Modeling of Intercity Transport Mode Choice Behavior in Libya: a Binary Logit Model for Business Trips by Private Car and Intercity Bus

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Abstract: Libya is one of the rich developing countries in terms of oil revenue. The discovery of oil contributed to a dramatic change which affected all public utilities and facilities, especially the transportation system. Some of the negative impacts include increased traffic congestion, road accidents on intercity highways, and environmental pollution. Therefore, a policy should be developed to improve intercity public transport and control car ownership. This pioneering research seeks to contribute improved details on car user mode choice behavior and better understand the possible measures that can be taken to encourage greater intercity public transport use. In this study, the intercity binary logit mode choice model was developed for business trips to identify the respective behaviors of car users and intercity public transport users and investigate their responses to a scenario of reduced intercity bus out-of-vehicle travel time. This paper surveyed 325 intercity travelers from all major cities in Libya; the intercity bus users were identified through revealed preference, and the private car users were identified through revealed and stated preference surveys. Out-of-vehicle travel time, total travel cost, gender, age, nationality, income level, car ownership, convenience, comfort, and weather conditions significantly influence car user mode choice behavior. The probability of car drivers shifting to the use of intercity buses was also examined based on a scenario of a reduced intercity bus out-of-vehicle travel time. This reduction is the most important element in a program aimed to attract car users to use intercity buses. The results can assist decision-makers on all levels to wisely allocate resources to public transportation improvement, reduction of road accidents on intercity highways, and enhancement of road safety. This study, which is the first of its type in Libya, investigates intercity model choice behavior for business trips.

Key words: improve intercity transportation, intercity mode choice behavior, modal shift, disaggregate analysis, revealed and stated preferences survey, road safety

INTRODUCTION

Mobility in Libya is higher today than that enjoyed by Libyans in the past. Private cars, buses, and airplanes are now readily available to intercity travelers, and gasoline in Libya is relatively cheaper. However, continued reliance on automobiles in Libya and in other developed countries causes severe adverse impacts such as travel congestion, accidents, and environmental pollution. In addition, road accidents cause 10% of all deaths in Libya. Compared with European countries and the US, Arab countries have a very high road accident fatality rate. In 2001, 22.3, 14.8, and 7.3 persons per 10,000 vehicles were killed in Libyan, Saudi, and Qatari road traffic, respectively (Bener et al., 2003).

Most traffic accidents in Libya happen on intercity highways. The accident rate on intercity highways is about one-ninth of that on ordinary roads. However, once an accident occurs, the number of fatalities can be so high because public awareness on traffic safety on these highways is low. In recent years, 1200 to 1800 people have been killed on intercity highways in Libya (Public Administration of Traffic, 2010). The intercity public transport needs to be improved, thus prompting the Libyan government to undertake various studies to address the problem of road accident deaths and injuries (Manssour and Riza 2011, 2012).

Travel demand models are used to forecast demand for travel activities as well as to determine the value that commuters place on the various factors that affect their choices. A prominent example is the intercity mode choice problem which describes travelers’ choices between available travel modes. Mode choice is influenced by various factors, including level-of-service attributes, subjective factors, land use and accessibility, and individual and household characteristics. The choice models relate traveler’s choices with the characteristics of the available modes (such as the time and cost of traveling to each city, purpose of travel, and level of service), the characteristics of the trip, and the characteristics of the traveler (such as age, gender, and income). The
models provide estimates of travelers’ willingness to pay for changes in mode attributes, such as level of service and travel time. Since the 1950s, intercity travel in Libya has been dominated by automobiles. Air service is second in rank and is becoming an important component in corridors where traffic is heavy enough to require frequent service. Buses service a small percentage of total trips but are an important alternative to cars in low-density corridors that serve rural communities and small cities.

All over the world, several intercity mode choice models have been developed and are used to predict travelers’ choices. This modeling is important for planning because transportation systems usually receive huge investments (Ben-Akiva and Lerman, 1985).

Intercity travel has received comparatively less attention than urban travel. Since the mid-1960s, some mode choice models have been calibrated for intercity trips. In the USA, most intercity models were developed in conjunction with the Northeast corridor project (Koppelman et al., 1984). Such models were developed to predict the share of potential new models as well as that of existing models. However, these models were calibrated mostly by using aggregate data.

