Mitigating the impact of errors in travel time reporting on mode choice modelling

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ABSTRACT

Travel time is a major component in understanding travel demand. However, the quantification of demand and forecasting hinges on understanding how travel time is perceived and reported. Travel time reporting is typically subject to errors and this paper focuses on the mitigation of their impact on choice models. The aim is to explain the origin of these errors by including elements of travel behaviour (e.g., activities during the trip), which have been shown to significantly affect mode choices and commuting satisfaction. Based on responses from a revealed preferences survey, we estimate a mode choice model that treats travel time as a latent variable and incorporates different sources of data along with information on travel activities. Employing these multiple – sometimes incongruent – sources of information in the choice model appears to be beneficial. Results from comparing a logit model assuming error-free inputs and the integrated hybrid model revealed significant impacts on the generated policy scenarios. The model results also contributed to identifying the main travel activity features that affect travel time reporting, providing indications that can assist in understanding and mitigating the impact of imprecise measurements.

1. Introduction

Travel behaviour models typically rely on data afflicted by errors, both in measurement (e.g., software or researcher imputation error) and reporting (e.g., over/under-estimation by traveller). The impact of these errors on choice model outputs has been extensively investigated since the 1970s (McFadden, 2000). Several studies (Bhatta, 2011; Brownstone and Small, 2005; Daly and Ortúzar, 1990; Ghosh, 2001; Ettema et al., 2012; McFadden and Talvitie, 1977; Ortúzar and Ivelic, 1987; Reid and Small, 1976; Small et al., 2005; Walker et al., 2010) have shown that key forecasting indicators such as value of time (VOT) are quite sensitive to the accuracy of travel attributes and to individual-specific explanatory variables. Parameter estimation might be significantly biased when temporally aggregated travel times (Reid and Small, 1976) and spatially aggregated level of service measurements (Ortúzar and Ivelic, 1987; Daly and Ortúzar, 1990) are used instead of individual measurements. Moreover, measurements calculated by researchers (or software) and those reported by users typically differ and result in significantly different model outputs (Brownstone and Small, 2005; McFadden and Talvitie, 1977; Small et al., 2005). Most of these studies have shown in empirical applications that errors in travel behaviour measurements can downward bias VOT up to 50%. Since this indicator is often used for the cost-benefit appraisal of transport projects, errors in travel behaviour measurements can result in significantly lower estimations of willingness to pay of individuals to reduce their trip duration.

Despite the relevant impact of these errors, few attempts to explain their origin have been made. The presence of multiple measurements of travel variables, and a lack of consensus on which to rely on or how to reconcile these different origins has given rise to important debates in the travel behaviour field. One approach would be to seek to identify the most revealing measurement input and disregard other (inconsistent) ones when constructing models. The question then arises of which measurement is most likely to effectively drive the choices of respondents. Research has addressed the question of modelling with reported versus calculated data for various aspects: quality of service

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(Bordagaray et al., 2014; Eboli and Mazzulla, 2011) and level of crowding in public transport (Li and Hensher, 2013), travel distances (Witlox, 2007), life-style and life situation (Scheiner and Holz-Rau, 2007), walking behaviour (Lin and Moudon, 2010), safety of driving patterns of older adults (Molnar et al., 2013), and travel time inputs (Carrion, 2013; Curl et al., 2015; Li, 2003; Peer et al., 2014).

In this research, we focus on results related to travel time measurements while the debate extends to a broader set of travel variables such as cost, income, etc. To date, most studies rely on software calculated travel time, typically considering these measurements as “objective”, and unaffected by errors. In line with this thinking, self-reported travel times are seen as uninformative, or biased. However, reported measurements can be argued to provide better indications of the perceived values that are ultimately driving the choice process (Daly and Ortúzar, 1990; McFadden and Talvitie, 1977). Indeed, it is well established that travellers often overestimate or underestimate the actual travel time of their journey and this perceived value could influence the travel decisions. A few studies have attempted to control for these differences in travel time measurements by using advanced choice models (Diaz et al., 2015; Ribeiro et al., 2014), but the formulations proposed are not suitable in case a variable is available only for users who made a certain choice (e.g., reported travel time for the chosen alternative) and gained limited insight into the potential sources of error affecting reported travel time.

The aim of this paper is to explain discrepancies between reported and calculated travel times and to explicitly capture the impact of these different travel time measurements on mode choices. The research hypotheses are detailed in Section 2.4. The issue of poorly reported travel times is explored in a real mode choice case study for a university campus in Trieste (Italy). The paper is structured as follows. Section 2 provides a literature review of approaches to model transportation choices with multiple measurements of travel time and formulates the research questions. Section 3 presents the transport mode choice case study. Section 4 presents the methodology and specification of the logit and the hybrid choice models. Section 5 discusses the estimation results obtained by using the extended software package BIOGEME (Bierlaire and Fetiarison, 2009). Section 6 presents the validation and policy analysis. Section 7 gives conclusions and suggestions for future research, discussing the limitations concerning the dataset used and possible extensions.

2. Literature review

The literature review focuses on studies proposing comparative choice model structures to analyse travel time measurements and to quantify the impact of these measurements on policy outputs. Section 2.1 introduces the concept of time perception in psychology and transportation. Section 2.2 presents current approaches to deal with reported and calculated travel time measurements in choice models. Section 2.3 summarizes literature to support a model framework which has the potential to account for different types of errors and missing values in travel time measurements. Section 2.4 discusses the research gaps and hypotheses that are addressed in this study. While we acknowledge that the debate surrounding travel time measurements is relevant to other factors influencing travel decisions (Bordagaray et al., 2014; Eboli and Mazzulla, 2011; Li and Hensher, 2013; Lin and Moudon, 2010; Scheiner and Holz-Rau, 2007), it is beyond the scope of the paper to make parallel assessments for other types of variables. An important reason for this is the lack of consistent model approaches and methods to compare inputs for most of these research fields.

2.1. Subjective perspectives on time

The subjective nature of temporal judgment has been established in psychological research. Evidence from the literature has suggested perceived time as a power function of the clock time (Roeckelein, 2000). Block (1985) proposed a cognitive model in which the duration experienced was influenced by several elements, such as activities during time periods and subject's characteristics. In addition, Hornik (1992) found that good mood led to retrieving biased memories of time congruent with the mood. Following these studies, the interest of transportation researchers in travel time has increased. Bates et al. (2001) argued that it was likely that travellers were maximizing utility according to their own divergent views of the travel time distribution notwithstanding actual measurements. Consequently, travellers differed in their optimal choices depending on the degree of distortion of their subjective distribution with regards to the actual measurement distribution. Rietveld (2002) noted that in travel surveys most respondents applied rounding of departure and arrival times to multiples of 5, 15 and 30 min. A possible explanation for this effect is that scheduled activities force people to plan their trips in advance which provide them with anchor points for their memory afterwards. These findings should be integrated into transportation models.

