Bus passenger path choices after consulting ubiquitous real-time information

Abstract

Ubiquitous real-time passenger information (URTPI) enables public transport (PT) users to make better travel choices at both pre-trip and en-route stages. A significant amount of URTPI usage is evident in the existing literature. This study investigates the impact of URTPI on bus passenger path choice. To this end, a bus passenger survey was conducted in the City of Edinburgh, UK, and a total of 1645 completed responses were collected. More than half of the survey participants used at least one source of ubiquitous information. The survey results reveal that about 55% of the URTPI users changed at least one aspect of their trip. Changing the time of departure from the start and boarding time are the two most popular actions taken by bus passengers after consulting URTPI. Passengers' decisions are influenced by information on bus arrival time, bus route, and walking distance. The study demonstrates the potential impact of the change in passenger choices on PT demand distribution. We find that the demand distribution for bus runs could potentially be changed by 17% and for bus lines by 15%. The overall network demand distribution could be affected in 42% of cases as a result of consulting URTPI. This study advocates that transport planners and operators should take the potential impact of URTPI into account to make better predictions of PT demand distribution.

Keywords: Ubiquitous real-time information, travel behaviour, path choice, PT demand distribution

1. Introduction

Passenger information plays an important role for intelligent mobility. Since the introduction of public transport (PT), travel information assists passengers to plan and execute their journeys. From printed timetables to recent smart-phone based information, travel information has evolved over time and technological advancement has now made real-time information available to passengers. Real-time information is characterised by continuous data updating in response to real-world events. It may include both predictions about departure and arrival times depending on network or service condition, as well as information about the nature and causes of disruptions. The information is updated in a very short span of time, for example Citymapper (2016) updates information every minute. In the context of PT systems, real-time information can refer to the remaining time until the arrival of the next vehicle, to service disruptions, to crowding conditions (Cats et al., 2012). This information is based on real-time data where any disruptions or changes are taken into account.

Over the past decades, the provision of information for PT has become ubiquitous (Schweiger, 2011). Ubiquitous real-time passenger information (URTPI) allows access to PT passenger information from anywhere at any time. URTPI is now widely consulted by the PT passengers. A well-developed PT system requires the state-of-the-art information system, because it makes the existing users more willing to use PT for their trips (Sweeney, 2012). Passengers are enabled to make choices before and during the trip as a result of consulting information. Therefore, information might have an impact on their choices potentially influencing the demand distribution over the network. Previous studies demonstrate that an increasing number of methods of access to different information sources is associated with a higher likelihood of changing travel decisions (change route, time, or mode, or cancel a trip) and internet-based information is associated with the highest propensity of changing any aspects of trips (Khattak et al., 2008).

Research studies have been mostly dedicated to driver behaviour under the influence of real-time information. The use of state-of-the-art PT information has been neglected in the existing literature. Therefore, our knowledge is limited and fragmented when it comes to understanding the impact of URTPI on passenger choices and their consequential impact on PT demand distribution. In particular, the impact of URTPI on passenger choices in an urban network and under regular PT service condition has not been studied. This study fills the gap by investigating the impact of URTPI on passenger path choice in a well-established PT network. We considered an urban bus network under regular network conditions for this investigation. Revealed Preference (RP) data was collected by means of an intercept survey within the bus passengers. Statistical analyses were conducted to assess the impact of URTPI. This study presents statistically significant evidence of the impact of information on passenger choices. It is observed that PT passenger path choice is influenced by trip characteristics, trip planning objectives and the importance of contents of information. On the other hand, adjustment of time after consulting information is dominated by demographics of participants. This study contributes to the understanding of the impact of information on decision-making and a better prediction of the demand distribution as a result of URTPI.

2. Impact of real-time information

Travel information is crucial for planning and executing a seamless journey especially in the case when a chosen mode does not offer door to door services such as travel by PT. Having access to information regarding the trip, travellers are expected to make better travel choices potentially leading to an efficient demand distribution over the network (Balakrishna et al., 2005; Gan et al., 2006). From transport planners and researchers' point of view, travel information is typically acknowledged as an effective travel demand management measure (Khattak et al., 1996; Polydoropoulou and Ben-Akiva, 1998; Abdel-Aty and Abdalla, 2004). Travel information impacts traveller choices with regard to mode, route and time adjustment (Mahmassani and Srinivasan, 2004; Lyons et al., 2007; Zhang et al., 2008; Frei and Gan, 2015; van Essen et al., 2016). Based on the existing literature, the impact of travel information can be broadly categorised into the following groups:

- Impact on traveller experience, i.e. reduction in effort and stress for planning, waiting time, etc.;
- Impact on mode choice and PT patronage;
- Impact on path choice.

Evidence of the necessity and popularity of PT passenger information are presented by Farag and Lyons (2008). The authors find that typically passengers do not intend to travel by PT without consulting pre-trip information. However, they might be indifferent in consulting information if the journey is not time sensitive, or PT services are considerably frequent. From passengers' point of view, real-time information provides additional benefits when travelling by PT. Impact of real-time passenger information (RTPI) may vary with the type of information provision. Location-specific RTPI (such as bus stop displays) limits user access to information before the trip which leads to limited choices associated with a trip. Reduction in perceived waiting time and uncertainty, and ease of use have been studied by Dziekan and Vermeulen (2006); Dziekan and Kottenhoff (2007) in the contxet of bus stop displays. At stop information displays are found to affect train passengers' route choice and a significant change in demand distribution is observed in a modelling study by Gentile et al. (2005). However, the latter author considered travel time reduction as the main objective of the passengers, which may not be valid in all cases, especially for bus passengers (Fonzone, 2015). URTPI offers a higher degree of freedom in terms of passenger choices. Therefore, the impact of URTPI is much diverse than location-specific real-time information. Passenger benefits gained by using URTPI with regard to waiting time (Watkins et al., 2011; Chen, 2012), as well as improvement in perceived image of PT services (Monzon et al., 2013) justifies the provision of URTPI.

Studies of the impact of URTPI are found to be limited to passenger experience and ridership. Watkins et al. (2011) found reduced actual waiting time experienced by the URTPI users. Similar results are also found by Brakewood et al. (2014) in a study within the bus passerngers in Tampa, USA. For a well developed PT service, an increase in ridership was observed as a result of real-time information provision (Tang and Thakuriah, 2012; Brakewood and Watkins, 2015). This ridership gain can be achieved as a result of the psychological effects of real-time information on passenger behaviour (Tang and Thakuriah, 2011). Nevertheless, an increase in PT ridership does not indicate a modal shift due to the provision of URTPI. It may be a result of the additional trips made by the existing bus passengers after consulting URTPI. Bus passengers in Seattle were observed to make more trips on weekly basis after consulting URTPI in subsequent studies by Ferris et al. (2010, 2011). Both the latter studies present a self-reported survey and observe a higher satisfaction with PT use among the URTPI users and an increase in number of non-commute trips made by them. Additionally, the impact of information on ridership is also subjected to other PT service-related factors such as accessibility, frequency, etc.