The disaggregate approach was the second generation of model building and came after the aggregate approach in mode choice modeling (Koppelman, et al., 1984). Disaggregate models provide a more effective tool for predicting an individual’s behavior in selecting one mode from among different available modes. The decrease in the explanatory power of the aggregate models due to data aggregation was avoided with the disaggregate models (Kanafani, 1983), thus greatly improving the predictive power of disaggregate models. For example, Watson (Watson, 1972, 1974) developed and evaluated aggregate and disaggregate binary (rail versus car) mode choice models in the Edinburgh-Glasgow corridor. His results indicated that the error in mode choice prediction for the same specification is 12 to 15 times higher for an aggregate model than those for a disaggregate model. Therefore, the use of disaggregate, behavioral, stochastic models in a predictive framework is preferable to the aggregate approach because the predictions of disaggregate models are extremely promising. Subsequently, a large number of studies have focused on disaggregate mode choice within the intercity context (Grayson, 1981; Banai-Kashani, 1984; Wilson, et al., 1990; Lyles and Mallick, 1990; Koppelman, 1990; Abdelwahab et al., 1992; Forinash and Koppelman, 1993; Algarad, 1993; Al-Sughaiyer, 1993; Algarad, 1993; Bhat, 1997; Mehdiriatta and Hansen, 1997; Mandel, et al., 1997; Vovsha, 1998; Al-Ahmadi, 2006 and Ashiabor, 2007a,b; Mukala and Chunchu, 2011). The studies contain probabilistic models which focus only on making a specific choice once the traveler has decided to make a trip. Studies progressed from a binary logit model to a multinomial logit model and to the nested logit model.

The use of disaggregate models is supported by their representation of the individual traveler’s decision, data efficiency, and superior estimation results. Most disaggregate models are based on the theory of utility maximization. They assume that a person makes a particular choice from a set of different alternatives depending on the maximum benefit he receives. For example, a person may wish to minimize travel time and cost, and maximize comfort and convenience. Therefore, the traveler will select a mode that meets such requirements. This research aims to identify the major factors that influence the choice of intercity travel mode and to develop intercity mode choice models based on completely disaggregated data for Libya. The explanatory variables included in the models are the demographic and socioeconomic characteristics of individuals, trip characteristics, and mode attributes. A binary logit model was used to identify significant factors in determining the choice of transport and to predict the probability of a change in intercity bus and airplane ridership with respect to various travel times and cost. An intercity model must predict the future modal split. The results of this study will provide the transportation agencies a tool to maximize their revenue and better allocate their resources.

**MATERIALS AND METHODS**

Similar to the approach used by Ortuzar and Willumsen (2001), the data in this study were obtained through revealed and stated preferences. In 2010, a total of 325 respondents were questioned over three months. A total of 250 observations were used to calibrate the binary mode choice model with car versus intercity bus. Moreover, 75 observations from a supplementary survey were used to validate business trip models. The revealed and stated preferences survey was designed to satisfy the requirements for the development of an intercity mode choice behavior model and to investigate the major factors that influence the choice of intercity travel mode.

Many intercity travelers in Libya are from different countries, and the most prevalent languages among travelers are Arabic and English. Therefore, the questionnaire forms were written in both Arabic and English. Two sets of questionnaires were used in two types of modes, namely, private car and intercity bus for business trips. Intercity bus terminals and natural journey break points, such as service areas and gasoline stations located between the cities, served as the survey locations. The interviews were conducted in safe areas without obstructing traffic flow.
The study was conducted in all major cities in Libya because of the high car ownership, availability of intercity public transport, and the adequate representation of travelers. Specifically, this study randomly selected respondents from Tripoli, Benghazi, Sirt, Sabha, and Al-Kufrah based on a stratified sampling approach to achieve a representative sample that reflects demographic and socioeconomic profiles.

