THE EFFECT OF TRAFFIC APPLICATIONS ON TRAVEL BEHAVIOUR

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ABSTRACT

THE EFFECT OF TRAFFIC APPLICATIONS ON TRAVEL BEHAVIOUR

Traffic information has been influenced the choice behavior of travelers while en route. The main goal of this study is to investigate the impact of real-time traffic information acquired through some traffic applications such as GPS navigation devices for car, mobile traffic applications and radio traffic reports on traveler behavior on highways. This study estimates binary logit mode choice model of the decision making for travel of people stayed at the civil engineering faculty of Istanbul Technical University. Commuter responses to traffic information were analysed seperately in two different commuters mode, including self-driving commute and public transit commute by using Binary Logit Model. The travel behaviour models developed in this study are based on a self deviced survey of travelers which was conducted for the civil engineering undergraduate-graduate students, academicians and supporting staff at Istanbul Technical University, Istanbul, in 2016. The attributes that influence travelers' decision-making patterns can be broadly categorized into three groups which were socioeconomics, travel and technological characteristics. Moreover, travelers who obtain traffic information from some traffic applications were more likely to switch with respect their different characteristics. In addition, a variety of features of all traffic applications obtained from some related websites were also analysed. There are some difference regarding their significant variables and their descriptive statistic results between traffic applications that use in Turkey and in the world. In this study, each traffic application were also analysed and compare them in terms of their categorical attributes with the help of developing regression model. The purpose of this analysis is to investigate the index of the rating of the traffic applications used in Turkey and in the world. Further outcomes were presented related to findings.

ÖZET

TRAFİK UYGULAMALRININ SÜRÜCÜ DAVRANIŞLARINA ETKİSİ

Trafik bilgileri seyahat halindeki yolcuların seçim davranışlarını etkilemektedir. Bu araştırmanın esas amacı araç GPS navigasyon uygulaması, trafik raporlarını veren radyo ve telefona yüklenen mobil uygulamalar gibi gerçek zamanlı trafik bilgilerini veren trafik uygulamalarının otoyollarda sürücü davranışları üzerindeki etkisini araştırmaktır. Bu çalışma İstanbul Teknik Üniversitesindeki kişilere uygulanmış olup, seyahat için karar verme davranışlarının modellenmesi için İkili Seçim Modeli uygulanmıştır. Sürücü davranışı modeli oluşturabilmek için gerekli veriler anket yoluyla toplanılmış olup, anket İstanbul Teknik Üniversitesi İnşaat Fakültesi'ndeki lisans, yüksek lisans ve doktora öğrencileri, akademisyenler ve fakülte de çalışan memur lar üzerine uygulanmıştır. Sürücü davranışlarının değişmesine etki eden karakteristikler 3 kısımda incelendi. Bunlar; sosyoekonomik karakteristikler, teknolojik karakteristikler ve seyahat karakteristikleridir. Trafik bilgilerini çeşitli trafik uygulamalarından elde eden yolcuların rotalarını değiştirme ihtimali farklı karakteristik özelliklere göre çeşitlilik gösterir. Bunlara ek olarak, çeşitli sitelerden elde edilen trafik uygulamalarının özellikleri incelenmiştir. Bu kapsamda, Türkiye'de ve Dünya'da kullanılan trafik uygulamalarının önemli değişkenleri ve uygulamaların betimleyici istatistikleri farklılık göstermiştir. Bu araştırmada, her bir trafik uygulaması geliştirilen Lineer Regresyon Modeli ile analiz edilip, kategorik özellikleri karşılaştırılmıştır. Bu analizin amacı trafik uygulamalarına 1'den 5'e kadar verilen yıldız oranının, trafik uygulamalarına yapılan yorumlara, cinsiyete ve kullanım amacına göre farklılık göstermesinin araştırılmasıdır. Analizlerle ilgili daha çok bilgi çalışmada sunulmuştur.

TABLE OF CONTENTS

ACKNOWLEDGEMENTS . . . iii
ABSTRACT . . . iv
ÖZET . . . v
LIST OF FIGURES . . . ix
LIST OF TABLES . . . xi
LIST OF SYMBOLS . . . xiv
LIST OF ACRONYMS/ABBREVIATIONS . . . xvi
1. INTRODUCTION . . . 1
1.1. Motivation and Problem Statement . . . 1
1.2. Goals and Objectives of the Research . . . 3
1.3. Thesis Contribution . . . 4
1.4. Scope and Limitations . . . 5
1.5. Thesis Outline . . . 6
2. LITERATURE REVIEW . . . 7
2.1. Studies on Real-Time Traffic Information . . . 7
2.1.1. Structure of the Traffic Information Distribution System . . . 13
2.2. Previous Studies in Literature . . . 15
3. METHODOLOGY . . . 26
3.1. Data Collection and Preliminary Analysis . . . 26
3.2. Elements of the Choice Decision Process . . . 27
3.3. Utility-Based Choice Theory . . . 29
3.3.1. Deterministic Choice Concepts . . . 30
3.3.2. Probabilistic Choice Theory . . . 31
3.4. Binary Choice Models . . . 32
3.4.1. Deterministic and Random Utility Components . . . 32
3.4.2. Common Binary Choice Models . . . 33
3.4.3. Binary Logit . . . 33
3.5. The Multinomial Logit Model . . . 34
3.6. Linear Regression Model for Traffic Applications . . . 36

3.6.1. Multiple Regression 38
3.6.1.1. The Wrong Signs in the Linear Regression Model . . . 39
4. DATA COLLECTION AND PRELIMINARY ANALYSIS 41
4.1. Information about Istanbul Technical University, Turkey 41
4.2. Data Collection 42
4.2.1. Collection of Data for All Traffic Applications 42
4.2.2. Collection of Data for Survey 42
4.3. Data Analysis 43
4.3.1. Traffic Applications for Public Transport Modes Used in Turkey 43
4.3.2. Traffic Applications for Private Car Modes Used in Turkey . . . 45
4.3.3. Traffic Applications for Public Transport Modes Used in the World 45
4.3.4. Traffic Applications for Private Car Used in the World 47
4.3.5. Interpretation for Traffic Applications 47
4.4. Descriptive Features of All Data 48
4.4.1. Descriptive Features of Traffic Applications Used in Turkey . . . 48
4.4.2. Descriptive Features of Traffic Applications Used in World . . . 53
4.4.3. Descriptive Features of Survey Data 58
4.4.3.1. Descriptive Features for Private Car Users 61
4.4.3.2. Descriptive Features for Public Transit Users 65
4.4.3.3. Some Statistics based on Work Status 69
5. ANALYSIS AND RESULTS 71
5.1. Multiple Linear Regression and Correlations Analysis 71
5.1.1. Investigation of Index of the Rating of the Traffic Applications Used in Turkey 72
5.1.1.1. Comments on Traffic Apps Used in Turkey: Being Accurate 72
5.1.1.2. Comments on Traffic Apps Used in Turkey: Being User Friendly 74
5.1.1.3. Comments on Traffic Apps Used in Turkey: Being Detailed 76
5.1.2. Investigation of Index of the Rating of the Traffic Applications Used in World 78

5.1.2.1. Comments on Traffic Apps Used in World: Being Accurate . . . 79
5.1.2.2. Comments on Traffic Apps Used in World: Being User Friendly . . . 80
5.1.2.3. Comments on Traffic Apps Used in World: Being Detailed 82
5.2. Binary Logit Model . . . 83
5.2.1. Population and Sample Size . . . 83
5.2.1.1. Sample Size Calculation . . . 84
5.2.1.2. Stratified Random Sampling . . . 84
5.2.1.3. Proportionate Stratified Random Sampling . . . 85
5.2.1.4. Disproportionate Stratified Random Sampling . . . 86
5.2.2. Using Binary Logit Model for Modelling Private Car Drivers' Behavior Under the Real-Time Traffic Information . . . 88
5.2.3. Using Binary Logit Model for Modelling Public Transit Users' Behavior Under fhe Real-Time Traffic Information . . . 91
5.3. Analysis Results . . . 91
6. CONCLUSIONS AND RECOMMENDATIONS . . . 97
6.1. Conclusions . . . 97
6.2. Recommendations . . . 99
REFERENCES . . . 100
APPENDIX A: QUESTIONNAIRE . . . 106

LIST OF FIGURES

Figure 2.1. Structure of Traffic Information Publishing Pattern (Ben-Akiva *et al.*, 1996). 14

Figure 2.2. Information Technologies, Urban Development, Mobility, Activity and Travel Decisions (Ben-Akiva *et al.*, 1996). 14

Figure 2.3. Decision Behavior with the Effect of Traffic Information (Wenjing *et al.*, 1995). 17

Figure 2.4. Changes in Travel in Response to Traveler Information (N=801 trips), (Peirce *et al.*, 2003). 19

Figure 2.5. Driver Decision Process (Ben-Akiva *et al.*, 1991). 23

Figure 4.1. Location of the Civil Engineering Faculty at Ayazaga Campus of ITU. 41

Figure 4.2. Frequency of Gender for the study of Turkish App. 49

Figure 4.3. Frequency of Traffic App Based on their Intended Purpose. 49

Figure 4.4. Frequency of Given Five Stars for Traffic Apps Used in Turkey. . . 50

Figure 4.5. Frequency of Interpretation for Traffic Apps Used in Turkey. . . . 50

Figure 4.6. The Selected Cut off for the Download Counts of Apps. 54

Figure 4.7. Frequency of Gender for the Study of All App. 54

Figure 4.8. Frequency of Traffic App Based on their Intended Purpose for all Apps. 55

Figure 4.9. Frequency of Given Five Stars for all Apps. 55

Figure 4.10. Frequency of Interpretation for All Traffic Apps. 56

Figure 4.11. Frequency of Gender of Survey Data. 59

Figure 4.12. Frequency of Gender of Survey Data for Private Car Users. 61

Figure 4.13. Types of Traffic App for Private Car Users. 62

Figure 4.14. Frequency of Gender of Survey Data For Public Transit Users. . . 65

Figure 4.15. Types of Traffic App for Public Transit Users. 66

Figure A.1. Questionnaire. 106

Figure A.2. Questionnaire 1. 107

Figure A.3. Questionnaire 2. 108

LIST OF TABLES

Table 2.1. Interaction among Departure Time, Travel Mode, and Route Choice (Wenjing *et al.*, (1995). 18

Table 4.1. Common Features for Public Transit Applications. 44

Table 4.2. Common Features for Private Car Applications. 45

Table 4.3. Common Features for Public Transit Applications. 46

Table 4.4. Common features for Private Car Applications. 47

Table 4.5. Interpretation for Traffic Applications. 48

Table 4.6. Interpretation for Each Traffic Applications Used in Turkey. 51

Table 4.7. Gender Based Interpretation Table for Traffic App Used in Turkey. 52

Table 4.8. Relationship between Five-Star Rating Scale and Interpretation for Traffic App Used in Turkey. 53

Table 4.9. Interpretation for Each Traffic Applications for All Traffic Apps. . 57

Table 4.10. Gender Based Interpretation Table for All Traffic Apps. 58

Table 4.11. Relationship Between Five-Star Rating Scale and Interpretation for All Traffic Apps. 58

Table 4.12. Frequency of Obtaining Traffic Information Sources. 60

Table 4.13. Average Trip Times for Each Modes. 60

Table 4.14. Average Trip Costs for Each Modes. 60

Table 4.15. Average Trip distance for Each Modes. 61

Table 4.16. Frequency of Using Private Car. 62

Table 4.17. Purpose of Using Traffic Applications for Private Car Users. 63

Table 4.18. Frequency of Traffic Applications Usage for Private Car Users. . . 63

Table 4.19. Frequency of Private Car Users' Behavior Under the Real-Time Information. 64

Table 4.20. Travel Behavior Relative to Traffic Applications for Private Car Users. 64

Table 4.21. Travel Behavior Relative to Car Usage Frequency. 65

Table 4.22. Frequency of Using Public Transit. 66

Table 4.23. Preference of Public Transport Modes. 67

Table 4.24. Purpose of Using Traffic Applications for Public Transit Users. . . 67

Table 4.25. Frequency of Traffic Applications Usage for Public Transport Users. 68

Table 4.26. Frequency of Public Transit Users' Behavior under the Real-Time Information. 68

Table 4.27. Travel Behavior Relative to Traffic Applications for Private Car Users. 69

Table 4.28. Travel Behavior Relative to Public Transit Usage Frequency. . . . 69

Table 4.29. Shares of Ranks, and Other Characteristics. 70

Table 5.1. Coefficients of Indicators for Traffic Apps used in Turkey for People who Interpret the Apps as Accurate or not (DV: Five-Scale Star). . 73

Table 5.2. Coefficients of Indicators for Traffic Apps used in Turkey for people who Interpret the Apps as User Friendly or Not (DV: Five-Scale Star). 75

Table 5.3. Coefficients of Indicators for Traffic Apps used in Turkey for People who interpret the apps as Detailed or not (DV: Five-Scale Star). . 77

Table 5.4. Coefficients of Indicators for Traffic Apps used in World for People who interpret the Apps as Accurate or Not (DV: Five-Scale Star). 79

Table 5.5. Coefficients of Indicators for Traffic Apps used in World for People who interpret the Apps as user Friendly or not (DV: Five-Scale Star). 81

Table 5.6. Coefficients of Indicators for Traffic Apps used in World for People who interpret the Apps as Detailed or not (DV: Five-Scale Star). . 82

Table 5.7. Binary Logit Model for Private Car Users. 89

Table 5.8. Binary Logit Model for Public Transportation Users 91

LIST OF SYMBOLS

A	Being Accurate
C_n	The choice which is set as i, j
D	Being Detailed
E	Establishments
F	F-statistic Value
f_h	Rate of sampling in each stratum
G	Gender
H_o	Null Hypothesis
i	Travel behavior choice alternative
k	Number of independent variables
n	Individual number
n	Number of observations
n	Strata of sample size
N	Population size
$Pr(i)$	The probability of the decision-maker choosing alternative i
$P_t(i)$	Probability of a person t choosing i
$P_t(j)$	The probability of choosing an alternative j
R^2	Coefficient of determination
s	Degree of Freedom
S_t	Vector of characteristics describing individual t, that influence his/her preferences among alternatives
Sig	Significance
Std	Standart
t	Characteristics alternative
t	T-statistic values
U_{it}	True utility of the choice i to the decision maker t
U	Being User Friendly
V_{it}	Deterministic or observable portion of the utility estimated by the analyst

x	Vector of explanatory variables in the binary logit's utility function
x_i	vectors of attributes describing alternatives i and j
X_n	Different factors affecting
y_{ij}	Observed numbers of travelers' trips generated at establishment i of travelers' characteristics j
$\hat{y}_{ij}$	Estimated numbers of travelers' trips generated at establishment i of travelers' characteristics j
ε_{it}	The error or the portion of the utility unknown to the analyst
β_n	Coefficients of the factors
σ	Random terms
η	the travel behavior (choice) parameter
μ	the scale parameter which determines the variance of the distribution

LIST OF ACRONYMS/ABBREVIATIONS

APP	Traffic Application
ATIS	Advanced Traveler İnformation Service
BL	Binary Logit
DV	Dependent Variable
GPS	Global Positioning System
IMM	Istanbul Metropolitan Municipality
ITS	Intelligent Transportation Systems
ITÜ	Istanbul Technical University
IV	Independent Variable
İETT	İstanbul Metropolitan Municipality Istanbul Electric Tramway and Tunnel
MNL	Multinomial Logit Model
MNP	Multinomial Probit Model
PT	Public Transit
TM	Travel Modes
VMS	Variable Message Sign

1. INTRODUCTION

1.1. Motivation and Problem Statement

Travel behaviour is crucial in travel demand management as well as in urban and transport planning. Over the past decade, with the advancement of data collection techniques, such as GPS, transit smart cards, and mobile phones, various types of travel trajectory data are increasingly complementing or replacing conventional travel diaries and stated preference data (Yue Yang, 2014)

People schedule the activities that they need to accomplish in a day based in part on the time taken by each activity and the time required to travel between activities in different locations. Because of uncertainty about travel times, people tend to incorporate "slack" in their scheduling decisions to reduce the risk of schedule disruptions due to worse-than-expected travel conditions. Reliable information on travel times and traffic conditions will allow people to eliminate some of this slack.

Real time traffic information enables road users to make decisions on the basis of more accurate estimates of travel times on different routes and at different moments. Individuals will be able to avoid unexpected severe congestion, and doing so may in turn limit expected travel times in case of an incident once more people get informed (Yie-Yen Tseng, 2011).

Information to support travel decisions is acquired actively (by reading, asking, listening) or passively (through experience) from various sources, and it is used, along with stored knowledge, to make choices, both long-term (e.g., auto purchase) and shortterm (e.g., departure time and route choice). Individuals have limited information processing capabilities and resources, and as a result their typical decision-making processes use simple choice rules and rely on limited search efforts, e.g., Simon's (1979) concept of "bounded rationality" to select a satisfactory option (Mahmassani and Chang, 1985). The search for options, such as the home-to-work route, may be well

short of the optimal route, depending on the importance of the decision, the expected costs and payoff of additional searching, and the availability of salient information.

Particularly, in the event of traffic incidents, travelers can avoid traffic congestion, through consulting means of traffic advisory devices such as variable message signs, cellular phones or the internet, in accessing relevant traffic incident and route guidance information. It was found that the provision of real-time traffic information significantly affects behavior of travellers on expressways which will result in the change of the trip generation and the distributing in the time or space (Chorus, 2005).

Road traffic systems should provide efficient and stable traffic service; however, in the real world, the traffic situation changes dramatically from moment to moment and day to day. The unreliability of the level of service produces large economic and environmental losses. Especially in peak periods, traffic congestion is a daily routine, due to the overconcentration of traffic demand at specific times and in specific areas. To relieve traffic congestion and provide efficient traffic service, it is important to dynamically distribute the traffic demand with respect to area and time, in response to the current traffic situation. In this sense, providing drivers with information about travel times and traffic congestion should improve the traffic flow.

Most travelers using such information today, however, may not choose the route that provides the shortest travel time among all sets of routes; the travel time information currently provided is not a highly accurate prediction, but a sort of descriptive one. Moreover, providing information on traffic conditions can even make the situation worse (Arnott *et al.*, 1991).

The current descriptive information does not consider the responses of drivers to the information provided. In other words, there is a lag between the point in time that the descriptive information refers to and the point in time when drivers actually travel along the route; thus, an overconcentration of travelers can respond to the information. To prevent this, drivers require “accurate” travel time information that predicts driver behavior, given the information and forecasts of the traffic situation in both the short

and long term; unfortunately, this is not technically practical due to the difficulty in forecasting traffic dynamics accurately. However, it is possible to provide drivers with travel time distribution information on the basis of a database. This information represents the uncertainty of travel times and can stimulate diversity in driver route choice behavior (Kanninen, 1996).

Information acquisition may update travellers' perceptions of travel alternatives in two ways. First, it may increase travellers' awareness of alternatives by introducing them to the traveller or by explaining them and, second, it may alter travellers' perception of the characteristics of travel alternatives. Eventually, travel information may, through the updating of perceptions, influence travellers' choice-behavior (Chorus *et al.*, 2006a).

Arentze and Timmermans (2004) and Sun *et al.* (2005) stress the importance of understanding and model the impact of travel information on traveller's decision processes, the authors have proposed a Bayesian framework. The value of information is conceptualized as the extent to which information about travel time (or any other relevant state of the system) improves activity-travel scheduling decisions at the beginning of the day and during execution of a schedule. The system takes the complete activity travel pattern of one day into account and explicitly represents the uncertainty and the perception of credibility of information source.

Tsirimpa and Polydoropoulou (2011) developed an integrated latent variable model of activity rescheduling after the acquisition of en route traffic information. The model estimation results indicate that the biggest impact of traffic information is reflected in route changes and rescheduling of activities. These two have a direct effect in the reduction of traffic, while causing a redistribution of travel demand.

1.2. Goals and Objectives of the Research

In this thesis, it is hypothesized that decision makers for travel are affected by traffic information acquisition when they are encountered with a trip mode choice for

their daily trip. So the main goal of this research is to investigate the travel behavior on freeways as a result of the provision of various types of real-time traffic information acquired by some traffic applications such as GPS navigation devices for car, mobile traffic applications and radio traffic reports. In addition, Linear Regression analysis were conducted in order to analyse traffic applications used in Turkey and all over the world. To achieve this main research goal, following research objectives were aimed at:

(i) To provide a theoretical information about discrete choice modeling as well as presenting further literatur review about modelling travel behaviour under the traffic information
(ii) To investigate effects of the provision of various types of real-time traffic information acquired by some traffic applications on travelers' behavior
(iii) To analyse relationship between dependent variables and independent variables about traffic application used in Turkey and all traffic application also studied
(iv) To recommend further research if needed in this area.

1.3. Thesis Contribution

The main contribution of this thesis is gaining more insights over the decision-making process of individuals after the acquisition of traffic information provided with some traffic applications while en route. The characteristics that influence travelers' decision making patterns were categorized into some different characteristics which were socioeconomics, travel and technological characteristics. All contributions of the thesis are listed below:

(i) In the socioeconomics characteristic perspective, for private car modes, females are more likely to switch their travel pattern when they use the traffic applications
(ii) Academicians has the significant and positive effect on changing route under the real time information acquired by traffic app for private car users. The estimation results show that academicians who use private car are more likely to change their route when using traffic apps
(iii) Unlike using public transit, travelers who use private car several times a day are

more likely shift their route through using traffic applications than they use it every second days

(iv) The estimation results show that as the trip cost increases, travelers are more willing to change their route under the real time traffic information

(v) Gender difference can influence interpretation for traffic applications in a different way as well as understanding the advantages of traffic applications which are used to solve the traffic congestion.

1.4. Scope and Limitations

This research is aimed at presenting decision makers for travel of people stayed at the civil engineering faculty of Istanbul Technical University, behave differently while obtaining traffic information from some traffic applications in their daily trip. That's why the research is constrained with location, namely, members of survey include students from undergraduate-graduate students, academicians and supporting staff stayed at civil engineering faculty. The second constraint contain that respondents should use the traffic applications either having traffic applications on mobile device or GPS navigation devices for car or something like that because the research analyze how real-time information acquisition during the daily tour affects the attitudes of respondents. Furthermore, in order to analyse traffic applications, data were obtained from some websites which include all traffic application people downloaded such as "Google Play Store" and "Similar Play".

As will be explained in the analysis part of the research, the questionnaire were conducted in this research and some data were eliminated in the analysis in order not to use traffic applications in their daily trips. This research focuses on relationship between various decision makers' travel behavior and traffic information acquisition and to study relationship between dependent variables and independent variables about traffic application used in Turkey and all traffic application also studied.

1.5. Thesis Outline

The remainder of this thesis is organized as follows. In the next chapter, literatur review about traffic applications and previous studies are provided. Then, in Chapter 3, the methodology of the study is explained with the relevant theory as well as the proposed framework. It is followed by the preliminary data analysis in Chapter 4 and results of the analysis of the study in Chapter 5. Finally, conclusions and recommendations are provided in Chapter 6.

2. LITERATURE REVIEW

2.1. Studies on Real-Time Traffic Information

Providing travelers with traffic information is considered to have a great possibility to change their behavior and consequently mitigate traffic congestion (Kanninen, 1996), and has been studied by many researchers as the context of intelligent transportation systems (ITS) and advanced traveler information service (ATIS) since the early 1990s (Chorus *et al.*, 2006).

Intelligent transportation systems (ITS) represents a set of advanced technologies, including the advanced traveler information system (ATIS), which provides necessary information for travelers, at home/office or en-route. This information forms a good basis for the travelers to determine their trips, mode and route choices, in order to reach their destinations safely and efficiently (Alder and Blue, 1998). To an individual, ATIS can enhance the efficiency of the travel, as well as relieve the stress relating to travel. To the system, ATIS can help to reduce significantly travel times, delay, fuel consumption and emission (Adler and Blue, 1998). It includes a broad area of research interests, such as drivers' utility of acquiring information (e.g. Chorus *et al.*, 2010; Levinson, 2003); influence of providing travel time information on network dynamics (e.g. Ben-Akiva *et al.*, 1991; Emmerink *et al.*, 1995a, 1995b), and drivers' information acquisition process and cognitive process (e.g. Polak and Jones 1993; Sun *et al.*, 2005). A number of relevant studies pointed out that the provision of information through ATIS can help to improve the network performance and service quality (Abdel-Aty and Abdalla, 2004; Mahmassani and Liu, 1999).

Among these, understanding travelers' behavior when information is provided is one of the most important topics toward designing successful ATIS. Advanced traveller information systems (ATIS) are generally believed to have a potentially significant impact on the performance of road transport networks. Real time traffic information enables road users to make decisions on the basis of more accurate estimates of travel

times on different routes and at different moments. Individuals will be able to avoid unexpected severe congestion, and doing so may in turn limit expected travel times in case of an incident once more people get informed. Bonsall (1992) focused on the accuracy of information and concluded that a driver's compliance with the provided information depended on the driver's knowledge of the network and the accuracy of information the driver got.

Unlike advanced traffic management system, the efficiency of ATIS depends upon whether travelers understand the information correctly, how they value the usefulness of information, and whether they follow the suggested routes. An efficient ATIS can help to relieve the recurrent traffic congestion happened during peak hours. However, its significance lies in its capability to reduce the uncertainties about road usage, especially traffic congestion due to incidents. Based on Busch (1987), the delay and disruption to traffic due to road incidents far exceeds those occurred during peak hour congestion caused by overcapacity. Therefore, traffic information can be broadcast to travelers when incidents occur. Information about downstream incidents, expected degrees of congestion, and alternative routes, can be provided to them to reduce the traffic impacts and inconveniences due to incidents (Al-Deek *et al.*, 1998).

