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# Modeling the effects of real time traffic information on travel behavior: A case study of Istanbul Technical University

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ABSTRACT

This article adds to the literature on the investigation of choice behavior of travelers under the 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. Self-deviced survey of travelers was conducted for the civil engineering undergraduate – graduate students, academicians and supporting staff at Istanbul Technical University, Turkey in 2016. Multinomial logit mode choice model of the decision making for travel and commuter responses to traffic information were estimated separately in two different commute modes, including private cars and public transit. The attributes that influence travelers' decision-making patterns were broadly categorized into three groups, which were socioeconomics, travel and technological characteristics. The analysis of the results indicated that travelers who obtained traffic information from some traffic applications were more likely to switch their route with respect to their different characteristics. Moreover, the travel pattern of the commuters regarding whether to change their choice of route or not varied with respect to their aforementioned characteristics as well as their selection of commute modes. The results of this research could also help to develop vehicular communication systems such as vehicle-to-infrastructure V2I communications.



## 1. Introduction and motivation

Real-time traffic information has a significant impact on the travel patterns of the commuters before and during their trips. Acquiring an update on the traffic can update travelers' perceptions of travel alternatives and affect their choice behavior, either by increasing their awareness about other modes, or changing their view on the characteristics of them (Chorus, Molin, & van Wee, 2006). This may result in the change of the trip generation; thus, the mitigation of traffic congestion (Bonsall, 2001; Golledge, 2002; Kanninen, 1996; Koppelman & Pas, 1980; Wang, Khattak, & Fang, 2009). Many studies emphasize the importance of understanding and modeling the impact of travel information on travelers' decision processes (Arentze, Hofman, & Timmermans, 2004; Sun, Arentze, & Timmermans, 2005). A modeling framework consisting of goal formation, information acquisition, driver information, processing capacity and computational ability, decision rules, reviewing, and actual decision was proposed in order to replicate the behavior of the travelers accurately (Ben-Akiva, de Palma, & Kaysi, 1996). There are also studies in which the impact of various types of information on route switching behavior of travelers are

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inspected (Khattak, Kanafani, & Le Colletter, 1994). Furthermore, the source and timing of the received information is crucial for the traveler and their decision making process.

The biggest impact of traffic information is reflected in route changes and rescheduling of activities (Tsirimpa & Polydoropoulou, 2011). Information received from radio stations, television or telephone can often influence the traveler to change their departure time (Khattak, Yim, & Stalker, 1999). According to Yim and Miller (2000), there is even a bigger ratio of drivers who make the same decision for their departure time as they spend considerable amount of time online. The ratio of drivers who make the same decision increase even further if they are dealing with websites or computers (Yim & Miller, 2000). The travelers who have access to the traffic information before their trip, has the advantage of changing their departure time instead of their route (Shah et al., 2001). For the drivers en route, variable-message signs may cause them to divert from a non-freeway to a freeway rather than vice versa (Hato et al., 1995). This decision making process is affected by their behavioral inertia in response to the advanced traveler information system (ATIS) (Srinivasan & Mahmassani, 2000). While the drivers are making multiple travel plans, the previous experiences of the driver also play a role (Chen et al., 2008). As the technology and the infrastructure is improved, there are more ways to obtain and share the real-time traffic information with the travelers, especially for the ones en route.

With the advancement of data collection techniques, GPS, transit smart cards, mobile phones, and various types of travel trajectory data are increasingly complementing or replacing conventional travel diaries and revealed preference data (Yue et al., 2014). There is also information to support travel decisions which are acquired actively (reading, asking, listening, etc.) or passively (i.e., through experience) which will aid in the long term (auto purchase, etc.) and short term (departure time and route choice, etc.). The fact that the most recent information, essentially the previous trip's travel time, being the most important factor for affecting current decisions, increases the importance of obtaining the most recent information (Chang & Mahmassani, 1988; Lida, Akiyama, & Uchida, 1992). With the introduction of smart phones, a new way of traffic information dissemination is created. This new way of provision has significant advantages over conventional tools, for its ability to be more flexible for travelers in obtaining traffic information. The biggest importance of the introduction of smart phones; however, is the increased availability of real time traffic information. Real time traffic information is much more available with the smart phones, as they become more common and improved in their capabilities. With real time information, people would be able to avoid unexpected severe traffic congestion (Tseng, Knockaert, & Verhoef, 2013). Moreover, with the ATIS, it is possible to reduce travel times, delay, fuel consumption and emission (Adler & Blue, 1998). Yet, for this system to work flawlessly the information needs to be accurate and reliable, otherwise there would be a large economic and environmental loss, especially in the rush hours (Arnott, de Palma, & Lindseyrnott, 1991). Due to the difficulty of applications' providing accurate data, the travelers do not always trust the information they receive. The trust is equally significant as the accuracy and the reliability of the information, in examining the response of travelers whether they actually follow the systems' advice.

A driver's compliance with the provided information depends on the driver's knowledge of the network and the accuracy of information the driver gets (Bonsall, 1992). Accuracy of the ATIS tools have a great influence on people's choice (Khoo & Ong, 2011). The applications for smart phones also provide very important and current information to the drivers. These travel apps can be divided into two categories, the informative apps that provide traffic information to users without route guidance advices and deliver information in the form of traffic images or maps, and the guidance type of traffic applications providing route guidance and advice for avoiding traffic congestion. Top factors that encourage people to use these applications are their ability to deliver real time traffic information in the form of detailed rerouting advice, and/or report on incident and delay estimation. Gokasar and Bakioglu (2016) gathered Google Play Store and App Store reviews under three main titles: accurate/ reliable or not, user friendly or not, and detailed or not. The star rating was taken as a dependent variable. In terms of independent variables, the gender of the reviewer, type of the application (whether it is for public transit or for a private vehicle) and the comment itself were considered. In the section of the article where the data were statistically analyzed, Yandex.Maps was found to be an accurate and a reliable application, due to the positive reviews it received. Moreover, the majority of those reviewers were males. In Gokasar and Bakioglu (2018), some of the traffic applications used in Turkey and around the world are compared. The results showed that Moovit, which is a very commonly used traffic app in Turkey, received many reviews, which mostly centered on its being accurate and reliable. Moreover, the reviews that GPS tracking applications of the cars received reveal that the apps do not give detailed results. Those applications are classified and referred as "Car GPS Tracking" throughout the article.