Route choice is one of the important aspects of traveller's decision-making. Researchers have been investigating how traveller choices are influenced in the context of journeys made by both car drivers and PT passengers. Car drivers are offered with more flexibility and options to make route choices compared to PT users. Since the introduction of travel information, a considerable number of studies on its impact has been dedicated to car drivers' route choice (such as Khattak et al., 1993; Emmerink et al., 1996; Abdel-Aty et al., 1997; Lotan, 1997; Wardman et al., 1997; Chen and Mahmassani, 1999; Hato et al., 1999; Srinivasan and Mahmassani, 2000; Dia, 2002; Chatterjee and Mcdonald, 2004; Mahmassani and Srinivasan, 2004; Tsirimpa et al., 2005; Buscema et al., 2009; Wang et al., 2009; Kattan et al., 2010; Lu et al., 2011; Tian et al., 2011; Ramos et al., 2012; Ben-Elia et al., 2013; Tseng et al., 2013; Ma et al., 2014; Venkatraman et al., 2014; Tsirimpa, 2015; van Essen et al., 2016). Existing literature on the impact of PT passenger information on path choice is still limited.

As URTPI offers pre-trip and en-route choices, potential impact on passenger choices such as route choice, time adjustment are also anticipated. Fonzone (2015) finds that passenger information influence all the choices of four step model, however, route choice is the most influenced one. Maréchal (2016a) studied the acquisition of information from multiple sources and travellers responses of commuters to the information under disruptions. The latter study found no impact of demographics on travel responses. Travel responses are rather influenced by trip characteristics. None of the studies paid attention to the impact that information has on passenger choices in regular service conditions. Regular PT service condition refers to the condition where the consultation of URTPI is not dominated by the service conditions (e.g. disruption). Passengers, however, might consider disruption or delay when making travel choices.

Simulation studies have been dedicated to assessing the impact of information on a PT network. A network simulation study by Cats and Jenelius (2014) finds a negative impact of URTPI during disruptions for some scenarios of a PT network in Stockholm, Sweden. The authors conclude that customization of information depending on the local conditions is required to benefit from real-time information. Another study by Cats et al. (2011) investigated train passengers' route choice with a mesoscopic transit and traffic simulation model. The model shows that comprehensive provision of real-time information might lead to route choice shifts and time-savings. Cats et al. (2012) also present the potential impact of real-time information on passenger load in PT lines due to the change in passenger choices (i.e. route choice, boarding time). Simulation by the latter authors reveal that real-time information provision may lead to a fluctuation in distribution of passenger load compared to the baseline (no real-time information) scenario. However, these studies have been carried out only in a simulation environment and do not explain passengers' actual choices after consulting URTPI. To quantify the impact of URTPI on PT demand distribution, it is very important to understand the impact of information on passenger choices, particularly on path choice.

The literature review identifies the fragmented knowledge of the impact of URTPI on passenger path choice. This study minimises the knowledge gap by investigating bus passenger path choices under the influence of URTPI.

3. Research methodology

PT passenger choices can be described by the path representing their journey in diachronic graphs, In such graphs, nodes (corresponding to entry and exit points or stops) and links (corresponding to waits, walks, or specific runs of a line) are defined by spatial and temporal coordinates. For more information, see Nuzzolo et al. (2001). In this study, we consider both the temporal and spatial dimensions of passenger paths in a diachronic graphs. The temporal dimension of path choice for a trip concerns time of departure from start and time of boarding bus. Departure and alighting stop, and bus line are the choice elements that belong to the spatial dimension of path choice. Hence, the following path choice elements are investigated to understand how passenger path choice is influenced after consulting URTPI.

- Time of departure from start
- Boarding time
- Departure bus stop
- Alighting bus stop
- Bus route/line

3.1. Case Study

The area of study for this research is Edinburgh, the capital city of Scotland (UK). Edinburgh has a population of 507,000 (Edinburgh City Council, 2017). 70% of the city population are of working age (16-64) and 51.3% are female. The city has the lowest unemployment rate (4.4%) among all the UK cities and annual earnings (median) per resident of £29.5k. It has a well-developed and largely used public transport system comprising bus and tram. Tram offers services to limited destinations. Edinburgh bus network has a hub and spoke structure (Figure 1).

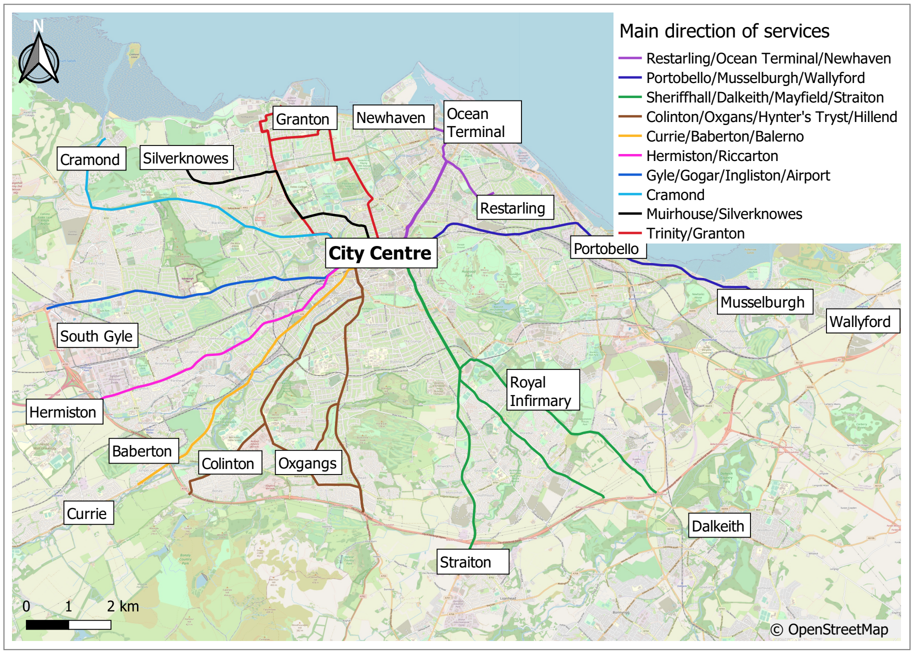

Figure 1: Direction of main services to and from Edinburgh City Centre

Lothian buses is the main transit option available to the passengers, which operates 70 services in the city with a fleet of around 800 vehicles. On an average 0.35 million passenger journeys per day were made by Lothian buses in 2014 (Transport for Edinburgh, 2014). 40% of the households do not own a car and 18.5% people use bus as their main mode of transport (Edinburgh City Council, 2017). Therefore, PT plays a key role to ensure mobility within the city and evolve towards sustainable mobility. Several ubiquitous sources of information are available for bus passengers including mobile bus tracker (descriptive), and journey planner (descriptive and prescriptive). Descriptive information refers to an account of the current or predicted conditions of network and services, such as arrival time of next bus, service disruptions, etc. Prescriptive information refers to the advice or alternatives suggested to the passengers based on computerised elaboration of descriptive information. For examples providing alternative routes based on travel time or number of transfers, etc.

