60.0	1440
ALT	1.5	0.500174	1.0	2.0	1440
ASET	2.0	0.0	2.0	2.0	1440
CHOICE	0.497222	0.500166	0.0	1.0	1440
VATT	27.77222	29.27635	0.0	131.0	1440
VEHICLE	20.42014	21.31811	0.0	50.0	1440
FULECOST	1.083333	1.222331	0.0	3.0	1440
WALKTIME	5.416667	6.111655	0.0	15.0	1440
PARKCOST	0.875	1.166327	0.0	3.0	1440
METRFARE	3.708333	4.098975	0.0	12.0	1440
AGE	37.18333	8.710286	20.0	58.0	1440
INCOME	11830.0	9448.974	4000.0	4,5000.0	1440
NOCARS	1.633333	0.894116	1.0	4.0	1440

5.3.1. Model Estimation

The utility function for car and Metro have been obtained; the general format of the Utility function of the car, for instance, would be as follows

$$U(\text{CAR}) = \text{constant} + \beta_1 * \text{traveltime} + \beta_2 * \text{fuelcost} + \beta_3 * \text{Parkingcost} + \beta * \text{SDC} \quad (7)$$

β , β_1 , β_2 are coefficient and SDC is the socioeconomic variable.

It is noteworthy that constant could take the value of zero, the SDC variable is dealt with as a generic value, so it appears in one mode only. The logistic regression model fit is measured by maximum likelihood (LL) estimation. This requires comparing the model with the base model that represents the mode market share with alternative constant only [35]. To determine the overall significance of the model, the LL of the estimated model is compared with the base model in the NLOGIT output to perform this comparison, as indicated below in Table 7. The table shows the logit model estimation for the coefficients.

Table 7. Model Estimation Output.

Discrete Choice (Multinomial logit) Model	
Dependent Variable	Choice
Log-likelihood function	−368.28641
Estimation based on N = 716	K = 10
Inf.Cr.AIC = 756.6 AIC/N	1.057
Chi-squared [9]	254.75660
Prob [chi squared > value]	0.0000
No of observation	720

5.3.2. Model Fit and Significance

The logistic regression model fit is measured by maximum likelihood (LL) estimation. This requires comparing the model with the base model that represents the mode market share that is the model with alternative constant only [35]. To determine the overall significance of the model, the LL of the estimated model is compared with the base model. The comparison in the NLOGIT platform returns a p -value of 0.000, which is less than the significance value of ($\alpha = 0.05$). Thus the null hypothesis that the estimated model is not better than the base model is rejected, which indicates a good fit model estimation.

Based on the estimated model, the utility functions of the two modes are derived below in a simple form by substituting the coefficients in the input function indicated below:

$$U(\text{car}) = \text{CCONST} + \text{B} \cdot \text{VATT} + \text{C} \cdot \text{FUELCOST} + \text{D} \cdot \text{PARKCOST} + \text{AG} \cdot \text{AGE} + \text{IN} \cdot \text{INCOME} + \text{NC} \cdot \text{NOCARS} \quad (8)$$

$$U(\text{metro}) = \text{G} \cdot \text{VEHICL} + \text{H} \cdot \text{WALKTIME} + \text{I} \cdot \text{METROFARE} \quad (9)$$

by substituting the numerical value, it yields the following two utility models for car and Metro:

$$V_{\text{car}} = -3.47 - 0.022 \text{ Travel Time} - 0.6 \text{ Fuel cost} - 0.79 \text{ parkingcost} + 0.04 \text{ Age} + 0.4 \cdot 10^{-4} \text{ income} + 0.21 \text{ no of Cars} \quad (10)$$

$$V_{\text{metro}} = -0.029 \text{ In Vehicle time} - 0.18 \text{ Walk time} - 0.26 \text{ fare} \quad (11)$$

The mathematical assumptions of the logit model illustrate the choice probabilities of each alternative as a function of the systematic portion of the utility of all the alternatives. The equation can be expressed as (Metro, car)

$$P(\text{Car}|\text{Metro}) = \frac{\text{Exp}(V_{\text{Car}})}{\text{Exp}(V_{\text{Car}}) + \text{Exp}(V_{\text{Metro}})} \quad (12)$$

The above equation along with the utility equation can be used to find out the probability of choosing a car over Metro due to a change in a specific attribute. For example, the increase of fuel price from 1 Saudi Riyal to 2 Saudi Riyals would cause a reduction of the probability of choosing a car over Metro service by approximately 50%.