Provision of traffic information is thought to be one of the key features to affect the traveller's behaviour (e.g. Koppelman and Pas, 1980; Bonsall, 2001; Golledge, 2002). Many studies have considered the impact of travel information and willingness to pay for information (e.g. Koppelman and Pas 1980; Emmerink *et al.*, 1995; Chen and Mahmassani, 2004). As Chorus *et al.* (2004) argued, these studies can be categorised into two streams, those that describe travel choices given travel information (e.g. Ben-Akiva *et al.*, 1991; Khattak *et al.*, 1993; Yim and Khattak 2002) and those that describe the process of information acquisition using ATIS (e.g. Polak and Jones 1993; Polydoropoulou and Ben-Akiva 1998; Hato *et al.*, 1999; Kenyon and Lyons 2003). Findings indicate that the adoption of ATIS information is linked to both the traveller's past experience and the credibility of the information source. Chang and Mahmassani (1988) found in their simulation experiments about how individuals adjust their departure time choice in response to previous experience, that the most recent information,

essentially the previous trip's travel time, is the most important factor in current decisions. In the laboratory experiment study of Lida, *et al.* (1992), which focused on route-choice behaviour and dynamic adjustment over time, the results also suggests that recent travel experience is more important than travel experience long-time ago. Much of this and similar research addresses just one aspect of travel behaviour, such as departure time or route choice and hence is inherently limited in the sense that travel information may influence the complete daily activity-travel pattern.

Smart phones provide a new way of traffic information dissemination system to travelers. The development of smart phone applications with expanding functions could be one of the boosting factors that contribute toward an elevated penetration rate. Apps comprise of software that is designed to carry out certain tasks and available for downloads in apps store. Some apps could be downloaded free-of-charge, while others are chargeable apps. The top three most popular apps are weather, social networking, maps or navigation types of apps (Sutherland, 2013). Traffic information apps are broadly classified into two types: informative and guidance. Informative apps provide traffic information to users without route guidance advices and information is delivered in the form of traffic images or maps. Snapshots of traffic images are continuously uploaded online which allow apps users to keep check on the latest traffic condition. The guidance type of traffic apps provides route guidance and advice to users to avoid traffic congestion. These apps give detailed rerouting advice and turn-by-turn guidance with voice instruction. Besides, it also offers additional features such as speed limit display, road alerts, weather report, and speed camera warning.

ATIS have been evaluated through operational tests, travel surveys or traffic simulators (Bonsall and Parry, 1991). Although these tests and experiments are very useful, they are very expensive to conduct and do not allow for effective evaluation of different alternatives. Computer simulation models, on the other hand, allow for testing alternative system designs before conducting operational tests, thus resulting in more effective operational tests and implementation. These simulation models typically consist of two main components: a dynamic driver behaviour model and a traffic simulation model.

Advanced Traveler Information Systems (ATIS) may offer significant benefits in terms of improving the travel experience of individuals and overall system performance. Despite the fact that much research has been conducted in this field, understanding traveler's response to ATIS is still unknown. ATIS are likely to influence travel decisions (such as mode, route, etc.), lifestyle decisions (location of residence, car ownership) and activity participation decisions (work, shopping) (Polydoropoulou and Ben-Akiva, 1999).

Many researchers have studied the impact of advanced traveler information systems on travelers decision making behavior. Prior research has been focused mainly in the following decisions: (i) Awareness of ATIS; (ii) Usage of ATIS; and (iii) Response to the information provided by ATIS. The factors that influence these decisions according to the most recent research can be distinguished into four major categories: (i) Personal and household socioeconomic characteristics; (ii) Individuals attitudes and perceptions; (iii) Information characteristics; and (iv) Travel characteristics. The analysis reveals that Seattle-area travelers seek information on a narrow share of their daily travel-just over 3 percent of respondents' recorded trip segments involved information usage, with radio traffic reports the most common source. The decision to seek information does not seem to be strongly influenced by traditional demographics such as sex or income, but is correlated with employment status, internet usage, and experience with congestion. Trip characteristics are also influential, with travelers much more prone to seek information where (i) information is likely to be available for the route or mode in question, (ii) the trip is arrival-time sensitive, and (iii) there is a great deal of variability or uncertainty about the travel time. Thus, a typical traveler is about 20 times more likely to seek information on a peak-period, 25-mile commute trip to work than on an off-peak shopping trip. However, studies of ATIS usage should not limit themselves to commute trips, since other time-sensitive trips, such as those to the airport and to medical appointments, also exhibit above-average levels of information acquisition.

Khattak (1998), conducted mail questionnaire surveys in San Fransisco and Chicago area and asked respondents about the effects of en-route travel information on their

trip-making decisions. 66.7% of the respondents in San Francisco, and 43% in Chicago acquired information from the radio. About 16% of the respondents in San Francisco and 42% in Chicago had diverted within the past three months in response to their most recent unexpected traffic delay. Automobile commuters' cognitive maps are influenced by duration of residence, personality, and locational characteristics. In addition, travel time on both usual and alternate routes, reception of delay information via radio, and personality aspects are important attributes in drivers' en route diversion behavior. Hato *et al.*, (1999) conducted a survey targeting drivers travelling on the Tokyo Metropolitan Expressway network, where drivers can actually make use of traffic information from multiple sources when choosing their route. Information acquisition behavior seems to be influenced by latent variables, which are determined by individual's driving experience and individual characteristics.

Mahmassani and Liu (1999) investigated departure time and route switching decisions made by commuters, in response to ATIS. The data was collected using a dynamic interactive travel simulator for laboratory studies of user responses under real-time information. The experiment involved actual commuters who simultaneously interacted with each other within a simulated traffic corridor that consisted of alternative travel facilities with differing characteristics. In the pre-trip departure time switching decision, older commuters tended to tolerate greater schedule delay than younger ones. Also, female commuters exhibited a wider mean indifference band than male commuters for pre-trip departure time and route decisions as well as en-route path switching decision. The reliability of the real-time information is a significant variable that influences commuters' pre-trip departure time and route switching decisions as well as en-route path switching decision. Travelers become more prone to switch routes when they perceive late arrival by following the current path than when they perceive early arrival by following the current path.

Traffic information transmission via smart phone apps has significant advantage over conventional tools, it provides more flexibility to travelers in obtaining traffic information. With travel apps, drivers are able to assess traffic information at any time and on a wider network unlike VMS where it can only be installed at certain

hotspot locations due to site limitation and budget constraint and thus only provide localized traffic information. As such, VMS provides en-route information only while its effectiveness is heavily dependent on its location. Drivers have limited response choice in which they can only divert to an alternative road and yet are uncertain on traffic conditions on alternative roads. Such uncertainty has reduced travelers' willingness. (Khoo and Ong, 2011).

In contrast to VMS, traffic information apps provide networkwide traffic information in which drivers will have better understanding on the overall traffic condition and thus able to make both pre-trip and en-route decision. While en-route, their willingness to divert will be higher if they know that the traffic condition on the alternative road is better. Compared to commercial radio, traffic apps allow drivers to access traffic information almost 24/7 with short update intervals. This helps drivers to avoid non-recurrent traffic congestion such as accident or vehicle breakdown during peak hours. In addition, traffic information could be better disseminated if drivers share the information obtained via social media.

Khoo and Ong (2011) conducted a research study on the willingness of drivers in the Klang Valley region of Malaysia to divert to alternative routes, having received traffic information from the conventional advanced traffic information system (ATIS) tools. It was found that 26% of the respondents (out of 1506 respondents surveyed) would choose to divert to alternative roads if traffic condition is slow moving or heavy. Among the reasons cited by others who do not change to alternative routes are: not convinced that the alternative routes have better traffic conditions (45%), alternative roads are toll roads (18%), not knowing the availability of alternative routes (13%), afraid of losing way on alternative routes (12%), and that alternative routes are longer in distance (12%). As we can see, accuracy of the ATIS tools have a great influence on people's choice. These reasons reveal that conventional ATIS tools have limitations in delivering traffic information which is not comprehensive enough to encourage drivers to change routes. However, traffic information apps could overcome these limitations by providing network-wide traffic information and turn-by-turn guidance to drivers.

The ability of traveler information to fulfill any of these goals depends on a number of factors, including the quality of the information provided, the characteristics of the user and of the particular trip, and the broader regional context (Lappin 2000). Moreover, the ability of ATIS and traveler information to improve the performance of transportation networks depends crucially on user habits, particularly the user response to information.

Responses to ATIS involving the tripmaking context include behavior that affects the way that trips are scheduled or integrated into daily activities. These include adjustments to residential and/or employment location decisions; adjustments to daily activity schedules; changes in habitual tripmaking behavior; effects on non-travel activities; and trip-related stress or anxiety relief.

Responses to ATIS involving tripmaking itself cover a wide range of trip-related decisions: the decision to travel or not; the choice of destination or destinations (trip chaining); choice of departure time, mode and route; the re-routing decision in response to an incident; driving behavior; and the choice of parking location.

2.1.1. Structure of the Traffic Information Distribution System

Traffic information release relays on the system platform to maintain the normal operation. Its existence is premise with the satisfaction of the traffic information demand, Therefore there must be a service platform for road capacity users; To raise the quality of traffic information release lies in the combination with advanced information system, So there will be a system platform to process information and provide mutual information; The operation of traffic information system, as well as other aspects of traffic information operations management work requires management platform to assume; The equipments of traffic information release need each industry platform to provide. Thus, the surface structure of traffic information distribution model can be expressed by management platform, system platform, service platform and industrial platform. And the structure of its model is shown in Figure 2.1

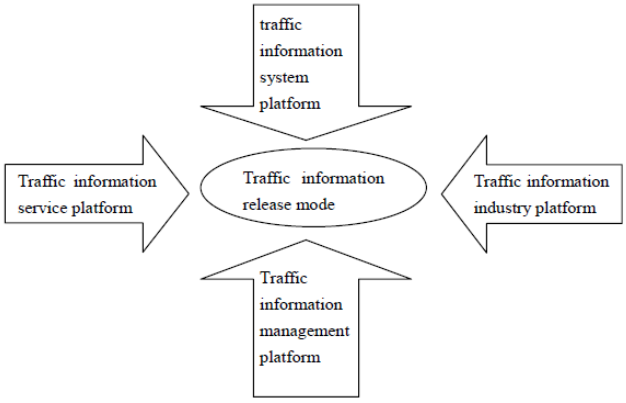


Figure 2.1. Structure of Traffic Information Publishing Pattern (Ben-Akiva *et al.*, 1996).

The influences of information on travelers' activity has two type: long-term and short-term. Moshe assert that travel demand model system of information era, analyzed the frame of the model of interaction between activities and transportation with the effect of information, as shown in Figure 2.1.

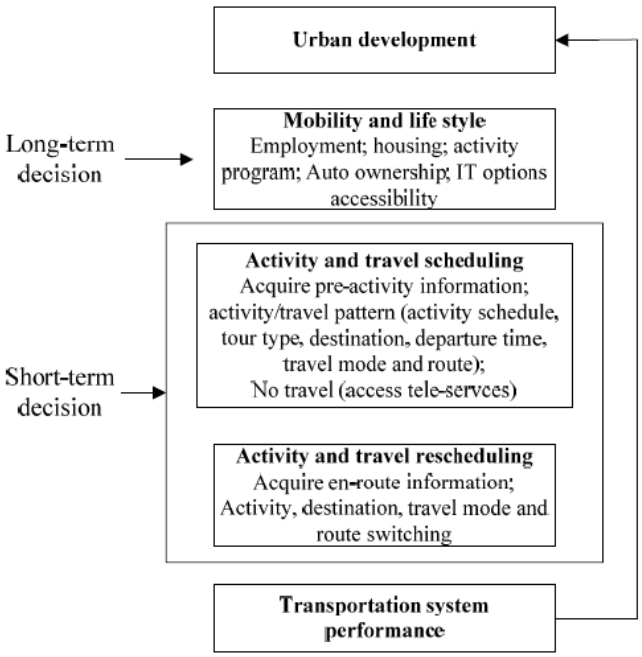


Figure 2.2. Information Technologies, Urban Development, Mobility, Activity and Travel Decisions (Ben-Akiva *et al.*, 1996).

Figure 2.2 illustrates, from the view point of long-term influence, the development of information technology and transportation system will surely have impacts on urban residents' motivations and living habits. These impacts include residence choice, employment state, work style, vehicle procession, and so on. For example, the internet enables certain work to be done at home and online purchase that change people's life style, as well as their travel demand. Short-term decision refers to those influences of the information, which is gained by the travelers through the internet, telephone or other ways, on travelers' original activity plans, so that they can adjust their original travel flexibly. These information include:

(i) Pre-travel information: Pre-travel information, which is gained before travel and can cause fundamental change to the original activity-travel plans; for instance, whether they will travel, whether going out or realizing through the internet; if they have decided to go out, then the following are the decisions about departure time, travel mode, and travel route.

(ii) Mid-travel information: If travelers get new information on their way, they may make adjustments to their original activity-travel plans, which include adjustment to departure time, travel mode, etc. In addition, travelers' activity-travel plans will change according to the dynamic change of information. And that is shown by changed plans for one week or even one day. Moreover, travelers' activities are influenced by the interaction between development of the city and the state of transportation system.

2.2. Previous Studies in Literature

As explained in Chapter 1, the study is focused on travel behavior modeling on freeways as a result of the provision of various types of real-time traffic information acquired by some traffic applications. In this section, information about previous studies is given.

Polydoroponlon studied the route choice behavior of the residents in California harbor areas under the impact of information, and analyzed the important factors of

route adjustment decisions. Mahmassahi and Liu studied committers' departure time and route adjustment behaviors with the influence of ATIS information, and found out that only if the time they could save surpassed a threshold, they could change the original travel behaviors. Rebeca studied the theme-park-travel-mode choice under the influence of information, and proved the leading effect of transportation information towards mode choice of entertainment travels. In China, on the basis of "prospect theory" Zhang analyzed travelers' learning renewing process and route choice behaviors under the condition of prior information. on the basis of generalized cost of travel, Li analyzed route choice behaviors in stochastic network under the influence of transportation information. Yang built a public transportation travelers' behavior model under ATIS, and studied its influence factors.

Previous surveys have found that over half of travelers will make a change to their travel route or departure time after accessing information over the radio, television, or telephone (Khattak *et al.*, 1999), and that this proportion can be even higher for website users (Yim and Miller 2000). There is also some evidence from simulated trials that pretrip information can indeed reduce the variability (if not so much the average duration) of the commute trip, and that travelers accessing pre-trip information are likely to reap the greatest benefit by shifting their departure time rather than by changing their route (Shah *et al.*, 2001). Research has also delved into even more specific topics. In the area of route choice, for example, it has been found that variable-message signs are more likely to divert drivers from a non-freeway to a freeway rather than vice versa (Hato *et al.*, 1995) and that behavioral inertia plays a part in drivers' choice of route in response to ATIS (Srinivasan and Mahmassani 2000).

Wenjing *et al.* (2010) claim that When travelers have obtained travel information, they will make several travel plans according to their experience. And they will choose the most beneficial one among them according to their subjective judgments, namely utility maximize; meanwhile, travelers' behaviors are confined by time and space. In addition, travelers' behaviors decisions under the influence of information have many influence factors, such as travelers' social economy characters, their family characters, experiences, as well as attitudes towards travel information. Whether travelers' believe

in the information or not, whether they hold negative or positive attitude to the information will influence their behaviors to some extent. What is more, the quality of travel information provided also has impact on travelers' activities. For example, instant and correct information will enhance travelers' trust in them, which is illustrated by more travelers' obeying the information; otherwise, it will lose its effectiveness.

Based on their analysis results travelers usually have the following three kinds of behavior decisions: the first one is canceling this travel. For example, the heavy traffic will make some travelers to quit their travel plans in holidays. The second one is making adjustment to the travel plan. For example, adjust their departure time, travel mode, or travel route. The third one is carrying out their original plans. Through the SP survey, it is found out that travelers belonging to the third kind accounts for 50%, because most of them are going out for school or work, which are confined by time and space and hard to make any adjustments. While one-third of the travelers changed their travel plan, like departure time, travel mode, or travel route. Figure 2.3 shows travelers' behavior decisions under the influence of information (The sequences of departure time, travel mode, and travel route can be adjusted).

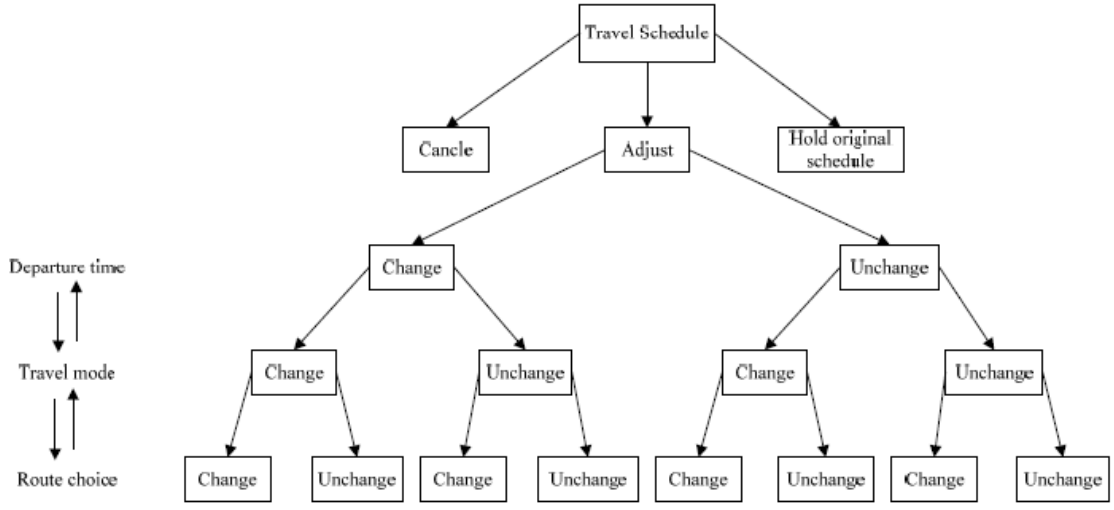


Figure 2.3. Decision Behavior with the Effect of Traffic Information (Wenjing *et al.*, 1995).

In addition, it can be concluded from the survey that travelers' behaviors adjust-

ments are related. Some travelers will change all their departure time, travel mode, and travel route, while others will only change one of them like departure time, or two of them. This article adds up travelers' choice decisions according to the effective data gained, which is shown in Table 2.1. It represents that, when departure time is changed, the samples of changed travel mode and travel route are obviously more than the unchanged ones, which also goes for when travel mode or travel route is changed. While departure time keeps unchanged, the samples of unchanged travel mode are twice as many as changed ones, but the route differences are not obvious. In addition, when the route is unchanged, the samples of unchanged travel mode are significantly more than the changed ones. As a conclusion, there are some potential relations among travelers' departure time, mode, and route choice decisions.

Table 2.1. Interaction among Departure Time, Travel Mode, and Route Choice (Wenjing *et al.*, (1995).

Items		Departure time		Travel mode		Route choice	
		Yes	No	Yes	No	Yes	No
Departure time	Yes			1765	1151	1770	1089
	No			447	912	636	713
Travel mode	Yes	1765	447			1488	619
	No	1151	912			874	1150
Route choice	Yes	1770	636	1488	874		
	No	1089	713	619	1151		

Peirce *et al.* (2003) conduct a survey and assert that about 37 percent of the information-using trips also involved some resultant change in travel behavior as shown in Figure 2.4. One stated-preference survey found that found that about 35 percent of respondents sometimes change their travel plans as a result of an information report (Khattak *et al.*, 1999), while a study of *SmarTraveler*® users in the Boston area (Lappin *et al.*, 1994) found that about 30 percent changed their travel behavior "frequently" in response to information. However, this latter study also found that 96 percent changed their trips "occasionally", and research in Chicago found that 85

percent of motorists said that they alter their behavior after hearing a traffic report (Lappin *et al.*, 1994).

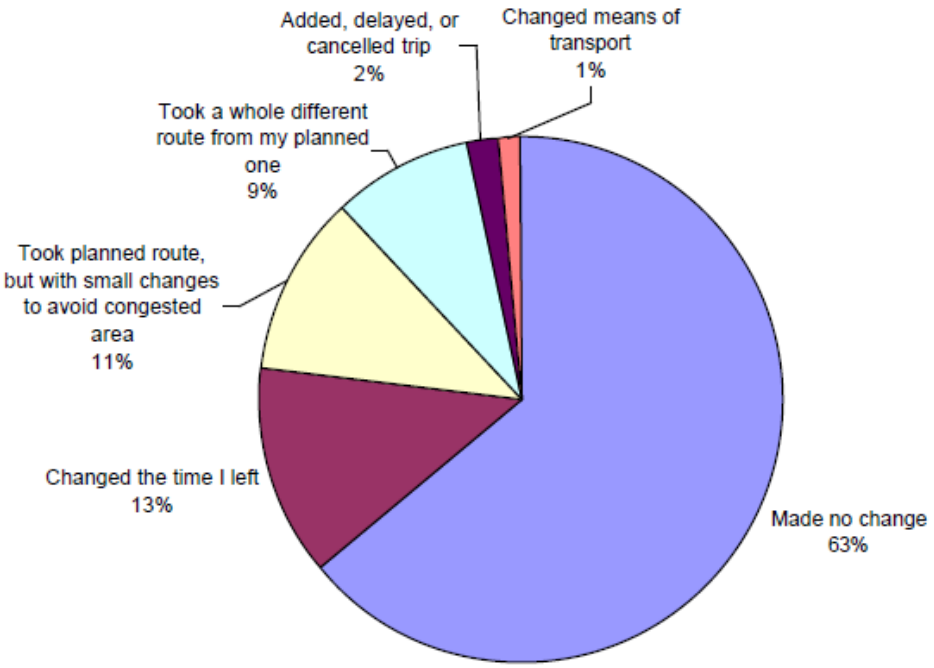


Figure 2.4. Changes in Travel in Response to Traveler Information (N=801 trips), (Peirce *et al.*, 2003).

Overall, then, trips that were changed in some way as a result of traveler information represent just over 1 percent of all trips recorded in the diaries-i.e., 37 percent of the 3.2 percent, for a total of about 1.1 percent. Among these changed trips, the most typical changes are changing departure time (13 percent) and making small changes to one's route (11 percent). Only rarely do people change travel mode as a result of the information (1 percent). The fact that very few trips involved a choice to switch modes is consistent with other research indicating that traveler information generally has no more than a modest effect on mode choice (Yim and Miller 2000).

While the travel diary data indicate that travelers decide not to make a travel change on about two-thirds of the trips on which information is consulted, the structure of the diary unfortunately does not allow us to conduct any further analysis of why this is so. Based on experience with ATIS, however, it can believe that the reasons for

this phenomenon are varied. In many cases, there is simply no reason to deviate from one's plans-there are no reported travel delays, or the delays reported are so minor as not to warrant a change. In other cases, the traveler may wish to change but cannot do so because there are no (feasible) alternative modes or routes. The traveler may also have limited knowledge of alternatives and/or an unwillingness to deviate from the routine. It is also possible for the traveler to react to the information in a way that does not involve an actual travel change, for example by calling ahead to say that he will be late, or by simply enjoying the peace of mind that comes with having additional information on travel conditions.

Mehndiratta, Kemp *et al.* (1999b) illustrate the application of combined factor and cluster analysis techniques, as described above, to delineate distinct segments of ATIS users. A detailed collection of data on travel behavior including use of travel information was conducted as part of the ongoing Puget Sound Regional Council's travel diary panel survey. The survey included conventional demographic and socio-economic information as well as responses to attitudinal questions. From this data, individuals with a high propensity to use travel information were identified. An initial attempt to correlate membership in this group with socio-economic characteristics, based on stereotypes of expected users types (e.g. road warriors, commuting mothers) proved only partially successful. Accordingly, a factor analysis of the entire survey population's attitudinal question responses was performed, and a cluster analysis using the factor scores was carried out to identify distinct segments. Although the segments were defined uniquely in terms of their attitudes, subsequent analysis showed that the segments also differed with respect to their travel behavior, demographic profile, and propensity to use ATIS. The incidence in each segment of individuals likely to use ATIS was then determined.

Polydoropoulou and Ben-Akiva (1999) have described a number of successive stages that travelers typically go through before they become regular ATIS users. These are:

- awareness, where the traveler begins to have basic information about the avail-

ability and attributes of a travel information system;

- consideration set formation, where the traveler generally begins to think of ATIS as a possible option to consider before making trips;
- choice set formation, where ATIS is definitely included as an option to assess in response to a specific identified travel need;
- trial use, where the traveler decides to try ATIS to gain more familiarity with its characteristics and potential benefits and costs;
- repeat use, where ATIS is assimilated into a traveler's continued or habitual travel behavior, although further experience may cause the continued use to be reconsidered.

At the point where repeat usage becomes established, it becomes possible to speak of a systematic traveler response to real-time information. These responses are divided here into two general categories: those involving the tripmaking context, and those involving tripmaking itself. The sections below discuss these responses, drawing on the literature review to indicate the extent of current qualitative and quantitative knowledge about the responses.

Responses to ATIS involving the tripmaking context include behavior that affects the way that trips are scheduled or integrated into daily activities. These include adjustments to residential and/or employment location decisions; adjustments to daily activity schedules; changes in habitual tripmaking behavior; effects on non-travel activities; and trip-related stress or anxiety relief.

Responses to ATIS involving tripmaking itself cover a wide range of trip-related decisions: the decision to travel or not; the choice of destination or destinations (trip chaining); choice of departure time, mode and route; the re-routing decision in response to an incident; driving behavior; and the choice of parking location.

Khattak, Yim *et al.* (1999) have conducted a research that mail questionnaire surveys carried out as part of the San Francisco-area TravInfo project. The surveys covered automobile and transit travelers and commute and non-commute (e.g. shop-

ping or personal) home-based trips. The surveys asked respondents about the effects of pre-trip travel information (available from television, radio or telephone sources) on their tripmaking decisions.

One of the findings was that non-commuters would occasionally decide to cancel their (presumably discretionary) trips because of unfavorable travel conditions reported by the various information sources, and particularly by radio. It is widely agreed that the demand for noncommuting trips is relatively elastic with respect to travel times and costs-in other words, an increase in travel times or costs leads to a reduction in tripmaking. In view of this, it is not surprising that information about bad travel conditions would lead, at the individual level, to non-commute trips being canceled.

