MATCHING OPEN DATA WITH SMARTPHONE TRAVEL SURVEY DATA TO EXPLORE PUBLIC TRANSPORT USERS' SATISFACTION

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Abstract

The aim of this study is twofold: 1. to describe the procedure of matching longitudinal smartphone based travel survey data with open operational data, and 2. to quantify the effect of both types of data on customers satisfaction with using rail-based public transport modes. The travel data utilized in this paper originate from the smartphone-based London Mobility Survey (LMS) and was collected between November 2016 to February 2017. The open data matched to the LMS data has been derived from the open TfL API. An ordered logit model is developed to quantify the effect of public transport service status, and individuals' socio-demographic and trip characteristics on satisfaction with using public transport mode for each one of their trip-stages. Our results indicate that customer satisfaction is indeed associated with the open public transport status data and that satisfaction depends on each trip and the conditions of the trip. Activities while travelling and trip purpose also affect customers satisfactions, while these results provide insights for offering products that can advance customers experience in the Mobility-as-a-Service and automated vehicles era that lies ahead.

Key words: public transport, satisfaction, happiness, open data, transit data, matching, machine learning, smartphone travel survey, ordered model

1. INTRODUCTION

The promotion of public transport usage is high in the agenda of most of the cities around the world. During the last decades, public transport authorities have done considerable efforts to evaluate the quality of their services and identify their customers' needs in an effort to acquire new ones and retain the existing. Especially nowadays, with the increase of on-demand and ridehailing services, which seem to compete with public transport modes (*1*), the customer retention may be as equal important to the attraction of new ones. As such, customer satisfaction surveys are increasingly applied by public transport authorities, as a way to identify the expectations of both existing and potential customers.

These surveys usually investigate customers' satisfaction and the perceived performance of public transport (*2-8*) and then they are compared to the objective operational data. However, there are several arguments on the importance of linking the perceived and the objective data to maximize the outcomes of satisfaction and performance surveys (*9-11*). So far, there are only few surveys that take into account both data types to assess customers' satisfaction. Carrel et al. (*9*) demonstrated the importance of complementing customer satisfaction data with automatic vehicle location data to better interpret the perceived satisfaction with using public transport modes. Bordagaray et al. (*10*) indicated the necessity of this approach by finding that even though accounting for customers' experience, reliability remained one of the key elements determining customer satisfaction. Friman and Felleson (*11*) also analyzed the relationship between these two data types in six different European cities, but they did not find any correlation concluding that this is probably due to the aggregate nature of the used data and not due to the fact that these two data types are not correlated.

Another characteristic of most of the available satisfaction surveys is that they typically use cross-sectional data to examine the factors affecting public transport customers' satisfaction and infer the magnitude of their effects (*2-8;12-16*). Satisfaction data is usually collected only at one point of time asking the public transport users to rate their last trip, or their last commute trip, or their satisfaction in general with the public transport services (*2-8;12-16)*. When individuals are repeatedly involved in an event/activity, they tend to remember only the most intense pleasant and unpleasant moments overall and the most recent events (*17;18*). Lately, there are several studies that use text-mining techniques to derive information about public transport users sentiments via social media to assess customer satisfaction (*50-52*). Although, this approach can offer spatio-temporal and longitudinal data, it has several limitations, such as the lack of information about the socio-demographic characteristics of the users, or the bias of the collected data as social media users tend to post their negative feelings about transport and not their positive thoughts (*50*).

Against this background, there is a necessity to investigate public transport customers' satisfaction using both perceived and objective data, but also longitudinal data to derive more and better information about the factors affecting satisfaction. The smartphone based travel survey tools have enabled the collection of longitudinal travel data, while the increasing availability of Open public transport data allows the acquisition of objective operational data. The aim of this study is twofold: 1. to describe the procedure of matching longitudinal smartphone based travel survey data with open operational data, and 2. to quantify the effect of both types of data on customers satisfaction with using rail-based public transport modes. The travel data utilized in this paper originate from the smartphone-based London Mobility Survey

(LMS) and was collected between November 2016 to February 2017. The open data matched to the LMS data has been derived from the open TfL API (Application Program Interface). An ordered logit model is developed to quantify the effect of public transport service status, and individuals' socio-demographic and trip characteristics on satisfaction with using public transport mode for each one of their trip-stages.

By reviewing the literature, only one study was identified that follows this approach. Carrel et al. (*9*) have used automatic vehicle location data (objective operational data) to infer waiting and in-vehicle travel times and then matched this to smartphone based travel data. Then an ordered logit model was developed to explore public transport customers satisfaction finding a strong sensitivity of passenger satisfaction toward in-vehicle delays. However, the focus was mainly on the effect of travel time and socio-demographic characteristics on customers' satisfaction. In addition, their satisfaction data was collected only once per day and it was not specific to each recorded trip. In this paper, we go one step ahead by also including trip-specific characteristics to investigate the satisfaction, such as trip purpose and activities while travelling. Furthermore, our satisfaction data is specific to each recorded trip-stage that an individual contacted by public transport mode. As such, we have very detailed information to explain public transport customers satisfaction and if this changes across the trips. To our best knowledge, there is no previous research that investigates customers satisfaction with public transport using both longitudinal and open performance data, while also compares the effect of activities while travelling on satisfaction. In addition, we did identified any previous research that investigates the effect of different trip purposes; most of the available studies focus only on commute trips, while there only few focusing on leisure trips as well. Heading to the Mobility-as-a-Service and automated vehicles era, it is important to investigate these factors as well to be able to offer to users products and services that really advance their experience and potentially increase the public transport demand.