The questionnaire is arranged based on relevance of the questions to the respondents’ experiences and trips. This questionnaire included a wide range of variables which characterize the trip (mode of travel, trip purpose, origin destination, duration of stay at destination, etc.), the service characteristics of the chosen mode and the perceived characteristics of other available but unselected modes (travel time, cost, etc.), the traveler’s characteristics (age, gender, income, occupation, income, nationality, vehicle ownership, and educational level etc.), and travel behavior. Information on how each transport mode user reacts to the scenarios of proposed policy variables (measures) of each transport mode user was also obtained. Moreover, the questionnaires were coded with the names of the two different modes under study: private car, and intercity bus.

The questions that address intercity bus users were contained only in the revealed preference survey and pertained to demographic and socioeconomic characteristics and mode attributes. The respondents were requested to report their current travel situation by answering a set of questions. For car users, the questionnaire addressed both revealed and stated preferences. The survey information included socioeconomic characteristics of individuals, trip information of individuals, and attitudes and perceptions on travel and policy measures.

The only way to ensure the practicability of the questionnaire is to test it with actual respondents. Hence, a pilot study was undertaken prior to formal data collection. The pilot survey was designed to test items used in the main survey instrument. Random samples of 100 observations from intercity drivers during the study period were collected and carefully analyzed. The analysis revealed that some questions need to be omitted from the questionnaire because participants had either not answered them or had answered them erroneously. The other questions were modified or rewritten. After the questionnaire was developed, the required data for the main survey were collected. Respondents were randomly selected by using a stratified sampling approach to obtain a representative sample that reflects demographic and socioeconomic profiles.

The logit function is an important part of discrete choice and logistic regression (Allison, 1999; Cox, 1972). Logit models were employed by using SPSS software version 20 and R Statistical Software version 2.15.2 for regression analysis because of their ability to represent complex aspects of travel decisions of individuals by incorporating important demographic and policy-sensitive explanatory variables. They do not assume linearity in the relationships between the independent and dependent variables, and do not require the variables to be normally distributed. The logistic regression estimates the probability that a certain event will occur based on the independent variables.

Mode choice models play a critical role in many transport applications. A discrete choice model is a mathematical function that predicts an individual’s choice based on utility or relative attractiveness (Ben-Akiva and Lerman, 1985). According to the aim of this study, the binary logit model under discrete choice methods is an analytically convenient modeling method. For the binary models, \(i\) and \(j\) are the two alternatives in the choice set of each individual.

\[
U_{in} = V_{in} + \varepsilon_{in}
\]

\[
U_{jn} = V_{jn} + \varepsilon_{jn}
\]

Hence, \(P_{in} = \text{Prob}\{U_{in} \geq U_{jn}\}\)

\[
= \text{Prob}\{V_{in} + \varepsilon_{in} \geq V_{jn} + \varepsilon_{jn}\}\)

\[
= \text{Prob}\{V_{in} - V_{jn} \geq \varepsilon_{jn} - \varepsilon_{in}\}\)

\[
= \text{Prob}\{V_{in} - V_{jn} \geq \varepsilon_{n}\}, \varepsilon_{n} = (\varepsilon_{jn} - \varepsilon_{in})
\]

The probability that individual \(n\) chooses alternative \(i\) \((P_{in})\) as proposed by Ben-Akiva and Lerman (1985) is as follows:

\[
P_{in} = \frac{1}{1 + e^{-V_{in}}} = \frac{e^{V_{in}}}{e^{V_{in}} + e^{V_{jn}}}
\]

where

\(P_{in}\) is the probability that individual \(n\) chooses alternative \(i\).

\(P_{in}\) is the probability that individual \(n\) chooses alternative \(i\).

\(V_{in}\) is the utility of alternative mode \(i\) to individual \(n\)

\(X_i = \text{a row vector of characteristics of alternative mode } i\)

\(S_n = \text{a row vector of socioeconomic characteristics of individual } n\)