2.2. Reported and calculated travel times in transportation models

The effect of multiple travel time measurements on choice models has originally been investigated in studies combining revealed preference (RP) and stated preference (SP) data. For instance, Small et al. (2005) and Brownstone and Small (2005) noted that VOT estimates using SP data (based on reported travel times) corresponded to less than half of VOT estimates based on RP data (relying on calculated travel times in real traffic) when choosing a congestion-free lane. They concluded that travellers overstate the travel time they experience in congestion in a SP experiment, due to either emotional aversion to traffic delays or over-estimation of the actual impact of tolled lanes. Similar findings were shown by Ghosh (2001) in a different congestion pricing project, in which the median VOT from SP responses was half to one third of RP values, depending on the model form.

Interestingly, recent studies relying on advanced travel tracking technology have reached opposite conclusions on the role and value of reported travel time data in choice modelling. Carrion (2013) analysed the role of reported and GPS-derived travel time in route choice, concluding that the goodness of fit statistics favoured the models with reported measurements, compared to those with calculated measurements. Peer et al. (2014) compared reported travel time by respondents to travel time measured by GPS and camera data in real traffic, noting that reported measurements were overestimated. However, this distortion (expressed as a ratio between reported and calculated travel time) did not seem to influence departure time choices in SP and RP settings. Therefore, they concluded that the reported travel time was affected by errors and did not represent the actual travel time perceived by respondents.

Early models included some subjective information to improve RP models. Ghosh (2001, sec. 5.2) included an ‘excess time savings’ term defined as perceived minus actual time savings in a RP mode choice model. People with more positive time saving biases were more likely to select the toll option, but the variable did not alter the VOT estimate. Recent studies have attempted to control for these differences in travel time measurements by using advanced choice models. Despite the significant differences in the travel time data available, Ribeiro et al. (2014) found similar model performances using GPS and self-reported travel times in mixed logit models which accounted for taste heterogeneity between individuals (panel effect) and random travel time parameters. They concluded that the choice of adequate model specification when using reported data allows results to align with those based on more precise GPS data. Therefore, the development of advanced models using reported travel times is particularly promising. Diaz et al. (2015) conducted an econometric analysis to identify the most suitable model structures that could deal with discrepancies between calculated and experienced measurements using synthetic and real data. They included a measurement equation directly in the utility function as previously proposed by Wansbeek and Meijer (2000). They concluded that an error component model assuming generic tastes in the population can deal with stochastic variables in most cases.

Notably, these formulations (Diaz et al., 2015; Ribeiro et al., 2014) are not suitable in case a variable is available only for users who made a certain choice (e.g., travel time reported only for the chosen alternative) and in the presence of missing values. Missing data can be treated analytically (Daly and Zachary, 1977), or assigned using multiple imputation (Steinmetz and Brownstone, 2005) originally proposed by Rubin (1987). Multiple imputations can be used when accurate data for a subsample of the observations are available. Bhat (1994) imputed a continuous variable for missing values, meaning that the variable is drawn from the observed variables.

These studies have all proposed formal comparisons and treatments of multiple and possibly biased transportation data. To date, the findings on the impact of multiple data sources (reported/measured) on the model fit, reasonableness and policy outputs do not point in the same direction. Moreover, there is still a dearth in understanding as to what constitutes the ideal framework to deal with different types of biases and missing observations. Similarly, there is little clarity on the potential sources of error affecting reported travel time (i.e., engagement in activities, personal characteristics, mood, rounding and perceptions). In addition, calculated travel time has been assumed to be an error-free measure. While it can be argued that GPS measurements lead to relatively small errors, other instruments which are commonly used in practice for time imputation (e.g., software, assignment models, and loop detectors) can result in relevant distortions.

2.3. Modelling measurement errors in transportation choices

Although there is a broad literature on measurement errors in the econometric literature, few studies directly address measurement errors in transportation modelling and in choice models. In the last decade, the popularity of hybrid choice models has grown considerably in a wide number of disciplines, including transportation (Ben-Akiva et al., 1999, 2002; Bolduc et al., 2005; Walker, 2001; Walker and Ben-Akiva, 2002). Integrated Choice and Latent Variable (ICLV) models have been primarily employed to include attitudes and perceptions as explanatory variables of the choice, using psychometric scales as indicators of unobservable latent constructs (Atasoy et al., 2013; Glerum et al., 2011; Schüssler and Axhausen, 2011). This methodology could potentially be used to deal with any type of variable which affects the choice.

Walker et al. (2010) focused on how to estimate travel demand models when the underlying quality of level of service data (times and costs) are poor. It was demonstrated that a choice model with measurement errors results in inconsistent estimates of the parameters, prompting development of methods to correct measurement errors. The authors proposed to use the hybrid choice framework to integrate travel time as a latent variable and used the calculated travel time as an indicator of the latent true travel time. The ICLV model for true travel time led to significant shifts in both the travel time and travel cost parameters, resulting eventually in a large increase in the value of time (+ 60%). In the context of their case study, the VOT calculated with the hybrid choice model seemed to be more realistic than the VOT calculated with the logit model.

Brey and Walker (2011) applied the hybrid choice framework to estimate the time of day demand in an airline itinerary choice model. They used the reported preferred departure time, which may be influenced by the provided schedule, as an indicator of the latent preferred departure time to account for measurement errors. The time of the day distribution was formulated as a mixture of normal distributions and a function of trip and traveller characteristics. The advantage of this approach is that the preferred departure time distribution can be jointly estimated with the choice model and directly used in forecasting. Notably, they found a significant measurement error in the preferred departure times and significant changes in the parameters associated with the explanatory variables when comparing the hybrid choice model to a similar model assuming error-free departure times.

Sanko et al. (2014) developed a latent variable approach to deal with missing values and measurement errors relating to income. The reported income was replaced by a latent income variable in the choice model, using the stated income as an indicator of the unobservable true income in a measurement model. In contrast with using imputation of missing values, the simultaneous estimation with the choice model allows the observed choices to affect the latent variable. Despite the theoretical advantages, the empirical results they obtained on two datasets showed very similar forecasting indicators using the imputed income and the hybrid choice model.

2.4. Research gaps and hypotheses

Several studies have shown that key forecasting indicators such as value of time are sensitive to accuracy and origin (software calculated vs traveller reported) of travel time measurements. A few studies have attempted to control for these differences by using advanced choice models, but the formulations proposed are not suitable when reported measurements are available only for the chosen alternative. Moreover, these studies have gained limited insight into the potential sources of error influencing reported travel times.

In this research, we develop a mode choice model which explains discrepancies in the assessment of travel time by introducing elements of travel behaviour (e.g., activities during the trip). These activities have been shown to significantly affect mode choices (Frei and Mahmassani, 2011) and commuters' satisfaction (Ettema et al., 2012). To correct measurement errors and to capture explicitly the cognitive process underlying travel time reporting, we adopt the ICLV framework (Brey and Walker, 2011; Sanko et al., 2014; Walker et al., 2010). The research hypotheses that are tested in each section of the paper are presented in Fig. 1. The dataset was collected in a revealed preference survey for a university campus in Trieste (Italy).