This research contributes to the literature by focusing on the travelers' response after they receive the information and estimating the relationship between the characteristics of the travelers and their responses through multinomial logit. It aims to analyze the impact of real-time traffic information attained through some traffic applications such as GPS devices, mobile traffic applications, and radio traffic reports on traveler behavior. While achieving the mentioned goal, a multinomial logit model is estimated:

- To analyze the effects of the provision of various types of real-time traffic information acquired by some traffic applications on travelers' behavior,
- To analyze traveler route choice with respect to some different characteristics, namely socioeconomics, travel and technological characteristics.

The main contribution of this paper is introducing more insights over the decision-making process of the individuals after receiving real-time traffic information through some traffic applications while en route.

## 2. Methodological approach

This paper estimates Multinomial Logit Model (MNL) used in the analysis of commuting trip choice under the real time traffic information acquired by various traffic apps. The choice distribution of four travel behaviors under the real-time traffic information for two types of modes, private car users and public transport users, which serves as dependent variable of the choice model and their abbreviations are given as follows:

1. Changes route by means of using traffic apps (CRT),
2. Does not change route in spite of using traffic apps (DCRT),
3. Changing route for the fastest alternative that the traffic app suggested (CRFT),
4. Changing route for the cheapest alternative that the traffic app suggested (CRCT).

Among the driver behaviours, defined as the dependent variable, choosing the fastest route and the cheapest one that the application recommends are added to the model. The fastest route is determined by the time it takes the drivers to reach their destinations. The cheapest route is chosen through the fastest route in order to make the vehicle owners save money on fuel. The public transport users can also find the fastest way through the suggested interchanges and the cheapest way through using single means of transport.

MNL is a classification method that generalizes logit regression to multiclass problems with more than two possible discrete outcomes. What the basis of this analysis is maximization of utility. In the following equations, index $i$ represents the choice whether commuters change their route or not and the index $t$ represents the $t$th individual. $U_{it}$ denotes the utility of commuter $t$ and implies choosing the $i$th choice behavior. The utility of a choice $i$ ($U_{it}$) is comprised of two parts, as indicated in Eq. (1) where $V_{it}$ and $\varepsilon_{it}$ are the deterministic (or observable) and stochastic (or random error) components (Ben-Akiva & Lerman, 1985; McFadden, 1974; Train, 1986):

$$U_{it} = V_{it} + \varepsilon_{it} \tag{1}$$

There are two alternatives in the special case where $C_n$ denotes the choice, which is set as $\{i, j\}$. The probability of a person $t$ choosing $i$ is shown in Eq. (2):

$$P_t(i) = P_r(U_{it} \geqslant U_{jt}) \tag{2}$$

The probability of choosing an alternative $j$ is given in Eq. (3).

$$P_t(j) = 1 - P_t(i) \tag{3}$$

As a result, this mathematical structure, which is led by those assumptions, presents the choice probabilities of each alternative as a function of the systematic portion of the utility of all alternatives. The general expression for the probability of making a choice '$i$' presented in Eq. (4) (Manski, 1981)

$$Pr(i) = \frac{\exp(V_i)}{\sum_{j=1}^{J} \exp(V_j)} \tag{4}$$

## 3. Data collection and descriptive statistics

The survey is conducted in Ayazaga Campus of the Istanbul Technical University, which is located in the Maslak region, the new business and trade center of Istanbul. 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 campus is near the ITU Ayazaga underground metro railway station. As shown in Fig. 1, there are two ways to reach the Faculty of Civil Engineering from the M2 metro line, ITU Ayazaga station. The distance between the metro station and entrance of the Faculty of Civil Engineering is almost 600 m and it takes around 10 min on foot. Therefore, people mostly choose to use the metro for public transit. There are also a number of bus stops near the ITU shown in Fig. 1. This study investigates the level of consciousness, usage, and the impact of real–time traffic information acquisition from some traffic applications. Moreover, it analyzes the relationship between socioeconomics and technological characteristics as well as the travel behavior on highways. A marked questionnaire is distributed to undergraduate and graduate students, academicians and supporting staff of the Civil Engineering Faculty of ITU, Istanbul, in 2016 (Bakioglu, 2016).

The survey included stated preference data, as well as frequency of using traffic applications, variety and content of these apps and motives of individual decision makers with the real–time information.

Individuals were asked about the traffic information acquired in their daily trips, as well as their tendency towards real–time traffic information acquired through some applications. This study focuses on the modeling and analysis of the stated preferences experiment.