3.2. Data Collection Method

RP data has been widely used to study traveller behaviour. The nature of data collection and real-world validity of the RP data has boosted their popularity and use in empirical research on travel information (see examples- Chen and Mahmassani, 1999; Jou, 2001; Peirce and Lappin, 2004; Tsirimpa et al., 2005; Chorus et al., 2007; Ferris et al., 2010; Politis et al., 2010; Ferris et al., 2011; Chorus et al., 2013; Kattan et al., 2013; Tseng et al., 2013; Veiga Simão, 2014; Brakewood et al., 2015; Tsirimpa, 2015; Zhang et al., 2015; Maréchal, 2016b; Ge et al., 2017).

A RP survey methodology was adopted in this study and a questionnaire survey was conducted at the bus stops in Edinburgh. We collected data on passengers' actual choices regarding the use of URTPI when they were making a trip, which minimises the recall bias (Bowling, 2005). An intercept survey can be associated with certain biases, such as length bias (Nowell and Stanley, 1991). The bus stop survey required between 3 and 4 minutes to be completed; therefore, passenger's participation was dependent on the arrival at the stops before the bus arrives. Therefore, we may have missed passengers who arrive at the stops close to the arrival of their bus. This is a limitation of this study.

The questionnaire design was inspired by the Theory of Planned Behaviour (TPB) that identifies norms and attitudes as determinants of choices (Ajzen, 1985). We assume that norms and attitudes are influenced by the characteristics of the decision maker and the context of choice. Combining the existing literature on real-time time information and TPB, we designed the questionnaire to collect data on the information passengers used, the choices they made, and several demographic variables and trip characteristics. Other potential influencing factors related to passengers' trip planning objectives such as reducing journey time, arrival time at destination, etc. were identified. Trips were characterised by perceived trip length and purpose, time of day, familiarity with the trip, availability of other modes and PT services for the trip. Participants were asked if they had made any changes in any of the choice elements after consulting URTPI. Socio-demographics were characterised by participants' age, profession, gender, level of education and residents. The final questionnaire was comprised of 17 questions.

The bus stops were selected considering several characteristics. The selected stops serve multiple bus lines and equipped with non-URTPI information sources (such as bus stop displays, printed maps and timetables). Bus stops with high demand were chosen so that the sample is large enough and contains mixed participants. To cover both direction of travel, bus stops on both sides of the road for each location were surveyed. The location of the fifteen surveyed bus stops are shown in Figure 2.

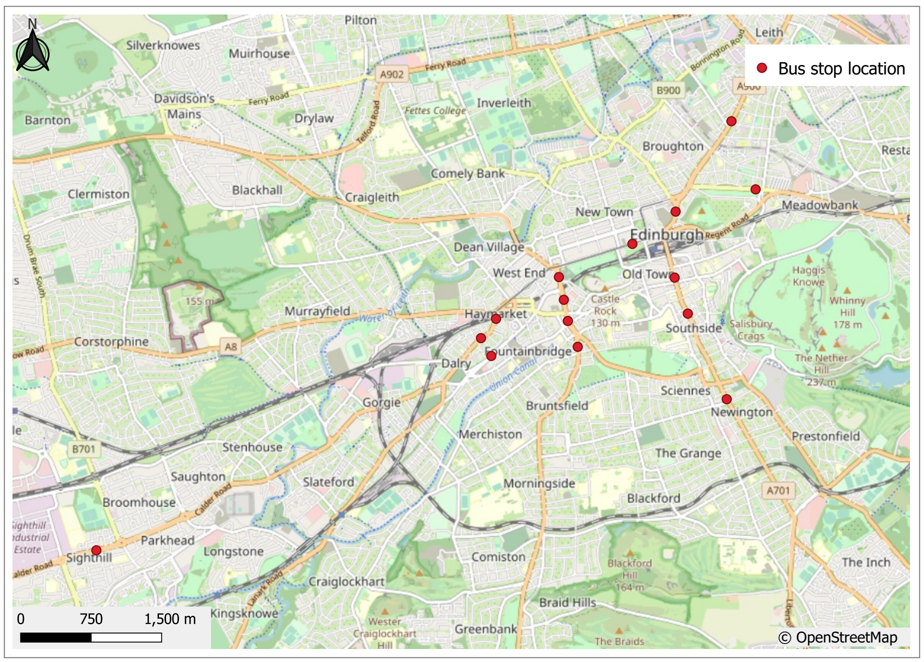

Figure 2: Location of the surveyed bus stops

The final survey took place for nine consecutive days from 4th July to 12th July 2016 including both weekdays and weekends. No special events were going on at that time; however, the summer break for schools had begun. The bus stop survey would not have been affected much due the beginning of school holidays, as the survey participants were at least 18 or older, although the city may have had slightly smaller numbers of regular PT passengers due to the holidays.

The data was collected during morning (07.30-10.30) and evening (16.00-18.00) peak hours and off-peak (11.00-13.00) hours around noon. The morning, evening and midday survey consist 37%, 34% and 29% of the responses respectively. The data collection at peak and off-peak may limit the study results for PT users at other times of the day such as night. Information for making trips at night may prove to be important to the users. The questionnaire was uploaded on a survey platform ("Questionpro") and carried out with android tablets. A total of 1645 responses were collected (with a completion rate of 93%). An analysis of the survey data discussing the sample representativenes and the use of URTPI is presented in Islam et al. (2019). The sample was found representative of Edinburgh bus passengers, hence no weighting is applied to the variables regarding demographics for model development.