3. Survey and data collection

A comprehensive data collection campaign was carried out in Trieste (northern Italy) between November 2009 and January 2010, in the framework of UniMob - a Mobility Management project for the university staff and students travel demand. The survey consisted of a quantitative part collecting socio-demographic data and information related to the position occupied, the employment/enrolment duration, the frequency of being at the university, the residence status and the transportation means available. Respondents made detailed reports on their last home-university trip, including origins, destinations, chosen travel modes, and arrival and departure times. In addition, they answered questions on travel habits, activities during travel, potential reasons for mode switching, perception of the risks associated with each mode and opinions on urban mobility related topics. The main data source used in this research consists of RP data on mode choice (Progetto UniMob, 2009-2010a). The survey was performed as an online questionnaire sent to the entire university population (24,685 users). During November 2009 all regularly registered students (21,601 users) and all teaching and administrative staff (3084 users) were invited by email to complete the questionnaire. The response rate was 16.11%. Descriptive statistics are available in Varotto et al. (2014).

3.1. Sample

The models presented in this paper are based only on regular trips (i.e., at least 4 times/month) completed within the province of Trieste to ensure more consistent reporting of travel attributes by respondents (a majority of respondents were classified as regular travellers). In addition, significant differences between the staff and the student samples were discovered with formal comparisons. In this paper, we

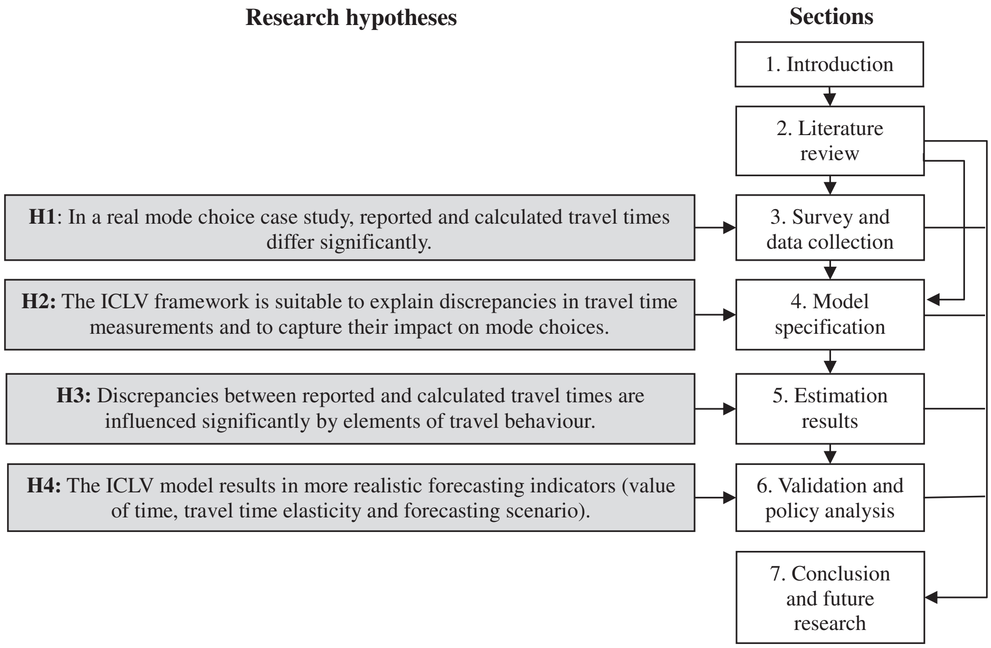

Fig. 1. Overview of the paper structure: relationships between sections (white boxes) and research hypotheses (grey boxes) addressed in each section.

analyse 901 valid staff observations reporting the first outbound home-university trip of the day.

3.2. Data processing

The available data were processed to extract the necessary variables to define the utility functions for the alternative modes. The choice of the transportation mode was assumed to be among four alternatives: car, motorcycle, public transport (PT) and walk. Individual choice sets were accounted for when users reported not having access to all alternatives.

Origin-destination matrices (OD) were constructed from a Visum (PTV Planung Transport Verkher AG) assignment model (Progetto UniMob, 2009-2010b). In this model, each zone was represented through a point placed in the barycentre of the zone and each trip was modelled as a trip between the barycentres of the corresponding OD zones. The OD pairs were assigned to each user. Distances between each origin and destination were calculated using Google Maps and based on the reported addresses of origin and destination. Travel time was imputed for each alternative mode separately accounting for the real speed experienced by travellers during the morning peak hour. Different devices were used such as Google Maps and the assignment model made in Visum. The walking travel time was calculated assuming an average speed of 4 km/h (Highway Capacity Manual, 2010). Travel and parking costs were calculated for the chosen and the unchosen alternatives. More details about the data processing are available in Varotto et al. (2014).

3.3. Travel time measurements

In line with the literature review, a first investigation focused on comparing the travel durations derived from reported and calculated sources. For the *chosen* alternative two measurements were used:

- Reported arrival and departure times;
- Calculated travel time, imputed from the assignment software Visum (for PT) and Google Maps (car and motorcycle), and corresponding to the in-vehicle time.

For the *unchosen* alternatives only the calculated travel time was available. Fig. 2 presents the distributions of reported and calculated travel times for the chosen alternative. The comparison reveals that the medians differ at the 5% confidence level for all instances (i.e., the notches do not overlap). Table 1 shows the difference and the ratio between reported and calculated travel times for the chosen alternative. Notably, reported travel time was higher than calculated measurements for all modes except walk. Possible explanations for the existing gap could be that, reporting travel time for the whole trip, some PT users included the time necessary to access the bus stop and the waiting time, while car users included the parking lot access time. Reporting and perception errors related to personal characteristics and trip activities are motivations that could be investigated as well. This analysis points towards the relevance of developing methods to account for imprecision in travel time reporting.

In this research, we focus on a detailed exploration of the impact of different sources of travel time data for a single mode, namely PT. There are three reasons for this. First, PT presents the most extreme difference in reported and measured travel times, and hence the most severe impact from taking either measure at face value and ignoring errors. Second, the ability to improve model accuracy has the largest policy relevance since PT has the greatest potential for democratizing access to the university and for minimizing external effects, compared to the competing private modes. Third, given the conflicted findings in the literature about the impact of advanced models of multiple input measurements, we propose an extensive investigation of the policy impacts. The focus on a specific mode allows us to make distinctive observations across numerous policy analyses. As noted above, PT was the mode affected by the largest gap between the two mean travel time measurements, in terms of absolute value (14.2 min) and ratio (reported 1.84 times higher than calculated). In addition, the imputation of travel time using the Visum assignment model potentially led to large measurement errors. In Section 4, we will describe a methodology to account for either measurement and also correct the travel time of public transport.

4. Model specification

In the following, we present an ICLV model in which the unobservable travel time assumed to drive the choices for public transport (*perceived travel time*) is jointly estimated with the choice model using the reported travel time as an indicator. Results are compared with a reference logit model in which the calculated travel time is directly included in the utility function for all the modes.