The rest of this paper is structured as follows. Section 2 describes the LMS survey design and its potentials. Section 3 presents the method used to match the open data with the LMS-tracking data. The characteristics of the sample used for this analysis are presented in Section 4. The customer satisfaction model specification and estimation results are presented in Section 5, while Section 6 concludes the paper.

2. SURVEY DESIGN

The data used in this study originate from the London Mobility Survey (LMS), which has been designed by the MaaSLab at University College London (UCL). LMS has been developed using a smartphone based travel survey tool, the Future Mobility Sensing (*19;22*). LMS incorporates several parts of the London Travel Demand Survey (the official travel survey of London that takes place every year[1]) to allow for comparisons, while it has been enhanced with additional detailed questions about usage of new mobility services (for a detailed description see *20*). LMS consists of 3 steps:

- *Step 1*: The participants create an account and answer to the pre-questionnaire that includes questions about their socio-demographic and mobility tool ownership characteristics along with their attitudes towards private vehicle ownership and shared mobility. This step provides a dataset with information

[1] https://tfl.gov.uk/corporate/publications-and-reports/london-travel-demand-survey

about the individual, a dataset about the household, and a dataset about vehicle characteristics (in case the household owns at least one vehicle).

- *Step 2*: after the completion of Step 1, participants are asked to download the FMS app (available for Android and iOS) on their smartphones and track their activities for 7 days. The tracking uses Wi-Fi, GSM, GPS and accelerometer readings to first store location traces and then to create the activity diary presented to users. As a prompted recall survey, respondents need to log back in online to validate their travel and non-travel activities and answer some additional questions for each of their activities; some of these additional questions are customised further to each activity type and mode. This step provides a dataset with the tracking data and the additional questions for each activity (LMS-tracking).
- *Step 3*: The exit section; when the 7-day tracking and validation are complete, respondents are shown with their Mobility Record (an aggregated summary of the number of trips, duration, travel time and cost broken down by each transport mode). Based on their Mobility Record hypothetical monthly mobility packages (stated preference experiments; see *21*) are generated including several combinations and amounts of the available transport modes in London. The final step gives the SP dataset and the mobility record dataset.

In the Step 2 of the survey, the application collects raw spatial and temporal data in the form of latitude-longitude coordinates and time stamps without user intervention. These provide the basis for the respondents' activity diary. The server stores the raw data. Once the raw data is collected an algorithm is applied to the data, which makes inferences and creates the activity diaries that are presented to the respondents (for details see *22*). This is also supported by Google maps API, which helps with visualizing the trajectory of each trip and assists respondents with recalling their travels. When presented with their activity diary on the online platform, users need to verify their trips and have the opportunity to edit any misidentified stops or modes. Then the participants are asked to provide more information for each activity. Since the focus of this paper is on public transport and satisfaction, we will only focus on the questions that follow when the participants conduct a trip with a TfL rail-based mode (these are: tube, overground, TfL rail, DLR and tram). These questions are:

i. *How many people travelled with you*? (options: 0 to 5+),
ii. *How did you pay for this trip*? (options: Oyster card-Pay as you go, Contactless, Smartphone pay, Travel pass, Other),
iii. *Which line did you travel with*? (options: the 15 rail-based lines, other),
iv. *Were you doing any of the following on your journey*? (options: Using mobile, Working, Listening to music, Watching movies, Playing games on mobile device, Reading adverts/posters, Daydreaming, Nothing, None of the above-could choose more than one), and
v. *How happy were you by using this mode*? (7-point Likert scale, with a frown and a smiling face on the extremes).

In addition, a number of extra data from Open sources is linked to each recorded and validated trip to decrease the respondent burden during survey processes, while improving the accuracy, quality and amount of the collected data (*23*). Figure 1 presents the open data that is linked to each recorded trip. Two types of open data is linked: (1) static, and (2) dynamic/real-time. The linked static data is presented on the left side of Figure 1 and allows us to automatically recognise transfers from one mode to the other, or even transfers from one tube/underground line to another since the TfL tube stations have wi-fi. The static TfL Fares, Capping Rates and StopPoint APIs across with the Oyster Zones shapefiles allow us to automatically derive public transport travel costs. Due to the fact that TfL uses a complicated pricing system (peak hours, travel zones, special fare zones, capping etc.), it is very difficult for travellers to recall the amount they pay for each of their trips (see 20). With this approach, there is no need to ask the participants for their travel costs.

Furthermore, numerous dynamic/real-time open data is linked to each recorded activity as presented in the right side of Figure 1. This data is utilised via:

- the Status of the public transport (PT) services API that offers information about delays. This API is further described in the following section, while its data is used in the model presented in Section 5 to investigate how different PT statuses affect PT users' satisfaction;
- the disruption API that provides information about the road network conditions and any potential incidents that may affect road traffic;
- the bike-points (that is static) and the cycle hire (that is dynamic) API offering information about docking stations locations, if there are available bikes at the stations or if there are free spaces to lock a shared-bike;
- the car parks occupancy API provides information about parking availability mostly around train stations and several other locations in the city of London;
- the TfL traffic cameras API offers audio-visual material from numerous locations across the city;
- the weather and air quality APIs provide data about weather conditions (i.e. temperature, rain, humidity etc.), and emissions;
- the National Rail API, which offers information about rail status and delays; and
- the Google maps API that allows deriving the alternative routes and the alternative transport modes that an individual could have used to go from A to B, and the characteristics of these alternatives (i.e. travel time).