3.3. Data Analysis

Our analysis aims to evaluate the influence of different potential predictors on the decision to change travel choices after retrieving real-time information. We have a mix of numerical and categorical variables, with a prevalence of the latter. Therefore, we perform a CATREG analysis. CATREG is a non-parametric method for multiple regression that, as such, allows to compute indicators representing the importance of the explaining factors and can deal with variables of any type. The method is based on non-linear transformations – or quantifications – of the variables which preserve the information included in the original variables that the modeller decides to retain, e.g. the order of categories in ordinal variables. Different kinds of transformation are available: nominal, nonmonotonic spline, ordinal, monotonic spline or numerical. CATREG applies scaling and simultaneously calculates the regression coefficients by solving the following minimisation problem:

$$min\left\| \boldsymbol{C}_r \boldsymbol{q}_r - \sum_{p \in P} b_p \boldsymbol{C}_p \boldsymbol{q}_p \right\|^2 \tag{1}$$

Where,

$\Vert \; \Vert^2$	Euclidean norm
r	Response variable
$\boldsymbol{C}_{v\in[r,P]}$	Matrix of $c_{(v)ij} = \begin{cases} 1 & \text{if case } i \text{ is in the } j\text{-th case of variable } v \\ 0 & \text{if case } i \text{ is not in the } j\text{-th case of variable } v \end{cases}$
$\boldsymbol{q}_{v\in[r,P]}$	Category quantifications for variable v
b_p	Regression coefficient for variable p

The transformed variables are centred and normalized to have sum of squares equal to number of cases. Details on the method can be found in Meulman and Heiser (2005) and Kooij (2007). We measure the importance of factors by means of the Pratt's Index, defined as-

$$PI_p = \frac{b_p \rho_{rp}}{R^2} \tag{2}$$

Where,

PI_p	Pratt's Index of importance of predictor p
ρ_{rp}	Zero-order correlation between the transformed response and the transformed predictor p
R^2	R^2 of the regression of the transformed variables

Since,

$$\sum_p b_p \rho_{rp} = R^2 \tag{3}$$

The metric can be used to partition the R^2 and thus to quantify he relative importance of the predictor.

4. Results

4.1. Descriptive analysis

About 85% of the participants use travel information, of which 56% (920 respondents) use at least one source of URTPI. More than half of the URTPI users change at least one of the aforementioned choice elements after consulting the URTPI (Figure 3). Among the six choice elements, all but mode of transport is considered for assessing the impact of URTPI on path choice. Time of departure from start is the most preferred choice made by the passengers after consulting URTPI. Change in time of departure from start or boarding time are considered as a change in temporal dimension of the trip, while spatial dimension is comprised of departure stop, alighting stop or bus line. Time of departure from start is the most frequently changed element after consulting URTPI, followed by the change of boarding time. Change of alighting stop is the least frequent choice made by the passengers.

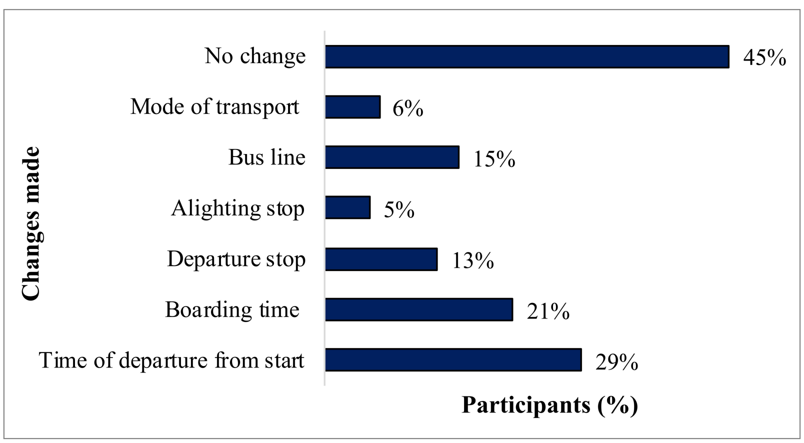

Figure 3: Changes made by the passengers

Figure 4 presents how changes in different choice elements affect PT demand distribution. About 42% of URTPI users make changes in their temporal choice dimension, whereas changes in spatial choice dimension are observed in 26% of cases. The impact of changes on PT demand distribution is estimated by combining the changes which occur in all the choice elements except the time of departure from the start. Consequently, for 39% of trips made by URTPI users, PT demand distribution is affected as a result of consulting information. Change of boarding time is observed in 21% cases; however, changes in passenger distribution for bus runs occur only if passengers shift their boarding time without changing the bus line. The demand distribution for bus runs is observed to be affected by 17% of the trips made by URTPI users.

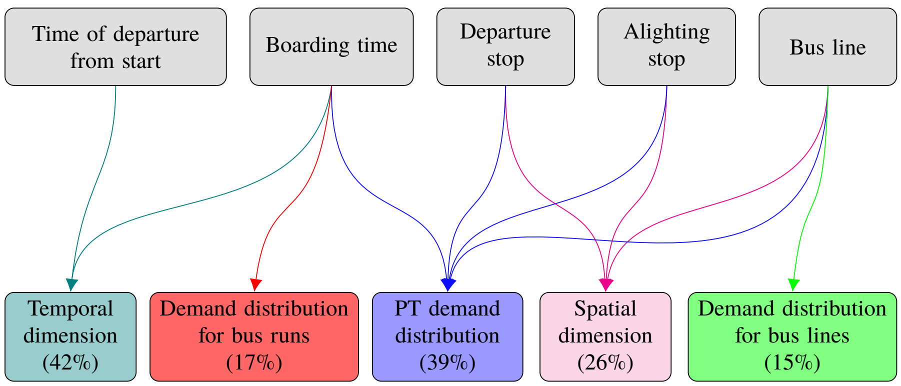

Figure 4: Potential impact of changes in choice elements on PT demand distribution

We then investigate the factors related to passengers' trip planning objectives and how they influence their choices (Figure 5). Arriving at the destination is moderately, strongly or very strongly influential for about two-thirds of the passengers. More than half of the passengers state that the attempt to reduce journey time is moderately, strongly or very strongly determining their choices. Walking distance, transfers, and change in bus stop location are not at all influential by the majority of passengers.

A Categorical Principle Component Analysis (CATPCA) is applied to reduce a large multivariate dataset and to interpret data (Johnson and Wichern, 1992; Washington et al., 2011), understand any underlying association between these variables and reduce the number of variables by combining the ones which are related. A CATPCA is used instead of Principle Component Analysis (PCA) (Johnson and Wichern, 1992; Washington et al., 2011) because a standard PCA assumes a linear relationship between numerical variables, whereas the afore-

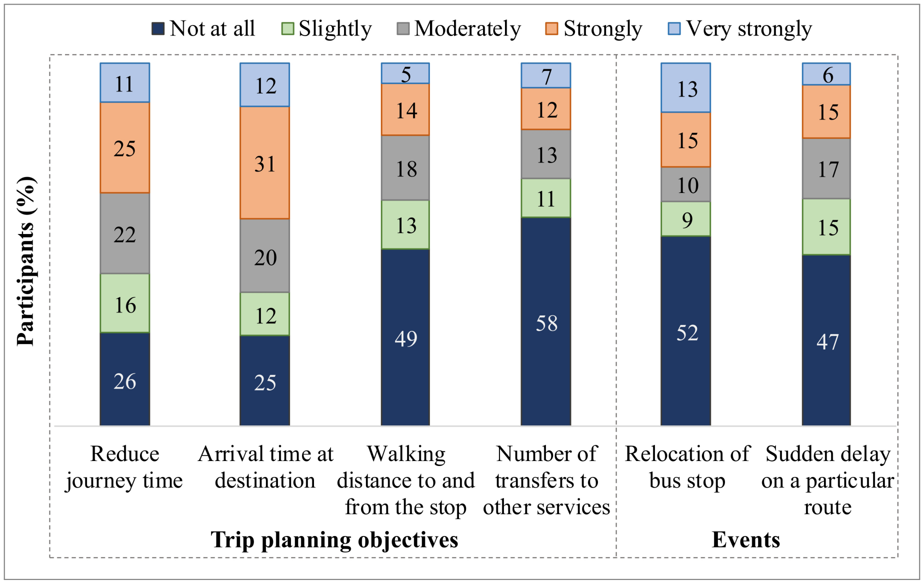

Figure 5: Influence of trip planning objectives and events in determining path choices

mentioned trip planning objectives were measured on 5-point Likert scales (i.e. categorical variable).