Overall, the signs of the coefficients are intuitively correct and match the global models where the travel time, fare, parking cost, and fuel cost are well documented in the literature in having a negative impact on mode choice. The coefficient magnitude of the parking cost has the highest effect on car mode shift as its effect is 1.17 times the effect of fuel price. In contrast, the income coefficient has a very low value and is almost negligible. Age has a limited effect, while car ownership has a considerable effect. It is worth noting the three coefficients (Age, Income, No of cars in the household) have a positive sign, considering that these coefficient are dealt with as generic terms (e.g., it appears only in one mode model); therefore, they have an incremental effect in the car mode in the sense that the larger the age, income and no of cars, the higher probability the individual choose the car

mode. Conversely, if we choose to calculate these coefficients in the Metro function, the same values will appear but with a negative sign.

The constant in the car mode expresses the unobserved utility that is accounted for hidden attributes, in other words, the alternative specific constant represents the average influence of the factors that are not included in the utility function, for instance, issues such as safety, privacy, and reliability could be excluded due to the complexity in assessing their effect [54].

Another important model estimation is the expression of the cross elasticity effect as the policymaker is interested in the percent change in ridership across different modes due to the percent change in a specific attribute. The term elasticity is defined as the proportional change in the attribute over the percent change in probability. The following tables illustrate the elasticity across car and Metro mode due to change in fuel cost, parking cost, car ownership, walking time from the NLOGIT model (Table 8)

Table 8. Cross elasticity effect.

Transport Mode	Attribute	CAR	METRO
CAR	FUELCOST	−0.4964	0.5398
	PARKCOST	−0.4595	0.4997
	NOCARS	0.1154	−0.1255
METRO	WALKTIME	0.6650	−0.7232
	METFARE	0.6374	−0.6931

The result illustrates that an increase in fuel cost by 1% cause the probability to take a car to decrease 0.49% and increase of Metro ridership probability by 0.53%, likewise increase in walking time to the nearest Metro station decrease the probability of taking the Metro by 0.66% and increase in the probability of car usage by 0.72%.

5.3.3. Sensitivity Analysis

Simulation enables the decision-maker to assess a set of policies using the estimated model. While the elasticity of the coefficient deal with the percentage change in one of the attributes, the simulation analysis allow for testing scenarios where the attribute take a real value keeping other attribute value unchanged.

When the park cost is maintained at 3 SAR/hour, 17% of car users will shift to Metro choice, assuming all other attributes remain unchanged. Similarly, if the parking cost is simulated in the range of 0–7 SAR. The positive values at x Axis in Figure 6a implies that the percentage of car users' shift to Metro due to the change in parking cost. There is no shift from car to Metro until the parking cost equals 1.3 SAR/hr. At a cut off parking cost value of 1.3 SAR, some percentage of car user start to shift preferences toward the Metro, and this percentage will increase as the parking cost increase.

The shift towards Metro choice starts at 2.4 SAR/liter for fuel cost, and at 2.5 SAR/liter, 3.17% of current car users shifted to Metro choice, as shown in Figure 6b. For the metro fare, it is observed that the choice shift from Metro to the car is at a fairly low rate between (6–7) SAR, while the effect of Metro fare is observed above 7 SAR as the mode choice shift at a high rate (Figure 6c). There is no effect of walking time on the mode share as long as it is below 11 min; at the value of 12 min, 4.2% of proposed Metro passengers modifies their preference to the car, as shown in Figure 6c. As the car travel time increases, the mode choice to Metro increases; the leverage value is 40 min, where at 60 min, 1.94% of car users modify their preferences to Metro Figure 6d.