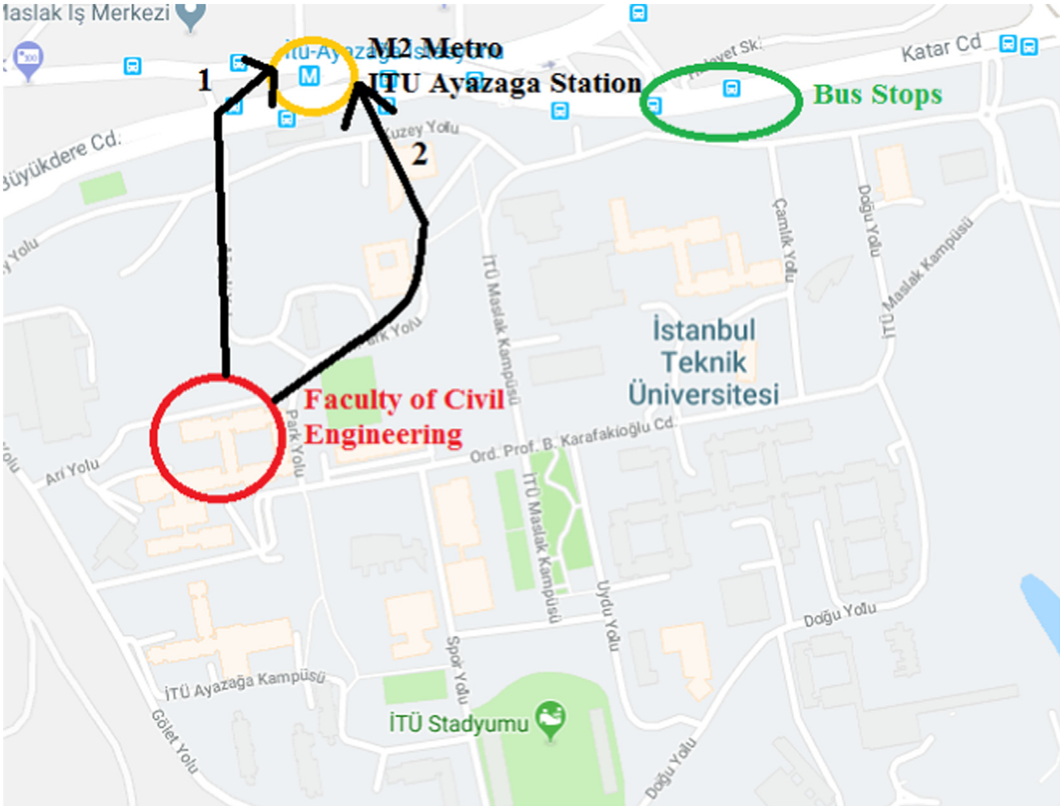


**Fig. 1.** Location of the Civil Engineering Faculty at Ayazaga campus of ITU.

The questionnaire used in this study targets the undergraduate and graduate students, academicians and the staff of the Civil Engineering Faculty building around Ayazaga Campus. Questionnaires were distributed to randomly selected individuals from Civil Engineering Faculty.

In the Civil Engineering Faculty, there are 2884 undergraduate and 330 graduate students and 295 academicians. The sample size was determined to be a total of 360 persons for the 95% confidence level according to Yamane formula (Yamane, 1967) which is used for calculating the sample size with 95% confidence level and P = 0.5 are assumed for the following Equation:

$$\mathrm{n} = \frac{N}{1 + N \cdot e^2}, \tag{5}$$

where n is the sample size, N is the population size, and e is the level of precision.

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 cars 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 are also enquired. The questionnaire also investigates technological characteristics, including most preffered traffic app, frequency, objective and the content of traffic applications. The questions presented in the questionnaire contain the most preferred public transport modes in Turkey such as bus, metrobus, taxi, metro, ferry, private minibus, etc. The most preferred traffic applications such as IMM mobile traffic, Yandex.Maps, Mobiett, Moovit Car GPS navigation, TRAFI, Waze etc. are also listed. Those characteristics are used as explanatory variables in the MNL model.

Multinomial Logit Model is developed using the survey data for two different modes including private car and public transit. 138 (38.3%) respondents of the survey use their private car as commuting trip alternative and the rest of them, 222 (61.7%) respondents, use the public transit for their daily commute.

The answers of respondents in the survey show that average age of the sample is approximately 27 and 72% of the individuals who responded to questionnaire are male.

Survey data show that unlike the private car users (47.8%), almost all the public transit users make several trips per day (85.6%) and respondents use their private cars every second day with the close frequency of using a car several times a day (30.4%). A low frequency (2.7%) of the survey participants commute only once a month.

The following table shows the distribution of the most common traffic application frequencies that respondents use for private car modes and public transit modes. In this respect, respondents' top three traffic apps for getting real – time information about traffic conditions for private car usage are Yandex.Maps (27.5%), IBB Cep Trafik (26.8%), and Car GPS Tracking (9.4%). The top three traffic apps for getting real-time information about public transit are listed as Mobiett (25.2%), Moovit (21.6%), Istanbul Ulaşım (12.6%) and the rest of those are presented in the Table 1.

All traffic applications consist of two categories with respect to their usage area; public transport and private cars. Public transit applications have various features, including information about bus routes, arrival time to the bus station and traffic conditions. The features for private car modes involve giving real – time traffic information about road hazards or traffic jams as well as displaying fastest and cheapest way for the travelers' choice. The types of features of traffic applications for two commute modes, including public transit and private cars are indicated in Tables 2 and 3, respectively.

The characteristics defined in two types of traffic applications are constructed with the most desired characteristics the users search in a traffic application. The aforementioned study conducted in 2016 also grouped the user comments in the categories such as accurate/reliable or not, detailed or not and user friendly or not. The below-mentioned characteristics in the table being present in the app lead to positive comments as well as a higher star rating.

Commuters who drive their car or take public transit use the traffic applications with a different frequency. As shown in Table 4, 57 respondents who use a private car (41.3%) and 79 public transit users (35.6%) prefer the traffic app usage several times a day, while 58 car users (42.0%) and 100 respondents who take public transit (45.0%), use it every second day. It can be briefly understood from the table that male respondents have a high frequency in using both private car and public transit. They are mostly making trips every second day through using their private car and public transit, but females mainly prefer using their car several times per day.

The respondents also replied to questions that determine their trips through various public transport modes. Table 5 presents the distribution of modes that reflect traveler preference frequencies regarding public tranport modes. "Metro" has the highest percentage (45.0%) among the other types of modes and frequencies indicated below.

Most of the car owners in the survey, 54 respondents (39.1%), use those applications for planning their route with respect to traffic conditions. Second top reason (34.1%) for the traffic app usage is to reduce their trip time with the help of using traffic applications. 26.8% of the survey participants acquire the real-time information through the traffic applications for determining route directions. In addition, out of the travelers who use public transit in the survey, 59 respondents (26.6%) use those applications for reducing their travel time. Second top reason is that 58 respondents (26.1%) who pick the public transport modes use the traffic applications in order to decide on the most suitable modes with the help of traffic apps. One fifth of the survey participants acquire the real-time information through as they plan their route with respect to traffic conditions. Similar findings exist in the literature. In Peirce et al.'s study (2004), respondents' top three motivations for seeking information were to anticipate traffic congestion (52%), to be sure of arriving on time (47%), and to get to their destination as fast as possible (34%). One stated-preference survey study in the literature reveals that about 35% of respondents sometimes change their travel plans as a result of an information report (Khattak et al., 1999), while in a study of SmarTraveler users in the Boston area (Lappin et al., 1994), it is found that about 30% changed their travel behavior "frequently" in response to information. However, this study also found that 96% changed their trips "occasionally". In a research conducted in Chicago, it is determined that 85% of motorists stated that they alter their behavior after hearing a traffic report.