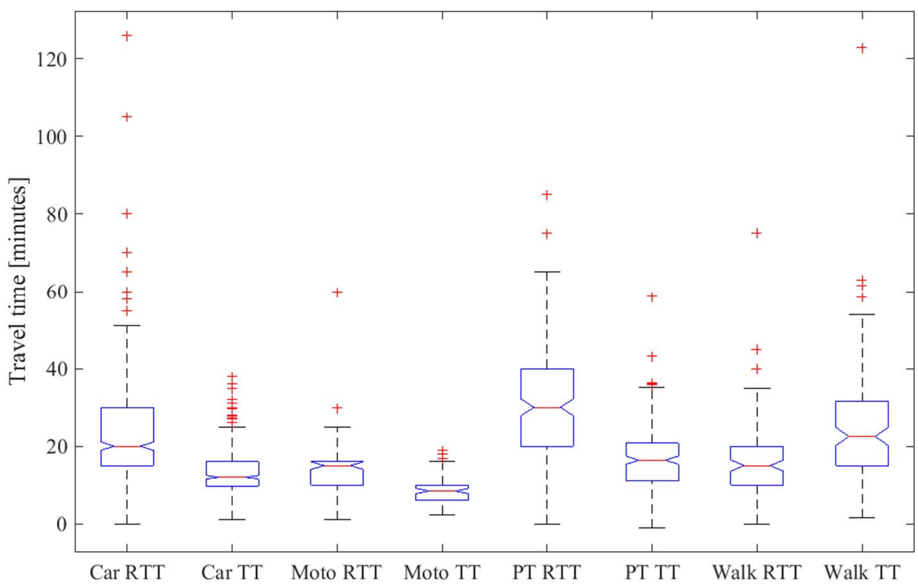

Fig. 2. Box-plot of reported (RTT) and calculated (TT) travel times for car, motorcycle, public transport and walk (chosen alternative). The central red mark indicates the median (q_2), the edges of the blue box the 25th (q_1) and 75th (q_3) percentiles. Given n the number of valid observations, the notch extremes ($q_2 - 1.57 \times (q_3 - q_1)/sqrt(n)$, $q_2 + 1.57 \times (q_3 - q_1)/sqrt(n)$) indicate the 95% confidence intervals of the median. The black whiskers ($q_1 - 1.5 \times (q_3 - q_1)$, $q_3 + 1.5 \times (q_3 - q_1)$) include the most extreme data points which are not considered outliers, while outliers are represented by red crosses. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 1
Statistics on travel time for the chosen alternative.

	Difference Mean reported travel time − mean calculated travel time [min]	Ratio Mean reported travel time/mean calculated travel time
Car	8.12	1.54
Moto	6.25	1.74
PT	14.2	1.84
Walk	− 7.10	0.71

4.1. *ICLV for the travel time which drives the choices of public transport*

The ICLV model (Fig. 3) consists of an integrated choice and latent variable model. Each part is composed of measurement equations and structural equations. Structural equations are represented by straight arrows while measurement equations are represented by dashed arrows. Observed variables such as explanatory variables, indicators, and choices are represented by rectangular boxes, and latent variables such as utilities and latent attributes are represented by ovals. This paper presents only the best overall specification based on statistical testing, with the following features:

- The calculated travel time is included in the structural equation of the perceived travel time as an explanatory factor;
- The reported travel time is used as an indicator of the perceived travel time, considered to be a manifestation of the unobservable travel time which drove the mode choices;
- Trip behaviour variables are included in the measurement equation, as explanatory factors of the discrepancies between calculated and reported travel times.

Notably, the model is applied only to the PT alternative. This specification allows specifying errors in reported travel times as a function of individual characteristics. The measurement equation in the latent variable model is estimated using only the observations in which PT

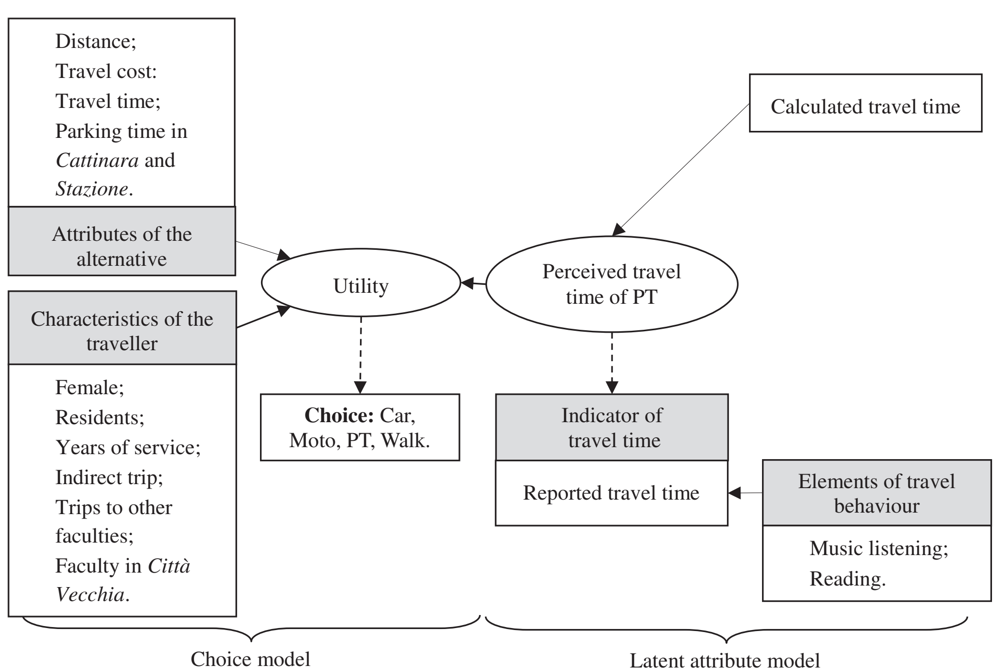

Fig. 3. ICLV for the travel time which drives the choices of public transport.

was the chosen alternative. The advantage of this approach consists in allowing the observed choices to influence the perceived travel time distribution.

4.1.1. Latent variable model: structural equation for latent attribute

In the latent variable model, the travel time which drives the choices TT_n^* (i.e., a latent attribute) is given in Eq. (1) for the public transport alternative and each individual n:

$$TT_n^* = c + \lambda_{TT} \cdot TT_n + \sigma \cdot \delta_n, \text{ with } \delta_n \sim N(0,1) \tag{1}$$

where TT_n is the calculated travel time, c, λ_{TT} and σ are parameters to be estimated.

4.1.2. Latent variable model: measurement equation for latent attribute

The measurement equation is built with the corresponding reported travel time RTT_n for each respondent n who chose PT, including the elements of travel behaviour $Reading_n$ and $Music_n$ as given in Eq. (2):

$$RTT_n = \alpha + \gamma_{TT^*} \cdot TT_n^* + \gamma_{Reading} \cdot Reading_n + \gamma_{Music} \cdot Music_n + \gamma_{MissReading} \cdot MissReading_n + \vartheta \cdot \delta_n, \text{ with } \delta_n \sim N(0,1) \tag{2}$$

where α and γ_{TT^*} are parameters which are fixed for normalization purposes, $\gamma_{Reading}$, γ_{Music}, $\gamma_{MissReading}$ and ϑ are parameters to be estimated, TT_n^* is the latent attribute, and $Reading_n$ and $Music_n$ are elements of travel behaviour of respondent n corresponding to the following statements:

- "I read during the home-university trip" (five-point Likert scale: 0.2 = always, 1 = never);
- "I listen to music during the home-university trip" (five-point Likert scale: 0.2 = always, 1 = never);

$MissReading_n$ is a dummy variable equal to 1 when the respondent did not report the frequency of reading. These elements of travel behaviour were selected based on an exploratory principal component analysis (PCA) which was performed with the whole set of travel behaviour variables, using the package *psych* version 1.2.8 developed by Revelle (2012) in the statistical software R. Non-linear functional forms were tested as well but did not result in significant improvements of the latent variable model. The measurement equation is based on a continuous scale.