Table 1: CATPCA analysis for factors affecting choices

Variables	Dimensions		
	1	2	3
Reduce journey time	0.982		
Arrival time at the destination	0.982		
Sudden delay on a particular line		0.489	0.754
Walking distance to and from the stop		0.997	
Number of changes to other services		0.821	
Change in bus-stop location due to construction work			0.934
	Temporal objectives	Physical and cognitive efforts	Service disruption

CATPCA results show that these variables are associated with three underlying factors. Reducing journey time and Expected Time of Arrival (ETA) are associated with Factor (1), whereas walking distance and transfers are grouped as Factor (2). Factors (1) and (2) can be referred to as "temporal objectives" and "physical or cognitive efforts" respectively and are associated with passengers' trip planning objectives. These two factors will be used as independent variables for modelling passengers' choices. Factor (3) is referred to as "service disruption" and indicates the events going on within the network.

4.2. Factors affecting passenger path choices

We have analysed the factors affecting the choices of the 920 respondents using URTPI. CATREG models were developed using each of the choice elements as a dependent (binary) variable. The independent variables are related to trip characteristics, demographics, importance of the contents of the information and factors related to trip planning objectives. Trip characteristics and demographics consist of both nominal and ordinal variables. The importance of the contents of the information is measured on a 5-point Likert scale. Table 2 shows the categories of the predictors with the corresponding initial code. The CATREG quantifications of the categories in each model are presented in Figures 6 to 10 as a function of the initial code (e.g. the original code of the "self-employed" category in the "Profession" variable is 2 (Table 2). In the model "Change in time of departure", the "Profession" category coded as 2, i.e. "self-employed", has the quantification 0 - see the red line in the top right plot of Figure 6). The CATREG results are also presented in each choice section (Tables 3 to 7). The coefficients presented in the tables must be interpreted in relation to the transformed variables, i.e. a positive coefficient indicates respondents in a category with a higher quantification on a given factor have a stronger tendency to change the analysed travel choice than respondents in categories with lower quantifications. The level of importance of each variable in the respective models is highlighted in green, orange and red to represent low (0-0.1), medium (0.1-0.25) and high (>0.25) importance respectively.

Table 2: Potential predictors of passenger path choices

	Variables	Levels (% of valid responses)
Demographics	Age	1-[18-25] (31%), 2-[26-35] (28%), 3-[36-45] (19%), 4-[46-55] (15%), 5-[56-65] (5%), 6-[>65] (2%)
	Profession	1- employed for wages (58%), 2- self employed (12%), 3- out of work (4%), 4- homeworker (2%), 5- student (21%), 6- retired/unable to work (3%)
	Gender	1- female (54%), 2- male (46%)
	Education	1- grammar school (6%), 2- high school or equivalent (13%), 3- some college credit, no degree (26%), 4- university degree (61%)
	Residence	1- Edinburgh resident (85%), 2- frequent visitor (9%), 3- infrequent visitor (3%), 4- first time visitor (3%)
Trip planning objectives	Temporal objectives	CATPCA scores: min (-1.875), max (0.928), range (2.802), std. dev (0.665)
	Physical or cognitive efforts	CATPCA scores: min (-1.356), max (1.765), range (3.121), std. dev (0.662)
Trip characteristics	Trip length	1- very short (3%), 2- short (22%), 3- medium (59%), 4- long (14%), 5- very long (2%)
	Time of day	1- midday (29%), 2- evening (33%), 3- morning (38%),
	Trip purpose	1- commute (45%), 2- work travel (20%), 3- shopping (9%), 4- p/f business (14%), 5- leisure (12%)
	Familiarity of trip	1- familiar (85%), 2- unfamiliar (15%)
	Alternative mode	1- not available (59%), 2- available (41%)
	Alternative route	1- not available (31%), 2- available (69%)
Importance of contents of information	Bus arrival time	1- not important (2%), 2- slightly important (5%), 3- important (34%), 4- very important (38%), 5- extremely Important (21%)
	Bus route map	1- not important (11%), 2- slightly important (22%), 3- important (41%), 4- very important (22%), 5- extremely Important (4%)
	Bus stop location	1- not important (12%), 2- slightly 3- important (18%), 3- important (35%), 4- very important (24%), 5- extremely Important (11%)
	Journey plan	1- not important (15%), 2- slightly important (31%), 3- important (34%), 4- very important (16%), 5- extremely Important (4%)
	Transfer to other services	1- not important (22%), 2- slightly important (24%), 3- important (32%), 4- very important (18%), 5- extremely Important (4%)

4.2.1. Change in time of departure from start

The model results show how passengers' time of departure is influenced by the consultation of URTPI. As mentioned in the previous section, changing the time of departure from start is the most preferred action taken by the URTPI users. The model results show that among the predictor variables, participants' age has the highest influence (Table 3). The strong relationship between changing departure time and passenger demographics mirrors the findings of Chen and Mahmassani (1999) in the context of car users. Trip characteristics and information have relatively smaller impact on the change of departure time.

Participants' age and profession are found to be significant in the model. Younger passengers are more likely to change their departure time than older passengers. It is observed that passengers who are out of work are the least likely, whereas retired passengers are the most likely to change departure time. Working people or students are more inclined to adjust their departure time than homemakers and unemployed passengers.

Time of day, familiarity of trip and availability of alternative mode of transport are the trip characteristics that influence the change of time of departure from start. Passengers are found to be less likely to change their departure time in the morning. This can be explained by the fact that morning trips mostly comprise commute trips. In addition, model results illustrate that the temporal objectives positively relate to the change in time of departure from start. Hence, this is evident that passengers may change their departure time to reduce journey time or to maintain their ETA, and it is in line with the findings from a simulation study carried out for car drivers by Toledo and Beinhaker (2006), where the authors observe the adjustments in drivers' departure time to avoid early or late arrival. They might also consider alternative travel options, such as taking another bus line with the aim of reaching their destination as soon as possible. Arriving at the destination was also found to be important by Fonzone (2015). Additionally, Tsirimpa et al. (2005) found commuters more prone to change their departure time. However, this study does not find any impact of trip purpose on the change in time of departure from start.