The choice distribution of the four travel behavior for users of both private car and public transport modes on freeways as a result of the provision of various types of real – time traffic information is given in Table 6. This variable serves as the dependent variable of the aforementioned choice model. As shown, for private car users, changing route by means of using traffic apps is the most frequently encountered behavior as they obtain real–time traffic information. According to this research, 50 respondents (36.2%) change their route, 23 respondents (16.7%) change their route for the fastest path, while 7.2% of drivers change route for the cheapest path under the traffic information and the rest of the 55 (39.9%) participants of the survey prefer not to change their route in spite of using traffic apps. For public transit users, changing route by means of traffic apps is the most frequently encountered behavior among the respondents. In this research, 153 commuters (68.9%) were found to change their route, while 26 respondents (11.7%) change their route for the fastest path and 7.2% of them were found to change their route for the cheapest path with respect to their acquisition of real – time traffic information. The rest of the survey members prefer not to change their route despite using traffic apps.

**Table 1**
Traffic applications with frequencies.

| Traffic apps for private car users | Frequency | % | Traffic apps for public transit users | Frequency | % |
|---|---|---|---|---|---|
| İBB Cep Trafik | 37 | 26.8 | BiTaksi | 19 | 8.6 |
| Google Maps | 17 | 17.4 | Mobiett | 56 | 25.2 |
| Yandex. Maps | 38 | 27.5 | İstanbul Ulaşım | 28 | 12.6 |
| Car GPS Tracking | 20 | 9.4 | Otobüsüm nerede | 23 | 10.4 |
| KGM Türkiye Trafik | 15 | 10.9 | Moovit | 48 | 21.6 |
| Trafik Rehberi | 11 | 8.0 | Nasıl Giderim? | 22 | 9.9 |
| | | | TRAFI | 26 | 11.7 |
| Total | 138 | 100.0 | | 222 | 100.0 |

**Table 2**
Various features for public transit applications.

| Traffic apps used in Turkey | BiTaksi | Mobiett | İstanbul Ulaşım | Otobüsüm nerede | Moovit | Nasıl Giderim? | TRAFI |
|---|---|---|---|---|---|---|---|
| Istanbul Metropolitan Municipality Istanbul Electric Tramway and Tunnel Establishments (İETT) data | X | √ | √ | √ | √ | √ | √ |
| Getting the information about bus routes and time tables | X | √ | √ | √ | √ | √ | √ |
| Reporting traffic jams, accidents, closures, etc | √ | X | √ | X | √ | X | X |
| Combining all transit options such as bus, metro, ferry and minibus together in a single app and creating the most convenient route | X | √ | √ | X | √ | X | √ |
| Storing the most used lines for quick and easy access | √ | X | X | X | √ | X | X |
| Listing the Istanbulkart charging points near the user's location | X | √ | X | √ | √ | √ | X |

**Table 3**
Various features for private car applications.

| Traffic app features | İBB Cep Trafik | Google Maps | Yandex. Maps | Car GPS tracking | KGM Türkiye Trafik | Trafik Rehberi |
|---|---|---|---|---|---|---|
| Planning routes for traveling on foot, by car, or bike | √ | √ | √ | √ | √ | √ |
| Alerting travelers before approaching police, accidents, road hazards or traffic jams | √ | √ | √ | √ | √ | √ |
| Viewing the details of the destination and quickly accessing the favorite destination through saving it to Favorites | √ | √ | √ | X | X | X |
| Using Internet connection to a GPS navigation system to provide turn-by-turn voice-guided instructions on arriving at a given destination | √ | √ | √ | √ | √ | X |

**Table 4**
Frequency of using traffic applications for private car and public transit users.

| Frequency of using traffic app | Frequency of using traffic app for private car users | | | Frequency of using traffic app for public transit users | | |
|---|---|---|---|---|---|---|
| | Male (%) | Female (%) | Total | Male | Female | Total |
| Several times a day | 37 (64.91%) | 20 (35.09%) | 57 | 60 (75.94%) | 19 (24.06%) | 79 |
| Every second day | 41 (70.69%) | 17 (29.31%) | 58 | 76 (76.77%) | 23 (23.23%) | 99 |
| Once a month | 14 (60.87%) | 9 (39.13%) | 23 | 32 (74.42%) | 11 (25.58%) | 43 |
| Total | 92 (66.67%) | 46 (33.33%) | 138 | 168 (76.02%) | 53 (23.98%) | 221 |

**Table 5**
Preference of public transport modes.

| Types of public transit | Frequency | % |
|---|---|---|
| Bus | 60 | 27 |
| Minibus | 9 | 4.1 |
| Metrobus | 37 | 16.7 |
| Private minibus | 4 | 1.8 |
| Taxi | 1 | 0.5 |
| Metro | 100 | 45 |
| Ferry boat | 7 | 3.2 |
| Others | 4 | 1.8 |
| Total | 222 | 100 |

**Table 6**
Frequency of travelers' behavior under the real – time information.

| | For private car users | | For public transit user | |
|---|---|---|---|---|
| | Frequency | % | Frequency | % |
| Changing route by means of using traffic apps (CRT) | 50 | 36.2 | 153 | 68.9 |
| Changing route for the fastest path that traffic app suggested (CRFT) | 23 | 16.7 | 26 | 11.7 |
| Changing route for the cheapest path that traffic app suggested (CRCT) | 10 | 7.2 | 16 | 7.2 |
| Does not change route in spite of using traffic app (DCRT) | 55 | 39.9 | 27 | 12.2 |
| Total | 138 | 100 | 222 | 100 |

With the help of cross tabulation, some important findings were also obtained. Travelers display different travel behaviors with regard to using various traffic applications. Car drivers who use Yandex.Maps and IMM Mobile Traffic are more likely to change their route when they are recieving information from them. On the other hand, public transit users who use Moovit and TRAFI are more likely to change their route when acquiring information from those apps.