4.1.3. Discrete choice models

The latent attribute TT_n^* is introduced into the utility function of public transport in place of the calculated travel time TT_{PT}. It is essential to note that including the calculated travel time TT directly into the utility function corresponds to assuming that the value is measured without error. Instead, including the latent attribute TT_n^* accounts for the distribution of the parameter. In the logit model, the deterministic part of the utility functions is given as follows in Eqs. (3)–(6):

$$V_{CAR} = ASC_{CAR} \cdot one + \beta_{Cost} \cdot C_{CAR} + \beta_{Time_{CAR}/D} \cdot \left(\frac{TT_{CAR}}{D}\right) + \beta_{ParkTime} \cdot ParkTime + \beta_{20Year_{CAR}} \cdot YearSer \cdot (YearSer > 20) + \beta_{IndTrip_{CAR}} \cdot IndTrip \tag{3}$$

$$V_{MOTO} = ASC_{MOTO} \cdot one + \beta_{Cost} \cdot C_{MOTO} + \beta_{Time_{MOTO}} \cdot TT_{MOTO} + \beta_{Female_{MOTO}} \cdot Female \tag{4}$$

$$V_{PT} = ASC_{PT} \cdot one + \beta_{Cost} \cdot C_{PT} + \beta_{Time_{PT}} \cdot TT_{PT} + \beta_{MissTime_{PT}} \cdot MissTime + \beta_{UnivBuild_{PT}} \cdot UnivBuild \tag{5}$$

$$V_{WALK} = \beta_{Time_{WALK}} \cdot TT_{WALK} + \beta_{CittaVec_{WALK}} \cdot CittaVec \tag{6}$$

where

- TT_{CAR}/D is the ratio of calculated travel time in minutes and distance in kilometres by car;
- TT_{MOTO}, TT_{PT}, TT_{WALK} are the calculated travel times in minutes;
- *MissTime*, is a dummy variable equal to 1 if the calculated travel time for PT is missing (14.21% of users);
- C_{CAR}, C_{MOTO}, C_{PT} are the travel costs in euros, which are equal to the cost of fuel for car and motorcycle, and equal to the ticket price (respondents who hold a ticket) or zero marginal cost (respondents who hold a pass) for PT;
- *ParkTime* is the time needed to find a parking lot in minutes;
- *Female* is a dummy denoting female respondents;
- $YearSer \cdot (YearSer > 20)$ is a variable equal to 0 when the years of service are below 20 and equal to the year of service otherwise;
- *IndTrip* is a dummy variable equal to 1 for respondents who reported to have stopped at least once during their home – university trip;
- *UnivBuild* is a dummy variable equal to 1 for respondents who travelled between university buildings;
- *CittàVec* is a dummy variable equal to 1 for respondents who travelled to the faculties located in the old town.

In addition, mixed logit models have been estimated to uncover unobserved heterogeneity in travel time sensitivities over the population. Each alternative specific parameter associated with the calculated travel time was assumed to be normally or lognormally distributed. The estimation results showed that the random parameter models did not improve the model specification significantly and for this reason the mixed logit results are not presented in the paper.

4.1.4. Integrated model framework

Under the assumption that the error terms are independent, y_{in} is the indicator of choice for an individual n (equal to 1 if alternative i was chosen, and 0 otherwise), the likelihood function for an individual n is given by the joint distribution of the observable mode choice and reported travel time, as presented in Eq. (7):

$$\mathcal{L}_n(y_{in}, RTT_n \mid X_{in}, X_n; \beta, \alpha, \gamma, \vartheta, c, \lambda_{TT}, \sigma) = \int_{TT^*} P(y_{in} \mid X_{in}, X_n, TT_n^*; \beta) \cdot f_2(RTT_n \mid TT_n^*; \alpha, \gamma, \vartheta) \cdot f_1(TT_n^*; c, \lambda_{TT}, \sigma) dTT^* \tag{7}$$

where

X_{in} is a vector representing the attributes of the alternative i for an individual n as defined in Eqs. (3–6);

X_n is a vector representing the characteristics of the decision-maker n as defined in Eqs. (3–6);

β is a vector of parameters to be estimated as defined in Eqs. (3–6);

γ is a vector of parameters and $\alpha, \vartheta, c, \lambda_{TT}, \sigma$ are parameters to be estimated as defined in Eqs. (1–2);

$P(y_{in} \mid X_{in}, X_n, TT_n^*; \beta)$ is the probability that alternative i is chosen by individual n;

$f_2(RTT_n \mid TT_n^*; \alpha, \gamma, \vartheta)$ is the density function of the reported travel time RTT_n;

$f_1(TT_n^*; c, \lambda_{TT}, \sigma)$ is the density function of the latent attribute TT_n^*.

This framework allows for the joint estimation of the perceived travel time distribution for public transport and the mode choice model in which the travel time is included as a latent variable. The parameters of the integrated model were estimated using maximum likelihood techniques as presented in Eq. (8):

$$\max_{\beta,\alpha,\gamma,\vartheta,c,\lambda_{TT},\sigma} \sum_n \log(\mathcal{L}_n(y_{in}, RTT_n \mid X_{in}, X_n; \beta, \alpha, \gamma, \vartheta, c, \lambda_{TT}, \sigma)) \tag{8}$$

When the parameters are estimated, the distribution of travel time, which drives the choices, is known and can be directly used for forecasting. This is a methodological advantage since the variable used as indicator (i.e., reported travel times for public transport) is only known for part of the estimation sample (i.e., respondents who chose this mode) which does not correspond to the forecast population. However, measurement errors in travel time reporting might be confounded with other phenomena, such as heterogeneity in travel time sensitivities

Table 2
Statistics and estimation results for the logit and ICLV model.

Statistics	Logit model		ICLV	
Number of parameters	15		21	
Number of parameters (choice component) K	15		14	
Number of observations	901		901	
Null log likelihood $\mathscr{L}(0)$	− 992		− 992	
Final log likelihood $\mathcal{L}(\hat{\beta})$	− 418		− 439	
Adjusted rho-bar-squared $\overline{\rho}^2 = 1 - \frac{(\mathcal{L}(\hat{\beta}) - K)}{\mathcal{L}(0)}$	0.564		0.544	
Parameters	*Estimate*	*t-test*	*Estimate*	*t-test*
ASC_{CAR}	1.28	2.70	1.29	2.08
ASC_{MOTO}	0.245	0.49*	0.0791	0.16*
ASC_{PT}	3.28	5.71	6.86	4.38
ASC_{SM}	–	–	–	–
β_{Cost}	− 4.83	− 11.98	− 4.75	− 11.43
$\beta_{Time\_CAR/D}$	− 0.893	− 5.59	− 0.927	− 5.83
β_{Time_MOTO}	− 0.142	− 3.29	− 0.129	− 3.05
β_{Time_PT}	− 0.109	− 7.13	− 0.178	− 4.59
β_{Time_WALK}	− 0.0834	− 9.33	− 0.0852	− 8.96
$\beta_{MissTime\_PT}$	− 5.43	− 6.62	–	–
β_{Park_CAR}	− 0.300	− 4.85	− 0.252	− 4.40
β_{Female_MOTO}	− 0.956	− 2.64	− 0.936	− 2.62
β_{20Year_CAR}	0.0181	2.35	0.0181	2.35
$\beta_{IndTrip\_CAR}$	1.49	5.16	1.59	5.48
$\beta_{UnivBuild\_PT}$	0.787	3.03	0.509	2.01
$\beta_{CittaVec\_WALK}$	0.780	1.96	0.848	2.19
Latent time − c	–	–	22.4	5.69
Latent time − λ_{TT}	–	–	0.587	6.26
Latent time − σ	–	–	− 1.32	− 1.08*
$\gamma_{Reading}$	–	–	− 7.90	− 2.69
γ_{Music}	–	–	6.25	2.16
$\gamma_{MissReading}$	–	–	− 2.20	− 0.20*
Measurement Equation − ϑ	–	–	2.39	34.68