Ben-Akiva *et al.* (1985) develops a dynamic network modeling framework that can be used to generate predictive information for a dynamic route guidance system and to predict the effects that travel decisions by informed drivers may have on overall traffic conditions. The approach builds on a number of prior analyses of traffic modeling needs for driver information systems. It is based on a dynamic network modeling framework that incorporates a driver behavior model and a network performance model. The framework explicitly treats the distribution of traffic by time of day, and also represents drivers' pre-trip and en route adjustment processes. The authors propose a modeling framework consisting of: goal formation; information acquisition; driver information processing capacity and computational ability; decision rules; reviewing; and actual decision.

Traditional travel behaviour frameworks described in the literature generally take into account the fact that an individual has access to limited information, has a limited capacity to process the information and attempts to find the best alternative within a time constraint. An example of dynamic driver behaviour modelling framework is shown in Figure 2.5 (Ben-Akiva *et al.*, 1991).

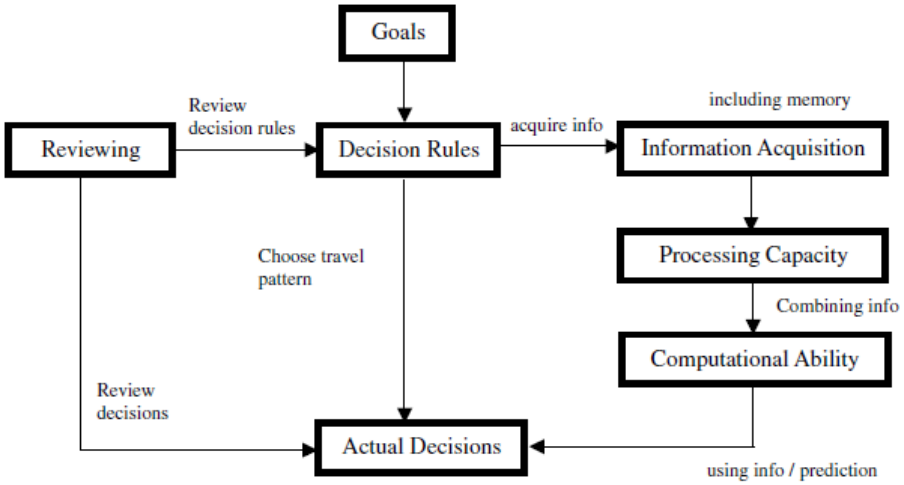


Figure 2.5. Driver Decision Process (Ben-Akiva *et al.*, 1991).

Mahmassani, (1991) formed Dynasmart simulation-assignment model, including in particular the route switching model based on either deterministic minimum path choice or on a boundedly-rational indifference band. The information reliability was analyzed in terms of whether the route recommended on the basis of prevailing times was actually the best in terms of experienced times and, if not, the magnitude of the time difference between the two. the overall conclusion is that basing messages on prevailing conditions may not be very reliable, especially at high market penetration rates.

According to the survey conducted by Khoo and Asitha (2016), all the traffic information apps have a significant influence on drivers' choice whether to gather traffic information via apps. Top factors that encourage people to use these apps are the ability to deliver real time traffic information, in the form of detailed rerouting advice, and/or report on incident and delay estimation. This shows that people are highly concerned on obtaining the latest traffic information that ease their trip planning. Apps that are equipped with junction view and voice navigation show added advantage to attract users as clear instruction assists in driving. The perceived accuracy levels of traffic information and the coverage area variables appear to be less of interest although significant. Generally, the higher the perceived accuracy level is, the more attractive the apps are. Likewise, the wider the traffic information coverage area, more users will

be attracted. Service subscription fee shows a negative sign which indicates that the cheaper the apps subscription fee is, the more attractive the apps is. As a result, if we want to make an ideal app, it should be without subscription fee, should content wide traffic info, very accurate, and equipped with user friendly tools inside.

Khattak *et al.* (1994) used linear regression models to study the impacts of various types of information to route switching behavior of travelers. They discovered that the probability of route switching increases when there is sufficient traffic information and is related to existing opportunities of switching, personal characteristics and weather conditions.

Abdel-Aty *et al.* (1994) studied the factors determining the use of traffic information and the propensity of using alternative routes. The Probit models they developed showed that long distance travel, females, college students, and those travelers who do not have fixed time of travel have a higher tendency to make use of traffic information, while high income and high education persons use traffic information more often with higher rates of switching.

Mandanat *et al.* (1995) combined with descriptive preference data in the structure integration model for route switching behavior and captured latent variables. They used it to study users' understanding of the certainty of traffic information and their attitude in complying with the traffic instructions. Their research shows that these two latent variables have significant impacts of route switching propensity.

Jou and Mahmassani (1996) used Poisson regression to show that the three factors affecting routes, departure times and their combined switching frequencies are commuter characteristics, work environment and traffic network. Commuters tend to change their departure times, routes, and more frequently doing so in the morning instead of evening.

According to Dia H. various aspects of travel information influence drivers decisions. The processing of information depends on its content or meaning, nature

(whether it is static, dynamic or predictive), type (whether it is quantitative or qualitative) and presentation style. In addition, drivers are more likely to rely on relevant and accurate information. For example, under incident congestion, the perception of delay and the quality of real-time information are critically important in changing travel behaviour.

Findings indicate that the adoption of ATIS information is linked to both the traveller's past experience and the credibility of the information source. Chang and Mahmassani (1988) found in their simulation experiments about how individuals adjust their departure time choice in response to previous experience, that the most recent information, essentially the previous trip's travel time, is the most important factor in current decisions.

In the laboratory experiment study of Lida *et al.* (1992), which focused on route-choice behaviour and dynamic adjustment over time, the results also suggests that recent travel experience is more important than travel experience long-time ago. Much of this and similar research addresses just one aspect of travel behaviour, such as departure time or route choice and hence is inherently limited in the sense that travel information may influence the complete daily activity-travel pattern.

3. METHODOLOGY

The study is focused on the impact of traffic information acquisition while en route in individuals' travel pattern. A set of stated preference data was obtained by to facilitate the calibration of models. The methodology also include a preliminary analysis of traffic applications in Turkey and all traffic applications used in world which consist of two parts with respect to their usage area. Those features for public transport modes include offering new options on public transit or telling people the station before. The features for private car modes involve sharing real-time traffic and road information and enable to find the shortest and the cheapest route for saving time. This was followed by descriptive statistics analysis which shows the relationship between independent variables and their frequencies. Then using the developed regression models, the associated tests were employed to understand how the typical value of the dependent variable changes when any one of the independent variables was varied, while the other independent variables were held fixed. Binary logit models were used due to the possible correlation between attitudes made by travelers. The models can be used to study the important factors that affect the dynamic behavior of travelers. Then also using the developed regression models, the associated tests were employed to understand how the typical value of the dependent variable changes when any one of the independent variables is varied, while the other independent variables are held fixed. Details of the theoretical approach, the methodology and the statistical tests used for each part are explained in the sections of this chapter.

3.1. Data Collection and Preliminary Analysis

A case study was developed for the civil engineering undergraduate-graduate students and academics in Istanbul Technical University, Istanbul, in 2016. Stated preference data are collected by distributed questionnaire and the BL model was formed. The worldwide traffic applications data were also analysed which were obtained from some related websites which include all traffic application people downloaded was investigated, and results were presented as "preliminary analysis" in Chapter 3. The data

of subject is composed of two parts with respect to their usage area, including features of traffic apps for public transport modes and features of traffic apps for private car modes. Detailed explanation will also be presented in this chapter.

3.2. Elements of the Choice Decision Process

Discrete choice models can be used to analyze and predict a decision maker's choice of one alternative from a finite set of mutually exclusive and collectively exhaustive alternatives. Such models have numerous applications since many behavioral responses are discrete or qualitative in nature; that is, they correspond to choices of one or another of a set of alternatives. The ultimate interest in discrete choice modeling, as in most econometric modeling, lies in being able to predict the decision making behavior of a group of individuals.

There are two basic ways of modeling such aggregate (or group) behavior. One approach directly models the aggregate share of all or a segment of decision makers choosing each alternative as a function of the characteristics of the alternatives and socio-demographic attributes of the group. This approach is commonly referred to as the aggregate approach. The second approach is to recognize that aggregate behavior is the result of numerous individual decisions and to model individual choice responses as a function of the characteristics of the alternatives available to and socio-demographic attributes of each individual. This second approach is referred to as the disaggregate approach.

The disaggregate approach explains why an individual makes a particular choice given her/his circumstances and is, therefore, better able to reflect changes in choice behavior due to changes in individual characteristics and attributes of alternatives. The disaggregate approach is more suited for proactive policy analysis since it is causal, less tied to the estimation data and more likely to include a range of relevant policy variables. The behavioral nature of disaggregate models, and the associated advantages of such models over aggregate models, has led to the widespread use of disaggregate discrete choice methods in travel demand modeling.

A proposed framework for the choice process is that an individual first determines the available alternatives; next, evaluates the attributes of each alternative relevant to the choice under consideration; and then, uses a decision rule to select an alternative from among the available alternatives (Ben-Akiva and Lerman, 1985, Chapter 3). Some individuals might select a particular alternative without going through the structured process presented above.

In the subsequent sections, four elements associated with the choice process are discussed; the decision maker, the alternatives, the attributes of alternatives and the decision rule (Ben-Akiva and Lerman, 1985).

- The Decision Maker; The decision maker in each choice situation is the individual, group or institution which has the responsibility to make the decision at hand. The decision maker will depend on the specific choice situation. To explain the heterogeneity of preferences among decision-makers, a disaggregate model must include their characteristics such as the socio-economic variables of age, gender, education and income. For example, in travel mode choice modeling, two individuals with different income levels and different residential locations are likely to have different sets of modes to choose from and may place different importance weights on travel time, travel cost and other attributes. These differences among decision makers should be explicitly considered in choice modeling; consequently, it is important to develop choice models at the level of the decision maker and to include variables which represent differences among the decision makers.

- The Alternatives; Analyzing individual decision making requires not only knowledge of what has been chosen, but also of what has not been chosen. Therefore, assumptions must be made about available options, or alternatives, that an individual considers during a choice process. The set of considered alternatives is called the choice set. A discrete choice set contains a fmite number of alternatives that can be explicitly listed. The choice of a travel mode is a typical example of a choice from a discrete choice set. The universal choice set contains all potential alternatives in the application's context. The choice set is the subset of

the universal choice set considered by, or available to, a particular individual. Alternatives in the universal choice set that are not available to the individual are therefore excluded from the choice set.

- Attributes of Alternatives; Each alternative in the choice set is characterized by a set of attributes. Note that some attributes may be generic to all alternatives, and some may bealternative-specific. An attribute is not necessarily a directly measurable quantity. It can be any function of available data. For example, instead of considering travel time as an attribute of a transportation mode, the logarithm of the travel time may be used, or the effect of out-of-pocket cost may be represented by the ratio between the out-ofpocket cost and the income of the individual. Alternative definitions of attributes as functions of available data must usually be tested to identify the most appropriate.

- The Decision Rule; The decision rule is the process used by the decision-maker to evaluate the attributes of the alternatives in the choice set and determine a choice. Most models used for travel behavior applications are based on *utility theory*, which assumes that the decision-maker's preference for an alternative is captured by a value, called utility, and the decision-maker selects the alternative in the choice set with the highest utility.

3.3. Utility-Based Choice Theory

Utility is an indicator of value to an individual. Generally, we think about utility as being derived from the attributes of alternatives or sets of alternatives; e.g. the total set of groceries purchased in a week. The utility maximization rule states that an individual will select the alternative from his/her set of available alternatives that maximizes his or her utility. Further, the rule implies that there is a function containing attributes of alternatives and characteristics of individuals that describes an individual's utility valuation for each alternative. The utility function, U, has the property that an alternative is chosen if its utility is greater than the utility of all other alternatives in the individual's choice set. Alternatively, this can be stated as alternative,

i, is chosen among a set of alternatives, if and only if the utility of alternative, i, is greater than or equal to the utility of all alternatives2, j, in the choice set, C. This can be expressed mathematically as:

$$IfU\left(x_i, S_t\right) \geq U\left(x_j, S_t\right) \forall_j \Rightarrow i > j \forall_j \in C \tag{3.1}$$

where $U(x_i, x_j)$ is the mathematical utility function, are vectors of attributes describing alternatives i and j, respectively (e.g. travel time, travel cost, and other relevant attributes of the available modes), S_t is a vector of characteristics describing individual t, that influence his/her preferences among alternatives (e.g. household income and number of automobiles owned for travel mode choice), $i > j$ means the alternative to the left is prefferred to the alternative to the right and, $\forall_j$ is the means all the cases, j, in the choice set.

That is, if the utility of alternative i is greater than or equal to the utility of all alternatives, j; alternative i will be preferred and chosen from the set of alternatives, C.

The underlying concept of utility allows us to rank a series of alternatives and identify the single alternative that has highest utility. The primary implication of this ranking or ordering of alternatives is that there is no absolute reference or zero point, for utility values. Thus, the only valuation that is important is the difference in utility between pairs of alternatives; particularly whether that difference is positive or negative.

3.3.1. Deterministic Choice Concepts

The utility maximization rule, which states that an individual chooses the alternative with the highest utility, implies no uncertainty in the individual's decision process; that is, the individual is certain to choose the highest ranked alternative under the observed choice conditions. Utility models that yield certain predictions of choice are called deterministic utility models.

3.3.2. Probabilistic Choice Theory

If analysts thoroughly understood all aspects of the internal decision making process of choosers as well as their perception of alternatives, they would be able to describe that process and predict mode choice using deterministic utility models. Experience has shown, however, that analysts do not have such knowledge; they do not fully understand the decision process of each individual or their perceptions of alternatives and they have no realistic possibility of obtaining this information.

As with deterministic choice theory, the individual is assumed to choose an alternative if its utility is greater than that of any other alternative. The probability prediction of the analyst results from differences between the estimated utility values and the utility values used by the traveler. This difference is represented by decomposing the utility of the alternative, from the perspective of the decision maker, into two components. One component of the utility function represents the portion of the utility observed by the analyst, often called the deterministic (or observable) portion of the utility. The other component is the difference between the unknown utility used by the individual and the utility estimated by the analyst. Since the utility used by the decision maker is unknown, we represent this difference as a random error. Formally, we represent this by:

$$U_{it} = V_{it} + \varepsilon_{it} \tag{3.2}$$

where U_{it} is the true utility of the choice i to the decision maker t, (U_{it} is the equivalent to $U(x_i, S_t)$) but provides a simpler notation), V_{it} is the deterministic or observable portion of the utility estimated by the analyst, ε_{it} is the error or the portion of the utility unknown to the analyst.

The analyst does not have any information about the error term. However, the total error which is the sum of errors from many sources (imperfect information, measurement errors, omission of modal attributes, omission of the characteristics of the individual that influence his/her choice decision and/or errors in the utility function)

is represented by a random variable. Different assumptions about the distribution of the random variables associated with the utility of each alternative result in different representations of the model used to describe and predict choice probabilities.

3.4. Binary Choice Models

In this model, considering the special case where C_n that we will denote the choice set as i, j contains exactly two alternatives. The probability of person t choosing i is (Ben-Akiva and Lerman, 1985).

$$P_t(i) = P_r(U_{it} \geq U_{jt}) \tag{3.3}$$

and the probability of choosing alternative j is

$$P_t(j) = 1 - P_t(i) \tag{3.4}$$

The main goal is to develop the basic theory of random utility models into a class of operational binary choice models.

In order to develop any binary choice model, 3 basic steps should be taken;

- The resolution of total utility into deterministic and random components of the utility function,
- The indication of the deterministic part
- The indication of the random part.

3.4.1. Deterministic and Random Utility Components

Remember that U_{in} and U_{jn} are random variables, dividing each of the utilities into two additive parts as follows:

$$U_{in} = V_{in} + \varepsilon_{in} \tag{3.5}$$

$$U_{jn} = V_{jn} + \varepsilon_{jn} \tag{3.6}$$

V_{in} and V_{jn} are called the systematic components of the utility of i and j; ε_{in} and ε_{jn} are the random parts anda re called the random components. It is important that V_{in} and V_{jn} are functions and assumed to be deterministic parts.

3.4.2. Common Binary Choice Models

In order to derivate any binary choice model, some assumption should be made regarding the distribution of the two disturbances or about the difference between them;

- The Linear Probability Model ($\varepsilon_{jn} - \varepsilon_{in}$, uniformly distributed between two fixed values)
- Binary Probit ($\varepsilon_{jn} - \varepsilon_{in}$, normally distributed)
- Binary Logit ($\varepsilon_{jn} - \varepsilon_{in}$, logistically distributed)

3.4.3. Binary Logit

There is at least some theoratical grounds for its assumptions about the distribution of $\varepsilon_{jn} and \varepsilon_{in}$, it has the unfortunate property of not having a closed form.

The binary logit model arises from the assumption that $\varepsilon_n = \varepsilon_{jn} - \varepsilon_{in}$ is logistically distributed, namely

$$\begin{aligned} F(\varepsilon_n) &= 1/(1 + e^{\mu\varepsilon n}) \qquad \mu > 0, -\infty < \varepsilon_n < \infty \\ f(\varepsilon_n) &= \mu\varepsilon^{-\mu\varepsilon n}/(1 + e^{\mu\varepsilon n})^2 \end{aligned} \tag{3.7}$$

where μ is a positive scale parameter. Besides approximating the normal distribution well, the logistic distribution is analytically convenient.

Under the assumption that ε_n is logistically distributed, the choice probability for alternative i is given by

$$\begin{aligned} P_n(i) &= Pr(U_{in} \geq U_{jn}) \\ &= \frac{1}{1+e^{-\mu(Vin-Vjn)}} \\ &= \frac{e^{\mu Vin}}{e^{\mu Vin}+e^{\mu Vjn}} \end{aligned} \tag{3.8}$$

3.5. The Multinomial Logit Model

The Logistic Probability Unit, or the Logit Model, was first introduced in the context of binary choice where the logistic distribution is used. Its generalization to more than two alternatives is referred to as the Multinomial Logit Model. The mathematical form of a discrete choice model is determined by the assumptions made regarding the error components of the utility function for each alternative as shown below;

$$U_{DA} = V(S_t) + V(X_{DA}) + V(S_t, X_{DA}) + \varepsilon_{DA} \tag{3.9}$$

$$U_{SR} = V(S_t) + V(X_{SR}) + V(S_t, X_{SR}) + \varepsilon_{SR} \tag{3.10}$$

$$U_{TR} = V(S_t) + V(X_{TR}) + V(S_t, X_{TR}) + \varepsilon_{TR} \tag{3.11}$$

where $V(S_t)$ is the represents the deterministic components of the utility for the alternatives, ε_i is the represents the random components of the utility, also called the error term.

The error term is included in the utility function to account for the fact that the analyst is not able to completely and correctly measure or specify all attributes that determine travelers' mode utility assessment. By definition, error terms are unobserved

and unmeasured. A wide range of distributions could be used to represent the distribution of error terms over individuals and alternatives. The specific assumptions that lead to the Multinomial Logit Model are (i) the error components are extreme-value (or Gumbel) distributed, (ii) the error components are identically and independently distributed across alternatives, and (iii) the error components are identically and independently distributed across observations/individuals.

The most common assumption for error distributions in the statistical and modeling literature is that errors are distributed normally. There are good theoretical and practical reasons for using the normal distribution for many modeling applications. However, in the case of choice models the normal distribution assumption for error terms leads to the Multinomial Probit Model (MNP) which has some properties that make it difficult to use in choice analysis. The Gumbel distribution is selected because it has computational advantages in a context where maximization is important, closely approximates the normal distribution and produces a closed-form probabilistic choice model.

The Gumbel has the following cumulative distribution and probability density functions:

$$F\left(\right) = \exp\left\{-\exp\left[-\mu\left(-\eta\right)\right]\right\} \tag{3.12}$$

$$f\left(\right) = \mu x\left\{\exp\left[-\mu\left(-\eta\right)\right]\right\} x \exp\left\{-\exp\left[-\mu\left(-\eta\right)\right]\right\} \tag{3.13}$$

where μ is the scale parameter which determines the variance of the distribution η is the location (mode) parameter.

The mean and variance of the distribution are:

$$Mean = \eta + \frac{0.577}{\mu} \tag{3.14}$$

$$Variance = \frac{\pi^2}{6\mu^2} \tag{3.15}$$

The second and third assumptions state the location and variance of the distribution just as μ and σ^2 indicate the location and variance of the normal distribution.

The three assumptions, taken together, lead to the mathematical structure known as the Multinomial Logit Model (MNL), which gives the choice probabilities of each alternative as a function of the systematic portion of the utility of all the alternatives. The general expression for the probability of choosing an alternative i $(i = 1, 2, .., J)$ from a set of J alternatives is:

$$\Pr(i) = \frac{\exp(V_i)}{\sum_{j=1}^{J} \exp(V_j)} \tag{3.16}$$

where $Pr(i)$ is the probability of the decision-maker choosing alternative i, V_j is the systematic component of the utility of alternative j.

3.6. Linear Regression Model for Traffic Applications

In linear regression modeling, both for pooled model and segment models, the relationship with dependent and independent variables can be explained as the following (Walpole *et al.*, 2012):

$$\hat{y}_{ij} = \beta_0 + \beta_1 x_{ij1} + \ldots + \beta_n x_{ijn} \tag{3.17}$$

$$y_{ij} = \hat{y}_{ij} + \varepsilon_{ij} \tag{3.18}$$

where y_{ij} and $\hat{y}_{ij}$ are the observed and estimated numbers of travelers' trips generated at establishment i of travelers' characteristics j, ε_{ij} is the associated error, β_o is the intercept, β_n is the model coefficient of independent variable x_{ijn} and n is the independent variable index.

The validity and goodness of fit of the regression equations can be measured by several statistical measures as well as with the coefficient of determination (R^2). First of all, R^2 indicates how much of the observed data is explained by the built regression model. It takes values between 0 and 1, and is expressed by (Walpole *et al.*, 2012):

$$R^2 = 1 - \frac{ErrorSumofSquares}{TotalSumofSquares} = 1 - \frac{\sum_{i=1}^{m} (y_{ij} - \hat{y}_{ij})^2}{\sum_{i=1}^{m} (y_{ij} - \bar{y}_{ij})^2} \tag{3.19}$$

where m is the number of establishments for logistical site type j, $\hat{y}_{ij}$ is the mean of y_{ij}'s. R^2 being close to 1 indicates that the model is a good fit. However, not all regression models having an R^2 value close to 1 mean they are good since adding highly correlated independent variables causes an increase in R^2 value and over fitting; one should not use highly correlated independent variables at once in a regression model (Walpole *et al.*, 2012). Also, making inferences only from R^2 value is not sufficient. The F-test for overall model and t-tests for each model coefficient should be made to statistically check the validity of the model obtained.

The F-test tests the null hypothesis of "All regression coefficients are equal to zero"; i.e., there is no relationship between the dependent variable and the independent variables. The null hypothesis is given as the following (Walpole *et al.*, 2012):

$$H_0 = \beta_0 = \beta_1 = \ldots = \beta_k = 0 \tag{3.20}$$

The F-statistic is calculated as follows (Walpole *et al.*, 2012):

$$F = \frac{R^2/k}{(1 - R^2)\,/\,(n - k - 1)} \tag{3.21}$$

where k is the number of independent variables, n is the number of observations. The F-statistic in Equation 3.1 is distributed with the F distribution with s degrees of freedom of k and *(n-k-1)*.

If the F-test results in rejection of the null hypothesis of "All regression coefficients are equal to zero", it will mean that at least one independent variable has a coefficient

that is significantly different from zero. Then, in order to see which coefficients are significantly different from zero, t-test for each model coefficient is carried out; which tests the null hypothesis of "Coefficient of the variable is equal to zero". This null hypothesis can be expressed as the following, with i being the coefficient index (Walpole *et al.*, 2012):

$$H_0 : \beta_i = 0 \tag{3.22}$$

The t-test, which has a t-distribution with *n-k-1* degrees of freedom, is as follows mathematically (Walpole *et al.*, 2012):

$$t = \frac{\beta_i}{st.error\,(\beta_i)} \tag{3.23}$$

3.6.1. Multiple Regression

This is an extension of the above for the case of more explanatory variables and, obviously, more regressors (β parameters). The solution equations are similar to linear regression, although more complex.

In this model, independent and dependent variables contain both scale and categoric data. Multiple regression help modelling regression analysis with categorical ones. Assuming that there are two explanatory variables x_1 and x_2, and that x_2 is categorical, and that we have a regression equation (Oxford journal)

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 \tag{3.24}$$

The problem of categorical variables is solved by having two values for the category and assigning value *1* to one group and *0* to the other. So for the category where x_2= 1, we have variable.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 \tag{3.25}$$

and for the category where $x_2 = 0$ we have

$$Y = \beta_0 + \beta_1 X_1 \tag{3.26}$$

In the case of several categories, most computer software allow the creation of 'dummy' indicator variables. In this paper, dummy was created for each categorical data, detailed explanation will be presented in following section.

3.6.1.1. The Wrong Signs in the Linear Regression Model. In a multiple linear regression model coefficients often have signs that are contrary to expectations. There is a variety of reasons that multiple linear regression produces the "wrong sign" for some coefficients (Mullet, 1976):

- Computational error. Some computational procedures for computing least squares have problems with precision when the magnitudes of variables differ drastically. To avoid this problem, it is recommended to convert variables to standard form (e.g. 0 mean and unit variance) for calculations and convert back to the original form for displaying the coefficients (Pazzani and Bay, 1999).
- Coefficients that do not significantly differ from zero. In this case, the sign of the coefficient does not matter because it is too small to significantly affect the equation. One recommended way to avoid this problem is to eliminate the irrelevant variables from forward stepwise regression methods where a variable is included in the model only if it significantly improves the fit of the model of the data (Draper and Smith, 1981).
- Multicollinearity. Multicollinarity causes inflated standard errors, which in turn make it more likely an "incorrect sign". When two or more explanatory variables are not independent, the sign of the coefficients of one of the variables may differ from the sign of that coefficient if the variable were the only explanatory variable. One approach to deal with this problem is to manually eliminate some of the variables from the analysis (Pazzani and Bay, 1999).