By connecting all these external data, we get a unique database for transport planning purposes that provides a plethora of information for each one of the activities and trips that the participants conduct.

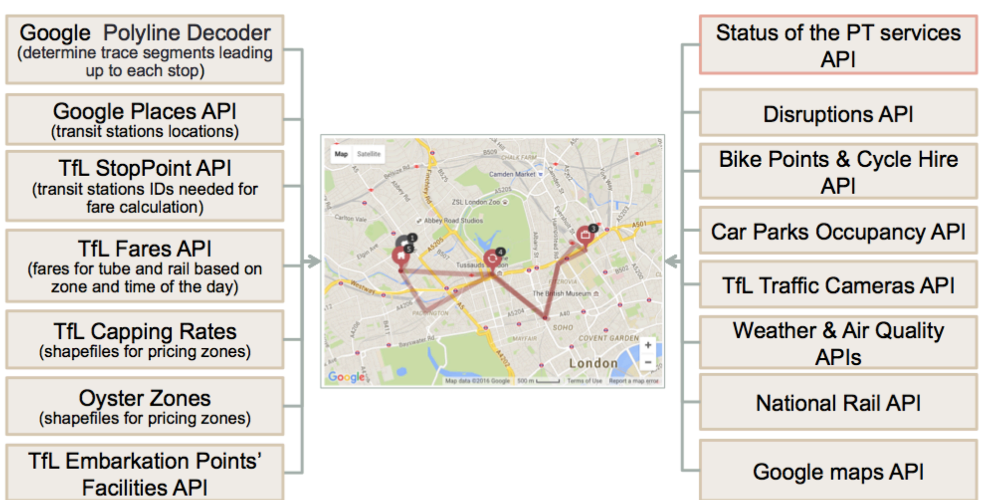

Figure 1: Open data linked to each recorded activity, trip and stage

3. MATCHING OPEN AND TRAVEL SURVEY DATA USING MACHINE LEARNING

In the context of this study we focus on linking TfL data concerning the status of each rail-based public transport mode line with an ultimate purpose to investigate its effect on users satisfaction with using these modes. This section further describes the open data that was linked to the LMS-tracking data and the method followed for the matching.

3.1 Description of the "status of the PT services" API

While collecting travel data using LMS, we also collect the "Status of the PT services" data (as well as all the data presented in Figure 1). For gathering the PT status data, we utilized the TfL Unified API[2]. This API lets one retrieve the status of all different TfL modes at any given time through HTTP (HyperText Transfer Protocol) requests. The status of a TfL line describes how the service is running at a given moment including information about possible disruptions. The request we use for our purposes receives as parameters a comma-separated list of the TfL rail-based modes and returns a status severity code for each PT line, which corresponds to a short description as shown in the table below (Table 1). By repeatedly making such requests in 10-minute intervals we collect the TfL status data into a MongoDB database.

Table 1: TfL statuses as derived from the TfL Unified API and definitions

Special Service	**Part Closure**	**Good Service**	Diverted
Closed	**Severe Delays**	Part Closed	Not Running
Suspended	Reduced Service	Exit Only	Issues Reported
Part Suspended	Bus Service	No Step Free Access	No Issues
Planned Closure	**Minor Delays**	Change of frequency	Service Closed

*TfL provides real time information using these descriptions, while sometimes it also provides the reason of a potential delay. No further explanation is provided to the users about the length of the delays. The service status of each line is calculated based on four criteria: 1.Headways: the intervals between trains; 2.Slow moving trains: whether the train service is operating more slowly than usual; 3. Stoppage/Sit Down: when trains are not moving for an extended period of time; 4.Percentage of trains in service: the actual number of trains in service compared to the scheduled service.

** The statuses that are in bold have been identified in our dataset and are used in the model presented in Section 5.

*** TfL does not provide any official definitions for the statuses, as they are self-explained. A further explanation about the statuses is provided by the authors to ease the reading of the paper: -*Special service*: when a line's service is limited; -*Part suspended*: part of the line's vehicles are suspended (is held); -*Part closure*: the line does not serve part of the stations; -*Severe delays*: the line's vehicles run with severe delays; -*Minor delays*: the line's vehicles run with minor delays; *Good service*: the line's vehicles operate without any delays and all the stations are available.

Dealing with missing values

Before being able to actually link the datasets it became apparent, even though LMS-tracking data is verified, that a few values of key variables were missing due to bugs in the system. In particular during the verification stage users were asked to fill in whether they travelled by bus or TfL rail-based modes and which line they picked. Many users did indeed indicate their transport mode, but failed to specify the exact line, which resulted in missing values (83 missing values –out of the 1,323- were identified in this variable). Without these values the matching process was intractable because for each unspecified line there were multiple possible TfL status values to match. Instead of deleting those entries or randomly filling these values we employed a different solution. Since tracking data was still available, regardless of the lack of a

[2] https://api.tfl.gov.uk

verified mode of travel, we opted for rectifying those missing values by making use of the Google Maps Directions API (see Figure 2). A request to this API receives as parameters a latitude and longitude pair as origin, another one as destination and the preferred mode of travel and time of the day, to return a proposed route of travel. For each missing value, we retrieved the exact line that was most probably used, by imposing the indicated mode travel in such a request between two consecutive stops and picking the recommended from Google route between those two points. Having dealt with missing values we could now proceed to linking the datasets.