\(V_{car} = \beta_0 + \beta_{1\text{car}} x_{\text{age car}} + \beta_2 x_{\text{G car}} + \beta_3 x_{\text{N car}} + \beta_4 x_{\text{EL car}} + \beta_5 x_{\text{HHC car}} + \beta_6 x_{\text{HOSHP car}} + \beta_7 x_{\text{TT car}} + \beta_8 x_{\text{DIST car}} + \beta_9 x_{\text{TTC(car)\text{fuel cost}+\text{parking fees}}} + \beta_{11} x_{\text{VTT car}} + \beta_{12} x_{\text{VTT(car)\text{at\text{time\text{areas}\&gas stations}}}} + \beta_{13} x_{\text{DOS car}} + \beta_{14} x_{\text{PRIV car}} + \beta_{15} x_{\text{CONV car}} + \beta_{16} x_{\text{COMF car}} + \beta_{17} x_{\text{RELJAB car}} + \beta_{18} x_{\text{SAFE car}} + \beta_{19} x_{\text{WEIGHT car}} + \varepsilon_i\)
where \((G)\) is gender, \((N)\) is nationality, \((EL)\) is educational level, \((HINC)\) is the household monthly income in Libyan dinar, \((HCOSHP)\) is the household car ownership, \((FT)\) is the family trip, \((DIST)\) is the distance of travel in kilometers, \((ACIST)\) is the access distance to intercity bus stations in kilometers, \((TTC)\) is total travel cost = for bus is the sum of - line hole travel cost \((LHTC)\) + access cost \((ACESC)\) to intercity bus stations + egress cost \((EGRSC)\) from intercity bus stations to final destination – and for private car is the sum of fuel cost + oil cost + parking fees in Libyan dinar \((LYD)\), \((IVTT)\) is in-vehicle travel time in hours, \((OOVTT)\) is out-of-vehicle travel time in minutes for bus, which is the sum of - access time \((ACEST)\) to intercity bus stations + waiting time \((WAITT)\) at intercity bus stations + egress time \((EGRST)\) from intercity bus stations to final destination – and for private car is the time at rest areas and gasoline stations, \((DOS)\) is the duration of stay at destination, \((PRIV)\) is privacy, \((CONV)\) is convenience, \((COMF)\) is comfort, \((RELIAB)\) is reliability, \((SAFE)\) is safety, \((WETHC)\) is weather conditions, \((\beta_0)\) is constant, and \((\beta_1, \beta_2, \beta_3 \ldots \beta_9)\) are the coefficients of variables \(x_i\). The probability that an individual will choose the intercity bus can be written as:

\[
P_{\text{bus}} = \frac{e^{\beta_0} x_{\text{age, bus}} + \beta_2 x_{G, bus} + \beta_3 x_{N, bus} + \beta_4 x_{EL, bus} + \beta_5 x_{HINC, bus} + \beta_6 x_{HCOSHP, bus} + \beta_7 x_{VT, bus} + \beta_9 x_{DIST, bus} + \beta_{10} x_{ADIST, bus} + \beta_{11} x_{TTC} = (LHTC + ACESC + EGRSC) + \beta_{12} x_{IVTT, bus} + \beta_{13} x_{OVOVT, bus} = (ACEST + ACAST + EGRST) + \beta_{14} x_{DOS, bus} + \beta_{15} x_{PRIV, car} + \beta_{16} x_{CONV, car} + \beta_{17} x_{COMF, car} + \beta_{18} x_{RELIEF, car} + \beta_{19} x_{SAFE, car} + \beta_{20} x_{WETHC, bus} + \epsilon_i}{e^{\beta_0} x_{\text{age, car}} + \beta_2 x_{G, car} + \beta_3 x_{N, car} + \beta_4 x_{EL, car} + \beta_5 x_{HINC, car} + \beta_6 x_{HCOSHP, car} + \beta_7 x_{VT, car} + \beta_9 x_{DIST, car} + \beta_{10} x_{ADIST, car} + \beta_{11} x_{TTC} = (LHTC + ACESC + EGRSC) + \beta_{12} x_{IVTT, car} + \beta_{13} x_{OVOVT, car} = (ACEST + ACAST + EGRST) + \beta_{14} x_{DOS, car} + \beta_{15} x_{PRIV, car} + \beta_{16} x_{CONV, car} + \beta_{17} x_{COMF, car} + \beta_{18} x_{RELIEF, car} + \beta_{19} x_{SAFE, car} + \beta_{20} x_{WETHC, car} + \epsilon_i}
\]

where \(P_{\text{bus}}\) is the probability that individual \(n\) chooses the intercity bus.