* Coefficient not significant at 95% level.

among the population, which cannot be controlled for in absence of reported data also for non-chosen alternatives.

5. Estimation results

The maximum likelihood method is used for model estimation employing the extended software package BIOGEME (Bierlaire and Fetiarison, 2009). The ICLV model is estimated using the simultaneous approach as described by Walker (2001). The log likelihood, the goodness of fit indicators and the estimation results are reported in Table 2. The final log likelihood values and rho-bar-squared are calculated for only the choice component of the ICLV to be comparable with the logit model. The fit and the likelihood function of the choice component of the ICLV are typically lower than those of the corresponding logit model, which is consistent with recent findings by Vij and Walker (2012, 2016). Indeed, they observed that any ICLV model can be reduced to a choice model without latent variables that fits the data at least as well as the original ICLV model from which it was obtained. For this reason, the goodness of fit statistic cannot be used in isolation to compare the two structures.

In this section, we discuss the signs and magnitudes of the parameters associated with the attributes and the other explanatory variables. In the logit model, all the parameters are statistically significant. The parameters related to the modal attributes of travel time, cost, distance and parking time, affect the utility negatively, in line with expectations. The interaction TT_{CAR}/D implies that the coefficient of TT_{CAR} (i.e., $\beta_{Time\_CAR/D}$) is scaled by distance D in Table 2. This interaction is significant and improves the model fit only for the car alternative. In addition, the parking time parameter is only significant for the staff members working at the faculties located near Ospedale Maggiore and the railway station, where available parking lots are limited and time to find parking is high (e.g., 10–15 min).

Moreover, several socio-economic variables have a significant effect on the choice of transport modes. The explanatory variables have the expected signs and the main findings are presented below:

- The negative sign of β_{Female_MOTO} implies that females are less likely to choose motorcycles than other modes.
- Respondents with > 20 years of service are more likely to choose car than any other mode and this effect increases linearly with the number of years of service (β_{20Year_CAR}). A possible explanation is that longer working experience correlates with higher income (not available in this dataset) linked to a car preference.
- Indirect trips are related to a higher likelihood to choose car. Possible explanations relate to car being more flexible for making stops during the travel or that the user may need to drive other passengers to different destinations.
- Need to visit other university buildings during the day leads to favouring PT over other modes. A possible explanation could be that finding an empty parking lot near the visited buildings is more complicated.

The parameters estimated in the logit model and in the choice component of the ICLV model are comparable, with the exception of the PT time parameter and the PT constant associated with the mode-specific latent time. This finding is in line with Walker et al. (2010) who noted significant shifts in the time parameter of the ICLV model after the correction was carried out. Similarly, this study shows that the magnitude of the PT time parameter increases in the ICLV (− 0.178) compared to the logit (− 0.109). Looking at the ICLV, we expect the mean of the perceived travel time to have a magnitude and sign comparable to the mean values of the reported travel time (31.2 min) and calculated travel time (17.0 min) present in the raw dataset. In line with the expectations, the mean of the perceived travel time is equal to 33.4 min (90% confidence bounds: 28.7, 39.6). The probability that the perceived travel time assumes a negative value is equal to $1.48{\cdot}10^{-141}$.

Notably, the ICLV model allows to decompose the influence of observable variables into different constituent effects and link them explicitly to unobservable behavioural constructs (Vij and Walker, 2016). The impact of the calculated travel time on the utility of PT is given by its influence on the perceived travel time in the structural equation of the latent variable model λ_{TT} and the impact of the perceived travel time in the choice model β_{Time_PT} ($0.587{\cdot}(-0.178) = -0.104$). In line with expectations, this impact is similar to the PT time parameter in the logit model. The mean effect of the perceived travel time on the choices can be calculated by multiplying the mean value of the perceived travel time and the PT travel time parameter ($33.4{\cdot}(-0.178) = -5.95$). Controlling for this component of the PT alternative specific constant, it is possible to identify the mean preference for PT which remains unobservable in the choice model (6.86–5.95 = 0.915). Finally, the standard deviation of the random heterogeneity associated with the perceived travel time can be calculated by multiplying the parameter σ in the structural equation of the latent variable model by the PT travel time parameter ($(-1.32){\cdot}(-0.178) = 0.235$).

In the measurement equation of the latent variable model, the mean of the reported travel time is related to the perceived travel time (magnitude equal to 1), and the habits of listening to music (6.25) and reading (− 7.90). The standard deviation ϑ is 2.39 min. The parameters $\gamma_{Reading}$ and γ_{Music} have the expected signs, according to the results obtained by the exploratory PCA. Clear conclusions for missing values cannot be drawn due to the low t-statistic of $\gamma_{MissReading}$. It should be noted that the inclusion of these parameters in the measurement equation improves the fit of the latent variable model significantly and therefore contributes to a better estimate of the travel time parameter. The positive sign associated with the habit of listening to music means that people who usually listen to music are more likely to report a travel time that is closer to the calculated one. The negative sign associated with the habit of reading for leisure means that people who usually read are more likely to report a travel time that is farther from the calculated one. While all reported measurements are higher than the calculated, there are important differences related to the activity and its frequency. Respondents who always listened to music reported a travel time higher than the calculated time by on average 6.81 min (s.d. = 10.6 min), significantly less than transit users who never listened to music (mean excess report = 16.4, s.d. = 12.8 min). People who always read for leisure reported a travel time higher than the calculated time by on average 15.5 min (s.d. = 11.4 min), more than respondents who never read (mean excess report = 12.6, s.d. = 11.7 min).