3.2 Matching the Open data to Travel Data using a machine learning algorithm

After the completion of each LMS data collection wave, we utilise a well-known machine learning algorithm, i.e. nearest neighbours (*23*), for temporally aligning the TfL service status data and all the open data presented in Figure 1 with the LMS-tracking dataset.

Each line in the LMS-tracking dataset represents a specific geographical point where the user stopped and contains a corresponding timestamp. Since every entry in both the LMS-tracking dataset and the TfL ones is characterized by a unique timestamp, the process of linking the TfL dataset to LMS-tracking is reduced to fetching the corresponding entry of the TfL dataset which is temporally closer to each entry in the LMS-tracking.

As shown in Figure 2 initially we retrieve the missing TfL line values from Google Maps API as described above. Then TfL status values corresponding to each TfL line are parsed from MongoDB into a dataframe, which is used to match their corresponding LMS-tracking entries. After the matching is complete the two datasets are merged into an augmented dataset containing only the matched TfL data entries along with those LMS data relevant for further analysis.

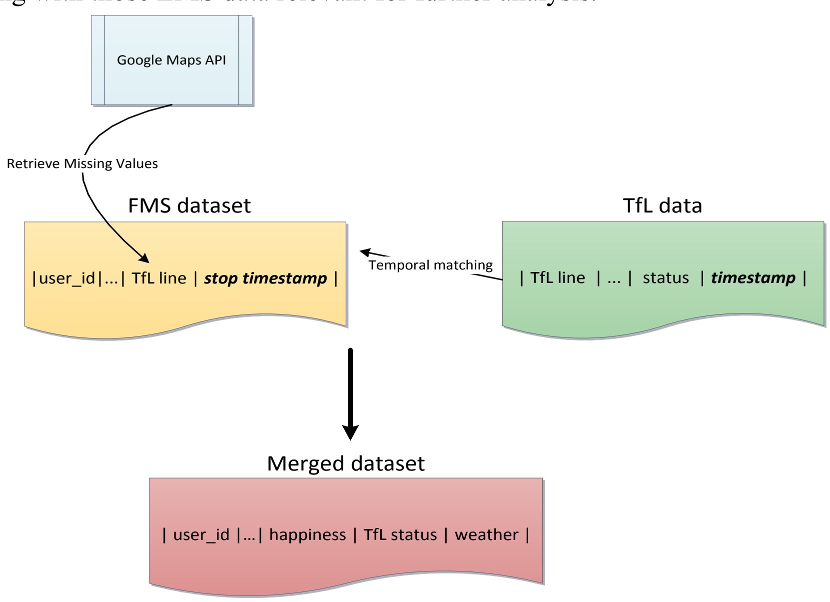

Figure 2: Linking TfL service status data to LMS-tracking data

A naive way to match a sequence of timestamps to another is to examine the first timestamp in the first sequence, compute the distance of this timestamp from each one on the second sequence and select the shortest of all. Then repeat this for each timestamp in the first sequence. Distance can be any sort of similarity measure but in the context of timestamp sequences the Euclidean distance is sufficient. For two sequences of size *n* and *k,* this procedure would involve the computation of *nk* distances and is known as *brute-force* nearest neighbours as it entails the computation of all distances (*24*). Naturally, this approach does not scale well with big datasets such as LMS-tracking data, which involves thousands of entries. In an effort to perform the matching operations in a more efficient manner with respect to the size of our data we searched for more scalable solutions.

One the most prominent methods especially when it comes to low dimensional data is the use of KD trees (*25*). Once the tree is built on the k-sized sequence this method can reduce the number of distance calculations to as low as *O(logk),* which constitutes a significant improvement over the *brute-force* approach. The basic idea that this method exploits, is that if a query point q is very far from another point x while x is very close to x' with $x' > x$ then x' cannot be a nearest neighbour to q therefore one can omit the calculation of the distance between q and x'. On applying this method to find the nearest neighbour of each LMS-tracking entry, we constructed a KD tree for holding the TfL timestamps while using LMS-tracking data as query points. We observed a major improvement in the matching speed in comparison to the *brute-force* approach.

The rest of the open data (Figure 1) is matched using the same methodology. The data matching has been conducted using Python machine learning algorithms. The datasets have been set up in MongoDB and can be extracted in any format for further analysis.

4. DATA COLLECTION AND SAMPLE CHARACTERISTICS

The LMS survey is an on-going survey, but the data used for the analyses in this paper was collected between November 2016 and February 2017 (excluding the holidays). The participants were recruited from the Exterion Media's community panel. Those who completed all the three steps of the LMS were entered into three small-scale lotteries for winning three vouchers of £20 each (a detailed description of the survey, the participants recruitment, and the completion rates, can be found in *20*). In general, 338 participants were registered and completed the Step 1 of LMS, while 252 individuals downloaded the app and started the tracking (Step 2).

157 individuals out of the 252 have used public transport modes and these individuals constitute the sample for this paper. These 157 individuals have conducted 1,323 stages[3] by TfL rail-based public transport modes. The minimum number of validated days is 1, the maximum is 9, while the average number of stages per individual is 8.4. The socio-economic characteristics of the sample are presented in the upper part of Table 2 and are also compared to the socio-economic characteristics of the LTDS. At this point, it is necessary to make clear that we compare the characteristics of our sample to the TfL rail-based modes users of LTDS (not the whole dataset). In addition, LMS recruits only adults (18+), and as such the LTDS sample used for comparison includes only adults. Due to the fact that LMS is smartphone based, it is also worthwhile noting that four out of five adults in the UK have a smartphone, while among 18-44 year olds -that is the age group that most of our survey participants belong-, smartphone adoption is higher than 91% (*21*). The lower part of the table presents the characteristics of the stages that the LMS-sample has conducted.