Based on previous literature, the data needed for specifying, calibrating, and testing transferability consist of three categories: socioeconomic variables, level of service or supply variables, and data on the trip. Some of these variables are qualitative while others are quantitative. The variables that best explain driver’s behavior cannot be predetermined during model calibration unless the effect of the other variables is tested in the preliminary modeling stage. Some of the tested models exhibited poor statistical goodness-of-fit and/or counterintuitive signs thus were rejected. For example, some models produced a very good fit but had a counterintuitive sign in the variable total travel time. In summary, the principles employed to move from one specification to another are: (i) variables with insignificant coefficients were dropped; and (ii) variables that had the “wrong” signs were dropped.

A binary logit model for intercity business trips was developed for two alternatives, namely, intercity bus and car, to compare the utility of these travel modes and identify the factors that would influence car users to move from traveling by car to choosing intercity buses. In this model, the dependent variable was “1” if the commuters’ traveled by intercity bus and “0” for car use (Allison, 1999; Kleinbaum et al., 2007). After the variables with insignificant coefficients were dropped from the model, the explanatory variables were age, gender, nationality, household monthly income, out-of-vehicle travel time, total travel cost, duration of stay at destination, car ownership, convenience, comfort, and weather conditions. Some of the explanatory variables such as age, household monthly income, and gender were categorized. For instance, the income was categorized as, < LYD 300, LYD 301–400, LYD 401–500, LYD 501–600, LYD 601–700, and >701 (1 US Dollar = LYD 1.27), and gender was categorized as 0 for male and 1 for female. Age was categorized as, < 20, 21–30, 31–40, 41–50, 51–60, and > 60.

The coefficients are estimated by fitting the data to the model(s). The maximum likelihood estimation method is a commonly used fitting technique. This method involves choosing values for the coefficients to maximize the likelihood (or probability) that the model will predict the same choices made by the observed individuals. The method yields highly accurate estimates.

After the calibration process was completed, the validity of the succeeding models was tested. Using 75 observers, this test was conducted by using the calibrated models to predict model-split for data other than that used for model calibration. The collected survey data was divided into two parts. The first part was for model calibration whereas the other was used for model validation. The validity of models was tested by comparing observed choices and the predicted choice by using the calibrated models.

**RESULTS AND DISCUSSION**

**Modeling Binary Logit Model for Business Trips by Car versus Intercity Bus:**

A summary of estimations from the binary logit model for business trips by car versus intercity bus is presented in Table 1. Several variables, sourced from literature, were evaluated during the calibration process. All the variables presented in the table have significant parameter estimates and logical signs.

Logistic regression coefficients for household monthly income, car ownership, total travel cost, out-of-vehicle travel time, convenience, and comfort were negative, which implies that an increase in these variables would increase car use (see Table 1). Thus, a negative coefficient for a variable in bus choice implies a decrease
in bus use such that a higher negative value indicates lower bus use. Conversely, drivers can shift to taking intercity buses if the out-of-vehicle traveling time (waiting time at intercity bus station, access and egress time to/from bus station) and total travel cost can be reduced.

Most authors agree that access time is more difficult than line-haul time, estimating that access time ranges from 1.5 to 10 times as difficult. Hensher (1997) assumed access and egress time to be approximately valued at 1.5 times in-vehicle time and considered this as a generally accepted ratio.

A variety of intercity and mode choice studies over the last several years have demonstrated the importance of travel time. Kumar et al. (2004) studied rural intercity bus service in India to understand users’ perceptions of different attributes of service. They analyzed attributes such as in-vehicle travel time, headway, discomfort, and fare. As expected, in-vehicle travel time had a negative effect on rider utility. While headway and discomfort levels were also important, they found in-vehicle travel time to be substantially more important. In the United States, Ashiabor et al. (2007) developed a nationwide intercity travel demand model and as expected, they found that as travel time increased for a given mode, traveler preference for that mode decreased. Proussaloglou et al. (2007) developed an intercity model choice model for long-distance travel in the state of Wisconsin, which included in-vehicle travel time and access and egress travel times as explanatory variables. Andrade et al. (2006) studied the commute of shoppers in the Japanese city of Sapporo and found that whenever travel time on the subway increased, a mode shift away from the subway towards both bus and automobile was observed.