It is likely that reporting of travel variables, like duration, is tied to the enjoyment of travel. Travel is known to incur positive utility related to trip activities (Redmond and Mokhtarian, 2001), whereas, overall, transit is the least enjoyable mode, with a higher desire to reduce current travel (Páez and Whalen, 2010). Reading and listening to music both lead to a more positive evaluation of the transit commute (Rasouli and Timmermans, 2014) and can therefore be related to reporting biases. However, there is little guidance on the potentially different impact of reading compared to music exposure. One difference consists in the possibility of listening to music for all modes, while reading is only an option in PT. In addition, the habit of reading for leisure can be related to the possibility of finding a seat, which can also influence the experience of travellers but has not been analysed in the questionnaire. Our results are consistent with findings by Frei and Mahmassani (2011) on the relationships between travel behaviour and activities while commuting for transit riders in Chicago. Interestingly, they found that the agreement with the statement ‘PT is a better use of time/money than driving’ was positively related to reading printed materials and negatively to using audio/visual electronics. This implies that travellers who read rated transit as a more worthy use of time/money, while travellers who used audio/visual devices did not. A possible explanation is that people do not listen to music for their own pleasure but perhaps to shield themselves from other passengers. Further analysis of the links between activities, travel evaluation, and perception of travel time is needed to explore the different results of reading and music listening in this study.

6. Validation and policy analysis

Several analyses are launched to investigate the performance and validity of the integrated model compared to the equivalent logit model. The latent variable and the choice model are examined. Aggregated time elasticities are calculated for each mode to explore the variations in the market shares caused by an increase or decrease in travel time. Value of time is computed for each mode to investigate the willingness to pay (WTP) of individuals to reduce the duration of their trip by one hour. Finally, a forecasting scenario is tested to analyse the impact of varying value of time estimations on mode choice.

6.1. Validation analysis

The validation analysis is composed of two phases, which focus on the latent variable model and the choice model. The residuals of the measurement equation of the latent variable model are analysed as a diagnostic of the normality assumption of the error term. A proper validation of the choice model will require its application on a different data set but no other similar dataset is available. Therefore, a hold-out approach is used with the model estimated on a first data sub-part and applied on the second.

6.1.1. Validation analysis of the latent variable model

The residuals of the measurement equation are calculated as presented in the Eq. (9):

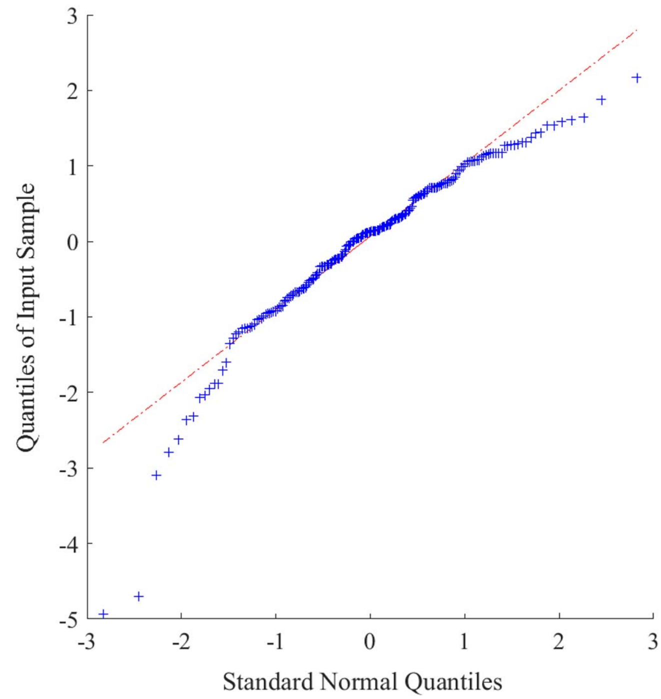

Fig. 4. Normal Q-Q plot of standardized residuals – latent variable model for travel time which drives the choices.

$$d_n = RTT_n - a - \gamma_{TT^*} \cdot TT^*_{nSIM} - \gamma_{Reading} \cdot Reading_n - \gamma_{Music} \cdot Music_n - \gamma_{MissReading} \cdot MissReading_n \tag{9}$$

where $TT_{n_{SIM}}{}^*$ are the fitted values of $TT_n{}^*$. The Q-Q plot is reported in Fig. 4 and shows a straight continuous line, suggesting that the measurement equation proposed fits the data well.

6.1.2. Validation analysis of the choice model

The dataset is split into two parts. The minimum size of the validation sample is calculated using the method based on the First Preference Recovery (FPR) concept, proposed by Ortúzar and Willumsen (2011). First, 70% of the observations are selected randomly and the model is estimated on the latter. Second, the models are applied on the remaining 30% of the observations. The null hypothesis that the two models are equivalent in terms of FPR is tested (Ortúzar and Willumsen, 2011). This hypothesis cannot be rejected at 0.05 significance levels and therefore it is possible to conclude that the models are equivalent on these terms. In addition, the average number of alternatives available for each respondent and the corresponding chance level, are calculated. Table 3 reports the percentages of choice probabilities higher than 0.333 (chance level), 0.500, 0.700 and 0.900. The choice probabilities are well predicted by both models.

6.2. Time elasticities

Table 4 presents the aggregate time elasticities, indicating the percent change in the market share with respect to a change of 1% in the corresponding time variable. Analysing the logit model, we note that the time elasticity of PT ($-$1.283) is higher in magnitude than those of

Table 3
Percentages of choice probabilities higher than given thresholds.

Threshold	Logit model	ICLV
33.3%	83.1%	83.1%
50.0%	75.6%	72.9%
70.0%	60.9%	59.8%
90.0%	40.6%	37.6%

Table 4
Time elasticities, value of time and forecasting scenario.

	Logit model	ICLV
Time elasticities		
Car	− 0.865	− 0.895
Moto	− 0.197	− 0.179
PT	− 1.28	− 2.15
Walk	− 5.63	− 5.75
Value of time		
Car	4.69 €/h	4.94 €/h
Moto	1.76 €/h	1.62 €/h
PT	1.36 €/h	2.25 €/h
Parking search time	3.73 €/h	3.19 €/h
Forecasting scenario		
Car	52.9% (− 0.0938%)	52.8% (− 0.135%)
Moto	9.75% (− 0.0130%)	9.74% (− 0.0195%)
PT	23.8% (+ 0.107%)	23.6% (+ 0.155%)
Walk	13.5% (− 0.000100%)	13.5% (− 0.00490%)

car and motorcycle, meaning that PT users are more sensitive than car and motorcycle users to changes in travel time. This result suggests that the market share of PT will increase if the travel time is reduced (e.g., introducing a faster bus line). However, pedestrians seem to be the most sensitive group. The time elasticities calculated appear to be similar to the referential value found in the literature. De Jong and Gunn (2001) reviewed elasticities of car travel demand in Europe and proposed short-term time elasticity equal to − 0.54 for commuters travelling by car in Italy. They analysed an Italian national model, considering trips between relatively large zones and dealing with different distance classes. Berni and Mealli (2013) proposed a choice experiment to staff and students at the University of Firenze, asking to report travel time using intervals. They found that, in an urban environment, the travel time elasticities varied from − 0.35 to − 1.01 for car, from − 0.11 to − 0.16 for motorcycle and from − 0.88 to − 1.54 for bus, depending on the characteristics of the respondents and the alternatives available.