Table 3: Change in time of departure from start: CATREG results

Factors	Variables	β	Pratt's Imp.
Demographics	Age	-0.228***	0.518
	Profession	0.105***	0.009
Trip planning objectives	Temporal objectives	0.113*	0.140
Trip characteristics	Time of day	0.058*	0.019
	Familiarity of trip	0.088**	0.082
	Alternative mode	0.091*	0.144
Importance of contents of information	Bus arrival time	0.082*	0.087

Number of cases in the model: 760
Significance: *p<0.05 **p<0.01 ***p<0.001

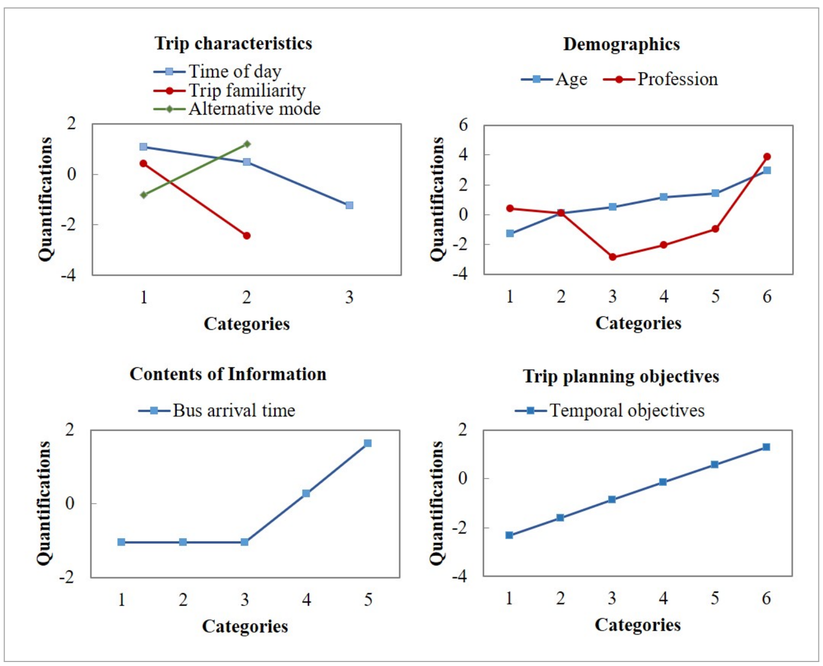

Figure 6: Change in time of departure: CATREG quantification plots

Information is also found to influence passengers' departure time. Consultation of bus arrival time leads to a higher likelihood of changing departure time. This is supported by Parvaneh et al. (2014) where the author demonstrated a higher likelihood of changing departure time after consulting descriptive information. On the other hand, the impact of information on changing departure time is rather modest (Table 3).

4.2.2. Change of boarding time

Change of boarding time refers to whether a passenger would keep their initial plan of taking a bus at a certain time or would decide to change their boarding time by taking a bus earlier or later than the original plan. Unlike the time of departure from start, boarding time is found to be influenced dominantly by passengers' objectives and trip characteristics (Table 4). Demographics and the importance of contents of information have little influence on the decision of changing boarding time.

Table 4: Change of boarding time: CATREG results

Factors	**Variables**	β	**Pratt's Imp.**
Demographics	Profession	0.055*	0.032
	Gender	0.067	0.044
Trip planning objectives	Temporal objectives	0.218***	0.407
	Physical/cognitive efforts	-0.154**	0.149
Trip characteristics	Time of day	0.110***	0.139
	Trip purpose	0.102***	0.106
	Alternative bus line	0.085*	0.089
Importance of contents of information	Transfer to other services	0.082**	0.035

Number of cases in the model: 645
Significance: *p<0.05 **p<0.01 ***p<0.001

Passengers are likely to change their boarding time around midday and less likely in the morning period. This might happen because trips in the morning are normally time-sensitive (i.e. they need to arrive at the destination by certain time) and getting to destination as soon as possible is very important for them. Shopping trips show higher likelihood for changing the boarding time. In addition, the availability of alternative bus lines positively influences the boarding time factor. This suggests that passengers may change their boarding time either by changing bus lines or getting an earlier or later bus on the same line.

Factors related to passengers' trip planning objectives are found to be significant for the decision of changing the boarding time. Here, temporal objectives, i.e. reducing journey time or maintain their ETA is the most dominant factor. Furthermore, physical or cognitive efforts negatively influence the change

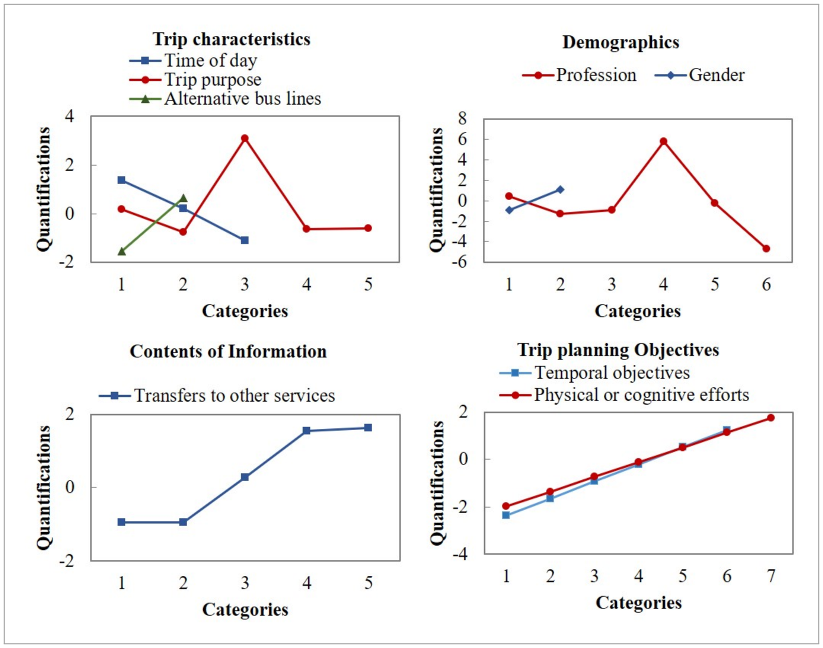

Figure 7: Change of boarding time: CATREG quantification plots

of boarding time. This means passengers who are not bothered by the transfers or walking distances are more likely to change their boarding time. Besides, the decision of changing the Boarding time depends on participants' profession, e.g. homemakers show higher likelihood in changing their boarding time.

4.2.3. Change of departure stop

Change of departure stop refers to the situation where a passenger decides to board a bus from a different stop than according to their original trip plan (itinerary). The model results show that passengers' decision of changing departure stop is dominated by trip planning objectives, trip characteristics and the importance of contents of information (Table 5).