### Table 1: Estimations from the binary mode choice model (car versus intercity bus) (n = 250) for business trips

<table>
<thead>
<tr>
<th>Variable Code</th>
<th>B</th>
<th>S.E.</th>
<th>Sig.</th>
<th>Odd Ratio</th>
<th>95% C.I. Lower</th>
<th>95% C.I. Upper</th>
</tr>
</thead>
<tbody>
<tr>
<td>G</td>
<td>-2.630</td>
<td>0.903</td>
<td>0.004</td>
<td>0.072</td>
<td>0.012</td>
<td>0.423</td>
</tr>
<tr>
<td>N</td>
<td>-5.506</td>
<td>1.286</td>
<td>0.000</td>
<td>0.004</td>
<td>0.000</td>
<td>0.051</td>
</tr>
<tr>
<td>Age</td>
<td>2.885</td>
<td>0.764</td>
<td>0.000</td>
<td>17.900</td>
<td>4.006</td>
<td>79.995</td>
</tr>
<tr>
<td>HINC</td>
<td>-1.311</td>
<td>0.544</td>
<td>0.000</td>
<td>0.270</td>
<td>0.137</td>
<td>0.530</td>
</tr>
<tr>
<td>HCOSHP</td>
<td>-2.648</td>
<td>0.770</td>
<td>0.000</td>
<td>0.071</td>
<td>0.016</td>
<td>0.320</td>
</tr>
<tr>
<td>TTC</td>
<td>-0.040</td>
<td>0.010</td>
<td>0.000</td>
<td>0.961</td>
<td>0.943</td>
<td>0.979</td>
</tr>
<tr>
<td>OOVTT</td>
<td>-1.117</td>
<td>0.330</td>
<td>0.000</td>
<td>0.327</td>
<td>0.171</td>
<td>0.624</td>
</tr>
<tr>
<td>CONV</td>
<td>-1.766</td>
<td>0.397</td>
<td>0.000</td>
<td>0.171</td>
<td>0.079</td>
<td>0.373</td>
</tr>
<tr>
<td>COMF</td>
<td>-1.225</td>
<td>0.369</td>
<td>0.000</td>
<td>0.294</td>
<td>0.143</td>
<td>0.606</td>
</tr>
<tr>
<td>WETHC</td>
<td>3.251</td>
<td>0.664</td>
<td>0.000</td>
<td>25.823</td>
<td>7.028</td>
<td>94.888</td>
</tr>
<tr>
<td>Constant</td>
<td>24.338</td>
<td>6.904</td>
<td>0.000</td>
<td></td>
<td>3.7156E+10</td>
<td></td>
</tr>
</tbody>
</table>

Summary of Statistics

- C(2) log likelihood: 71.518
- Model chi-square: 250.238
- Cox and Snell’s R²: 0.651
- Nagelkerke value: 0.878
- Number of observations: 250

Explanation of Variables Included in the Selected Model

- G = Gender
- N = Nationality
- Age = Age
- HCOSHP = Household Car Ownership
- HINC = Household monthly income in (LYD)
- TTC = Total travel cost (LYD)
- IVTT = Out-of-Vehicle Travel Time (min)
- CONV = Convenience
- COMF = Comfort
- WETHC = Weather Conditions

**Model:**

\[
\ln \frac{p}{1-p} = 24.338 - 2.630 \times (G) - 5.506 \times (N) + 2.885 \times (Age) - 1.311 \times (HINC) - 2.648 \times (HCOSHP) - 0.040 \times (TTC) - 1.117 \times (OOVTT) - 1.766 \times (CONV) - 1.225 \times (COMF) + 3.251 \times (WETHC)
\]

In the model used in this study, demographic variables such as age and gender contributed significantly to explain the mode choice behavior. Males were more likely to use public transport than to drive. The B for gender is negative. The reference is female (variable coding female = 0), which implies that male is less likely to shift to public transport. Gender and travel behavior in two Arab communities were studied previously (Elias et al., 2008). Their statistical analyses revealed that demographic factors, such as gender, affect travel mode differently for women and men. Effective policy interventions must consider these gender distinctions to address the travel needs of individuals in Arab communities. Gender analysis needs to be incorporated into all transport planning to study and take the impact of gender into consideration before project implementation. Most importantly, gender analysis challenges the traditional, neoclassical analysis which looks at households as black boxes and assumes that household behavior reflects the preferences of all its individuals, regardless of the power structures and gender relations within these household units. In this sense, gender analysis is part of a general re-
orientation of transport planning away from a focus on facilitating the movement of motorized vehicles to a people-centered perspective that starts with an analysis of basic household mobility needs.