- Nonlinearity. If the true relationship between the dependent variable and the explanatory is nonlinear, the coefficients can be biased with changing (different or wrong) signs.
- The variable in question is a proxy for another variable. In some cases the variable in question may be highly correlated with other variables which have been excluded from the analysis. Such variables are also known as "confounding variables". The wrong sign might be attributable to an excluded confounding variable (Rinott and Tam, 2003).
- Improper interpretation of parameters. The interpretation of a parameter is entirely dependent upon the model in which the parameter appears. Even with "incorrect signs", the model still may be useful for prediction in the region of X-values from which the model was built, e.g. the model is still useful as a predictive model, as long as the extrapolation does not go beyond the region of the data

4. DATA COLLECTION AND PRELIMINARY ANALYSIS

4.1. Information about Istanbul Technical University, Turkey

The data for this study was obtained from civil engineering faculty of Istanbul Technical University (ITU) which is the world's third oldest technical university dedicated to engineering sciences as well as social sciences recently, and is one of the most prominent educational institutions in Turkey.

The study area is settled in Ayazaga campus of ITU, being the main campus, is located in the Maslak region which is the new business and trade center. Stretching over a 247-hectare area, Ayazaga campus hosts Rectorate and Administrative units along with 8 of the 13 faculties and 5 of the 6 institutes. The data of this study was obtained from civil engineering faculty which is one of those of faculty at Ayazaga Campus of ITU (Figure 4.1).



Figure 4.1. Location of the Civil Engineering Faculty at Ayazaga Campus of ITU.

4.2. Data Collection

In order to different analyses, including regression analysis and binary logit model were conducted in this research, data were collected in two different way.

4.2.1. Collection of Data for All Traffic Applications

The data for lineer regression analysis was obtained from some related websites which include all traffic application people downloaded such as “Google Play Store” and “Similar Play”. Ranging from the most preffered traffic applications to the least one are obtained from these websites and their features for the travel modes, including both public transport and private car modes are received by means of these. Download counts of traffic applications which are determined as count range, namely, data type is categorical variables and given five-star rating scale are also obtained. In addition to these, gender of traveler who use the traffic applciations and their interpretation concerning positive and negative comments are taken from web sites.

4.2.2. Collection of Data for Survey

The objective of the survey was to investigate the level of consciousness, usage, and the impact of real-time traffic information acquisition from some traffic applications, as well as to test the understanding of relationship between some different characteristics which are socioeconomics, travel and technological ones and the travel behavior on freeways. The survey was conducted in the Istanbul Technical University and marked questionnaire was collected from undergraduate-graduate students, academicians and supporting staff stayed at civil engineering faculty.

The survey included both revealed and stated preference data, as well as frequency of using traffic applications, variety and content of these apps and intentions of individual decision makers as a result of real-time information. Individuals were asked about the traffic information acquired in their daily trip, moreover, regarding their tendency toward real-time traffic information acquired through some applications. This

study focuses on the modeling and analysis of stated preferences experiment conducted.

The questionnaire used in this study targets the students, academicians and staff stayed at civil engineering faculty building around the Ayazaga campus. Questionnaire were distributed randomly selected individuals from civil engineering faculty. In total, individuals participated in the survey which the data consists of the answers of 360 individuals from different ranks. The data set comprise of the some characteristics that categorized into some different characteristics which were socioeconomics, travel and technological characteristics. Detailed explanation will be given in the descriptive features section.

4.3. Data Analysis

In this section, traffic applications used in Turkey and traffic applications used in the world which consist of two parts with respect to their usage area, including features of traffic apps for public transport modes and features of traffic apps for private car modes as well as survey results were analysed with their frequencies.

4.3.1. Traffic Applications for Public Transport Modes Used in Turkey

One of the features having traffic applications is the features of public transport. Public Transit Applications have some common features including getting information about bus route, time to arrive the bus station and traffic condition and so on. Table 4.1. shows those of common features that traffic applications for public transports have.

Table 4.1. Common Features for Public Transit Applications.

APP Name	Types of Apps	Common Features
Mobiett	Public Transit Apps	These type of traffic application that work with Istanbul Metropolitan Municipality Istanbul Electric Tramway and Tunnel Establishments (IETT) data. With the most robust and precise information of public transit app, travelers can get the information about bus route and time to arrive the bus station. The apps show and up to date bus, metro, ferry, minibus and other schedules which allows us to detect traffic jams and offer the most optimal route to traveler's destination. It reports traffic jams, accidents, closures and all other stuff that happens in public transport. Combining all transit options together in a single app, public transport apps give total control over travelers' travels so travelers can finally enjoy peace of mind when riding public transportation. Because public transportation is always unpredictable, the public transit apps constantly update as transit operators change schedules or alter service, so traveler don't end up at a station that is closed, or waiting for a bus that isn't coming. Real Time Arrival information (where available) lets travelers know when to be at the stop so travelers can spend their time doing something more valuable than sitting around and waiting.
Istanbul Ulasim		
Moovit: Otobüs Metrobüs & Tren		
TRAFI		
Otobüsüm Nerede?		
Buradan Oraya Yolculuk Planlama		
Nasil Giderim ?		

4.3.2. Traffic Applications for Private Car Modes Used in Turkey

One of the features having traffic applications is the features of private car. Private car Applications have some common features including giving real-time traffic information and road hazards or traffic jams and also to present shortest and cheapest way for the travelers' choice and so on. Table 4.2 shows those of common features that traffic applications for private cars have.

Table 4.2. Common Features for Private Car Applications.

APP Name	Types of Apps	Common Features
KGM Türkiye Trafik	Private Car Apps	Private car types of traffic applications offer street maps, a route planner for traveling by foot, car, or bike and an urban business for numerous countries around the country. locator. It is a community-based traffic and navigation app that lets travelers share real-time traffic and road information. It will alert travelers before approaching police, accidents, road hazards or traffic jams and let's travelers sync with friends to coordinate meetups. With new additional features, travelers can also search to find the cheapest gas station along their route to save a little bit of dough and top-rated restaurants or local businesses, wherever you are. They can mark a location as a "favorite" if they have rhe exact address. Some applications use an Internet connection to a GPS navigation system to provide turn-by-turn voice-guided instructions on how to arrive at a given destination. The application's traffic congestion map shows the route marks with different colours based on the current traffic along the route. The traffic is measured by data from local road services such as highway cameras, as well as speed and location information from other devices that are accessing Maps for Mobile. By means of the private car traffic application, travelers choose several journey options that consider traffic jams and public transport connections and it keep updated with real-time information on heavy traffic, accidents, speed cameras, road blocks, etc.
IBB Cep Trafik		
Trafik Rehberi		
Hiz Kamerasi Türkiye		
ABB Türkiye		
BITAKSI		
GOOGLE MAPS		
YANDEX MAPS		
GOOGLE MAPS NAVIGATION		
YANDEX NAVIGATOR		

4.3.3. Traffic Applications for Public Transport Modes Used in the World

Public Transit Applications that in this research just Yahoo Maps are used for the purpose of public transit have some common features that are shown in Table 4.3.

Table 4.3. Common Features for Public Transit Applications.

APP Name	Types of Apps	Common Features
Yahoo Maps	Public Transit Apps	The apps show and up to date bus, metro, ferry, minibus and other schedules which allows us to detect traffic jams and offer the most optimal route to traveler's destination. It reports traffic jams, accidents, closures and all other stuff that happens in public transport. Combining all transit options together in a single app, public transport apps give total control over travelers' travels so travelers can finally enjoy peace of mind when riding public transportation.

4.3.4. Traffic Applications for Private Car Used in the World

Public Car Applications have some common features that are shown in Table 4.4.

Table 4.4. Common features for Private Car Applications.

APP Name	Types of Apps	Common Features
Google Maps	Private Car	Private car types of traffic applications
Waze		offer street maps, a route planner for
Sygic GPS Navigation	Apps	traveling by foot, car, or bike
Yandex Maps		and an urban business locator for
Google Maps Navigation		numerous countries around the country.
Yandex Navigator		It is a community-based traffic
Google Earth		and navigation app that lets travelers
Here Maps		share real-time traffic and road
2GIS		information. It will alert travelers
Map Factor GPS Navigation		before approaching police, accidents,
MapQuest GPS		road hazards or traffic jams and let's
Navigation & Maps		travelers sync with friends to coordinate
AT&T Navigator:		meetups. With new additional features,
Maps, Traffic		travelers can also search to find the
Maps Me		cheapest gas station along their route
GPS Route Finder		to save a little bit of dough and top-
Route 66		rated restaurants or local businesses,
OruxMaps		wherever you are. They can mark a
OsmAnd		location as a "favorite" if they have rhe
Google Streetview		exact address. Some applications use
GPS Navigation &		an Internet connection to a GPS
Maps-Scout by Telenav		navigation system to provide turn-by-
NAVIGON MobileNavigator		turn voice-guided instructions
CoPilot Live		on how to arrive at a given destination.
TomTom		The application's traffic congestion map
Locus Map		shows the route marks with different
ViaMichelin: Route		colours based on the current traffic
GPS Traffic		along the route. The traffic is measured
Beat the Traffic		by data from local road services such
Traffline: Traffic & Parking		as highway cameras, as well as speed
INRIX Traffic Maps & GPS		and location information from other
7 Ways Navigator		devices that are accessing Maps for
Maps 3D and Navigation		Mobile. By means of the private car
		traffic application, travelers choose
		several journey options that consider
		traffic jams and public transport
		connections and it keep updated
		with real-time information on heavy
		traffic, accidents, speed cameras, road
		blocks, etc.

4.3.5. Interpretation for Traffic Applications

Interpretation concerning positive and negative comments are obtained from web sites that negative interpretations are taken as being opposite of positive interpretation and these are presented in Table 4.5.

Table 4.5. Interpretation for Traffic Applications.

Positive Interpretation	
Accuracy/Reliability	Giving all the outcomes that it enables travelers to get the information about bus route, time to arrive the bus station or giving real-time traffic information, including traffic jams, accidents, closures as being accurate and reliable.
User Friendly	The app usage and its interface are quite understandable and simple to use it
Detailed	All details, including street maps, density maps and all other detailed has been existed in the apps
Negative Interpretation	
Unreliable/In accurate	Giving all the outcomes are given as inaccurate and unreliable.
Not User Friendly	The app usage and its interface are quite deficient and inadequate
Not Detailed	The apps do not include any detail in its interface

4.4. Descriptive Features of All Data

In this section, Traffic applications used in Turkey and in the World and survey data features are explained statistically.

4.4.1. Descriptive Features of Traffic Applications Used in Turkey

The data set comprise of the traffic applications based on their features, download counts, gender, given stars for each apps and interpretation, including both positive and negative ones. 510 responses were given for each variables. In this section, frequency distribution of these data set and relationship between variables are presented by using cross tabulation.

Most of the respondents who interpret the applications and give them star for evaluating their feasibility of this research (81%) were male shown in Figure 4.2.

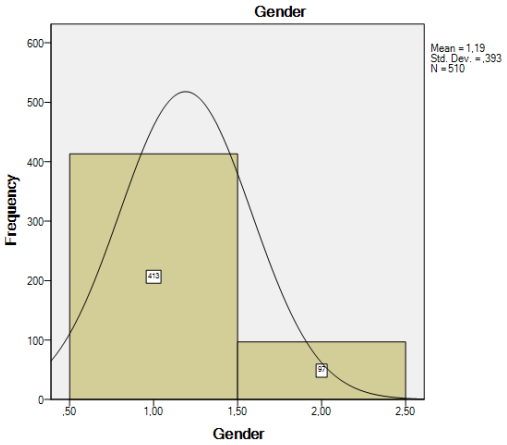


Figure 4.2. Frequency of Gender for the study of Turkish App.

There are 17 traffic applications that people generally use in Turkey. Figure 4.3 shows the frequency of traffic app based on their intended purpose. 41.2% of traffic app for the features of public transport modes and 58.8% of apps use for private car.

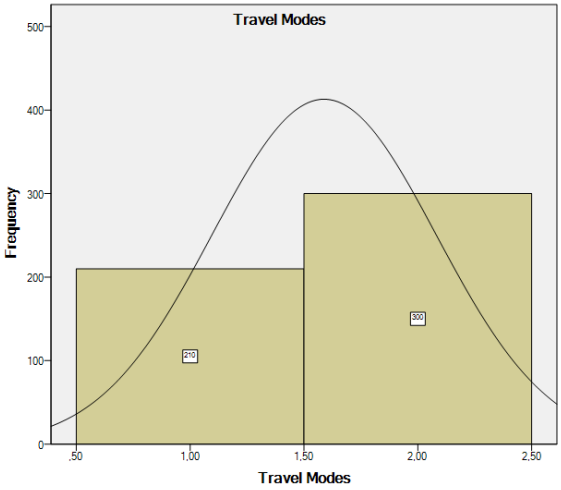


Figure 4.3. Frequency of Traffic App Based on their Intended Purpose.

Respondents evaluate the traffic applications with giving the star ranging from 1 to 5. Most positive experiences are given five stars, while one star is given if any problems are encountered. People associate a five-star with “strongly good” and a one-star with “too poor”. As shown in Figure 4.4, Almost 45% of people gave the five star for the apps and the frequency of given star percentage decrease with the star rating scale. 5.7% of people gave the one-star for traffic applications.

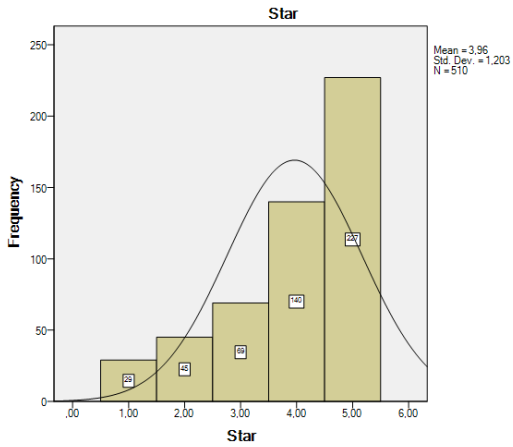


Figure 4.4. Frequency of Given Five Stars for Traffic Apps Used in Turkey.

Interpretation for the apps also gives an idea about feasibility of applications. In this research positive interpretation contains being Accuracy/Reliability, being user friendly and being detailed. On the other hand, negative interpretation includes the oppsite of the positive ones such as being unreliable/inaccurate, not user friendly and not being detailed. People interpret the apps both as user friendly and accurate and reliable with almost an equal percentage (28%). In compare with this, approximately one fifth of respondents (17%) interpret the apps as being not user friendly. The frequency of interpretation for traffic app are presented in Table 4.5.

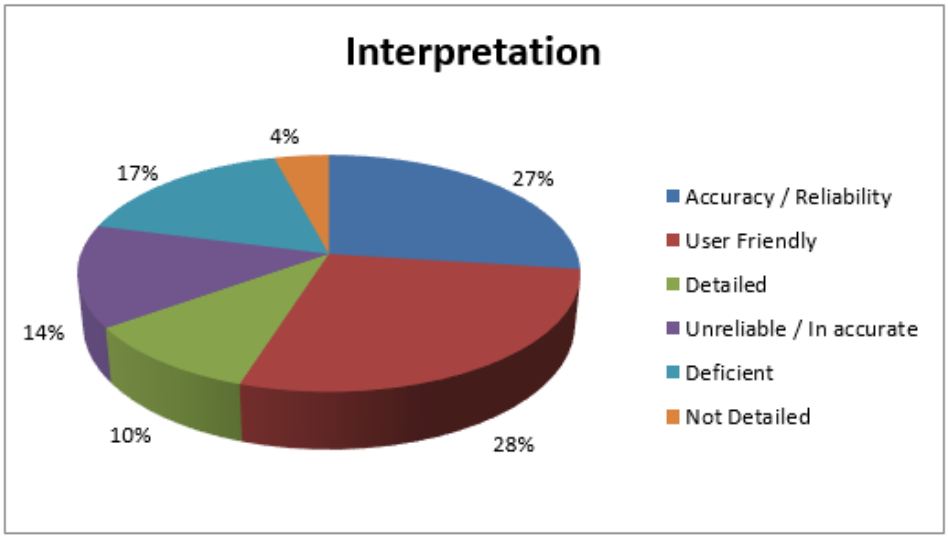


Figure 4.5. Frequency of Interpretation for Traffic Apps Used in Turkey.

Interpretation of each traffic application gives information about its feasibility and area of usage. The applications in this study have both positive and negative interpretation. Negative comments on the app makes people consider inadequate attributes it has. Most of the people generally control the comments on application in their mobile device before downloading the apps. With the help of the cross tabulation, positive and negative comments for each traffic applications can be made. The people interpret the apps within the framework of their own ideas and commented on them based on the comments which correlate independent variables. Outstanding interpretation for specific traffic applications are shown in Table 4.6.

In this regard, "Google Maps", "Moovit" and "Yandex Navigator" are mostly commented as accurate and reliable, as well as, "Buradan oraya yolculuk planlama", "Bitaksi" and "Hiz kamerasi Türkiye" are thought to be more user friendly. Moreover, in the light of the interpretation, the most detailed traffic application is found as "Trafik Rehberi". However, in the negative interpretation perspective, "Otobüsüm nerede?" has the most negative interpretation in terms of being unreliable/in accurate. Yet, "KGM Turkiye" is also found as more not user friendly than others.

Table 4.6. Interpretation for Each Traffic Applications Used in Turkey.

	Interpretation						Total
APP Name	Accuracy/ Reliability	User Friendly	Detailed	Unreliable/ in accurate	Not User Friendly	Not Detailed	
Mobiett	7	7	2	7	4	3	30
KGM Türkiye Trafik	10	6	1	3	7	3	30
IMM Mobile Traffic	7	8	5	4	6	0	30
Istanbul Ulasim	9	7	4	4	4	2	30
Moovit	12	11	2	3	1	1	30
TRAFI	10	10	2	2	5	1	30
Trafik Rehberi	4	7	12	4	3	0	30
Otobüs nerede	3	3	0	13	8	3	30
Buradan Oraya Yolculuk Planlama	7	13	4	1	4	1	30
Hiz Kamerasi Türkiye	6	13	3	2	6	0	30
Nasil Giderim?	3	7	2	9	5	4	30
ABB Trafik	5	7	3	7	7	1	30
Bitaksi	10	13	0	1	6	0	30
Google Maps	13	7	2	3	4	1	30
Yandex Maps	11	8	3	2	6	0	30
Google Maps Navigation	9	7	6	3	5	0	30
Yandex Navigator	12	8	1	3	5	1	30
Total	138	142	52	71	86	21	510

Gender difference can influence interpretation for traffic applications in a different way. In this study, it is found out that males mostly comment on traffic applications as “user friendly”. Moreover, females mostly find the traffic applications as “accurate and reliable”. In this regard, female can more attach importance to its accuracy and giving reliable information than male. In addition, at the negative interpretation perspective, both female and male find the applications as not user friendly more than other attributes. They generally comment download websites regarding adding new and requested attributes of apps due to its deficiency features. Gender based interpretation for traffic applications both as positive and negative are presented as Table 4.7.

Table 4.7. Gender Based Interpretation Table for Traffic App Used in Turkey.

	Interpretation						
Gender	Accuracy/ Reliability	User Friendly	Detailed	Unreliable/ in accurate	Not User Friendly	Not Detailed	Total
Male	112	122	33	58	68	20	413
Female	26	20	19	13	18	1	97
Total	138	142	52	71	86	21	510

Rating or grading schemes are mostly made up of compulsory and voluntary requirements (Ingram 1996) However, people generally express their appreciation or dissatisfaction about their experience of the traffic applications through giving a five star rating or criticizing its features voluntarily. The star rating system should provide an accurate appraisal of the property that is consistent with the expectations of the user and, thus, they need to be monitored regularly in order to check that standards are being maintained or improved over time and have not deteriorated (Kozak and Rimmington 1998). In a similar way, interpretation for the traffic apps almost gives same results about apps. Positive recommentation and given high star rates always make a good impression. The relationship between star rates and positive/negative interpretation are shown in Table 4.8.

Table 4.8. Relationship between Five-Star Rating Scale and Interpretation for Traffic App Used in Turkey.

	Interpretation						
Star	Accuracy / Reliability	User Friendly	Detailed	Unreliable / in accurate	Not user friendly	Not Detailed	Total
too poor	0	0	0	20	6	3	29
poor	0	0	0	25	13	7	45
medium	2	2	0	22	33	10	69
good	36	51	22	4	26	1	140
strongly good	100	89	30	0	8	0	227
Total	138	142	52	71	86	21	510

4.4.2. Descriptive Features of Traffic Applications Used in World

The data set comprises of the traffic applications based on their features, download counts, gender, given stars for each apps and interpretation, including both positive and negative ones. 900 responses were given for each variables. In this section, frequency distribution of these data set and relationship between variables are presented by using cross tabulation.

There are 102 traffic applications that people generally use in world. These data were collected from some related websites in which people interpret and evaluate the traffic apps. The last 24 category of traffic apps were excluded because of the fact that there weren't any comment on those. In this research, first 30 traffic applications were selected with respect their download counts. The cut off was determined through the maximum difference between download counts. Traffic applications were chosen up to 1M-5M download count interval. The cut off can be clearly shown in Figure 4.6.

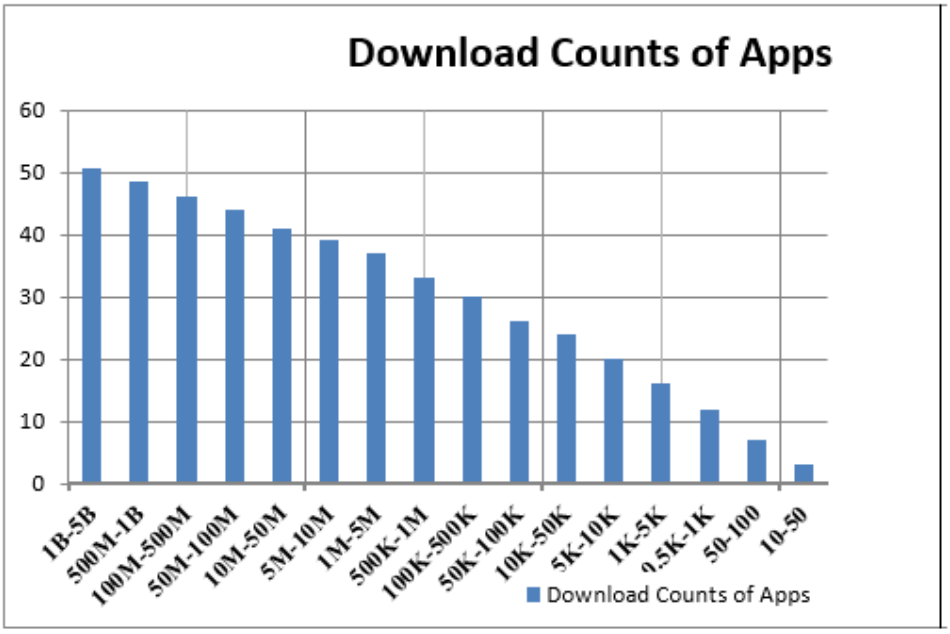


Figure 4.6. The Selected Cut off for the Download Counts of Apps.

As shown in Figure 4.7, most of the respondents who interpret the applications and give them star for evaluating their feasibility of this research (84%) is male.

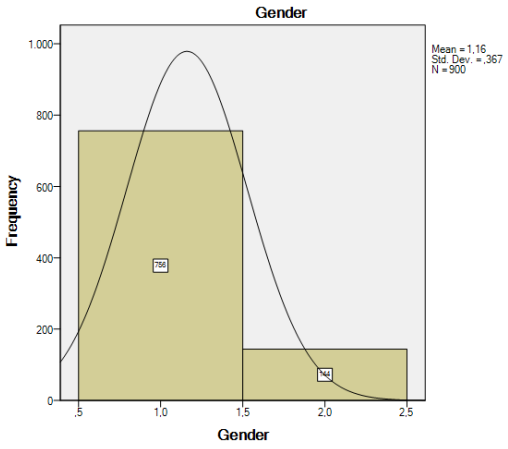


Figure 4.7. Frequency of Gender for the Study of All App.

Figure 4.8 shows the frequency of traffic applications based on their intended purpose. 3.3% of the traffic applications were used for public transport modes and 96.7% of apps were used for private cars. It can be understood that the most downloaded traffic applications have the purpose of private car usage.

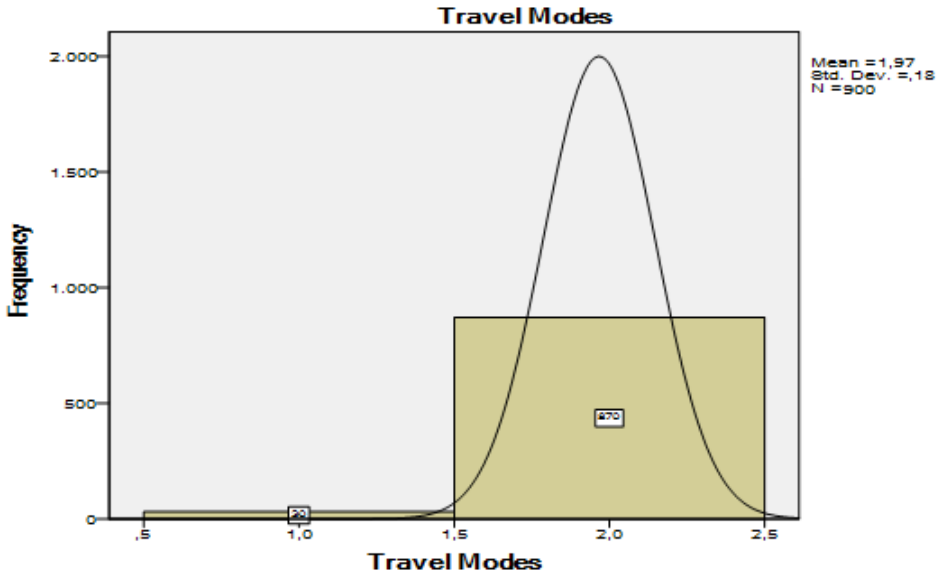


Figure 4.8. Frequency of Traffic App Based on their Intended Purpose for all Apps.