Passengers' objectives to reduce journey time, physical or cognitive efforts and maintaining their ETA are key factors that influence the change of departure stop. Higher likelihood of changing departure stop is observed for shopping and leisure trips. Additionally, departure stop is likely to be changed when

Table 5: Change of departure stop: CATREG results

Factors	**Variables**	β	**Pratt's Imp.**
Demographics	Profession	0.074***	0.039
Trip planning objectives	Temporal objectives	0.137**	0.269
	Physical/cognitive efforts	0.122*	0.230
Trip characteristics	Trip purpose	0.130***	0.136
	Familiarity of trip	0.092*	0.059
	Alternative bus line	0.104**	0.089
Importance of contents of information	Transfer to other services	0.121**	0.179

Number of cases in the model: 644
Significance: *p<0.05 **p<0.01 ***p<0.001

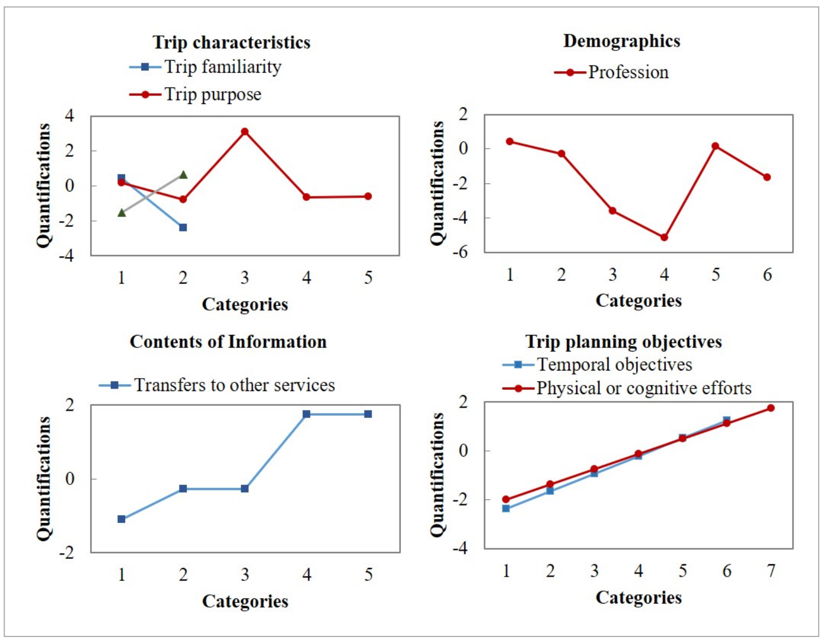

Figure 8: Change of departure stop: CATREG quantification plots

making familiar trips. Again, availability of alternative bus lines increases the likelihood of changing departure stop. This decision-making can be explained by two scenarios. On one hand, passengers may take the decision of changing departure stop after consulting information to get a particular bus line among the alternatives. On the other hand, they may decide to go to a different bus stop due to availability of alternative lines, and a bus line could be chosen after arriving at the stop. This may also be deemed by passengers that missing one bus would not be a problem, which infers to their risk aversion attitude.

The importance of contents of information influences the decision of changing the departure stop. Specifically, consultation of information on transfer to other services leads to a higher likelihood of changing departure stop. This may happen if departure stop is changed as a result of bus line choice.

Among the demographics, only profession is observed to have statistically significant influence on changing departure stop. It is observed that working people and students are more likely to change departure stop, whereas Home-makers and passengers without work are less likely to change this choice factor.

4.2.4. Change of alighting stop

Change of alighting stop refers to alighting from the bus at a different stop than according to an original trip plan. This may occur at two stages of decision-making. At the pre-trip stage, passengers may decide to change the bus line which may take them to a different alighting stop. Additionally, change of alighting stop may occur because of passengers' en-route decision of alighting at a different stop. The later scenario is more likely in case of transfers to other services. Survey results show that only 5% of the URTPI users changed their alighting stop. The CATREG model results show that change in alighting stop is strongly influenced by trip characteristics and the importance of contents of information (Table 6).

The highest likelihood for changing alighting stop is observed when passengers make shopping trips, followed by work travel and personal or family business trips. Passengers are less likely to change the alighting stop for commuting and leisure trips. In addition, availability of alternative mode relates positively with the decision to change alighting stop. Therefore, passengers may try to make connection between different modes by changing alighting stop, i.e. change the alighting stop to take a tram, or walk to the destination.

Finally, the importance of information is found to be most influential on the decision of changing alighting stop. Passengers who consult journey planning information are more likely to change their alighting stop.

Table 6: Change of alighting stop: CATREG results

Factors	Variables	β	Pratt's Imp.
Demographics	Profession	0.056	0.087
	Residence	-0.056***	0.100
Trip planning objectives	Temporal objectives	0.070	0.129
Trip characteristics	Trip purpose	0.084***	0.201
	Alternative mode	0.085*	0.229
Importance of contents of information	Journey plan	0.098***	0.253

Number of cases in the model: 665
Significance: *p<0.05 **p<0.01 ***p<0.001

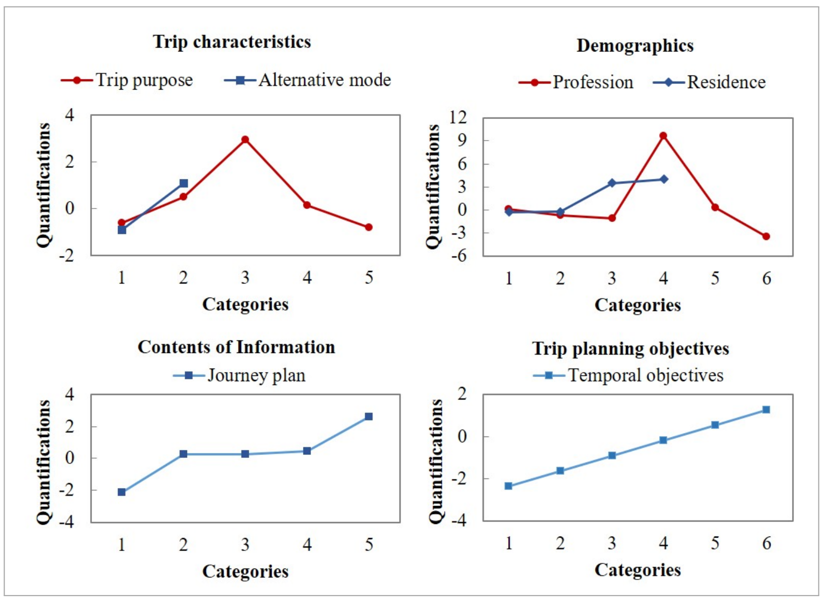

Figure 9: Change of alighting stop: CATREG quantification plots

4.2.5. Change of bus line

This model investigates the factors that influence passengers to choose a different bus line than the one they originally intend to as a result of consulting URTPI.