## 4. Model estimation results

In this study, two different commute modes, private car and public transit were analyzed separately. Bicycle or other modes such as walking and motorcycle are found to be insignificant for this model. Because of the fact that there were just four people who chose the bicycle or other modes, accurate outcomes could not be taken from the model. Thus, two common modes, private car and public transit commute modes were modeled. Using multiple transportation modes for public transportation users were also included in the model. 53 public transit users chose more than two transportation modes, while 76 users preferred only two transportation modes for reaching the destination. The remaining 93 out of 222 commuters used only one transportation mode.

The MNL model (Steven, 1996) has been estimated using SPSS Statistics Software, version 23. An advantage of MNL is that both categorical and continuous independent variables can be incorporated as predictors. The presented models were selected on the basis of statistical goodness-of-fit, including likelihood ratio tests, estimated coefficient and significance, wald statistics, the rho-square ($\rho^2$), and adjusted rho-square ($\rho'^2$) statistics.

Explanatory variables that are utilized in the MNL model are; sociodemographic characteristics such as gender, age, occupation and household income level. Travel characteristics can be listed as frequency of using private car and public transit, and total trip time. Moreover, technological characteristics contain most preferred traffic apps, frequency and objective of using those applications.

Tables 7 and 8 present the estimation results of MNL model for private car and public transit, respectively, which includes their wald statistics and significance. Both significant variables and insignificant variables for each category at 95% confidence level were included. Consequently, there exist three utility functions, and the interpretation of estimation results are submitted on a relative basis with respect to the reference mode. In this analysis, "changing route for the cheapest way that traffic app suggested (CRCT)" is selected as the reference mode. It is compared to the other types of travel behavior under the provision of real – time traffic information with other parameters. This is one of the main strengths of MNL—different estimates are computed for all paired groupings of the dependent variable. In other words, different effects of particular variables within each group can be identified.

**Table 7**
Estimation results for private car users.

| Variables | Coefficient (Significance) | Wald statistics |
|---|---|---|
| ***Private car*** | | |
| **Changing route by means of using traffic app** | | |
| Gender (Male) | 0.577 (0.037) | 4.371 |
| Trip time | −0.059 (0.486) | 0.792 |
| Frequency of using Traffic App (Several times a day) | 1.315 (0.010) | 6.328 |
| Objective of using traffic app (Planning for traffic cond.) | 1.151 (0.018) | 6.134 |
| Traffic App (Yandex.Maps) | 1.706 (0.030) | 7.001 |
| Constant | −2.150 (0.077) | 7.12 |
| **Does not change route in spite of using traffic app** | | |
| Income | 0.000 (0.346) | 0.370 |
| Trip Time | 0.067 (0.997) | 0.860 |
| Occupation (Academicians) | −2.450 (0.006) | 8.584 |
| Frequency of using private car (Once a month) | 1.494 (0.024) | 6.883 |
| Traffic App (Car GPS Tracking) | 1.887 (0.033) | 7.551 |
| Constant | 0.113 (0.927) | 0.008 |
| **Changing route for the fastest path that traffic app suggested** | | |
| Occupation (Academicians) | 1.560 (0.040) | 6.584 |
| Frequency of using private car (Several times a day) | 2.528 (0.002) | 9.237 |
| Objective of using traffic app (Reducing travel time) | 1.144 (0.011) | 5.763 |
| Frequency of using Traffic App (Several times a day) | 1.381 (0.012) | 6.747 |
| Constant | −1.366 (0.373) | 5.793 |
| Number of observation | 138 | |
| LL (0) | 916.484 | |
| LL (M) | 758.619 | |
| 2LL | 157.865 | |
| Rho-squared | 0.274 | |

**Table 8**
Estimation results for public transit users.

| Variables | Coefficient (Significance) | Wald statistics |
|---|---|---|
| ***Public transit*** | | |
| **Changing route by means of using traffic app** | | |
| Age | 0.781 (0.033) | 3.887 |
| Income | 0.001 (0.891) | 0.922 |
| Frequency of using public transit (Once a month) | 0.035 (0.005) | 1.927 |
| Purpose of Traffic App Usage (Determining road direction) | 0.284 (0.006) | 2.158 |
| Constant | −1.130 (0.103) | 5.21 |
| **Does not change route in spite of using traffic app** | | |
| Frequency of using Traffic App (Several times a day) | 0.901 (0.013) | 3.945 |
| Traffic App (Moovit) | −1.801 (0.030) | 7.099 |
| Traffic App (TRAFI) | −1.732 (0.022) | 7.915 |
| Transportation Mode (more than two modes) | −0.693 (0.024) | 3.011 |
| Constant | 0.213 (0.927) | 1.088 |
| **Changing route for the fastest path that traffic app suggested** | | |
| Gender (Male) | −1.080 (0.042) | 4.971 |
| Occupation (Student) | −1.134 (0.030) | 6.894 |
| Frequency of using public transit (Every second day) | −1.011 (0.006) | 6.237 |
| Frequency of using Traffic App (Once a month) | 0.381 (0.012) | 3.324 |
| Constant | 1.930 (0.573) | 7.876 |
| Number of observation | 222 | |
| LL (0) | 611.576 | |
| LL (M) | 431.628 | |
| 2LL | 179.948 | |
| Rho-squared | 0.356 | |

The indicators for gender (G), frequency of using public transit/private car (FUP), occupation (O), objective of using traffic app (OUT) and the number of modes used by public transportation users reaching the university (NMP) can be defined as follows:

$$\text{Gender (G)} = \begin{cases} G(1) & \textit{Male} \\ G(2) & \textit{Female} \end{cases}$$

$$\text{Frequency of using public transit/private car (FUP)} = \begin{cases} FUP\ (1) & \textit{Several Times a Day} \\ FUP\ (2) & \textit{Every Second Day} \\ FUP\ (3) & \textit{Once a Month} \end{cases}$$

$$\text{Occupation (O)} = \begin{cases} O\ (1) & \textit{Academician} \\ O\ (2) & \textit{Student} \\ O\ (3) & \textit{Staff} \end{cases}$$

$$\text{Objective of using traffic app (OUT)} \begin{cases} OUT\ (1) & \textit{Reducing Travel Time} \\ OUT\ (2) & \textit{Planning with respect to Traffic Condition} \\ OUT\ (3) & \textit{Determining Road Direction} \end{cases}$$

$$\text{The number of modes used by public transportation users reaching the university (NMP)} = \begin{cases} NMP\ (1)\ \textit{Using 1 mode} \\ NMP\ (2)\ \textit{Using 2 mode} \\ NMP\ (3)\ \textit{Using more than 2 modes} \end{cases}$$

Tables 7 and 8 indicate that the -2LL test is used for comparing improved models with the base model. The calculation of likelihood ratio test is as follows:

$$-2LL = -2 \times (LL_{base} - LL_{improved})$$

where $LL_{base}$ is a null model having only intercept without any constant or coefficients [LL(0)] and $LL_{improved}$ is a market share model having only constants and the highest loglikelihood value [LL(M)].