[3] Stage is a subsection of a trip. Each individual element of a trip done by one single mode and one single PT-line. A trip could be substituted from more than one stage; for example someone may conduct part of his/her trip by tube line A, and part of his/her trip by tube line D. In our survey, we ask the happiness question for each stage of a trip.

Table 2: Sample characteristics

Socio-demographic characteristics (N=157) *-derived from LMS-Step 1*			Comparison to LTDS N = 6,432 obs. (source: LTDS 2013, 18+ only)
Age	18-29 years old	20%	26%
	30-45 years old	47%	38%
	46-60 years old	24%	20%
	over 60 years old	9%	16%
Gender	Female	65%	49%
	Male	35%	51%
Household Income	Up to £14,999	7%	12%
	£15,000-£34,999	15%	19%
	£35,000-£49,999	17%	10%
	£50,000-£74,999	20%	12%
	More than £75,000	29%	17%
	Not stated	11%	30%
PT pass holders		37%	35%
Disabled		2%	2%
Travel related characteristics (N=1,323 stages) *– derived from LMS-Step 2*			
Travel time		Average: 33.5min Min.: 0.100 Max.: 234.183	
Trip started in peak hour		22%	
Trip ended in peak hour		21%	
Accompanied by someone else		15%	
Activity while travelling*: Working while travelling		16%	
Activity while travelling: Listening to music while travelling		30%	
Activity while travelling: Watching movies while travelling		16%	
Activity while travelling: Playing games while travelling		21%	
Activity while travelling: Doing nothing while travelling		29%	
Trip-stage purpose: return home		17%	
Trip-stage purpose: work/ education		21%	
Trip-stage purpose: work related		7%	
Trip-stage purpose: Personal errands / Pick-up, drop-off		8%	
Trip-stage purpose: Grocery shopping		5%	
Trip-stage purpose: Sports/exercise		5%	
Trip-stage purpose: Entertainment / leisure		9%	
Trip-stage purpose: Change modes		27%	

*Participants could choose more than one activity while travelling

The upper part of Figure 3a presents the number of the recorded stages with TfL rail based modes per day of week (red column;), while it is also indicated the instances of the status of the mode that was matched from the TfL Unified API. It is noticed, in general, that for most of the stages the status is "Good Service" meaning that there are no delays. The lower part of Figure 3b indicates the happiness level (the dependent variable of the satisfaction model). The average satisfaction/happiness level of our sample is 5.05 (7-point Likert scale) indicating that the participants are quite happy with using these public transport modes for their recorded stages.