Respondents evaluate the traffic applications with giving the star ranging from 1 to 5. Most positive experiences are given five stars, while one star is given if any problems are encountered. People associate a five-star with "strongly good" and a one-star with "too poor". As shown in Figure 4.9, Almost 56.1% of people gave the five star for the apps and the frequency of given star percentage decrease with the star rating scale. 5.9% of people gave the one-star for traffic applications.

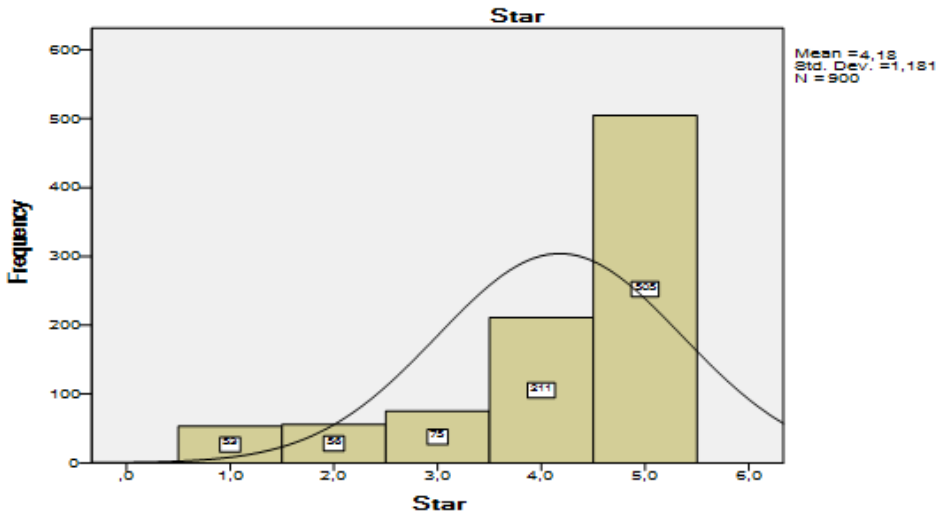


Figure 4.9. Frequency of Given Five Stars for all Apps.

Interpretation for the apps also gives an idea about feasibility of applications. In this research positive interpretation contains being Accuracy/Reliability, being user friendly and being detailed. On the other hand, negative interpretation includes the oppsite of the positive ones such as unreliable/inaccurate, not user friendly and not being detailed. People interpret the apps both as user friendly and accurate and reliable with almost an equal percentage (33%). The frequency of interpretation for traffic app are presented in Figure 4.10.

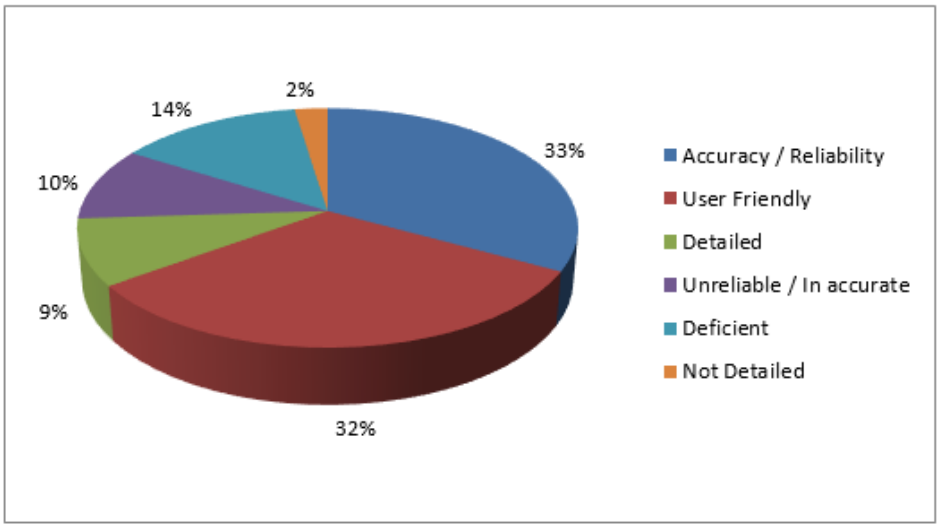


Figure 4.10. Frequency of Interpretation for All Traffic Apps.

Interpretation of each traffic application gives information about its feasibility and usage area. The applications in this study have both positive and negative interpretation. Negative comments on the app makes people consider inadequate attributes it has. Most of the people generally control the comments on application in mobile device before download the apps. With the help of the cross tabulation, positive and negative comments for each traffic applications can be shown in Table 4.9. In this context, "INRIX Traffic Maps and GPS", "Waze", "Google Maps Navigation","Yandex Navigator", "ViaMichelin: Route GPS Traffic" and "GPS Navigation and Maps-Scout by Telenav" are thought to be more accurate/reliable. In addition, "Google maps", "Maps me", "Tom Tom", "2GIS" and "Map Factor GPS Navigation" are mostly commented as user friendly. In the light of the interpretation, the most detailed traffic application is found as "OsmAnd". In the negative interpretation perspective, "AT and T Navigator: Maps,

Traffic" and "Beat the Traffic" has the most unreliable/inaccurate interpretation, as well as, "NAVIGON MobileNavigator" are found to be not user friendly.

Table 4.9. Interpretation for Each Traffic Applications for All Traffic Apps.

APP Name	Interpratation						Total
	Accuracy / Reliability	User Friendly	Detailed	Unreliable / In accurate	Not user friendly	Not Detailed	
Google Maps	7	16	0	2	5	0	30
Waze	14	10	0	2	3	1	30
Sygic GPS Navigation	9	12	2	4	2	1	30
Yandex Maps	10	11	2	1	6	0	30
Google Maps Navigation	13	9	1	2	5	0	30
Yandex Navigator	13	9	1	1	5	1	30
Google Earth	11	11	2	2	4	0	30
Here Maps	9	11	3	3	3	1	30
2GIS	7	13	5	0	3	2	30
Map Factor GPS Navigation	8	13	3	2	4	0	30
MapQuest GPS Navigation & Maps	10	11	1	4	3	1	30
AT & T Navigator: Maps, Traffic	5	8	2	7	5	3	30
Maps Me	6	16	2	1	4	1	30
GPS Route Finder	9	10	2	5	3	1	30
Yahoo Maps	8	8	8	2	2	2	30
Route 66	12	6	3	6	2	1	30
OruxMaps	11	6	9	1	3	0	30
OsmAnd	8	2	11	3	6	0	30
Google Streetview	13	9	0	2	6	0	30
GPS Navigation & Maps-Scout by Telenav	14	5	4	5	2	0	30
NAVIGON MobileNavigator	11	7	1	2	7	2	30
CoPilot Live	7	13	2	4	3	1	30
TomTom	4	15	2	3	4	2	30
Locus Map	13	9	3	0	5	0	30
ViaMichelin: Route GPS Traffic	14	6	2	5	3	0	30
Beat the Traffic	8	8	3	7	4	0	30
Traffline: Traffic & Parking	12	10	0	5	3	0	30
INRIX Traffic Maps & GPS	16	4	3	0	7	0	30
7 Ways Navigator	9	10	2	4	5	0	30
Maps 3D and Navigation	6	10	2	4	6	2	30
Total	297	288	81	89	123	22	900

Gender difference can influence interpretation for traffic applications in a different way. In this study, male mostly comment on traffic applications as "accurate and reliable". Moreover, female equally find the traffic applications both as "accurate and reliable" and "user friendly" Gender based interpretation of both positive and negative for traffic applications table are presented as Table 4.10.

Table 4.10. Gender Based Interpretation Table for All Traffic Apps.

Gender	Interpratation						Total
	Accuracy / Reliability	User Friendly	Detailed	Unreliable / In accurate	Not user friendly	Not Detailed	
Male	256	247	69	73	96	15	756
Female	41	41	12	16	27	7	144
Total	297	288	81	89	123	22	900

People generally express their appreciation or dissatisfaction about traffic application usage through giving five star rating scale or criticise about its features as voluntarily. In a similar way, interpretation for the traffic apps almost gives same results about apps. Positive recommentation and given high star rates enable people to pick those of traffic applications. The relationship between star rates and positive/negative interpretation are shown in Table 4.11.

Table 4.11. Relationship Between Five-Star Rating Scale and Interpretation for All Traffic Apps.

Star	Interpratation						Total
	Accuracy / Reliability	User Friendly	Detailed	Unreliable / In accurate	Not user friendly	Not Detailed	
too poor	0	0	0	46	6	1	53
poor	0	0	0	28	23	5	56
medium	0	5	0	15	42	13	75
good	70	78	13	0	47	3	211
strongly good	227	205	68	0	5	0	505
Total	297	288	81	89	123	22	900

4.4.3. Descriptive Features of Survey Data

The questionnaire used in this study targets the students, academicians and staff stayed at civil engineering faculty building around the Ayazaga campus. Questionnaire were distributed randomly selected individuals from civil engineering faculty. In total, individuals participated in the survey which the data consists of the answers of 360 individuals from different ranks. The questionnaire contains questions about a variety of socioeconomic characteristics such as gender, age, occupation, education and household income level. Moreover, travel characteristics such as frequency of using private car and public transportation, total trip time and trip cost, most preferred public transport mode, trip purpose, trip mode alternative for commuting and origin

of trip. The questionnaire also enquires about technological characteristics, including most preffered traffic app, frequency, objective and content of using traffic applications, obtaining traffic information sources. Therefore, each respondent is asked to decision making for travel under real-time information which are taken from some traffic app about all trip alternatives. The questions presented in the questionnaire contain most preferred public transport mode in Turkey such as bus, metrobus, taxi, metro, ferry boat, private minibus etc. and traffic app that such as IMM mobile traffic, Yandex.maps, mobiett, car GPS navigation, TRAFI, waze etc. These characteristics were used as explanatory variables in BL model. Travel behavior on freeways including whether changing travelers' route or not as a result of the provision of various types of real-time traffic information acquired by some traffic applications were taken as a response variable.

Binary Logit Models were developed with using those of survey data for two different modes including using private car and public transit. 138 (38.3%) respondents of the survey use their private car as of commuting trip alternative and 222 (61.7%) respondents, use the public transit for their daily commute. Therefore, descriptive features of survey data were analysed under the two different title.

The answers of respondents in survey show that average age of the sample is approximately 27. As indicated in Table 4.11, most of the individuals who respond to questionnaire 72% are male.

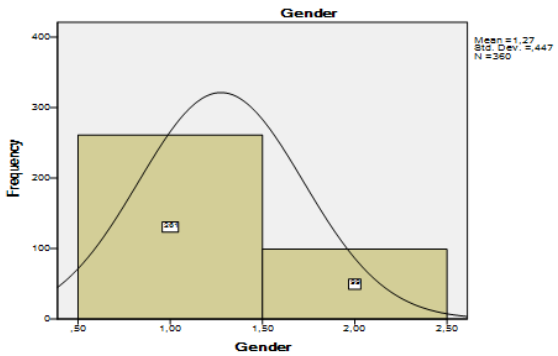


Figure 4.11. Frequency of Gender of Survey Data.

Two-third of respondents (66.3%) acquire the real- time traffic information from mobile phone applications, 62 respondents (17.7%) obtain information through Internet and the both 28 respondents (8%) access the traffic information by means of radio. All top sources for obtaining traffic information are indicated in Table 4.12. Similar finding are consistent with statistics in the other literature. Peirce *et al.* (1997) report that on the recorded trips using some form of traveler information, the most common sources of information were broadcast traffic reports. En-route radio was the top source listed, having been consulted on the trips where information was consulted. Pierce and Lappin (2004) found that 22% of drivers actually use the information obtained from website.

Table 4.12. Frequency of Obtaining Traffic Information Sources.

		Frequency	%	Valid	Cumulative %
Valid	Mobile Device Traffic Applications	242	67.2	66.3	66.3
	Radio	28	7.8	8	74.3
	Internet	62	17.2	17.7	92
	Vehicle GPS Navigation	28	7.8	8	100
	Total	350	97.2	100	
Total	360	100			

Each travel mode has different average duration, trip cost and trip distance are shown in Table below;

Table 4.13. Average Trip Times for Each Modes.

Average Trip Time For Private Car	Average Trip Time For Public Transit	Total
23	51.7	74.7

Table 4.14. Average Trip Costs for Each Modes.

Average Trip Cost For Private Car	Average Trip Cost For Public Transit	Total
9	5.2	14.2

Table 4.15. Average Trip distance for Each Modes.

Average Trip Distance For Private Car	Average Trip Distance For Public Transit	Total
20	18.6	38.6

4.4.3.1. Descriptive Features for Private Car Users. The answers of respondents in survey show that average age of the sample is approximately 30. As indicated in Table 4.11, most of the individuals who use the private car 66.7% are male.

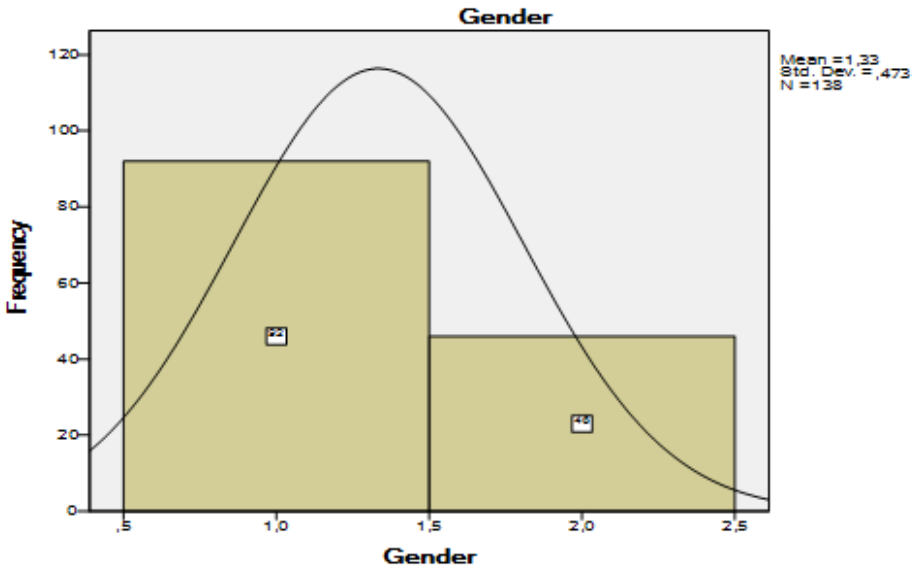


Figure 4.12. Frequency of Gender of Survey Data for Private Car Users.

The majority of sample members are making trip several times per day through using their private car (47.8%) and the rest of the distribution of frequency of using private car are shown in Table 4.16.

Table 4.16. Frequency of Using Private Car.

Frequency of using private car					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Several times a day	66	47.8	47.8	47.8
	Every second days	42	30,4	30,4	78,3
	Once a month	30	21.7	21.7	100.0
	Total	138	100.0	100.0	

The following chart shows the distribution of most common traffic application frequencies that respondents use for private car modes. In this respect, respondents' top three usage traffic app for getting real-time information about traffic condition were: Yandex.Maps (27.5%), IBB Cep Trafik (26.8%), Araç GPS navigasyonu (13.4%) and the rest of those are presented in the Figure 4.13.

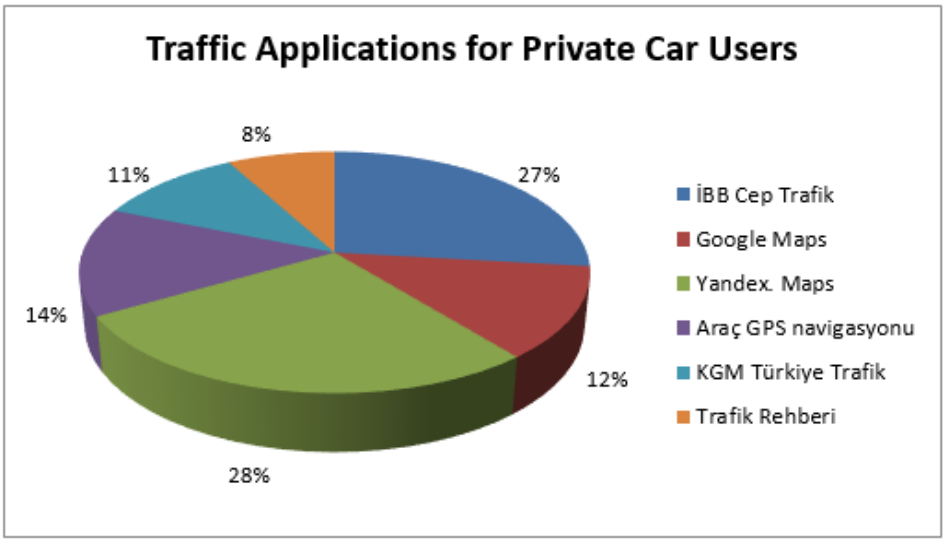


Figure 4.13. Types of Traffic App for Private Car Users.

As shown in Table 4.17, most of the travelers in the survey, 54 respondents (39.1%), use those applications due to planning their route with respect to traffic conditions. Second top reasons (34.1%) for the traffic app usage is to reduce their trip time with the help of using traffic app. Members of the survey also acquire the

real-time information through the traffic applications because of determining route directions (26.8%). Similar findings have also been existed in the literature. According to Peirce *et al.* (1996) respondents' top three motivations for seeking information were: that they anticipated traffic congestion (52 percent), that they wanted to be sure of arriving on time (47 percent), and that they wanted to get to their destination as fast as possible (34 percent). These value of these statistics is somewhat limited by the possibilities for different semantic interpretations.

Table 4.17. Purpose of Using Traffic Applications for Private Car Users.

Objective of using traffic app					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Reducing Travel Time	47	34.1	34.1	34.1
	Planning direction with respect to traffic condition	54	39.1	39.1	73.2
	Determining road direction	37	26.8	26.8	100.0
	Total	138	100.0	100.0	

Private car users use the traffic applications with a different frequency. As shown in Table 4.18, 57 respondents (41.3%) prefer the traffic app usage everday, in compare with this, 58 respondents (42%) use it every second days.

Table 4.18. Frequency of Traffic Applications Usage for Private Car Users.

Frequency of using traffic app					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Several times a day	57	41.3	41.3	41.3
	Every second days	58	42	42	83.3
	Once a month	23	16.7	16.7	100
	Total	138	100.0	100.0	

The choice distribution of two travel behavior for private car users under the real-time traffic information acquired through mobile devices during drivers' daily trip included in the questionnaire is given in Table 4.19. This variable serves as the dependent variable of the choice model mentioned before. As shown, changing route by means of using traffic apps is the most frequent encountered behavior under the real-time traffic information obtained by some traffic applications. In this research, 83 respondents (60.1%) change their route with respect to acquisition of real-time traffic information. The rest of the members of the survey prefer not to change their route

in spite of using traffic apps. One stated-preference survey in the literature found that found that about 35 percent of respondents sometimes change their travel plans as a result of an information report (Khattak *et al.*, 1999), while a study of SmarTraveler users in the Boston area (Lappin *et al.*, 1994) found that about 30 percent changed their travel behavior "frequently" in response to information. However, this latter study also found that 96 percent changed their trips "occasionally", and research in Chicago found that 85 percent of motorists said that they alter their behavior after hearing a traffic report (Lappin *et al.*, 1994).

Table 4.19. Frequency of Private Car Users' Behavior Under the Real-Time Information.

Travel Behavior					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Changing route by means of using traffic apps	83	60.1	60.1	60.1
	Does not change route in spite of using traffic app	55	39.9	39.9	100
	Total	138	100.0	100.0	

With the help of cross tabulation some important findings were also obtained. Travelers display different travel behavior with regard to using various traffic applications. According to Table 4.20, travelers who use Yandex.Maps and IMM Mobile Traffic are more likely to change their route when obtaining information from those of traffic apps.

Table 4.20. Travel Behavior Relative to Traffic Applications for Private Car Users.

		Travel Behavior		Total
		Changing route by means of using traffic apps	Does not change route in spite of using traffic app	
Traffic Applications	IBB Cep Trafik	25	13	38
	Google Maps	5	8	13
	Yandex. Maps	30	14	44
	Araç GPS navigasyonu	11	6	17
	KGM Türkiye Trafik	7	8	15
	Trafik Rehberi	5	6	11
Total		83	55	138

Car usage frequency gives another finding. Drivers who use their private car several times a day mostly obey the traffic applications direction and changing their route with respect to its provided information. Travelers who haven't got private car, as expected, mostly use a variety of public transportation for the shortest path that apps suggested. Relationship between traveler decision and frequency of using private car are indicated Table 4.21.

Table 4.21. Travel Behavior Relative to Car Usage Frequency.

		Travel Behavior		Total
		Changing route by means of using traffic apps	Does not change route in spite of using traffic app	
Frequency of using private car	Several times a day	48	18	66
	Every second days	23	19	42
	Once a month	12	18	30
Total		83	55	138

4.4.3.2. Descriptive Features for Public Transit Users. The answers of respondents in survey show that average age of the sample is approximately 24.10. As indicated in Figure 4.14, most of the individuals who use the private car 76.1% are male.

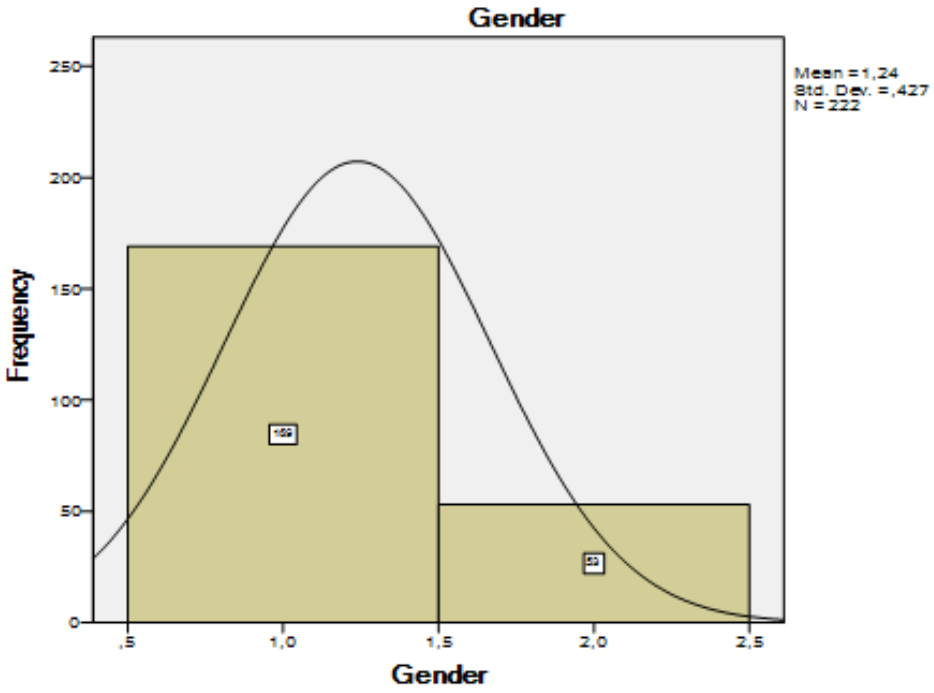


Figure 4.14. Frequency of Gender of Survey Data For Public Transit Users.

The majority of sample members are making trip several times per day through using public transit (85.6%) and the rest of the distribution of frequency of using public transit are shown in Table 4.22.

Table 4.22. Frequency of Using Public Transit.

Frequency of using public transit					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Several times a day	190	85.6	85.6	85.6
	Every second days	26	11.7	11.7	97.3
	Once a month	6	2.7	2.7	100
	Total	222	100.0	100.0	

The following chart shows the distribution of most common traffic application frequencies that respondents use for public transit modes. In this respect, respondents' top three usage traffic app for getting real-time information about riding suitable public transit: Mobiett (26.1%), Istanbul Ulasim (20.7%), Otobüsüm nerede (13.4%) and the rest of those are presented in the Figure 4.15.

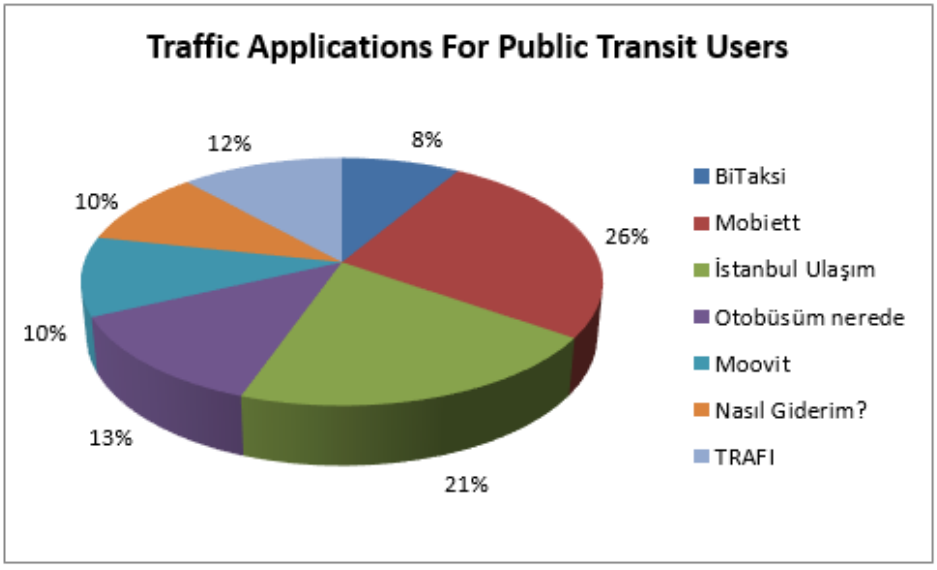


Figure 4.15. Types of Traffic App for Public Transit Users.