The pseudo – $R^2$ ($\rho^2$) values for three models also suggest decent models on the basis of goodness-of-fit based on the evaluation by Tabatchnick and Fidell (2007) that propose the translation of a $\rho^2$ value between 0.2 and 0.4.

The negative signs of the values of the estimated alternative specific constants show that there is a tendency towards not to change the route despite using the traffic app, if the respondents know the route. However, the relative magnitude of the estimated constants suggests that travelers are more reluctant to change routes by means of using traffic applications and less reluctant to change route for the fastest path that traffic app suggested.

According to Tables 7 and 8, the following comparative results can be made;

- The ages of the survey participants display different travel patterns in response to the provided traffic information. In the case of public transit users, the significant and positive coefficient of age indicates that the elderly people are more likely to change their route under traffic information by using traffic apps than the younger people. The reason may be that the younger people doubt the information of traffic application or may not rely on that of information and check a different platform. Contrary to Abdel-Aty, Kitamura, and Jovanis's findings (1997), age does affect route diversion in this study.
- According to Table 7, for private car modes, gender has a significant and positive effect on the travel behavior of changing route with using traffic applications compared with behavior of the changing route for the cheapest way that the application suggested. In a broad sense, males are more likely to switch their travel patterns when they use the traffic applications. Similar findings have been supported by some researchers. Caplice and Mahmassani (1992) asserted that females are more reluctant to alter routes while Abdel-Aty et al. (1997) found that males are more risk prone and willing to change their route. On the other hand, unlike the car drivers, males who use public transportation are less willing to change their routes for the fastest path when they use the traffic applications.
- Occupation of the individuals reveals another important finding. For car users, academicians have the significant and negative effect on not changing their route under the real time information, while having positive effect on changing their route for the fastest path. The estimation results show that academicians who use private cars are less likely to change not their route as well as more likely to switch their route in order to reach the destination in a short time. These findings are consistent with those from other surveys presented in the literature. Abdel-Aty et al. (1997) developed the probit models that people with high incomes and education levels use traffic information more often with higher rates of switching. On the other hand, for public transit users, students acquire traffic information from traffic applications yet do not change their routes for the fastest path.
- Another important finding is related to the frequency of private car usage that has different implications for two travel modes. Unlike using public transit, travelers who use private cars several times a day are more likely to shift their route for the fastest path through the real-time information they recieve. In addition, travelers who use private car once a month are reluctant to change their routes with respect to traffic information. Chen et al. (2008) claimed that drivers' tendency of diversion increases with the driving experience and Spyridakis, Barfield, Conquest, Haselkorn, and Isakson (1991) asserted that drivers are more likely to divert to known routes compared to unknown routes. For public transportation users, who use it once a month are more likely to switch their route under the traffic information, while public transit users in every second day are not willing to find the fastest path through traffic applications.
- The estimation results show that the positive signed alternative specific constant associated with frequency of usage indicates that car drivers are more likely to change their route when they use the traffic application several times a day. What is more, respondents who use their car are also more likely to change their route for the fastest path when using traffic application several times a day. For the public transit users, travelers who use the traffic application likewise are not willing to change their route. However, they may use the fastest path suggested when using the app once a month.
- The purpose of usage is significant for making a decision about changing the route by means of traffic applications. In terms of private car users, respondents of the survey use the traffic applications with the purpose of having alternative routes depending on the traffic condition and change their routes with respect to the traffic information they recieve. In addition, drivers using the traffic apps for the objective of reducing travel time may try to find the fastest path by means of using apps. From the perspective of public transit users, travelers whose purpose of using traffic app is to determine road direction are more likely to switch their route under the travel information.
- Public transit users can change their transportation modes more than one time. Number of using multiple transportation modes may affect the travel behavior. In this model, travelers who use more than two transportation modes for reaching destination are not willing to change their route in spite of using traffic apps. Namely, those people may change their route with the received information while en route.
- Traffic applications that travelers use reveals another substantial finding. The positive value of the estimated coefficient associated with type of traffic applications demonstrate that car drivers ignore the traffic information coming from Car GPS Tracking and do not change their route in spite of taking some information, while the car drivers can change their route as a result of taking traffic information from Yandex.Maps. On the other hand, public transit users may rely on information of some traffic applications such as Moovit and TRAFI for changing their route. When comparing that of two applications with respect to magnitude of coefficient, Moovit may be used more than TRAFI for changing routes for the public transit users, while Yandex.Maps is the most preferable traffic application for the travelers who use their private car.
- The estimation results for the daily household income are generally insignificant. All the coefficients for different travel behavior are zero. It means that daily household income does not effect on the choice of decision making for travel with two commute modes. According to Abdel-Aty et al. (1997) drivers' income do not affect route diversion.

- Travel time can change with respect to different travel patterns regarding provided traffic information. In the case of car users, changing their travel pattern in response to obtaining real – time traffic information has just the insignificant and negative estimated coefficient associated with travel time. It demonstrates that travelers are less likely to make a decision about travel concerning changing routes by means of using traffic applications compared with the behavior of the using types of public transport for the fastest path that traffic applications suggested. However, the estimation results also show that as the trip time increases, travelers are more likely not to change their route even though using traffic apps. Abdel-aty et al. (1997) claimed that travel time is not a dominant in route choice criterion.