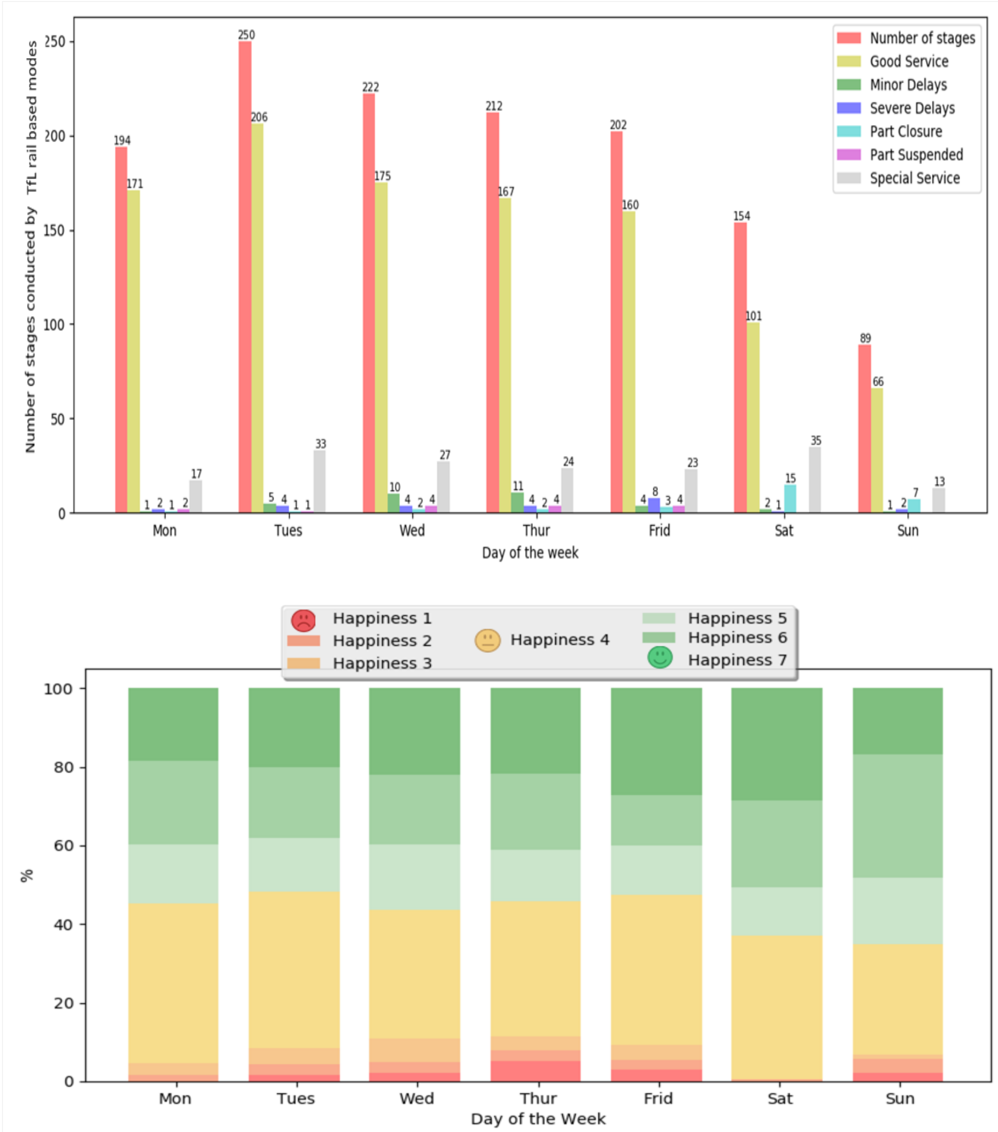

Figure 3: (a) Number of stages per day of the week and PT statuses, (b) Satisfaction with using TfL rail-based modes [the data has not been collected within the same week-it can be any day from November 2016 to February 2017]

5. MODEL SPECIFICATION AND ESTIMATION RESULTS

5.1 Model specification

The ultimate goal of this study is to explore and model the magnitude of the factors that affect the satisfaction of the public transport users using both travel survey and open data. The dependent variable is "*How happy were you by using this mode (for this specific stage)*?". Participants were requested to indicate their level of satisfaction to a 7-point Likert scale. Since the dependent variable is ordinal, the ordered logit model would be appropriate. The ordered logit model is a regression model for an ordinal response variable. The model is based on the cumulative probabilities of the response variable. In particular, the logit of each cumulative probability is assumed to be a linear function of the covariates with regression coefficients constant across response categories (*26*). A regression model would not be appropriate as it assumes differences between categories of the dependent variable to be equal, whereas, the data are ordinal (*27*). The results would be substantially different if an ordinal dependent variable was analyzed using regression instead of the ordered logit model (*27; 28; 29*).

The estimated model has an ordinal dependent variable Y_i (satisfaction/happiness) with seven categories ($c=1,\ldots,7$). It is defined by a set of $c-1$ equations where the cumulative probabilities $g_{ci} = \Pr\,(Y_i \le y_c \mid x_i)$ are related to a linear predictor β (vector for the unknown parameters) through the logit function:

$$\text{logit}(g_{ci}) = \log[g_{ci}/(1-g_{ci})] = \mu_c - \beta x_i, \quad \text{with } c = 1,\ldots,6 \quad (1)$$

The parameters μ are the thresholds and are in increasing order ($\mu_1 < \mu_2 < \ldots < \mu_6$). The vector of the slopes β is not indexed by the category index c; thus, the effects of the covariates are constant across response categories. The probability of choosing response c on the Likert scale is given by:

$$P(c) = \frac{1}{1+e^{(\mu_c - \beta x_i)}} - \frac{1}{1+e^{(\mu_{c+1} - \beta x_i)}} \qquad (2)$$

Due to the fact that our data has been collected over time and over the same individuals, an additional mixing coefficient σ is incorporated in our model to account for correlation across the responses given by a single individual i (panel effect). The model has been developed in SPSS 22 using also a tailored script written in Python.

Before we arrive to the final model that is presented in Table 3, we estimated several models using other explanatory variables as well. For example, we tested employment and marital status, and educational level but no effect was found on satisfaction. The same results were obtained from the "*day of the week*" variable, indicating that there is no considerable difference in satisfaction across the days. Since London is one of the most ethnically diverse cities in the world, we also tested ethnicity. The results were plausible but not significant and as such we decided to drop this variable. Another variable that was incorporated was the zone that individuals live that gave implausible results being difficult to interpret and as such further investigation is needed. Income variable was also tested in the format of income levels providing similar results to those when the variable is used as continuous; as such we decided to incorporate income as continuous variable. The model presented in Table 3, apart from the fact that all the variables are plausible, has also the highest goodness-of-fit score across all the estimated models.

5.2 Model estimation results and discussion

This section presents and elaborates on the model estimation results. Three sets of variables have been used in the public transport satisfaction model: 1. The variables that have been matched to our dataset from the TfL "Status of PT Service" Open API indicating the status of the rail-based public transport modes, 2. Variables that have been generated using the tracking app and the validation (Step 2 of the survey) and are related to trip characteristics. Such variables are duration of the trip (in vehicle travel time), trip purpose, and activities conducted while travelling. 3. Socio-economic characteristics of the participants that have been collected in Step 1 of the survey. Table 3 presents the results.