Comparing the ICLV model to the logit, we find that the time elasticities are marginally higher for car and lower for motorcycle. It is interesting to note that the PT time elasticity increased in magnitude by over 65% (from − 1.28 to − 2.15) in the ICLV. These results indicate that, accounting for stochasticity in travel times, users appear to be more sensitive to PT travel time changes. However, it is not possible to directly compare this elasticity to previous literature, because the above-mentioned examples used travel time data potentially affected by errors, in measurement (De Jong and Gunn, 2001) and reporting (Berni and Mealli, 2013). In addition, elasticities were not calculated by previous studies proposing the hybrid choice framework to correct errors in travel time. The main observation from computing the elasticities relates to the large change in magnitude as the latent nature of the travel time is accounted for.

6.3. Value of time

The value of time (VOT) is presented in Table 4. In the logit model, the VOT is higher for car than for all the other modes. The VOT calculated for car seems consistent with contextually similar VOT in Italy found in the literature. Indeed, many authors reported a value of time for urban commuting trips by car around 4.00–5.00 €/h for workers (Catalano et al., 2008; Cherchi, 2003; Fiorello and Pasti, 2003). The VOT obtained for PT seems to be lower than expected.

In the ICLV, the time parameter for PT increases in magnitude and the estimated VOT increases significantly, in line with the case study presented by Walker et al. (2010). The value of time increases by over 65%, from 1.36 €/h to 2.25 €/h. This result seems to be consistent with the increase in time sensitivity indicated by the elasticity. In addition, the 90% confidence bounds for the VOT of PT are calculated: in the logit model, the confidence interval is equal to (1.15, 1.55); in the ICLV, it is (1.58, 2.86). The confidence intervals do not overlap confirming that the different treatments of the time variable reveal significantly different VOTs. The VOT obtained for PT within the hybrid choice framework seems to be more realistic but it is not possible to directly compare this value to previous literature, given that the travel time data in those cases are potentially affected by errors. However, it is interesting to note that accounting for variability in travel time sensitivities among respondents led to similar results. Accounting for these variations in a mixed logit model, Cherchi (2003) found a VOT for urban work commute trips by PT around 2.00 €/h. She concluded that the VOT are largely underestimated using the parameters estimated with a logit.

6.4. Forecasting scenario

The scenario proposed evaluates the effects related to the introduction of an “express” bus line service to the main campus of the University of Trieste (Piazzale Europa) and the corresponding reduction in PT travel time. The aim is to understand if a decrease in PT travel time would encourage a mode shift from car in favour of PT. An origin - destination pair (Villa Opicina - Piazzale Europa) including 28 users in this sample is selected. In the assignment model, Villa Opicina was represented by a large zone, due to its location in the suburbs of the city. Given this, the travel time calculated for PT could potentially be affected by large measurement errors. Analysing these observations, we note that the gap between reported and calculated measurements for respondents who choose PT is larger than the average (16.4 min). In addition, the ICLV predicts higher choice probabilities when car is chosen.

In the simulated scenario, the travel time of PT is assumed to decrease by 2 min, due to skipping some intermediate bus stops. This variation is directly introduced in the utility function, changing the calculated travel time in the logit and the perceived travel time in the ICLV. The market shares predicted are presented in Table 4. The logit forecasts an increase of the PT share equal to 0.107%, while the ICLV predicted an increase equal to 0.155%. This result is consistent with the elasticities calculated, indicating that, accounting for stochasticity, users are more sensitive to changes in PT travel time.

7. Conclusion and future research

Travel demand models typically rely on multiple data sources, each valuable to understand choices, but each affected by unique errors and biases. The aim of the paper is to account for limitations in available data and explain errors in reported travel variables such as travel time. In order to deal with these errors, a hybrid choice modelling approach is proposed integrating travel time as a latent variable. Using data from a revealed preference survey, a hybrid choice model is estimated that treats travel time as a latent variable and incorporates different sources of data (revealed and software-based) along with information on travel activities affecting the reported travel time measurement. In particular, the methodology is employed to correct the travel time of PT viewed as particularly problematic due to the use of network derived level of service (i.e., zone-to-zone travel time calculated by Visum as opposed to point-to-point measurements). In a preliminary analysis, the data show a significant gap between the travel time reported by respondents (1.84 times higher) and the one calculated by instruments. In the latent variable model, the reported travel time is used as an indicator of the perceived travel time and the calculated travel time is included in the structural equation of the perceived time as an explanatory factor. This specification accounts explicitly for errors in the reported measurements. In addition, trip behaviour variables, such as the habits of listening to music and reading during the home-university trip, are included to explain the gap between reported and calculated time. Interestingly, these habits have an opposite relation with travel time reporting in spite of an apparently similar entertainment function.

Respondents who usually listen to music are more likely to report a travel time that is closer to the calculated one, while respondents who usually read are more likely to report a travel time that is farther from it. Further research is needed to determine the origin of this effect. The inclusion of these elements in the measurement equation improves the fit of the latent variable model and contributes to a more realistic estimate of the travel time parameter.

In terms of demand analysis, results indicate that the reference logit specification, which does not correct for measurement errors, produces a significantly lower value of time (1.36 €/h). The ICLV model with error mitigation generates more consistent parameters for the travel time variable and a more realistic value of time (2.25 €/h), closer to the referential value found in the literature for urban public transport in Italy when accounting for stochasticity in the travel time parameter (Cherchi, 2003). Similarly, the ICLV produces higher travel time elasticities and market share increases for PT suggesting that users are more sensitive to changes in travel time than the logit predicts. However, measurement errors in travel time reporting might be confounded with other phenomena, such as heterogeneity in travel time sensitivities among the population, and it is very difficult to isolate them.

The key point in this research is that measurement errors can cause serious biases and methods that explicitly recognize and explain the origin of such errors are necessary to improve the realism of the resulting analysis. The case study analysed shows that standard methods to determine VOT estimates (e.g., logit), often used for the cost-benefit appraisal of transport projects, can result in significantly lower willingness to pay of individuals to reduce their trip duration. By integrating reported travel time and elements of travel behaviour, the ICLV produced higher VOT and more sensitive responses of the model. Indeed, users may prefer longer travel times because of the activities they perform during the trip (e.g., reading for leisure). Therefore, favouring these activities with appropriate policies (e.g., free newspapers distributed on buses) can have an effect on mode choices equivalent to travel time reductions.

The findings suggest several directions for future research. Other types of reporting and measurement distortions may affect the behaviour of travellers. Specifications with mixed discrete-continuous distributions of travel time could be introduced in the measurement equation of the latent variable model, explicitly addressing the rounding of reported travel time. A second extension is to expand the specification to correct measurement errors for more attributes or for each alternative mode. A third development would be applying the mitigation of biases to travel time reported for both the chosen and the unchosen alternatives (if available) using two different measurement equations. In addition, an ideal future application of frameworks accounting for errors would require richer information to be collected at the survey stage. This includes more detailed information on user choice sets, disaggregated travel time data (e.g. access time, waiting time, number of transfers, in-vehicle time and the egress time), reports of performance for both the chosen and the non-chosen alternatives. Finally, further work on identifying the causes of biased reporting is needed. Models of travel enjoyment, aspirations, mental shortcuts and personality are all likely to be linked to how trips are perceived and to the degree of error in reporting (e.g., findings in Hess and Stathopoulos (2013) on decision rules and travel time acceptance, and Milakis et al. (2015) on perceptions, feelings and travel time acceptance need to be linked to reporting distortions).

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