## 5. Limitations of the study

This research aims to present decision makers for travel among the people from the Civil Engineering Faculty of Istanbul Technical University, who behave differently while obtaining traffic information from some traffic applications in their daily trip. That is why the research is constrained with location, namely, survey participants include students from undergraduate to graduate levels, academicians and supporting staff of the Civil Engineering Faculty. The second constraint is that respondents are required to have used the traffic applications, either by having them on their mobile devices or GPS navigation devices as the research analyzed how real–time information acquisition during the daily tour affects the attitudes of respondents. In addition, from the questionnaire conducted in this research, some data are eliminated in the analysis as some of them did not use traffic applications in their daily trips.

## 6. Conclusion

This study examines travelers' route choice behavior in response to real time traffic information within the frame of different characteristics including socioeconomics, travel and technology. In this study, the effects of real-time traffic information obtained from some traffic applications on travelers' behavior are analyzed through the survey data, which are collected from both graduate and undergraduate students, academicians, and staff of the Civil Engineering Faculty of Istanbul Technical University. Multinomial logit model (MNL) is developed in order to predict a nominal dependent variable given one or more independent variables.

The model contains six factors; gender, occupation, income, car usage frequency, usage frequency and the objective of traffic application usage and trip time. In addition, the traffic applications that are used in Turkey and the most popular traffic applications in the world are analyzed through developed logit models for two commute modes. Moreover, the associated tests are also employed to understand how the typical value of the dependent variable changes are when any one of the independent variables vary, while the other independent variables are held fixed.

Multinomial Logit (MNL) Model was proposed with four travel behavior; Changing route by means of using traffic applications, does not change route in spite of using traffic apps, changing route for the fastest path that app suggested, changing route for the cheapest path that app suggested. Regarding the factors that influences the decisions just mentioned, it appears that both travel characteristics such as car usage frequency and technological characteristics, the type, usage frequency and the usage purpose of the traffic applications, significantly affect individuals' travel behavior. These findings are consistent with findings from various surveys presented in the literature (Abdel-aty et al., 1997; Al-Deek, Chandra, & Flick, 2009; Han, Timmermans, Dellaert, & van Raaij, 2008; Mahmassani & Liu, 1999).

According to the significant findings from the estimated model, the increase in the male travelers cause the frequency of private car usage to increase. Moreover, the increase in using traffic applications for a purpose such as route planning and reducing travel time, increase the likelihood of changing routes compared to the behavior of the public transport users who use a traffic application for changing their direction. Tsirimpa (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. Also, the academicians are more likely to change their route when using traffic apps which suggests a relation between the level of education and likeliness to change one's route according to real-time traffic information. Provision of various types of real-time traffic information acquired by some traffic applications affect each individual's travel pattern in a different way. The usage frequency is statistically important for each travel behavior that presents similar results to the findings of Van Bladel, Bellemans, Janssens, and Wets (2009), who claims that travel characteristics (such as tour purpose, selected tour mode) affect travel behavior.

This research aims to provide additional insight on the role of behaviors toward the acquisition of traffic information. The model developed can be used to predict the route changes that take place in the daily life in terms of travelers' aforementioned characteristics. The study can be useful for suggestion of choice dependent technology to decision makers through using travel behavior under real-time information. The current technology depends on in-vehicle driver behavior and wireless communications. For instance, due to the advances in information technology, vehicle-to-infrastructure V2I communications have the ability to "connect" to travelers in a way that was never possible before. In the system, the infrastructure plays a coordination role by gathering global or local information on traffic and road conditions and then suggesting or imposing certain behaviors on a group of vehicles. In this respect, smartphone sensing capabilities such as travel pattern of travelers regarding whether to change their choice or route or not under the real-time traffic information acquired by smartphones gain importance for developing those new technologies. The understanding of characteristics affecting drivers' route choice behavior will also assist the traffic app developers to develop their apps in the future for greater impact. As the results of the model suggest, females, younger and highly educated individuals use more traffic apps than other ones, so some features such as color, shape, detailed map commonly used by those group should be added to apps and advertisement of the apps should be prepared for those target groups. Satisfaction and complaints of those groups must be taken into account to develop the apps in coming decades.

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 samples.
- Scenario analysis can be investigated by manipulating some relevant variables and predictions can be made under particular changes in the system.
- Some explanatory variables related to traffic condition including unexpected time delay, congestion, road hazard/closures, and speed restrictions can be added.
- Real–time traffic information based predictors such as willingness to acquire traffic information, response to ATIS can be analysed.

## Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.trf.2018.07.013.