Table 3: Public transport satisfaction model estimation results

Variable name	Coefficient	t-stat
Threshold 1	*-3.743*	*-1.926*
Threshold 2	*-2.997*	*-1.204*
Threshold 3	*-2.365*	*-0.582*
Threshold 4	*0.162*	*1.934*
Threshold 5	0.846	2.618
Threshold 6	1.926	3.702
Linked Open Variables		
PT status: Part suspended (1=yes, 0=otherwise)	-0.442	-4.56
PT status: Part closure (1=yes, 0=otherwise)	-0.138	-3.79
PT status: Severe delays (1=yes, 0=otherwise)	-1.274	-7.92
PT status: Minor delays (1=yes, 0=otherwise)	*-0.216*	*-1.25*
PT status: Good service (1=yes, 0=otherwise; *PT status: limited service* was used as baseline)	0.168	3.25
Travel-related Variables (extracted from activity diaries)		
Travel time (in vehicle travel time; in minutes)	-0.004	-2.961
Trip started in peak hour (1=yes, 0=otherwise)	0.679	1.967
Trip ended in peak hour (1=yes, 0=otherwise)	*0.251*	*0.560*
Accompanied by someone else (1=yes, 0=otherwise)	0.556	2.30
Working while travelling (1=yes, 0=otherwise)	0.26	1.986
Listening to music while travelling (1=yes, 0=otherwise)	1.134	2.764
Watching movies while travelling (1=yes, 0=otherwise)	0.291	2.845
Playing games while travelling (1=yes, 0=otherwise)	0.505	3.366
Doing nothing while travelling (1=yes, 0=otherwise)	-0.260	-2.066
Trip purpose: return home (1=yes, 0=otherwise)	*-0.206*	*-1.722*
Trip purpose: work/ education (1=yes, 0=otherwise)	-0.309	-1.996
Trip purpose: work-related (1=yes, 0=otherwise)	0.367	2.004
Trip purpose: Personal errands / Pick-up, drop-off (1=yes, 0=otherwise)	-1.07	-3.053
Trip-stage purpose: Grocery shopping (1=yes, 0=otherwise)	*0.179*	*1.306*
Trip-stage purpose: Sports/exercise (1=yes, 0=otherwise)	*0.294*	*1.527*
Trip-stage purpose: Entertainment / leisure (1=yes, 0=otherwise)	0.426	2.168
Trip-purpose purpose: Change mode (1=yes, 0=otherwise)	*0.634*	*1.845*
Socio-economic variables		
Gender (0=male, 1=female)	*1.66*	*1.262*
Age: 18 to 30 years old (1=yes, 0=otherwise)	0.17	6.636
Age: 31 to 45 years old (1=yes, 0=otherwise)	0.91	5.674
Age: 45 to 60 years old (1=yes, 0=otherwise; baseline is the *More than 60 years old*)	-0.76	-3.457
Income (continuous in £)	-0.004	-2.892
Income not stated (1=yes, 0=otherwise)	-0.78	-1.969
PT pass holders (1=yes, 0=otherwise)	*0.679*	*0.917*
Having a disability (1=yes, 0=otherwise)	-1.887	-3.096
σ (parameter accounting for correlation accross the trips of the same individual)	0.662	1.275
Nagelkerke pseudo ρ		0.589
Observations		1,323

**coefficients and t-stat that are not statistically significant at 95% confidence interval are in Italics*

Public transport service status

As mentioned above, TfL has 20 different categories to indicate and communicate the status of the rail-based public transport services to the public. In our dataset we identified 6 out of the 20 statuses, which have been incorporated in the satisfaction model as it is shown in Table 3 (leaving out the status "Special Service" as a baseline for comparison). All the service status variables have the expected coefficient signs and are statistically significant at 95% confidence interval except the "Minor Delays" status.

The "Good service" status is positively associated with satisfaction meaning that when the public transport modes run without any delay, the users tend to be happier /more satisfied. The rest of the variables indicate different levels of delay and as it is expected, they are negatively associated with passengers satisfaction with using these modes. When there are "Minor delays", the users satisfaction is affected in a negative way, but this variable is not statistically significant. When the delays of the public transport modes are higher/more severe, users satisfaction is again negatively affected, but in this case the magnitude of the effect on the satisfaction level is higher. As such, when the lines statuses are "Part suspended", "Part closure" and "Severe delays" users dissatisfaction increases. "Severe delays" is the most statistically significant variable across those used in this model indicating that users satisfaction strongly decreases when the services are running extremely late.

The TfL status categories are related to vehicle delays and as such to increased waiting and travelling (in vehicle) time for the passengers. Although we did not find any previous research that uses these TfL statuses to compare our results, there are numerous surveys that investigate the effect of waiting and in vehicle travel time on public transport customers satisfaction. Our results are inline with the results of the previous surveys indicating that delays (in general) decrease the satisfaction of public transport users (indicatively: *3;9;8;30;31*)

Travel-related characteristics

The second set of variables used in our model is related to travel characteristics and activities the participants conducted while travelling. In vehicle travel time is negatively associated with individuals' satisfaction with the used public transport mode and it is statistically significant at 95% confidence interval. This finding is similar to the findings of other researchers who have found that as the travel time increases, passengers tend to be less satisfied (*2;9;32;15;33;31*). When the trip starts or ends during peak hours the satisfaction of the passengers is positively affected. These signs may seem odd and as such further investigation is needed on this. However, we can assume that during peak hours the TfL services is very frequent and thus users do not have to wait a lot to catch the rail-based public transport modes. Indicatively, some of the underground lines have a service every 1.5-2 minutes during peak hours (*34*).

Travelling with someone else is positively associated with passengers' satisfaction being also statistically significant at 95% confidence interval. Accompanied by a friend, colleague or family member probably distracts passengers' attention to system performance and thus they tend to enjoy more their trips. This finding is similar to (*35*) who found that talking to other passengers positively affects travel satisfaction.