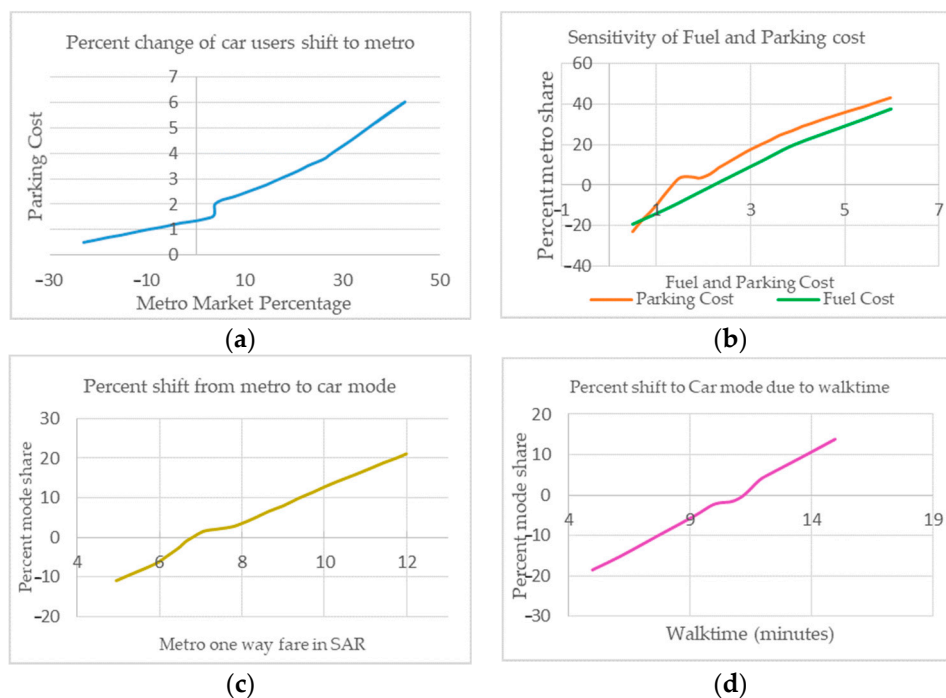


Figure 6. Sensitivity analysis of different factors in mode choice (a) Percent change of car users shift to Metro due to parking cost (b) Sensitivity of fuel and parking cost on percent metro share (c) Sensitivity of Metro one way fare on percent mode share (d) Sensitivity of walk time on percent mode share.

The findings of this study are consistent with some notable studies conducted in other countries. Analogous to the broader literature, findings like income and age have a limited effect on mode choice whereas car ownership has a significant effect on mode choice. However, a contrasting result from some other studies has been observed [26,29,32], where travel time was found to have a low effect on shifting from Metro to car and vice-versa.

6. Conclusions

The discrete choice model has been estimated based on the stated preferences approach (SP) in this study. Two utility models for cars and the metro were developed. The objective of these models is to test the socioeconomic variables that would be significant in mode choice. The income has no effect on the mode choice for a business trip. This can be explained by transportation's low cost compared to income, yet it does not impose real constraints on transportation choice. Age has a low effect (the coefficient of age as low as 0.04), considering that 50% of the sample fall in the rank (25–39) years, no significance in the age range is expected within this range. Saudi citizens tend to behave differently in the mode choice decision as their probability of choosing a car is higher than non-Saudi (the coefficient of nationality –1.5), and so the probability of Saudi citizens to fall in the Metro choice is less than non-Saudi. Car ownership is a significant factor that increases the probability of private car choice so that reducing car ownership by 1% will increase Metro ridership by 0.12%. The travel time as mentioned earlier has a low effect on mode choice shifting either towards Metro or private car, therefore improving travel time has lesser effect compared to fuel cost, parking cost, metro fare and walking time. The results of elasticity conclude the following recommendation to the policymakers:

- To reduce car dependency and improve metro ridership, tax fuel or parking in the CBD is recommended as a 10% increase in fuel price will increase the Metro ridership by 5.3%.
- Increase Metro fare by 10% will decrease metro ridership by 6.9%

- Reducing the average walk time to the nearest metro station by 10%, the Metro Ridership will increase by 7.2%. As the walking time reaches 11 min, the choice of metro service is reduced by 4.2%
- The parking and fuel cost has a similar sensitivity to some extent; the cut-off value of mode shifting is 1.3 SAR/hour for parking costs, while it is 2.4 SAR/liter for fuel, which is much higher than the prevailing price.
- The Metro fare has low sensitivity; the soaring value from 6 to 7 SAR for a one-way trip caused a decrease in Metro choice by 4%.

The mode choice of transport analysis plays a vital role in regional boundary with a holistic territorial vision on sustainability, as it integrates social, economic, environmental, psychological, cultural factors, and governance aspects of a trip [55]. The findings of this study are based on stated preference (SP) surveys, which are often criticized for biases, caused by the difference between stated and the decision of the interviewee or improper experiment execution. Nevertheless, apart from a few limitations, SP has gained popularity in transportation planning as it can capture the choice decision of a traveler for a not-yet-existing transportation mode [49]. This research is expected to aid transport authorities and planners to gain knowledge on the perception of travelers towards Metro service and the factors that limit the choice of Metro use, resulting in the development of sustainable transport in Riyadh, Saudi Arabia [6]. In a wider range, knowledge from this study can assist in the development of public policies aimed at urban management by offering more sustainable modes of transport [56].

The study considered only the business trip due to its weight in the overall trip generation. Leisure and shopping trips should be considered in the following research as it is more involved in nature. Building a demand model from dis-aggregate mode has benefits in terms of cost and time. The results of this research could be a base for building an aggregate model for Metro demand. Research on the effect of more socioeconomic variables on the mode choice for business and other trip types should be considered in future research by studying a larger sample of heterogeneous neighborhoods.

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