Passengers' decision of changing bus line is related to the importance of contents of URTPI (Table 7). Trip objectives and passenger demographics also influence the choice of bus line. In contrast, trip characteristics possess the lowest impact on the change of bus line.

Table 7: Change of bus line: CATREG results

Factors	Variables	β	Pratt's Imp.
Demographics	Profession	0.153***	0.172
	Education	0.093***	0.058
Trip planning objectives	Temporal objectives	0.116*	0.135
	Physical/cognitive efforts	0.093	0.137
Trip characteristics	Trip purpose	0.108***	0.092
Importance of contents of information	Bus stop location	0.145***	0.229
	Transfer to other services	0.115**	0.177

Number of cases in the model: 594
Significance: *p<0.05 **p<0.01 ***p<0.001

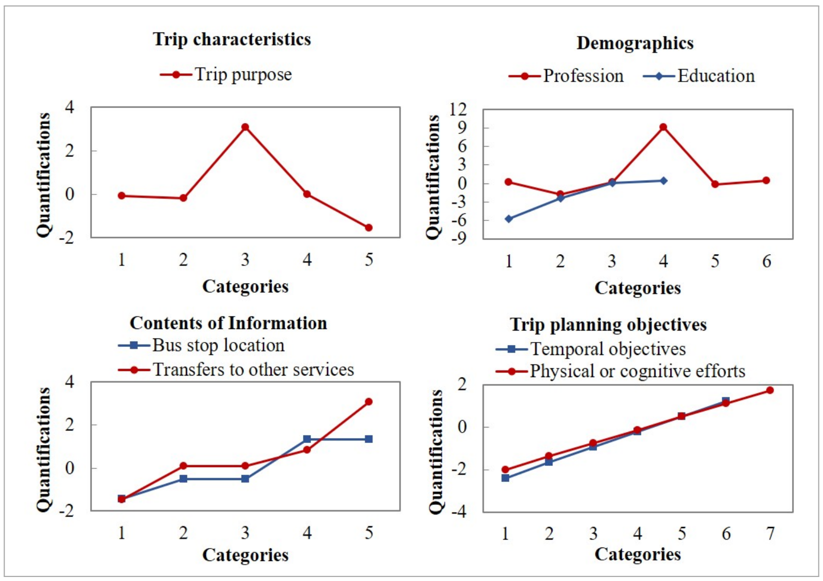

Figure 10: Change of bus line: CATREG quantification plots

The model results reveal that the likelihood to change bus line increases when URTPI is consulted. Among the contents of information, the importance of bus stop location and transfers to other services is found to be significant. This indicates that changing bus line requires a combination of static and real-time information. Bus stop location is important for passengers to choose a bus line. This may be associated with reducing journey time which is also found significant in the model. Additionally, information on transfers is important as it requires both physical and cognitive efforts as well as additional monetary cost if passengers have to pay for transfers.

The choice of bus line is influenced by the purpose of trip. Shopping trips exhibit the highest likelihood for changing bus line. This also indicates the flexibility to make changes as shopping trips are not typically time bound.

Participants' demographics show that homemakers are in the leading position for changing bus line, among the profession groups. This shows their flexibility to make changes when making a journey. In the previously presented models, working people and students have been observed to be less likely to change temporal choice elements, i.e. time of departure from start and boarding time. Hence, passengers who belong to these groups of profession, may be more strict about their journey plan including bus line. However, they are also likely to change the departure stop after consulting URTPI. This suggests that working people and students tend to keep their bus line unchanged even if they change departure stop. On the other hand, homemakers may take a tactical decision, which implies no rigorous planning or particular preference of bus line. Educated passengers exhibit higher likelihood of changing bus line.

5. Discussions and Conclusions

This study investigates bus passenger choices under influence of URTPI. To this end, a passenger survey was carried out and choice models were estimated using CATPCA and CATREG. Model results show that the contents of information have relatively smaller impact on the two elements of the temporal dimension of path choice, i.e. change of time of departure and boarding time (Pratt's importance in Tables 3 to 7). The use of information related to the temporal dimension are rather confirmatory, i.e. passengers consult URTPI to check if the bus is on time without making any changes in their plan. The choice elements related to the spatial dimension of path choice are strongly influenced by information on bus stop location, transfer to other services and journey plan. This indicates that the use of URTPI may trigger more changes in networks with complex topology, which eventually results in a higher impact on passenger demand distribution. This study finds that 39% of the URTPI users changed at least one aspects of path choice that has an impact on demand distribution. The model shows that passengers' boarding times, and so is the demand distribution across bus runs, are affected by trip purpose and time of day. The decision of changing bus line is influenced by passenger demographics and the contents of information. Therefore, passenger demographics profile along with the disseminated contents of information could be used to anticipate the change in demand distribution for bus lines.

The study results indicate that making a path choice decision may not really require prescriptive information, as passengers make changes with descriptive information as well. This suggests that either passengers' prior knowledge help them to find the best alternative after partial consultation of URTPI, or they do not really have any objective in terms of maximising journey experience.

The demand distribution across bus runs and bus lines is affected in 17% and 15% of cases respectively. These changes may have important consequences on on-board crowdedness, above all in peak times. Transport operators should take the potential impact of URTPI into account when making demand prediction and make necessary changes in PT services consequently. The study results show that passengers change the aspects of path choice considering information on transfers, bus stop location and journey plan. Hence, information should be crafted considering these contents and the alternatives should be prescribed accordingly.

The following are the identified limitations to the study findings.

- This study focused on bus passenger's decision-making under the influence of URTPI; hence decision-making by the non-users of URTPI was not studied. Location-specific real-time information, i.e. displays at stops enable passengers to make changes in some of the choice elements, such as decision of taking a bus in an alternative line after arriving at the stop. However, making changes without consulting URTPI would not be effective in terms of achieving a particular trip planning objective, such as reducing transfer time. Additionally, some changes are not even possible to make without consulting URTPI, i.e. change in departure time. Given the study aim, it is not possible to single out the impact of URTPI only.

- The present study was carried out with cross-sectional data. Therefore, the impact of URTPI on decision-making at different times of a year is not studied.
- The impact of URTPI was studied considering the availability of alternatives, such as frequent buses and alternative lines. Although URTPI may be more important to the passengers when alternatives are not available, this was not captured in the bus stop survey. In addition, bus stop survey provides data on bus journeys made during the day only. Therefore, the study results would be valid for day trips in the medium to medium-large cities.

This study only considered bus passenger behaviour under the influence of information; therefore, a study on passenger behaviour in a multi-modal network could provide a better understanding of the impact of URTPI. In addition, Wang and Khattak (2013) discussed the existence of spatial heterogeneity in travel decisions, which indicates that the association between travel decisions and influencing variables (i.e. travel time, household income) varies over the study area. Therefore, studies in different PT networks could be carried out to validate the results in terms of spatial heterogeneity.

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