The age had a statistically significant ($p < 0.05$) contribution to the explanation of mode choice behavior. The positive sign of the coefficient (+2.885) implies that old people are more likely to use their private cars than public transport facilities; this finding is consistent with European results. For example, Mackett and Ahen (2000) found that young people drive less than the elderly, being more willing and able to cycle and take the bus.

The household income coefficients for the bus were negative, so an increase in their incomes would decrease their bus use, and household with higher incomes and more vehicles per capita are less likely to use buses than to take a car. This finding agrees with Ried et al. (2004). Ashiabor et al., Kumar et al., and Proussaloglou included income in their models. Kumar et al. (2004) also included age, gender, education, and profession. Socioeconomic factors can affect how sensitive travelers are to travel time and cost. For example, Ashiabor et al. (2007) found that high-income travelers are less sensitive to travel cost.

The coefficient of car ownership in the model was significant such that the negative sign of the coefficient indicates that an increase in car ownership in the households is likely to decrease resistance to switching from private car to intercity bus. Car ownership is also a major factor that determines the choice of mode of transport. The results from the survey indicated that an increase in car ownership in the household is likely to decrease resistance to a mode change. Resistance to switching was observed among respondents who owned one vehicle, and respondents who owned two to three and more than three vehicles are less resistant to a mode change (Riza, 2004 and Nurdeen et al., 2007).

Nationality was introduced into the questionnaire to determine if a difference in travel behavior for intercity mode choice exists between Libyan and non-Libyan citizens. The coefficient of this variable also significantly affected the choice of the traveler for business trips. The probability of selecting intercity bus by Libyan is greater because nationality (N) had a negative coefficient.

Perceptual variables were introduced into the calibration model to investigate the effect of incorporating these variables in explaining the mode choice behavior of the traveler. The perception of mode comfort, convenience, and weather condition significantly affect the choice of the traveler for business trips.

Chi-square omnibus tests of model coefficients gave the value of 250.238 on 10 df, significant beyond 0.000. This is a test of the null hypothesis which states that addition of the independent variables to the model does not significantly increase its ability to predict the decisions made by the study subjects. Therefore, the coefficients of the present model are statistically significant. With probability $p < .000$, at least one of the population coefficients differs from zero.

To assess how well the model fitted the data, Hosmer and Lemeshow’s goodness-of-fit test statistic was calculated and a chi-square test between the observed and expected frequencies was conducted (see Table 2). The observed and predicted values for both modes of transport did not differ considerably, as confirmed by the significant chi-square value and the good fit of the models.

The observed and predicted values were very close, which indicates the good fit of the model (Figures 2 and 3). Classification matrices were also calculated to assess how well the model fitted the data. It correctly classified 97.9% of the car cases and 93.8% of the bus cases. The predictions were 96.2% accurate.

| Table 2: Hosmer–Lemeshow test for (car versus intercity bus) model |
|---------------------|---------------------|---------------------|---------------------|
|                     | Car                 | Intercity Bus       | Total              |
|                     | Observed Expected   | Observed Expected   |                     |
| Step 1              |                     |                     |                     |
| 1                    | 24                  | 24.000              | 0                   | 0.000               | 24                  |
| 2                    | 21                  | 21.000              | 0                   | 0.000               | 21                  |
| 3                    | 24                  | 23.998              | 0                   | 0.002               | 24                  |
| 4                    | 22                  | 23.854              | 2                   | 0.146               | 24                  |
| 5                    | 25                  | 23.080              | 0                   | 1.920               | 25                  |
| 6                    | 22                  | 18.446              | 2                   | 5.554               | 24                  |
| 7                    | 2                   | 5.562               | 22                  | 18.438              | 24                  |
| 8                    | 0                   | 1.027               | 24                  | 22.973              | 24                  |
| 9                    | 1                   | 0.032               | 23                  | 23.968              | 24                  |
| 10                   | 0                   | 0.000               | 24                  | 24.000              | 24                  |
| Chi-square df Sig.  | 61.812              | 8                   | 0.000               |                     |                     |
The -2 log likelihood reflects the prediction deviation (error) by the model. Therefore, a smaller value indicates a better fit. Aside from the goodness-of-fit measures, another important criterion for logistic regression model is the pseudo $R^2$. SPSS presents two $R^2$ measurements to estimate how much of the variation is accounted for by the model. Cox and Snell’s $R^2$ imitate the linear regression $R^2$ based on the likelihood, and Nagelkerke’s $R^2$ is a modification of the Cox and Snell’s coefficient to ensure that it varies only from 0 to 1. As Table 1 shows, the model has Cox and Snell’s $R^2 = 0.651$ and a Nagelkerke value of 0.878, which explains 87.8% of the variation in the dependent variable.