The respondents also replied to questions that can be used to decide their trips through various public transport modes. Table 4.23 presents the distribution of modes

that reflect traveler preferences frequency regarding public tranport modes and it seems "metro" has the highest percentage (45.0%) among the other types of modes and other frequencies are indicated below.

Table 4.23. Preference of Public Transport Modes.

Types of Public Transit					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Bus	60	27	27	27
	Minibus	9	4.1	4.1	31.1
	Metrobus	37	16.7	16.7	47.7
	Private minibus	4	1.8	1.8	49.5
	Taxi	1	0.5	0.5	50
	Metro	100	45	45	95
	Ferry boat	7	3.2	3.2	98.2
	Others	4	1.8	1.8	100
	Total	222	100.0	100.0	

As shown in Table 4.22, most of the travelers in the survey, 59 respondents (26.6%) use those applications due to reduce their travel time . Second top reasons that 58 respondents (26.1%) who pick the public transport modes use the traffic applications in order to make decision about choosing most suitable modes with the help of using traffic app. One fifth of members of the survey also acquire the real-time information through the traffic applications because of planning their route with respect to traffic conditions.

Table 4.24. Purpose of Using Traffic Applications for Public Transit Users.

Objective of using traffic app					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Reducing Travel Time	59	26.6	26.6	26.6
	Planning direction with respect to traffic condition	56	25.2	25.2	51.8
	Determining road direction	49	22.1	22.1	73.9
	Make decision about choosing most suitable modes	58	26.1	26.1	100.0
	Total	222	100.0	100.0	

Public transit users use the traffic applications with a different frequency. As shown in Table 4.25, 100 respondents (45.0%) prefer the traffic app usage every second

days, in compare with this, 79 respondents (35.6%) use it several times per day.

Table 4.25. Frequency of Traffic Applications Usage for Public Transport Users.

Frequency of using traffic app					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Several times a day	79	35.6	35.6	35.6
	Every second days	100	45	45	80.6
	Once a month	43	19.4	19.4	100
	Total	222	100	100	

The choice distribution of two travel behavior for public transport users under the real-time traffic information acquired through mobile devices during drivers' daily trip included in the questionnaire is given in Table 4.26. This variable serves as the dependent variable of the choice model mentioned before. As shown, changing route by means of using traffic apps is the most frequent encountered behavior under the real-time traffic information obtained by some traffic applications. In this research, 195 respondents (87.8%) change their route with respect to acquisition of real-time traffic information. The rest of the survey members do not change their route in spite of using traffic apps.

Table 4.26. Frequency of Public Transit Users' Behavior under the Real-Time Information.

Travel Behavior					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Changing route by means of using traffic apps	195	87.8	87.8	87.8
	Does not change route in spite of using traffic app	27	12.2	12.2	100.0
	Total	222	100.0	100.0	

With the help of cross tabulation some important findings were also obtained. Travelers display different travel behavior with regard to using various traffic applications. According to Table 4.27, travelers who use Mobiett and Istanbul Trafik are more likely to change their route when obtaining information from those of traffic apps.

Table 4.27. Travel Behavior Relative to Traffic Applications for Private Car Users.

		Travel Behavior		Total
		Changing route by means of using traffic apps	Does not change route in spite of using traffic app	
Traffic Applications	BiTaksi	16	3	19
	Mobiett	54	4	58
	Istanbul Ulasim	40	6	46
	Otobüsüm nerede?	26	2	28
	Moovit	20	3	23
	Nasil Giderim?	19	3	22
	TRAFI	20	6	26
Total		195	27	222

Car usage frequency gives another finding. Travelers who ride the public transport several times a day mostly obey the traffic applications direction and changing their route with respect to its provided information. Travelers who haven't got private car, as expected, mostly use a variety of public transportation for the shortest path that apps suggested. Relationship between traveler decision and frequency of using private car are indicated Table 4.28.

Table 4.28. Travel Behavior Relative to Public Transit Usage Frequency.

		Travel Behavior		Total
		Changing route by means of using traffic apps	Does not change route in spite of using traffic app	
Frequency of using public transit	Several times a day	166	24	190
	Every second days	24	2	26
	Once a month	5	1	6
Total		195	27	222

4.4.3.3. Some Statistics based on Work Status. In this study, there are three different status, including students, academicians and supporting staff among the respondents.

Most of the respondents, 254 travelers (70.6%) are students and almost one fourth of respondents (23.1%) are academicians and the rest of them constitute supporting staff. Table 4.29 presents shares of each rank among the sample. The table also contains the average age and household income level of each rank and the averages of the trip time and trip cost. As well as, the table include the most preferred mode and traffic applications.

Table 4.29. Shares of Ranks, and Other Characteristics.

Work Status	Frequency	Percent	Averge Age	Averge Household Income (tl/ month)	Most Preffed Mode	Average Trip Time (Min/day)	Average Trip Cost (Tl)	Most Preffed Traffic App
Student	254	70.6	23.02	1114	Public Transport	55.01	5.92	IMM Mobile
Academicians	83	23.1	40.2	419.46	Private Car	49.11	7.27	Yandex. Maps
Staff	23	6.4	34.74	3213.04	Subscription Bus	56.91	6.78	Yandex. Maps

According to Table 4.29, as expected, the younger rank is students and the oldest rank is academicians. We can say that age and household income increase as the academic rank increases. Moreover, the most preferred travel mode shows an alteration among the work status. Academicians more prefer the private car than others. Staff also use subscription bus for commuting in their daily trip. Students mostly pick public transport as their most preferred travel mode. The private car is also perceived as a very expensive mode compared to public transport and subscription bus, however, private car is regarded as the fastest travel mode than the others. What's more, interestingly, IMM Mobile Traffic is the most preferred traffic applications among the students, as well as, both academicians and staff choose Yandex.Maps as the traffic applications.

5. ANALYSIS AND RESULTS

In this chapter, two different analysis are examined that contain Linear Regression Analysis with two types of data set including traffic application used in Turkey and all traffic application used in all over the world, as well as, Binary Logistic Regression are modelled with survey data.

5.1. Multiple Linear Regression and Correlations Analysis

The linear regression equation will be multiple and take the following form:

$$\begin{bmatrix} Y_1 \\ : \\ : \\ Y_n \end{bmatrix} = \begin{bmatrix} 1 & & \\ : & X_{11}X_{21}X_{31}\dots X_{n1} & \\ : & \dots & \\ 1 & X_{n1}X_{n2}X_{n3}\dots X_{np} & \end{bmatrix} \begin{bmatrix} \beta_0 \\ : \\ : \\ \beta_p \end{bmatrix} \tag{5.1}$$

where Y_i to Y_n are the interpretation of traffic apps; X_i to X_n is the different factors affecting, β_0 to β_p is the coefficients of the factors.

From this equation R^2, adjusted R^2, and F values will be determined. R^2 can be thought of as the proportionate reduction of the total variation coefficient explained through the independent variables (X).

Adjusted R^2 is used to account for the changes in the degrees of freedom as a result of different numbers of model parameters and allows for a reduction in adjusted R^2 as additional, potentially insignificant variables are added. Another measure of assessing model fit is the generalized F test. This approach is a general and flexible approach for testing the statistical difference between competing models.

Equation 5.1 is computed along with the selected influencing factors to generate the linear relationship between interpretation of traffic applications and the influencing

factors. The description of the selected independent variables is illustrated in section below.

5.1.1. Investigation of Index of the Rating of the Traffic Applications Used in Turkey

Data in this model are all categorical variables, therefore, dummy variables should be formed due to understanding effect of dependent variables on each independent variables. A Dummy variable or Indicator Variable is an artificial variable created to represent an attribute with two or more distinct categories/levels. The logic of dummy variables can also be extended to enable them to include nominal level variables with more than two categories in multiple regressions.

In this part, all the categorical variables are transformed as dummy variables. Thus, it takes two variables, these are 1 and 0 for each category. All categorical variables behaves as one independent variable after the transformation. In order to analyse effect of rating on each dummy variables, including gender, both positive and negative interpretation for traffic applications, and traffic applications' features, the multiple regression is made between these variables.

The data was collected as whether the traffic application is accurate, user firiendly and detailed or not that the respondents interpret in this respect. Therefore, index of rating will be investigated with the help of three analysis for traffic applications used in Turkey.

5.1.1.1. Comments on Traffic Apps Used in Turkey: Being Accurate. This analysis was made only people who interpret traffic app accurate or not. In this survey, there are 209 people who find those apps to be accurate or inaccurate. The coefficients on dummy variables measure the average difference between the group coded with the value "1" and the group coded with the value "0" (the "default" or "base group"). The indicators for gender (G), travel mode that is related to the features of traffic

applications (TM) and being accurate (A) can be defined as follows:

$$Gender(G) = \begin{cases} 1 & if \quad male \\ 0 & otherwise \end{cases} \tag{5.2}$$

$$TravelMode(TM) = \begin{cases} 1 & if \quad Public \quad Transportation \\ 0 & otherwise \end{cases} \tag{5.3}$$

$$BeingAccurate(A) = \begin{cases} 1 & if \quad accurate \\ 0 & otherwise \end{cases} \tag{5.4}$$

In order to measure average difference between two groups Table 5.1 indicates the coefficient and significance of parameters. It can be shown in table below that interpretation of being accurate (A), and the traffic applications having features of public transit (PT) are significantly different from zero since the significance values less than a threshold value of 0.05. It indicates that one can reject the null hypothesis. They are significantly different from zero at the 95% confidence level. The reference (default) category in this regression is five-scale star. The Equation 5.5 for the normal multiple regression is:

$$Y\,(Rating) = 2,274 + 2,510xA - 0,331xPT \tag{5.5}$$

Table 5.1. Coefficients of Indicators for Traffic Apps used in Turkey for People who Interpret the Apps as Accurate or not (DV: Five-Scale Star).

Variable	Coefficients	P-value
(Constant)	2.274	0.000
Accuracy	2.510	0.000
Public Transit	-0.331	0.000
Male	0.06	0.602
R^2	0.791	
F (Sig)	258.655 (0.000)	
a. Dependent Variable: Star		

The coefficients presented in Table 5.1 indicate that the coefficient for being accurate has positive value of coefficient. In this context, for every unit increase in making interpretation for traffic application as being accurate, a 2.510 unit increase in star scale is estimated.

Furthermore, for males who find the traffic applications as accurate, the estimated star scale rating would be 0,060 points higher than for females. Namely, men give more high star rate than women do. What's more, traffic applications that its feature is suitable for public transit have negative coefficient value. It means that, for public transport features that app has, the estimated star scale rating would be 0.331 points lower than features for private car that traffic app has. Namely, Traffic applications for private car take more high star rate than public ones.

Coefficient of determination tells us the goodness of fit. R^2 values of 0.791 indicates that there are good fit between observed variables.

As one can observe from the F- statistics of the linear regression models, the null hypothesis stating that all variables are equal to zero can easily be rejected with at least 95% level of confidence. Furthermore, all coefficients of explanatory variables are statistically different from 0 with at least 95% level of confidence.

5.1.1.2. Comments on Traffic Apps Used in Turkey: Being User Friendly. The analysis is made for the people who interpret the traffic applications as user friendly or not. In this survey, there are 228 people who think those apps to be user friendly or not user friendly. The indicators for gender (G), travel mode (TM) and being user friendly (U) can be defined as follows:

$$Gender(G) = \begin{cases} 1 & if \quad male \\ 0 & otherwise \end{cases} \tag{5.6}$$

$$TravelMode(TM) = \begin{cases} 1 \;\; if \;\; Public \;\; Transportation \\ 0 \;\; otherwise \end{cases} \tag{5.7}$$

$$BeingUserFriendly(U) = \begin{cases} 1 \;\; if \;\; user \;\; friendly \\ 0 \;\; otherwise \end{cases} \tag{5.8}$$

In order to measure average difference between two groups Table 5.5 indicates the coefficient and significance of parameters. It can be shown in table below that interpretation of being user friendly (U) is significant which is less than cut-off (<0,05). It indicates that one can reject the null hypothesis. They are significantly different from zero at the 95% confidence level. The reference (default) category in this regression is five-scale star. The Table **??** for the normal multiple regression is:

$$Y\,(Rating) = 3,215 + 1,414xU \tag{5.9}$$

Table 5.2. Coefficients of Indicators for Traffic Apps used in Turkey for people who Interpret the Apps as User Friendly or Not (DV: Five-Scale Star).

Variable	Coefficients	P-Value
(Constant)	3.215	0.000
Public Transit	-0.119	0.248
Male	0.076	0.575
User Friendly	1.414	0.000
R^2	0.457	
F (Sig)	62.893 (0.000)	
a. Dependent Variable: Star		

The coefficients presented in Table 5.2 indicate that the coefficient for being user friendly has positive value of coefficient. In this context, for every unit increase in making interpretation for traffic application as being user friendly, a 1.414 unit increase

in star scale is estimated.

Furthermore, for males who find the traffic applications to be user friendly, the estimated star scale rating would be 0.076 points lower than for females. Namely, women thought to be the traffic apps as user friendly give more high star rate than men do. What's more, traffic applications that its feature is suitable for public transit have positive coefficient value. It means that, for public transport features that app has, the estimated star scale rating would be 0.119 points higher than features for private car that traffic app has. Namely, Traffic applications for public transit take more high star rate than private ones.

Coefficient of determination tells us the goodness of fit. R2 values of 0.457 indicates that there are moderate fit between observed variables.

As one can observe from the F- statistics of the linear regression models, the null hypothesis stating that all variables are equal to zero can easily be rejected with at least 95% level of confidence. Furthermore, all coefficients of explanatory variables are statistically different from 0 with at least 95% level of confidence.

5.1.1.3. Comments on Traffic Apps Used in Turkey: Being Detailed. Analysis is made for the people who interpret the traffic applications as detailed or not. In this survey, there are 73 people who find those apps to be detailed or not detailed. The indicators for gender (G), travel mode (TM) and being detailed (D) can be defined as follows:

$$Gender(G) = \begin{cases} 1 & if \quad male \\ 0 & otherwise \end{cases} \tag{5.10}$$

$$TravelMode(TM) = \begin{cases} 1 & if \quad Public \quad Transportation \\ 0 & otherwise \end{cases} \tag{5.11}$$

$$BeingDetailed(D) = \begin{cases} 1 & if \quad detailed \\ 0 & otherwise \end{cases} \tag{5.12}$$

In order to measure average difference between two groups Table 5.3 indicates the coefficient and significance of parameters. It can be shown in table below that interpretation of being detailed (D) is significant which is less than cut-off (<0,05). It indicates that one can reject the null hypothesis. They are significantly different from zero at the 95% confidence level. The reference (default) category in this regression is five-scale star. The Equation 5.13 for the normal multiple regression is:

$$Y\,(Rating) = 2,528 + 2,106xD \tag{5.13}$$

Table 5.3. Coefficients of Indicators for Traffic Apps used in Turkey for People who interpret the apps as Detailed or not (DV: Five-Scale Star).

Variable	Coefficients	P-Value
(Constant)	2.528	0.000
Detailed	2.106	0.000
Male	-0.062	0.724
Public Transportation	-0.057	0.725
R^2	0.728	
F (Sig)	61.711 (0.000)	
a. Dependent Variable: Star		

The coefficients presented in Table 5.3 indicate that the coefficient for being detailed has positive value of coefficient. In this context, for every unit increase in making interpretation for traffic application as being detailed, a 2.106 unit increase in star scale is estimated.

Furthermore, for males who think the traffic applications to be detailed, the estimated star scale rating would be 0.062 points lower than for females. Namely,

women thought to be the traffic apps as user friendly give more high star rate than men do. What's more, traffic applications that its feature is suitable for public transit have negative coefficient value. It means that, for public transport features that app has, the estimated star scale rating would be 0.057 points lower than features for private car that traffic app has. Namely, Traffic applications for private car take more high star rate than public ones.

Coefficient of determination tells us the goodness of fit. R^2 values of 0.728 indicates that there are good fit between observed variables.

As one can observe from the F- statistics of the linear regression models, the null hypothesis stating that all variables are equal to zero can easily be rejected with at least 95% level of confidence. Furthermore, all coefficients of explanatory variables are statistically different from 0 with at least 95% level of confidence.

5.1.2. Investigation of Index of the Rating of the Traffic Applications Used in World

Data in this model are all categorical variables, therefore, dummy variables should be formed due to understanding effect of dependent variables on each independent variable. A Dummy variable or Indicator Variable is an artificial variable created to represent an attribute with two or more distinct categories/levels. The logic of dummy variables can also be extended to enable them to include nominal level variables with more than two categories in multiple regressions.

The data was collected as whether the traffic application is accurate, user firiendly and detailed or not. Therefore, index of rating will be investigated with the help of three analysis for traffic applications used in. The indicators for gender (G), travel mode (TM) and interpretation of traffic applications can be defined as follows:

$$Gender(G) = \begin{cases} 1 & if \quad male \\ 0 & otherwise \end{cases} \tag{5.14}$$

$$TravelMode(TM) = \begin{cases} 1 \;\; if \;\; Public \;\; Transportation \\ 0 \;\; otherwise \end{cases} \tag{5.15}$$

$$InterpretationofTrafficApps = \begin{cases} 1 \;\; Interpretation \;\; of \;\; Traffic \;\; Apps \\ 0 \;\; otherwise \end{cases} \tag{5.16}$$

5.1.2.1. Comments on Traffic Apps Used in World: Being Accurate. Analysis is made for the people who interpret the traffic applications as accurate or not. In this survey, there are 386 people who find those apps to be accurate or inaccurate. In order to measure average difference between two groups Table 5.4 indicates the coefficient and significance of parameters. It can be shown in table below that interpretation of being accurate (A) and the traffic applications having features of public transit (PT) is significant which is less than cut-off (<0,05). It indicates that one can reject the null hypothesis. They are significantly different from zero at the 95% confidence level. The reference (default) category in this regression is five-scale star. The Equation 5.17 for the normal multiple regression is:

$$Y\,(Rating) = 1,706 + 3,114xA + 0,356xPT \tag{5.17}$$

Table 5.4. Coefficients of Indicators for Traffic Apps used in World for People who interpret the Apps as Accurate or Not (DV: Five-Scale Star).

Variable	Coefficients	P-Value
(Constant)	1.706	0.000
Accuracy	3.114	0.000
Male	-0.076	0.307
Public Transit	0.356	0.033
R^2	0.867	
F (Sig)	829.361 (0.000)	
a. Dependent Variable: Star		

The coefficients presented in Table 5.4 indicate that the coefficient for being accurate has positive value of coefficient. In this context, for every unit increase in making interpretation for traffic application as being accurate, a 3.114 unit increase in star scale is estimated.

Furthermore, for males who think the traffic applications to be accurate, the estimated star scale rating would be 0.076 points lower than for females. Namely, women thought to be the traffic apps as user friendly give more high star rate than men do. What's more, traffic applications that its feature is suitable for public transit have positive coefficient value. It means that, for public transport features that app has, the estimated star scale rating would be 0.356 points higher than features for private car that traffic app has. Namely, Traffic applications for public transit take more high star rate than private ones.

Coefficient of determination tells us the goodness of fit. R^2 values of 0.867 indicates that there are good fit between observed variables.

As one can observe from the F- statistics of the linear regression models, the null hypothesis stating that all variables are equal to zero can easily be rejected with at least 95% level of confidence. Furthermore, all coefficients of explanatory variables are statistically different from 0 with at least 95% level of confidence.

5.1.2.2. Comments on Traffic Apps Used in World: Being User Friendly. Analysis is made for the people who interpret the traffic applications as accurate or not. In this survey, there are 411 people who find those apps to be user friendly or not user friendly. Table 5.5 indicates the coefficient and significance of parameters. It can be shown in table below that interpretation of being user friendly (U) is significant which is less than cut-off (<0,05). It indicates that one can reject the null hypothesis. They are significantly different from zero at the 95% confidence level. The reference (default) category in this regression is five-scale star. The Equation 5.18 for the normal multiple regression is:

Table 5.5. Coefficients of Indicators for Traffic Apps used in World for People who interpret the Apps as user Friendly or not (DV: Five-Scale Star).

Variable	Coefficients	P-Value
(Constant)	3.242	0.000
User friendly	1.520	0.000
Public Transit	0.219	0.305
Male	-0.086	0.334
R^2	0.524	
F (Sig)	149.602 (0.000)	
a. Dependent Variable: Star		

The coefficients presented in Table 5.5 indicate that the coefficient for being user friendly has positive value of coefficient. In this context, for every unit increase in making interpretation for traffic application as being user friendly, a 1.520 unit increase in star scale is estimated.

Furthermore, for males who think the traffic applications to be user friendly, the estimated star scale rating would be 0,086 points lower than for females. Namely, women thought to be the traffic apps as user friendly give more high star rate than men do. What's more, traffic applications that its feature is suitable for public transit have positive coefficient value. It means that, for public transport features that app has, the estimated star scale rating would be 0,219 points higher than features for private car that traffic app has. Namely, Traffic applications for public transit take more high star rate than private ones.

Coefficient of determination tells us the goodness of fit. R^2 values of 0.524 indicates that there are moderate fit between observed variables.

As one can observe from the F- statistics of the linear regression models, the null hypothesis stating that all variables are equal to zero can easily be rejected with at

least 95% level of confidence. Furthermore, all coefficients of explanatory variables are statistically different from 0 with at least 95% level of confidence.

5.1.2.3. Comments on Traffic Apps Used in World: Being Detailed. Analysis is made for the people who interpret the traffic applications as accurate or not. In this survey, there are 103 people who find those apps to be detailed or not detailed. Table 5.6 indicates the coefficient and significance of parameters. It can be shown in table below that interpretation of being detailed (D) is significant which is less than cut-off (<0,05). It indicates that one can reject the null hypothesis. They are significantly different from zero at the 95% confidence level. The reference (default) category in this regression is five-scale star.
The Equation 5.18 for the normal multiple regression is:

$$Y\,(Rating) = 2,778 + 2,012xD \tag{5.18}$$

Table 5.6. Coefficients of Indicators for Traffic Apps used in World for People who interpret the Apps as Detailed or not (DV: Five-Scale Star).

Variable	Coefficients	P-Value
(Constant)	2.778	0.000
Detailed	2.012	0.000
Male	0.05	0.685
Public Transit	0.067	0.671
R	0.762	
F (Sig)	105. 662 (0.000)	
a. Dependent Variable: Star		

The coefficients presented in Table 5.6 indicate that the coefficient for being detailed has positive value of coefficient. In this context, for every unit increase in making interpretation for traffic application as being detailed, a 2.012 unit increase in star scale is estimated.

Furthermore, for males who think the traffic applications to be detailed, the estimated star scale rating would be 0.050 points higher than for females. Namely, men thought to be the traffic apps as user friendly give more high star rate than women do. What's more, traffic applications that its feature is suitable for public transit have positive coefficient value. It means that, for public transport features that app has, the estimated star scale rating would be 0.219 points higher than features for private car that traffic app has. Namely, Traffic applications for public transit take more high star rate than private ones.

Coefficient of determination tells us the goodness of fit. R2 values of 0.762 indicates that there are good fit between observed variables.

As one can observe from the F- statistics of the linear regression models, the null hypothesis stating that all variables are equal to zero can easily be rejected with at least 95% level of confidence. Furthermore, all coefficients of explanatory variables are statistically different from 0 with at least 95% level of confidence.

5.2. Binary Logit Model

With the help of using survey data, Binary Logit model have been developed in order to capture the effect of traffic information on travelers' decisions, such as Changing route by means of using traffic applications, No change route even though using traffic app if the route is known. At first, sample size calculation and sampling modelling will be explained and then Logit model will be analysed. SPSS Statistics Software that is a widely used program for statistical analysis was used due to developing model. In this study, we worked with IBM SPSS Statistics version 23.

5.2.1. Population and Sample Size

Establishing the overall sample size is a key component of the sampling design. The sample size is generally calculated based on either precision requirements, such as limits on variance, or cost requirements. The type of sampling design and prior

knowledge about the expected sample outcomes both play a role in sample size determination.

5.2.1.1. Sample Size Calculation. A case study was developed for the civil engineering undergraduate-graduate students and academics in Istanbul Technical University, Istanbul, in 2016. Stated preference data are collected by distributed questionnaire. In the civil engineering faculty, in all, 2884 undergraduate students, 330 graduate students and 295 academic has existed. The sample size was determined to be 360 persons for the 95% confidence level according to Yamane formula for sample size determination.

$$n = \frac{N}{1 + N.e^2} \tag{5.19}$$

5.2.1.2. Stratified Random Sampling. In stratified sampling the population of N units is first divided into subpopulations of $N_1, N_2, ..., N_L$ units, respectively. These subpopulations are non-overlapping, and together they comprise the whole of the population, so that:

$$N_1 + N_2 + ... + N_L = N \tag{5.20}$$

The subpopulations are called strata. To obtain the full benefit from stratification, the values of the N, must be known. When the strata have been determined, a sample is drawn from each, the drawings being made independently in different strata. The sample sizes within the strata are denoted by $n_1, n_2, ..., n_L$, respectively. If a simple random sample is taken in each stratum, the whole procedure is described as stratified random sampling.

Stratification is particularly useful for studies that contrast different subgroups within a population. In such cases, a balanced allocation is often used, with the same number of samples selected from each stratum regardless of the number of population

elements in each stratum:

$$n_h = n/H for all h \tag{5.21}$$

Proportionate allocation is often a good choice when the sampling goal is to generate estimates that apply to the whole population. Under this allocation, the rate of sampling in each stratum is equal (Cochran, 1977).

$$f_h = n_h/H_h = constant for all h \tag{5.22}$$

5.2.1.3. Proportionate Stratified Random Sampling. In proportionate stratified sampling, the number of elements allocated to the various strata is proportional to the representation of the strata in the target population. That is, the size of the sample drawn from each stratum is proportional to the relative size of that stratum in the target population.

The same sampling fraction is applied to each stratum, giving every element in the population an equal chance to be selected. The resulting sample is a self-weighting sample. This sampling procedure is used when the purpose of the research is to estimate a population's parameters.