## References


Abdel-Aty, M. A., Kitamura, R., & Jovanis, P. P. (1997). Using stated preference data for studying the effect of advanced traffic information on drivers' route choice. *Transportation Research Part C, 5*(1), 39–50.
Adler, J. L., & Blue, V. J. (1998). Toward the design of intelligent traveler information systems. *Transportation Research C, 6*, 157–172.
Al-Deek, H., Chandra, R. S., & Flick, J. (2009). The impact of dynamic message signs on satisfaction and diversion of toll road travelers. *Journal of the Transportation Research Board (TRB)*, 1–13.
Arentze, T., Hofman, F., & Timmermans, H. (2004). Predicting multi-faceted activity-travel adjustment strategies in response to possible congestion pricing scenarios using an Internet-based stated adaptation experiment. *Transport Policy, 11*, 31–41.
Arnott, R., de Palma, A., & Lindsey, R. (1991). Does providing information to drivers reduce traffic congestion? *Transportation Research A, 25A*(5), 309–318.
Bakioglu, G. (2016). *Effect of traffic application on travel behavior*. Bogazici University [M.S. Thesis].
Ben-Akiva, M., de Palma, A., & Kaysi, I. (1996). The impact of predictive information on guidance efficiency: An analytical approach. In L. Bianco & P. Toth (Eds.), *Advanced methods in transportation analysis* (pp. 413–432). Springer-Verlag.
Ben-Akiva, M., & Lerman, S. R. (1985). *Discrete choice analysis: Theory and applications to travel demand*. Cambridge, MA: MIT Press.
Bonsall, P. (2001). Predicting travelers' response to uncertainty. In D. A. Hensher (Ed.), *Travel behavior research: The leading edge. Pergamon, Amsterdam*. .
Bonsall, P. (1992). Research methods for the study of driver response to in-vehicle and roadside guidance methods. In Selected Proceedings of the 6th World Conference on Transport Research, Lyon (pp. 2519–2530).
Caplice, C., & Mahmassani, H. S. (1992). Aspects of commuting behavior: Preferred arrival time, use of information and switching propensity. *Transportation Research Part A, 26*, 409–418.
Chang, G. L., & Mahmassani, H. S. (1988). Travel time prediction and departure time adjustment behavior Dynamics in a traffic system. *Transportation Research, 22B*, 217–232.
Chen, S., Liu, M., Gao, L., Meng, C., Li, W., & Zheng, J. (2008). Effects of variable message signs (VMS) for improving congestion. In *Proceedings of International Workshop on Modelling, Simulation and Optimization* (pp. 416–419).
Chorus, C. G., Molin, E. J. E., & van Wee, G. P. (2006). Use and effects of advanced traveller information services (ATIS): A review of the literature. *Transport Reviews, 26*(2), 127–149.
Gökaşar, I., & Bakioğlu, G. (2018). The role of gender in evaluating the traffic apps: In Turkey and the World. Technical Journal of Turkish Chamber of Civil Engineers [in preparation].
Gökaşar, I., & Bakioğlu, G. (2016). the effect of user comments on traffic application usage. *International Journal of Civil, Environmental, Structural, Construction and Architectural Engineering: Urban and Civil Engineering, 10*(11), 1352–1359.
Golledge, R. G. (2002). Dynamics and ITS: Behavioural response to information available from ATIS. In H. S. Mahmassani (Ed.), *In perpetual motion: Travel behavior research opportunities and application challenges. Pergamon, Amsterdam*. .
Han, Q., Timmermans, H., Dellaert, B. G. C., & van Raaij, F. (2008). Route choice under uncertainty: Effects of recommendation. *Transportation Research Record*, 72–80.
Hato, E. et al (1995). Influence of traffic information on drivers' route choice. In *Proceedings of the 7th World Conference on Transportation Research, Sydney, Australia* (pp. 27–40).
Kanninen, B. (1996). Intelligent transportation systems: An economic and environmental policy assessment. *Transportation Research, 30A*, 1–10.
Khattak, A., Yim, Y., & Stalker, L. (1999). Does travel information influence commuter and non-commuter behavior? Results from the San Francisco Bay area TravInfo project. *Transportation Research Record, 1694*, 48–58.
Khattak, A., Kanafani, A., & Le Colletter, E. (1994). Stated and reported route diversion behavior: implications on the benefits of ATIS. In Preprint No. 940394, Transportation Research Board, 73rd Annual Meeting, Washmgton, D.C.
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 Research Record: Journal of the Transportation Research Board* (2239), 101–111.
Koppelman, F. S., & Pas, E. I. (1980). Travel choice behavior: Models of perceptions, feelings, preference, and choice. *Transportation Research Record, 765*, 26–33.
Lappin, J. et al (1994). *A market analysis of the commercial traffic information business. Report for the Office of Policy Development*. Federal Highway Administration.
Lida, Y., Akiyama, T., & Uchida, T. (1992). Experimental analysis of dynamic route choice behavior. *Transportation Research B, 26*, 17–32.
Mahmassani, H., & Liu, Y. (1999). Dynamics of commuting decision behavior under advanced traveler information systems. *Transportation Research Part C, 7*, 91–107.
Manski, C. F. (1981). Structural models for discrete data: The analysis of discrete choice. *Social Methodology, 11*, 58–109.

McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. In P. Zarembka (Ed.), *Frontiers in Economics* (pp. 105–142). New York: Academic.

Shah, V. P. et al (2001). Time management impacts of pre-trip ATIS: Findings from a Washington, DC case study. *Transportation Research Board 80th Annual Meeting*.

Spyridakis, J., Barfield, W., Conquest, L., Haselkorn, M., & Isakson, C. (1991). Surveying commuter behavior: Designing motorists information systems. *Transportation Research Part A, 25*, 17–30.

Srinivasan, K., & Mahmassani, H. S. (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* (3rd ed.). Hillsdale, NJ: Erlbaum.

Sun, Z., Arentze, T. A., & Timmermans, H. J. P. (2005). *Modeling the impact of Systems*. Aldershot: Ashgate.

Tabatchnick, B. G., & Fidell, L. S. (2007). *Using multivariate statistics* (5th ed.). Boston: Pearson Education.

Train, K. (1986). *Qualitative choice analysis: Theory, econometrics and an application to automobile demand*. Cambridge, MA: MIT Press.

Tseng, Y.-Y., Knockaert, J., & Verhoef, E. T. (2013). A revealed preference study of behavioural impacts of real-time traffic information. *Transportation Research Part C, 30*, 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, 19*, 125–133. https://doi.org/10.1080/15472450.2015.1012865.

Tsirimpa, A., & Polydoropoulou, A. (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, 5*(2). https://doi.org/10.4018/ijoris.2014040101.

Van Bladel, K., Bellemans, T., Janssens, D., & Wets, G. (2009). Activity travel planning and rescheduling behavior: Empirical analysis of influencing factors. *Transportation Research Record, Washington, D.C., 2134*, 135–142.

Wang, X., Khattak, A.J., Fan, Y. (2009). Role of dynamic information in supporting changes in travel behavior two-stage process of travel decision in transportation research record: Journal of the Transportation Research Board, No. 2138 Transportation Research Board of the National Academies, Washington, D.C., pp. 85–93.

Yamane, T. (1967). *Statistics, an introductory analysis* (2nd ed.). New York: Harper and Row.

Yim, Y. B., & Miller, M. A. (2000). *Evaluation of the travinfo field operational test. California PATH Program*. Berkeley: Institute of Transportation Studies, University of California.

Yue, Y., Lan, T., Yeh, A. G. O., & Li, Q.-Q. (2014). Zooming into individuals to understand the collective: A review of trajectory-based travel behaviour studies. *Travel Behaviour and Society, 1*(2), 69–78.