**Probability Prediction:**

One of the most important uses of mode choice models is to predict the effects of policy measures. To promote the use of public transport, this study examined the incentives of reducing the intercity bus out-of-vehicle travel time. This was done by solving the binary logit equation by using the R Statistical Software programming for probability with a range of out-of-vehicle travel times (access, waiting and egress time) while keeping the other variables constant by assigning them their mean values. The mode choice probabilities categorized by various levels of travel time are shown in Figure 4. Mode choice probabilities ranged from 98% likelihood of car use with current intercity bus out-of-vehicle travel time per trip (60 minutes) to 2% likelihood of car use with a reduction in intercity bus out-of-vehicle travel time per trip (10 minutes). At the same time, the probability of intercity ridership increased from 2% with current bus out-of-vehicle travel time of (60 minutes) to 98% of likelihood with a 10-minute reduction in out-of-vehicle travel time for intercity bus travel for business trips. A 50:50 split may be achieved when the out-of-vehicle travel time is set at 15 minutes per trip for intercity bus travel to business trips.
Conclusion:
A general approach to calibrate intercity mode choice behavior models for business trips in Libya was successfully developed and validated. This study, which is the first of its type in Libya, investigated the intercity choice behavior by travelers for two modes of transport, namely, the car and the intercity bus, and to determine the trade-offs travelers make with their choices. Comparing the utilities of the two modes identified the important reasons behind the choice of a particular mode and the circumstances behind changes in their choices.

To determine what influences intercity mode choice behavior, the binary logit model examined the characteristics of car versus intercity bus for business trips in terms of travel time (in-vehicle and out-of-vehicle travel time), total travel cost (access, egress, and ticket costs), distance traveled, access/egress distance from/to intercity bus station, duration of stay at destination, demographic and socioeconomic characteristics, and mode characteristics (privacy, convenience, comfort, reliability, safety, and weather conditions). The major reasons car users do not take intercity transport include age, gender, nationality, out-of-vehicle travel time, size of family travel, total travel cost, high income, duration of stay at destination, convenience, comfort, weather conditions, and higher household car ownership, as cars outperformed intercity buses in all these factors. Moreover, the most effective means to encourage a switch from car to a safer mode of intercity transport is through reduced intercity bus travel time. In summary, the research hypothesis that the car is the primary mode of transport due to its lower travel time and the lack of intercity bus transport was proven.

Perceptual variables were introduced into the calibration model to investigate the effect of incorporating these variables in explaining the mode choice behavior of the traveler. The perception of mode comfort, convenience, and weather condition significantly affect the choice of the traveler for business trips. In Libya, hot weather, especially during the summer, discourages travelers from using ground public transportation because of poor quality of service and lack of air conditioning.

The models explanatory power, the two R-Square values indicate the model’s strong explanatory power. The factors included in the model account for 88% of the variation for the Nagelkerke, while Cox and Snell can explain 65%. The overall accuracy of the prediction model was 96.0%. McFadden (1979) notes that the values of 0.2 to 0.4 for $R^2$ represent an excellent fit whereas the values of $R^2$ in this study are always greater than 0.8 for model.

The model generated by this pioneering research will facilitate the intercity travel demand analysis of the Ministry of Transportation. This will also aid the government, public transportation agencies, and private carriers in making important decisions and to prevent under- or over-design of their facilities.

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REFERENCES