The sample size of each stratum in this technique is proportionate to the population size of the stratum when viewed against the entire population. This means that the each stratum has the same sampling fraction.

With proportionate stratification, the sample size of each stratum is proportionate to the population size of the stratum. Strata sample sizes are determined by the following equation:

$$n_h = (N_h/N) * n \tag{5.23}$$

where n_h is the sample size for stratum h, N_h is the population size for stratum h, N is total population size, and n is total sample size.

First of all, this paper stratifies the sample of people in accordance with work status. Total sample size were taken 360 persons by using Yamane Formula. In order to determine sample size of each strata, proportionate stratified random sampling were used. According to this sampling method, 324 respondents belong to students strata, 30 respondents comes from academicians strata and the rest of them belongs to supporting staff. Binary logit model has been developed with these strata at first, however, the results did not give an accurate outcomes because of singularities in the Hessian matrix problem. In order to solve this problem, perfect prediction which only one value of a predictor variable is associated with only one value of the response variable should be applied. Therefore, strata should compensate for the response variable count with the predictors.

5.2.1.4. Disproportionate Stratified Random Sampling. Disproportionate stratified sampling is a stratified sampling procedure in which the number of elements sampled from each stratum is not proportional to their representation in the total population. Population elements are not given an equal chance to be included in the sample. The same sampling fraction is not applied to each stratum. On the other hand, the strata have different sampling fractions. In order to estimate population parameters, the population composition must be used as weights to compensate for the disproportionality in the sample. However, for some research projects, disproportionate stratified sampling may be more appropriate than proportionate stratified sampling.

Disproportionate stratified sampling may be broken into three subtypes based on the purpose of allocation that is implemented. The purpose of the allocation could be to facilitate within-strata analyses, between-strata analyses, or optimum allocation. Optimum allocation may focus on the optimization of costs, the optimization of precision, or the optimization of both precision and costs.

- Disproportionate allocation for within strata analyses; The purpose of a study may require a researcher to conduct detailed analyses within the strata of the sample. If using proportionate stratification, the sample size of a stratum is very small; it may be difficult to meet the objectives of the study. Proportionate allocation may not yield a sufficient number of cases for such detailed analyses. One option is to oversample the small or rare strata. Such oversampling would create a disproportional distribution of the strata in the sample when compared to the population. Yet, there may be a sufficient number of cases to carry out the within-strata analyses required by the study's objectives.
- Disproportionate allocation for between-strata analyses; The purpose of a study may require a researcher to compare strata to each other. If this is the case, sufficient numbers of elements must be selected for each category. A researcher may desire to maximize the sample size of each stratum. For such a study, equal allocation (also referred to as "balanced allocation" and "factorial sampling") may be appropriate. A researcher may seek to select an equal number of elements from each stratum. The study includes this disproportionate sampling sections because of the fact that perfect prediction is provided with those of method.
- Optimum allocation; Although proportionate stratified sampling may yield smaller margins of error than simple random sampling in estimating population parameters, it may be possible to do better yet. Optimum allocation is designed to achieve even greater overall accuracy than that achieved using proportionate stratified sampling. It sets the sample size of the different strata, taking into account two important aspects of doing research: costs and precision. The sampling fraction varies according to the costs and variability within the various strata. Disproportionate stratified sampling, more specifically, optimum allocation, may be more appropriate for a study than proportionate stratified sampling when the strata differ in terms of data collection costs and the variability of the variables of interest. Optimum allocation may be applied focusing on cost only, precision only, or both cost and precision jointly.

Homogeneous strata with a smaller sample size can have the same level of precision as heterogeneous strata with a larger sample size. Applying this principle, it may

be useful to make the number of elements selected from each stratum directly related to the standard deviation of the variable of interest in the stratum. The greater the variability of the variable in a stratum, the higher the sample size of the stratum should be. Moreover, taking into account data collection costs, the higher the data collection costs of a stratum, the lower the targeted sample size.

5.2.2. Using Binary Logit Model for Modelling Private Car Drivers' Behavior Under the Real-Time Traffic Information

In this section Binary Logit model was developed in order to investigate the effects of the real-time traffic information acquired through some traffic applications on travelers' behavior by using survey data which was conducted in Istanbul Technical University. In this study, two different commute modes, including self-driving commute and public transit commute were analysed seperately. An advantage of binary logit model is its use of odds ratios as estimators for the predictor variables. This provides researchers and practitioners with a more intuitive interpretation to the final model produced (Stevens, 1996).

BL assigns a reference group to which other level of the dependent variable is compared. As stated earlier, the dependent variable that choice distribution of two travel behavior for either private car users and public transport users on highways as a result of the provision of various types of real-time traffic information are given; (i) Changing route by means of using traffic apps (ii) Does not change route in spite of using traffic app.

The independent variables that were used in the choice model are: socioeconomic characteristics such as gender, age, occupation, household income level. Travel characteristics such as frequency of using private car and public transit and total trip time. In addition, Technological characteristics, including most preffered traffic app, frequency and objective of using traffic applications.

Table 5.7 presents the estimated results of Binary Logit model that includes their wald statistics and significance. Only the significant variables for each category at 90% confidence level were included. As a consequence, there exist two utility functions, and the interpretation of estimation results are submitted on a relative basis with respect to the reference mode. In this analysis, "Does not change route in spite of using traffic app" is selected as the reference mode. It is compared to the other type of travel behavior under the real time information with seperate parameter.

For the binary logit part of the conditional model, significance values of the chi-squared test statistic for all modes, including private car and public ones are less than threshold value of 0.10, therefore, it can be concluded that the null hypothesis stating that all variables in the utility function of the binary logit model are equal to zero can be rejected with at least 90% level of confidence. Cox and Snell R^2, Nagelkerke R^2, McFadden's R^2 ($\acute{\rho}^2$) and Adjusted McFadden's R^2 ($\acute{\rho}^2$) values, which are measures of pseudo R^2, show that the fits of the binary logit are good, and all models has correct percent prediction around 70%. Examining the significance values of all variables and constants, it can be seen that the null hypothesis that the coefficients being equal to zero can be rejected with at least 90% level of confidence.

Table 5.7. Binary Logit Model for Private Car Users.

	Coefficient	Std.Error	t statistics	Significance
Gender(1)	-0.896	0.471	-1.904	0.057
Occupation				0.011
Occupation(1)	-2.072	0.717	-2.890	0.004
Income	0	0	1.915	0.055
Trip Time	-0.039	0.015	-2.661	0.008
Objective of using traffic app				0.059
Objective of using traffic app(2)	-1.249	0.528	-2.367	0.018
Constant	2.368	1.330	1.780	0.075
-2Log Likelihood	131.877			
Chi-Sq. test statistic (Significance)	13.861 (0.040)			
Cox & Snell R2	0.225			
Nagelkerke R2	0.304			
Percent Correct Predictions	69.6			
N	138			

It is important to assess the model for possible numerical errors. One quick way is to check for standard errors that are greater than 2. This could mean high multi-collinearity between independent variables. As in logit regression, it is also a good idea to check the 95% confidence intervals. For the significant variables, smaller confidence intervals suggest greater precision of the variable. Confidence intervals containing 1 also denote a lack of significance because this would mean the range of the odds was both higher and lower than 1, making it simultaneously more and less likely to occur (Hosmer and Lemeshow, 2000; Tabatchnick and Fidell, 2007). Multicollinearity occurs when you have two or more explanatory variables that are highly correlated with each other. This leads to problems with understanding which variable contributes to the explanation of the dependent variable and technical issues in calculating a multinomial logistic regression. Determining whether there is multicollinearity is an important step in binary logit regression. In this model, one of the highly correlated variables were excluded. As shown in Table 5.7, there are no standard errors that are greater than 2, so high multicollinearity do not exist between independent variables.

The table above also gives the Pseuda R-square measures that SPSS generates three different pseudo R^2 summary statistics, used by some to assess model fit by determining the effect size of the model. For this analysis, pseudo R^2 statistics were as follows: contains the Cox and Snell R Square and Nagelkerke R Square values, which are both methods of calculating the explained variation. However, they are interpreted in the same manner, but with more caution. Therefore, the explained variation in the dependent variable based on our model ranges from 22.5% to 30.4%, depending on whether you reference the Cox and Snell R^2 or Nagelkerke R^2 methods, respectively. Nagelkerke R^2 is a modification of Cox and Snell R^2, the latter of which cannot achieve a value of 1. For this reason, it is preferable to report the Nagelkerke R^2 value. It can be seen from the table that Nagelkerke's R^2 is 0.304 which indicates that the model is moderate and 22.5% probability of driver behavior is explained by the logistic model.

5.2.3. Using Binary Logit Model for Modelling Public Transit Users' Behavior Under fhe Real-Time Traffic Information

Table 5.8. shows the estimated results of Binary Logit model that includes their wald statistics and significance. Only the significant variables for each category at 90% confidence level were included. In this analysis, "Does not change route in spite of using traffic app" is selected as the reference mode that compare with the travelers' choice of "Changing route by means of using traffic apps". In addition, there are no standard errors that are greater than 2, so high multicollinearity do not exist between explanatory variables.

Table 5.8. Binary Logit Model for Public Transportation Users

	Coefficient	Std.Error	t statistics	Significance
Age	0.105	0.064	1.646	0.100
Income	0.000	0.000	-1.686	0.092
Frequency of using public transit				0.013
Frequency of using public transit (1)	-1.798	0.64	-2.808	0.005
Frequency of using public transit (2)	-1.050	0.499	-2.107	0.035
Constant	-2.439	1.795	-1.359	0.174
-2Log Likelihood	145.265			
Chi-Sq. test statistic (Significance)	7.493 (0.013)			
Cox & Snell R2	0.082			
Nagelkerke R2	0.157			
Percent Correct Predictions	87.4			
N	222			

The table above also includes three different pseudo R2 summary statistics, used by some to assess model fit by determining the effect size of the model. The chi-square that gives the goodness of fit test with its Sig. values is given as well. The model is statistically significant because the p-value is less than cut-off (<0.10)

5.3. Analysis Results

In this study, BL models were developed for two different commute mode choice including private car and public transportation modes. The comperative results are shown as follows;

The positive signs of the values of the estimated alternative specific constants show that there is a tendency toward changing route by means of using traffic applications for private car users. On the other hand, the relative magnitude of the estimated constants suggests that public transportation users are more reluctant to change their route in spite of using traffic applications.

The age of members of survey has different travel pattern in response to the provided traffic information. In the perspective of car users, the insignificant and negative coefficient of age is shown that elderly individuals ignore more likely the traffic information and not change their route than the younger ones. Contrary to car drivers, the significant and positive coefficient of age demonstrate that older people are more likely to change their route under the real-time traffic information when they use the public transit.

The estimation results for the daily household income are significant for the both mode choice, however all the coefficients for different travel behavior are almost zero. It means that daily household income does not effect on the choice of decision making for travel. According to Abdel-Aty *et al.* (2006) Drivers' age and income do not affect route diversion.

According to Table 5.7, gender has different implication for choice of decision making for travel. In broad sense, for private car modes, females are more likely to switch their travel pattern when they use the traffic applications. Similar finding has been found by some researchers. Pierce and Lappin (2004) asserted that females change travel patterns more often than males while Mannering *et al.* (1995), Spyridakis *et al.* (1991) and Caplice and Mahmassani (1992) found that female drivers more listen to radio to obtain traffic information and males are less likely to perceive traffic information as important. On the other hand, unlike the car drivers, males who use public transportation are more willing to change their route when they use the traffic applications.

This is the binary logit estimate comparing males to females for the travel behavior of changing route relative to not changing route in spite of using traffic apps. The binary logit for males who are car ownership relative to females are 0.896 unit lower for preferring changing route by means of using traffic apps, however, males who use public transit are 0.89 unit higher for changing their route by means of using traffic apps. In other words, females are more likely than males to prefer the travel behavior of changing route under the real- time traffic information acquired through some traffic apps when they use the car. Furthermore, compare to using public transit, males change their route less often when they use the private car.

Occupation of individuals gives another important finding. Academicians has the significant and positive effect on changing route under the real time information acquired by traffic app for private car users. The estimation results show that academicians who use private car are more likely to change their route when using traffic apps. These findings are consistent with finding from other surveys presented in the literature. Abdel-Aty *et al.* (1994) developed the probit models that high income and high education persons use traffic information more often with higher rates of switching. The Wald test statistic for the predictor academicians 2.072 with an associated p-value of 0.10. At the 90% confidence level, the null hypothesis can be rejected and conclude that the occupation has been found to be statistically different for preferring changing route relative to not to change travel pattern in spite of using traffic apps.

Note that when analyzing all the characteristics, including socioeconomic, travel and technological characteristics into one model, almost no socioeconomic characteristics were found significant, which implies that the taste variations and population heterogeneity were captured by the random terms s. This is consistent with some other studies (e.g. Mahmassani *et al.*, 2003), while several other studies have found socioeconomic characteristics significant.

Another important finding is related to the frequency of private car usage that has different implication for two travel modes. Unlike using public transit, travelers who use private car several times a day are more likely to shift their route through

using traffic applications than they use it every second days. On the other hand, for public transportation users, travelers are more reluctant to change their route in spite of using traffic applications when they use the public transit several times a day than they use it every second days. Namely, travelers who use public transit frequently are likely not to change their route in spite of obtaining real-time traffic information as well. Chen *et al.* (2008) claimed that Drivers tendency of diversion increase with the increase of driving experience and Spyridakis *et al.* (1991) asserted that drivers are more likely to divert to known routes compared to unknown routes.

The effect of purpose of traffic applications usage is significant for the different types of travel behavior. For the private car users, travelers use the traffic applications with the purpose of planning their route with respect to traffic condition are more likely to change their route than using traffic applications for the purpose of reducing travel time and the purpose of determining road direction. In addition, for public transit users, the insignificant alternative specific constant indicates that travelers use the traffic applications with the purpose of reducing travel time are more likely to change their route than using traffic applications for the purpose of planning their route with respect to traffic condition.

According to Table 5.7, for the private car users, trip time has a significant and positive effect on the choice of decision making for travel. Travel time can change with respect to different travel pattern under provided traffic information. The estimation results show that as the trip time increase, car drivers are more likely to switch their travel pattern. In addition, changing their travel pattern in response to obtaining real-time traffic information has just the insignificant and positive estimated but almost zero coefficient associated with travel time for public transit users. Abdel-aty *et al.* (1997) claimed that travel time is not dominant in route choice criterion

The effect of the trip cost on the modal preferences of both private car and public transit users that has an insignificant and positive effect on travel behaviour. The estimation results show that as the trip cost increases, travelers are more willing to change their route under the real time traffic information.

The estimation results show that the positive signed alternative specific constant associated with trip distance are generally insignificant and all the coefficients for different travel behaviour are almost zero. It means that trip distance does not affect on the choice of decision making for travel.

As a result of Multiple Linear Regression Analysis with Dummy Variables for traffic application that use in Turkey and in the world, some comperative outcomes can be emerged.

Gender difference can influence interpretation for traffic applications in a different manner. In this study, males generally comment on traffic applications both as "accurate and reliable" when the traffic apps used in Turkey are mostly commented as "user friendly". It can express that males in Turkey attach more importance to its understandable and simple interface in order to use more and those features enable Turkish males to give higher star rate. Likewise, males in the world generally give high star rate to traffic applications having higher perceived accuracy level.

Females mostly find the traffic applications "accurate and reliable" for all types of apps. Women can be more interested in taking accurate real-time information from traffic applications. According to Khoo and Ong (2011) The perceived traffic information accuracy and reliability attribute defines the drivers' trust of information accuracy from apps. This attribute is found to influence drivers' route choice behavior under the ATIS.

At the perspective of negative interpretation, both female and male mostly find the traffic applications as not user friendly in order to inadequate interface more than other attributes. They generally comment download websites regarding adding new and requested attributes of apps due to its deficiency features.

As a result of analyzing each indicators gives important finding. The gender difference can also influence giving star rating in a different way. Unlike traffic applications used in Turkey, women who interpret the traffic applications as accurate, user

friendly and detailed or not give higher star rate than men for all traffic apps. It is undertood from the analysis that males use the traffic applications more frequently than females. It can be said that, actually, Turkish females are more critical for evaluating applications functions than males. In order to evaluate the traffic apps, females take account of all features including not only taking accurate information but also detailed functions. Namely, giving accurate outcomes is not enough due to giving high star rate for Turkish females. On the other hand, if the apps give some accurate results that supply with Turkish males need, they give high star rate. What's more, It can be understood from the analysis that purpose of evaluating traffic apps for Turkish females coincide with the males in the world.

What's more, traffic applications that its different features causes giving different mark on star scale rating for both traffic applications used in Turkey and used in world. Compared to traffic apps used in Turkey, traffic applications having features of public transit have positive coefficient value. Namely, traffic applications used in world for public transit take higher star rate than private ones, however, traffic applications used in Turkey for private car get higher star rate than publis ones. Turkish people who use public transport actually do not need the traffic applications for choosing alternatives, because there are not much options in order to pick different types of public transport. On the other hand, especially in Istanbul, traffic congestion is mostly encountered problems, therefore, drivers generally use those traffic applications due to switching their route and finding the shortest path. In this context, Turkish people generally use and evaluate more traffic applications for private car than public ones.

6. CONCLUSIONS AND RECOMMENDATIONS

6.1. Conclusions

The study has mainly investigated effects of the provision of various types of real-time traffic information acquired by some traffic applications on travelers' behavior by using survey data which was conducted in Istanbul Technical University and marked questionnaire was collected from undergraduate-graduate students, academicians and supporting staff stayed at civil engineering faculty. Binary logit model (BL) is developed in order to predict a nominal dependent variable given one or more independent variables. The model contains 6 factors, including gender, occupation, car usage frequency, traffic applications usage frequency, objective of traffic applications usage and all the traffic applications that existed in the survey and 2 covariates which are trip time and income are existed. In addition, the traffic applications that use in Turkey and the most used traffic applications in the world were analysed through using developed regression models as well as the associated tests were also employed to understand how the typical value of the dependent variable changes when any one of the independent variables is varied, while the other independent variables are held fixed.

Data were collected in two different way in order to test the associated analysis. Data were obtained by means of distribution of questionnaire and some related websites which include all traffic application people downloaded. In BL model, with the help of the correlation matrix, some variables that are higly correlated with each other were excluded and the rest of the characteristic variables were included. In regression model, all data were used without any exclusion. After that, each data that obtaining from different way were analysed with respect to their statistical descriptives features.

Binary Logit (BL) Model was proposed with two travel behavior; Changing route by means of using traffic applications and No change route even though using traffic app, if the travelers know the route. Regarding the factors that influence the decisions

just mentioned, it appears that both travel characteristics such as car usage frequency and technological characteristics, considering Traffic applications type, Traffic applications usage frequency, Purpose of Traffic App Usage, significantly affect individuals' make decision for travel behavior. These findings are consistent with findings from various surveys presented in the literature (Al-Deek, Chandra and Flick, 2009; Han, Timmermans, Dellaert and van Raaij, 2008; Khattak, Yim and Stalker, 1999; Mahmassani, Huynh, Srinivasan and Kraan, 2003; Mahmassani and Liu, 1999; Roorda and Andre, 2007; Tsirimpa and Polydoropoulou, 2011)

Significant finding from the estimated model include the effect of increases in travelers whose gender is male and private car frequency usage as well as increase in having some purpose of using traffic applications such as planning their route with respect to traffic conditions and determining road directions that likely increase the travel behavior of changing route with using traffic applications compared with behavior of the using types of public transport for the shortest path that traffic applications suggested. Tsirimpa, A. (2015) emphasized that in the application of the estimated model, an increased willingness for traffic information acquisition from mobile devices can result in a significant change in the rescheduling of individual activities along with a trip-specific change. As expected, the academicians are less likely to behave no changing route when using traffic apps. Provision of various types of real-time traffic information acquired by some traffic applications affect the individual's travel pattern in a diffrent way. Furhermore, car usage frequency is statistically important for each travel behavior that traveler present while similar to the findings of van Bladel *et al.* (2009), travel characteristics (such as tour purpose, selected tour mode) affect travel behavior.

A variety of features of all traffic applications obtained from some related websites were also analysed. There are some difference regarding their significant variables and their descriptive statistic results between traffic applications that use in Turkey and in the world. For this analysis, lineer regression model were found to be sufficient.

6.2. Recommendations

The application of the proposed methodology can prove to be very helpful for researchers and policymakers. The model developed can be used to realistically predict the changes that take place in the individuals' travel pattern, after the acquisition of traffic information while en route. Changing route or not with respect travelers' traffic application usage can change in terms of some different characteristics which were socioeconomics, travel and technological characteristics.
For future studies, some recommendations are given below;

- Larger sample size may give different results so that the model can be repeated with much more sample
- Scenario analysis can be investigated by manipulating some relevant variables and make prediction under particular changes in the system
- Some explanatory variables related traffic condition including unexpected time delay, congestion, road hazard/closures, speed restrictions situations can be added
- Real-time traffic information based predictors such as willingness to acquire traffic information, response to ATIS can be analysed.

REFERENCES

Abdel-Aty, M. A., R. Kitamura and P.P. Jovanis, 1994, "Using Stated Preference Data for Studying the Effect of Advanced Traffic Information on Drivers' Route Choice", *Transportation Research Part.*

Abdel-Aty, M.A., R. Kitamura, P.P. Jovanis, 1997, "Using Stated Preference data for Studying the Effect of Advanced Traffic Information on Drivers' Route Choice", *Transportation Resistance*, Vol. 5, No. 1, pp. 39-50.

Adler, J.L., and V.J. Blue, 1998, "Toward the design of Intelligent Traveler Information Systems", *Transportation Research C*, Vol. 6, pp. 157-172.

Al-Deek, H., R.S. Chandra and J. Flick, 2009, "The Impact of Dynamic Message Signs on Satisfaction and Diversion of Toll Road Travelers", *Journal of the Transportation Research Board*, Vol. 1, pp. 1-13.

Arentze, T., F. Hofman, and H. Timmermans, 2004, "Predicting Multi-Faceted Activity-Travel Adjustment Strategies in Response to Possible Congestion Pricing Scenarios Using an Internet-Based Stated Adaptation Experiment", *Transport Policy*, Vol. 11, pp. 31-41.

Arnott, R., A. Palma and R. Lindsey, 1991, "Does Providing Information to Drivers Reduce Traffic Congestion?" *Transportation Research A*, Vol. 25, No. 5, pp. 309-318.

Ben-Akiva, M., A. de Palma and I. Kaysi, 1996, "The Impact of Predictive Information on Guidance Efficiency: An Analytical Approach", *Advanced Methods in Transportation Analysis*, Vol. 1, pp 413-432.

Ben-Akiva, M., and S. R. Lerman, 1985, "Discrete Choice Analysis: Theory and Applications to Travel Demand", *Massachusetts Institute of Technology Press*, Cam-

bridge, Massachusetts.

Bonsall, P., 1992, "Research Methods for the Study of Driver Response to In-Vehicl and Roadside Guidance Methods", *Selected Proceedings of the 6th World Conference on Transport Research*, Lyon, Vol. 1, pp. 2519-2530.

Bonsall, P., 2001, "Predicting Travelers' Response to Uncertainty", In D.A. Hensher (ed.) Travel Behavior Research: the Leading Edge, Pergamon, Amsterdam.

Caplice, C., H.S. Mahmassani, 1992, "Aspects of Commuting Behavior: Preferred Arrival Time, use of Information and Switching Propensity", *Transportation Resistance Part A*, Vol. 26, pp. 409-418.

Chang, G.L. and H.S. Mahmassani, 1988, "Travel Time Prediction and Departure Time Adjustment Behavior Dynamics in a Traffic System", *Transportation Research 22B*, Vol. 1, pp. 217-232.

Chen, S., M. Liu, L. Gao, C. Meng, W. Li, J. Zheng, 2008, "Effects of Variable Message Signs for Improving Congestion, Proceedings of International Workshop on Modelling", *Simulation and Optimization*, Vol. 1, pp. 416-419.

Chorus, C.G., E.J.E. Molin, G.P. Wee, 2006, "Use and Effects of Advanced Traveller Information Services: A Review of The Literature", *Transport Reviews*, Vol. 26, No. 2, pp. 127-149.

Golledge, R.G. 2002, "Dynamics and Information Technology Systems: Behavioural Response to Information Available from Automatic Terminal Information Service", In H.S. Mahmassani (ed.) In Perpetual Motion: Travel Behavior Research Opportunities and Application Challenges. Pergamon, Amsterdam.

Han, Q., H. Timmermans, B:G.C. Dellaert and F. van Raaij, 2008, "Route Choice Under Uncertainty: Effects of Recommendation", *Transportation Research Record*, Vol. 1, 72-80.

Hato, E., 1995, "Influence of Traffic Information on Drivers' Route Choice", *Proceedings of the 7th World Conference on Transportation Research*, Sydney, Australia, Vol. 1, pp. 27-40.

Kanninen, B., 1996, "Intelligent Transportation Systems: An Economic and Environmental Policy Assessment", *Transportation Research 30A*, Vol. 1, pp. 1-10.

Khattak, A., 1999, "Does Travel Information Influence Commuter and Non-Commuter Behavior? Results from the San Francisco Bay area TravInfo project", *Transportation Research Record 1694*, Vol. 1, pp. 48-58.

Khattak, A., A. Kanafani and E. Le Colletter, 1994, "Stated and Reported Route Diversion Behavior: Implications on the Benefits of Automatic Terminal Information Service, Preprint No. 940394", *Transportation Research Board, 73rd Annual Meeting*, Washmgton, District of Columbia.

Khoo H.L. and K.S. Asitha, 2016, "User Requirements and Route Choice Response to Smart Phone Traffic Applications", *Travel Behaviour and Society*, Vol. 3, pp. 59-70.

Khoo, H.L., Ong, G.P., 2011, "Analysis of Awareness and Utilization of Traffic Information System Using Revealed Preference Data: A Case Study of Klang Valley", Malaysia Transportation Resistance Recorded, *Journal Transportation Resistance Board*, Vol. 2239, pp. 101-111.

Koppelman, F.S., E.I. Pas, 1980, "Travel Choice Behavior: Modelsof Perceptions", Feelings, Preference and Choice, *Transportation Research Record*, Vol. 765, pp. 26-33.

Lappin, J., 1994, "A Market Analysis of the Commercial Traffic Information Business", Report for the Office of Policy Development, Federal Highway Administration.

Lida, Y., T. Akiyama and T. Uchida, 1992, "Experimental Analysis of Dynamic Route

Choice Behavior", *Transportation Research B*, Vol. 26, pp. 17-32.

Mahmassani, H.S. and G.-L. Chang, 1985, "Dynamic Aspects of Departure-Time Choice Behavior in a Commuting System: Theoretical Framework and Experimental Analysis", *Transportation Research Record*, Vol. 1037, pp. 88-101.

Mahmassani, H., Y. Liu, "Dynamics of Commuting Decision Behavior under Advanced Traveler Information Systems", *Transportation Research Part C*, Vol. 7, pp. 91-107.

Mahmassani, H., N. Huynh, K. Srinivasan, M. Kraan, 2003, "Trip Maker Choice Behavior for Shopping Trips Under Real-Time Information: Model Formulation and Results of Stated-Preference Internetbased Interactive Experiments", *Journal of Retailing and Consumer Service*, Vol. 10, No. 6, pp. 311-321.

Mannering, F., Kim, S.-G., Ng, L., Barfield, W., 1995, "Travelers' preferences for in-vehicle information systems: an exploratory analysis", T*ransportation Resistance Part C*, Vol. 3, No. 6, pp. 339-351.

Manski, C.F. 1981, "Structural Models for Discrete Data: The Analysis of Discrete Choice", *Sociol Method*, Vol. 11, pp. 58-109.

McFadden, D., 1974, "Conditional Logit Analysis of Qualitative Choice Behavior", *Frontiers in Economics*, P. Zarembka, ed., Academic, New York, Vol.1, pp. 105-142.

Peirce, S., and J. Lappin, 2003, "Evolving Awareness, use, and Opinions of Seattle Region Commuters Concerning Traveler Information: Findings from the Puget Sound Transportation Panel Survey, 1997 and 2000", Transportation Research Board 82nd Annual Meeting.

Pierce, S., J. Lappin, 2004, "Why Don't More People use Advanced Traveler Information? Evidence from the Seattle area", Paper Presented in the 83rd Transportation

Research Board Annual Meeting, Washington, District of Columbia.

Shah, V.P., 2001, "Time Management Impacts of Pre-Trip Automatic Terminal Information Service: Findings from a Washington, District of Columbia Case Study", Transportation Research Board 80th Annual Meeting.

Simon, H., 1995, "A Behaviour Model of Rational Choice", *Quarterly Journal of Economics*, Vol. 1, pp. 99-118.

Spyridakis, J., W. Barfield, L. Conquest, M. Haselkorn, C. Isakson, 1991, "Surveying Commuter Behavior: Designing Motorists Information Systems", *Transportation Resistance Part A*, Vol. 25, pp. 17-30.

Srinivasan, K., H.S. Mahmassani, 2000, "Modeling Inertia and Compliance Mechanisms in Route Choice Behavior Under Real-Time Information", *Transportation Research Board 79th Annual Meeting.*

Stevens, J., 1996, "Applied Multivariate Statistics for the Social Sciences", Hillsdale NJ:Erlbaum.

Sun, Z., T.A. Arentze, H.J.P. Timmermans, 2015, "Modeling the Impact of Systems", Aldershot Ashgate.

Sutherland, E., 2013, "Forrester the IPhone is Still Most-Used Smartphone The Mobile Movement Study", *The Mobile Movement: Understanding Smartphone users.*

Train, K., 1986, "Qualitative Choice Analysis: Theory, Econometrics and an Application to Automobile Demand", *Massachusetts Institute of Technology Press*, Cambridge, Massachusetts.

Tseng, Y.-Y., J. Knockaert and E.T.A. Verhoef, 2013, "Revealed Preference Study of Behavioural Impacts of Real-Time Traffic Information", *Transportation Research Part C*, Vol. 30, pp. 196-209.

Tsirimpa, A., 2015, "Modeling the Impact of Traffic Information Acquisition From Mobile Devices During the Primary Tour of the Day", *Journal of Intelligent Transportation Systems*, Vol. 19, pp. 125-133.

Tsirimpa, A., A. Polydoropoulou, 2011, "The Impact of Traffic Information Acquisition on the Traffic Conditions of the Athens Greater Area", Special Issue Entitled Operation Research and Its Application in Transportation International, *Journal of Operations Research and Information Systems*, Vol. 5, No. 2, pp. 201-220.

Van Bladel, K., T. Bellemans, D. Janssens, G. Wets, 2009, "Activity Travel Planning and Rescheduling Behavior: Empirical Analysis of Infuencing Factors", *Transportation Resistance Recience*, Vol. 1, pp.135-142.

Wang, X., 2009, "Transportation Research Record: Journal of the Transportation Research Board", *Transportation Research Board of the National Academies*, Vol. 1, pp. 85-93.

Yamane, T., 1967, "Statistics, An Introductory Analysis", 2nd ed., *Harper and Row*, New York.

Yim, Y.B., and M.A. Miller, 2000, "Evaluation of the TravInfo Field Operational Test, California Partnerships for Access to Higher Education Program", *Institute of Transportation Studies*, University of California, Berkeley.

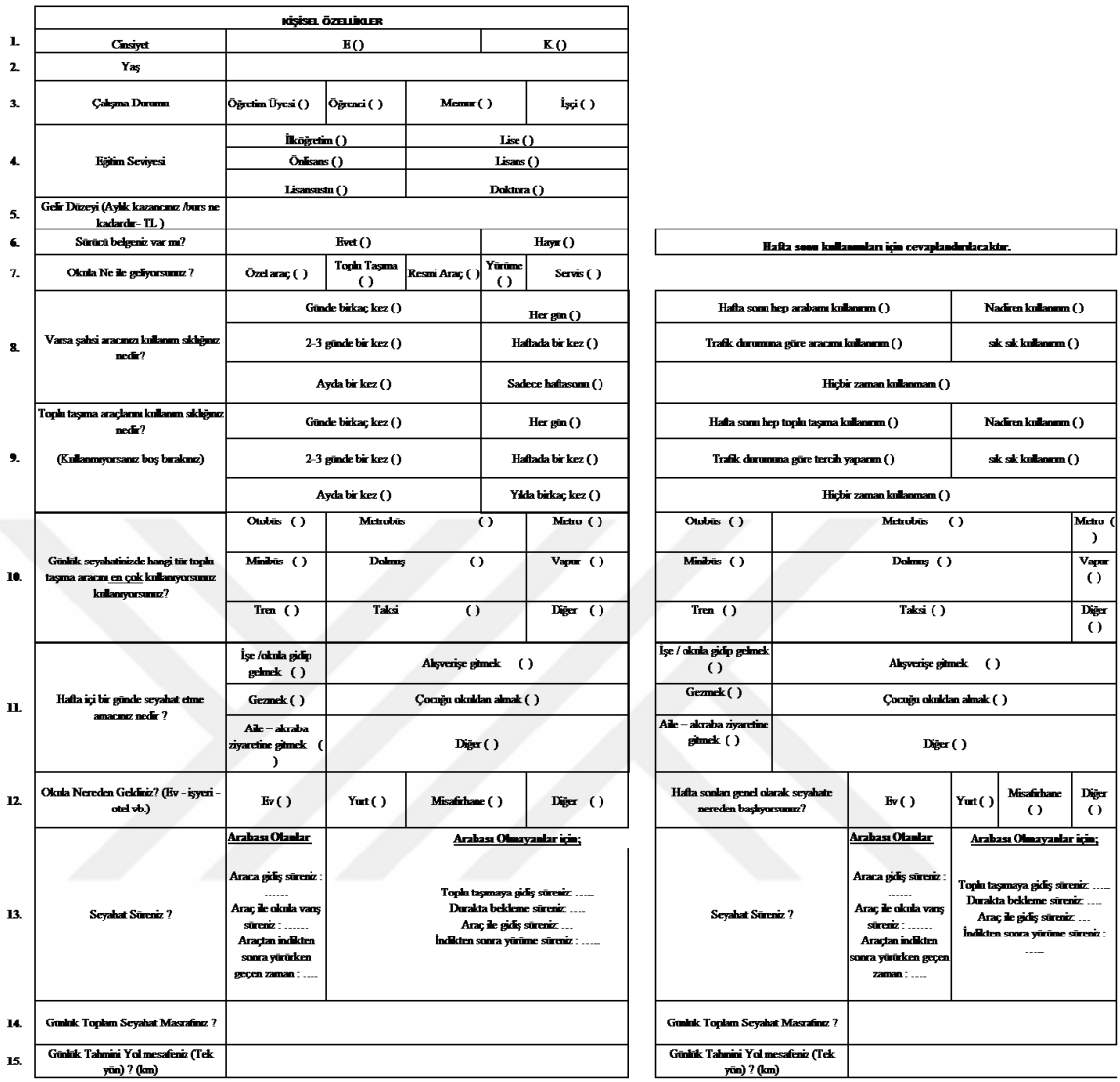
Yue, T., 2014, "Zooming into Individuals to Understand the Collective: A Review of Trajectory-Based Travel Behaviour Studies", *Travel Behaviour and Society*, Vol. 1, No. 2, pp. 69-78.

APPENDIX A: QUESTIONNAIRE

	KİŞİSEL ÖZELLİKLER					
1.	Cinsiyet	E ( )			K ( )	
2.	Yaş					
3.	Çalışma Durumu	Öğretim Üyesi ( )	Öğrenci ( )	Memur ( )	İşçi ( )	
4.	Eğitim Seviyesi	İlköğretim ( )		Lise ( )		
		Önlisans ( )		Lisans ( )		
		Lisansüstü ( )		Doktora ( )		
5.	Gelir Düzeyi (Aylık kazancınız /burs ne kadardır- TL)					
6.	Sürücü belgeniz var mı?	Evet ( )			Hayır ( )	
7.	Okula Ne ile geliyorsunuz ?	Özel araç ( )	Toplu Taşıma ( )	Resmi Araç ( )	Yürüme ( )	Servis ( )
8.	Varsa şahsi aracınızı kullanım sıklığınız nedir?	Günde birkaç kez ( )			Her gün ( )	
		2-3 günde bir kez ( )			Haftada bir kez ( )	
		Ayda bir kez ( )			Sadece haftasonu ( )	
9.	Toplu taşıma araçlarını kullanım sıklığınız nedir? (Kullanmıyorsanız boş bırakınız)	Günde birkaç kez ( )			Her gün ( )	
		2-3 günde bir kez ( )			Haftada bir kez ( )	
		Ayda bir kez ( )			Yılda birkaç kez ( )	
10.	Günlük seyahatinizde hangi tür toplu taşıma aracını en çok kullanıyorsunuz kullanıyorsunuz?	Otobüs ( )	Metrobüs ( )		Metro ( )	
		Minibüs ( )	Dolmuş ( )		Vapur ( )	
		Tren ( )	Taksi ( )		Diğer ( )	
11.	Hafta içi bir günde seyahat etme amacınız nedir ?	İşe /okula gidip gelmek ( )	Alışverişe gitmek ( )			
		Gezmek ( )	Çocuğu okuldan almak ( )			
		Aile – akraba ziyaretine gitmek ( )	Diğer ( )			
12.	Okula Nereden Geldiniz? (Ev - işyeri - otel vb.)	Ev ( )	Yurt ( )	Misafirhane ( )	Diğer ( )	
13.	Seyahat Süreniz ?	**Arabası Olanlar** Araca gidiş süreniz : ..... Araç ile okula varış süreniz : ..... Araçtan indikten sonra yürürken geçen zaman :	**Arabası Olmayanlar için;** Toplu taşımaya gidiş süreniz: .... Durakta bekleme süreniz: .... Araç ile gidiş süreniz: ... İndikten sonra yürüme süreniz :			
14.	Günlük Toplam Seyahat Masrafınız ?					
15.	Günlük Tahmini Yol mesafeniz (Tek yön) ? (km)					

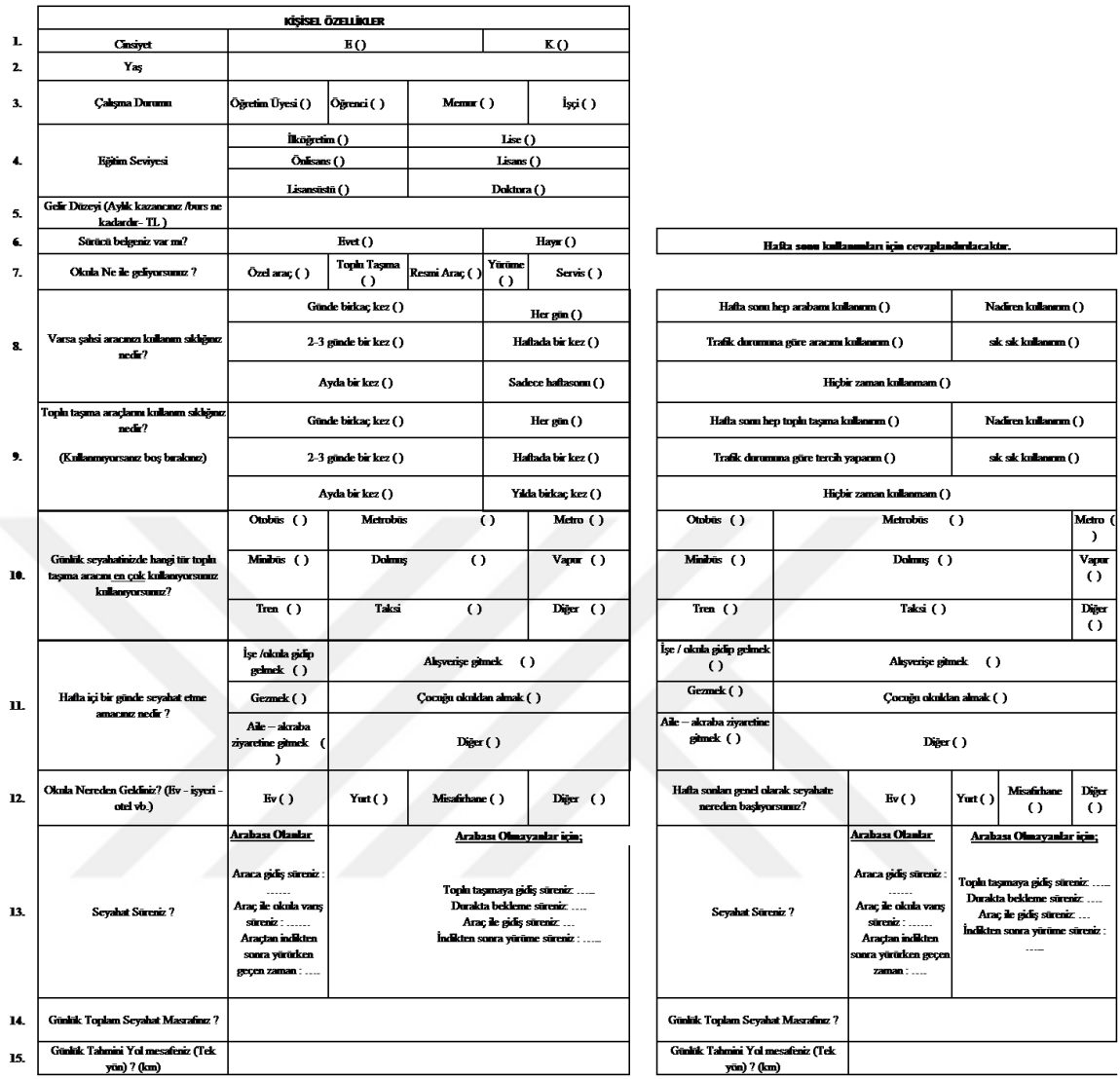
Hafta sonu kullanımları için cevaplandırılacaktır.				
Hafta sonu hep arabamı kullanırım ( )			Nadiren kullanırım ( )	
Trafik durumuna göre aracımı kullanırım ( )			sık sık kullanırım ( )	
Hiçbir zaman kullanmam ( )				
Hafta sonu hep toplu taşıma kullanırım ( )			Nadiren kullanırım ( )	
Trafik durumuna göre tercih yaparım ( )			sık sık kullanırım ( )	
Hiçbir zaman kullanmam ( )				
Otobüs ( )	Metrobüs ( )		Metro ( )	
Minibüs ( )	Dolmuş ( )		Vapur ( )	
Tren ( )	Taksi ( )		Diğer ( )	
İşe / okula gidip gelmek ( )	Alışverişe gitmek ( )			
Gezmek ( )	Çocuğu okuldan almak ( )			
Aile – akraba ziyaretine gitmek ( )	Diğer ( )			
Hafta sonları genel olarak seyahate nereden başlıyorsunuz?	Ev ( )	Yurt ( )	Misafirhane ( )	Diğer ( )
Seyahat Süreniz ?	**Arabası Olanlar** Araca gidiş süreniz : ..... Araç ile okula varış süreniz : ..... Araçtan indikten sonra yürürken geçen zaman :	**Arabası Olmayanlar için;** Toplu taşımaya gidiş süreniz: .... Durakta bekleme süreniz: .... Araç ile gidiş süreniz: ... İndikten sonra yürüme süreniz :		
Günlük Toplam Seyahat Masrafınız ?				
Günlük Tahmini Yol mesafeniz (Tek yön) ? (km)				

Figure A.1. Questionnaire.



	KİŞİSEL ÖZELLİKLER					Hafta sonu kullanımları için cevaplandırılacaktır.
1.	Cinsiyet	E ( )		K ( )		
2.	Yaş					
3.	Çalışma Durumu	Öğretim Üyesi ( )	Öğrenci ( )	Memur ( )	İşçi ( )	
4.	Eğitim Seviyesi	İlköğretim ( )		Lise ( )		
		Önlisans ( )		Lisans ( )		
		Lisanstüstü ( )		Doktora ( )		
5.	Gelir Düzeyi (Aylık kazancınız /burs ne kadardır- TL)					
6.	Sürücü belgeniz var mı?	Evet ( )		Hayır ( )		
7.	Okula Ne ile geliyorsunuz ?	Özel araç ( )	Toplu Taşıma ( )	Resmi Araç ( )	Yürüme ( ) / Servis ( )	
8.	Varsa şahsi aracınızı kullanım sıklığınız nedir?	Günde birkaç kez ( )		Her gün ( )		Hafta sonu hep arabamı kullanırım ( ) / Nadiren kullanırım ( )
		2-3 günde bir kez ( )		Haftada bir kez ( )		Trafik durumuna göre aracımı kullanırım ( ) / sık sık kullanırım ( )
		Ayda bir kez ( )		Sadece haftasonu ( )		Hiçbir zaman kullanmam ( )
9.	Toplu taşıma araçlarını kullanım sıklığınız nedir? (Kullanmıyorsanız boş bırakınız)	Günde birkaç kez ( )		Her gün ( )		Hafta sonu hep toplu taşıma kullanırım ( ) / Nadiren kullanırım ( )
		2-3 günde bir kez ( )		Haftada bir kez ( )		Trafik durumuna göre tercih yaparım ( ) / sık sık kullanırım ( )
		Ayda bir kez ( )		Yılda birkaç kez ( )		Hiçbir zaman kullanmam ( )
10.	Günlük seyahatinizde hangi tür toplu taşıma aracını en çok kullanıyorsunuz kullanıyorsunuz?	Otobüs ( )	Metrobüs ( )	Metro ( )		Otobüs ( ) / Metrobüs ( ) / Metro ( )
		Minibüs ( )	Dolmuş ( )	Vapur ( )		Minibüs ( ) / Dolmuş ( ) / Vapur ( )
		Tren ( )	Taksi ( )	Diğer ( )		Tren ( ) / Taksi ( ) / Diğer ( )
11.	Hafta içi bir günde seyahat etme amacınız nedir ?	İşe /okula gidip gelmek ( )	Alışverişe gitmek ( )			İşe / okula gidip gelmek ( ) / Alışverişe gitmek ( )
		Gezmek ( )	Çocuğu okuldan almak ( )			Gezmek ( ) / Çocuğu okuldan almak ( )
		Aile – akraba ziyaretine gitmek ( )	Diğer ( )			Aile – akraba ziyaretine gitmek ( ) / Diğer ( )
12.	Okula Nereden Geldiniz? (Ev – işyeri – otel vb.)	Ev ( )	Yurt ( )	Misafirhane ( )	Diğer ( )	Hafta sonları genel olarak seyahate nereden başlıyorsunuz? / Ev ( ) / Yurt ( ) / Misafirhane ( ) / Diğer ( )
13.	Seyahat Süreniz ?	Arabası Olanlar: Araca gidiş süreniz : ..... Araç ile okula varış süreniz : ..... Araçtan indikten sonra yürürken geçen zaman :	Arabası Olmayanlar için; Toplu taşımaya gidiş süreniz: .... Durakta bekleme süreniz: .... Araç ile gidiş süreniz: ... İndikten sonra yürüme süreniz :			Seyahat Süreniz ? / Arabası Olanlar: Araca gidiş süreniz : ..... Araç ile okula varış süreniz : ..... Araçtan indikten sonra yürürken geçen zaman : .... / Arabası Olmayanlar için; Toplu taşımaya gidiş süreniz: .... Durakta bekleme süreniz: .... Araç ile gidiş süreniz: ... İndikten sonra yürüme süreniz : ....
14.	Günlük Toplam Seyahat Masrafınız ?					Günlük Toplam Seyahat Masrafınız ?
15.	Günlük Tahmini Yol mesafeniz (Tek yön) ? (km)					Günlük Tahmini Yol mesafeniz (Tek yön) ? (km)

Figure A.2. Questionnaire 1.



	KİŞİSEL ÖZELLİKLER					Hafta sonu kullanımları için cevaplandırılacaktır.				
1.	Cinsiyet	E ( )			K ( )					
2.	Yaş									
3.	Çalışma Durumu	Öğretim Üyesi ( )	Öğrenci ( )	Memur ( )	İşçi ( )					
4.	Eğitim Seviyesi	İlköğretim ( )		Lise ( )						
		Önlisans ( )		Lisans ( )						
		Lisanstistü ( )		Doktora ( )						
5.	Gelir Düzeyi (Aylık kazancınız /burs ne kadardır- TL)									
6.	Sürücü belgeniz var mı?	Evet ( )			Hayır ( )					
7.	Okula Ne ile geliyorsunuz ?	Özel araç ( )	Toplu Taşıma ( )	Resmi Araç ( )	Yürüme ( )	Servis ( )				
8.	Varsa şahsi aracınızı kullanım sıklığınız nedir?	Günde birkaç kez ( )			Her gün ( )		Hafta sonu hep arabamı kullanırım ( )		Nadiren kullanırım ( )	
		2-3 günde bir kez ( )			Haftada bir kez ( )		Trafik durumuna göre aracımı kullanırım ( )		sık sık kullanırım ( )	
		Ayda bir kez ( )			Sadece haftasonu ( )		Hiçbir zaman kullanmam ( )			
9.	Toplu taşıma araçlarını kullanım sıklığınız nedir? (Kullanmıyorsanız boş bırakınız)	Günde birkaç kez ( )			Her gün ( )		Hafta sonu hep toplu taşıma kullanırım ( )		Nadiren kullanırım ( )	
		2-3 günde bir kez ( )			Haftada bir kez ( )		Trafik durumuna göre tercih yaparım ( )		sık sık kullanırım ( )	
		Ayda bir kez ( )			Yılda birkaç kez ( )		Hiçbir zaman kullanmam ( )			
10.	Günlük seyahatinizde hangi tür toplu taşıma aracını en çok kullanıyorsunuz kullanıyorsunuz?	Otobüs ( )	Metrobüs ( )		Metro ( )		Otobüs ( )	Metrobüs ( )		Metro ( )
		Minibüs ( )	Dolmuş ( )		Vapur ( )		Minibüs ( )	Dolmuş ( )		Vapur ( )
		Tren ( )	Taksi ( )		Diğer ( )		Tren ( )	Taksi ( )		Diğer ( )
11.	Hafta içi bir günde seyahat etme amacınız nedir ?	İşe /okula gidip gelmek ( )	Alışverişe gitmek ( )				İşe / okula gidip gelmek ( )	Alışverişe gitmek ( )		
		Gezmek ( )	Çocuğu okuldan almak ( )				Gezmek ( )	Çocuğu okuldan almak ( )		
		Aile – akraba ziyaretine gitmek ( )	Diğer ( )				Aile – akraba ziyaretine gitmek ( )	Diğer ( )		
12.	Okula Nereden Geldiniz? (Ev – işyeri – otel vb.)	Ev ( )	Yurt ( )	Misafirhane ( )	Diğer ( )		Hafta sonları genel olarak seyahate nereden başlıyorsunuz?	Ev ( )	Yurt ( ) / Misafirhane ( )	Diğer ( )
13.	Seyahat Süreniz ?	Arabası Olanlar: Araca gidiş süreniz : ..... Araç ile okula varış süreniz : ..... Araçtan indikten sonra yürürken geçen zaman :	Arabası Olmayanlar için; Toplu taşımaya gidiş süreniz: .... Durakta bekleme süreniz: .... Araç ile gidiş süreniz: ... İndikten sonra yürüme süreniz :				Seyahat Süreniz ?	Arabası Olanlar: Araca gidiş süreniz : ..... Araç ile okula varış süreniz : ..... Araçtan indikten sonra yürürken geçen zaman :	Arabası Olmayanlar için; Toplu taşımaya gidiş süreniz: .... Durakta bekleme süreniz: .... Araç ile gidiş süreniz: ... İndikten sonra yürüme süreniz :	
14.	Günlük Toplam Seyahat Masrafınız ?						Günlük Toplam Seyahat Masrafınız ?			
15.	Günlük Tahmini Yol mesafeniz (Tek yön) ? (km)						Günlük Tahmini Yol mesafeniz (Tek yön) ? (km)			

Figure A.3. Questionnaire 2.