In our survey, we also asked participants to indicate what they were doing during each one of their recorded trip-stages. To our best of knowledge, there is limited research on the effect of activities while travelling on public transport usage satisfaction (see

35;36;37). As (*37*) and (*36*) indicated travel time could be used productively and could lead to a positive utility. Our findings support this hypothesis showing that there are certain activities that can be conducted while travelling that affect positively the satisfaction with using public transport modes. Working while travelling affects satisfaction in a positive and significant way. It seems that individuals are able to conduct some of their work-related tasks while travelling and as such they may arrive to their destination less stressed. However, this result is contradictory to (*35*) who found that working or studying while travelling has no effect on passengers' satisfaction. Listening to music, watching movies, and playing games on smartphones while travelling are also positively associated with satisfaction and compared to the other two activities while travelling (working and doing nothing) are the most statistically significant. Once again these results differ from the findings of (*35*) who found that entertainment activities (reading, listening to music) are marginally related to less positive satisfaction as they might take place just to kill time. But they are similar to (*38*) who provided evidence that travel time of car and public transport users is valued as less negative when listening to music. Smartphone penetration in the UK is very high and people are used to conduct several activities via their phones. Heading to the mobility as a service (MaaS) and autonomous vehicle era, all these are services that could be included in the MaaS plans to advance users experience while travelling (see *39*). Finally, a factor that decreases the satisfaction level is "doing nothing while travelling". The passengers who are not engaged in any other activity while travelling may pay more attention on the trip and service's characteristics since they do not have something to be distracted.

Trip purpose seems also to affect satisfaction with public transport usage with some trip purposes to affect it negatively and some positively. Trip purposes such as return home, work/education, and personal errands are associated negatively with satisfaction. Out of these three purposes, only work/education and personal errands are statistically significant, with personal errands to be the most statistically significant compared to the other seven trip purposes that were used in our model. Although travelling to work affects negatively passengers' satisfaction, travelling for work-related purposes increases satisfaction. This sign needs further investigation, but someone could assume that employees favour leaving their workplace and travel to other places to conduct work-related tasks (they may perceive this as a break from daily work). Travelling for grocery shopping, sports/exercise, and entertainment/leisure purposes affect positively satisfaction with public transport modes. Most of the available studies explore the satisfaction with public transport modes for commute trips (travelling to work; *35;15*), while there are only few studies that focus on satisfaction and different trip purposes (*40;41*); but their focus is different making it difficult to compare our results. (*37*) via a descriptive statistics analysis showed that their sample like travelling for entertainment and grocery shopping, while they dislike travelling to work/education. These findings are in line with the results of our model.

Socio-demographic characteristics

The last set of variables used in the public transport satisfaction model is socio-economic characteristics, such as gender, age, income, public transport pass ownership and having a disability. The results indicate that gender does not play any significant role on satisfaction, as it is statistically insignificant. This result is in line with the findings of (*9*), and (*35*), while differ from this of (*8*). Younger passengers, 18-30 and 31-45 age groups, seem to be more satisfied with the use of public transport modes compared to the 45-60 age group. The 45-60 age group variable has a negative co-efficient indicating that this age group is dissatisfied with the public transport. A potential explanation could be that older people may be more sensitive to convenience while they travel and the possibility that may not find an available seat or the possibility the vehicle to be crowded make them dissatisfied (*42;54*). Nevertheless, neither convenience nor seat availability and crowdedness have been explored in our survey. Similar surveys in the past indicate contradictory results with some showing that age affects satisfaction (*15*;*43;53*) and some proposing the opposite (*9*;*35*).

As household income increases, the satisfaction with public transport usage decreases. Wealthier Londoners' may have higher standards and more requirements from the public transport system of the city and as such they seem dissatisfied. The participants who did not state their income in our survey are also less satisfied with the public transport modes. Once again, these results are similar to some surveys (*43*) and contradictory to some others (*9*; *35*). Holding a public transport pass is associated positively with satisfaction, but it is statistically insignificant indicating that does not considerably affect satisfaction. The last variable that is included in the model is disability. Disabled participants are dissatisfied with the usage of public transport modes. Analysing further our data, disabled participants declared that it is very difficult for them to use some rail-based public transport modes without any help/assistance. These results are similar to other surveys who focus on disabled people (indicatively: *44;45;46;47*).

Model's goodness-of-fit and mixing co-efficient

Nagelkerke pseudo R square index show that the public transport satisfaction model has a very high goodness of fit, explaining 58.9% of the variation in overall satisfaction.

Finally, the σ coefficient is positively and statistically insignificant. This means that the answers of the same individual are correlated but not significantly allowing us to say that the satisfaction with public transport modes really depends on each trip. When satisfaction is aggregated into overall satisfaction with a specific transport mode, significant information is missed hindering transportation planning.

6. CONCLUSION

The aim of this paper was to investigate public transport customers satisfaction by using both longitudinal smartphone based travel survey data and open public transport performance data. An ordered logit model developed for this purpose the explanatory variables of which are the open data, and customers' socio-economic and trip characteristics.

Our results indicate that customer satisfaction is indeed associated with the open public transport status data. Activities while travelling and trip purpose also affect customers satisfactions, while these results provide insights for offering products that can advance customers experience in the MaaS and automated vehicles era that lies ahead. For example, listening to music, paying games and watching movies while travelling positively affects customers satisfactions. These are services that in the future could be included in MaaS subscription packages. In addition, these findings support the hypotheses that travel time could have a positive utility as it can be used productively for other purposes, such as working.

By comparing our results to other surveys, we identified both similarities and differences allowing us to conclude that the factors affecting customer satisfaction vary across cities as the cultural environments are different (and of course the samples). As such, it is probably not wise to transfer customer satisfaction survey results from one city to the other, and it is better each public transport authority or company to have each one customer satisfaction survey to manage to attract more customers or retain the existing.

One of the most worth noting findings is that customer satisfaction varies from trip-stage to trip-stage as each trip-stage has each one conditions and characteristics. When satisfaction is aggregated into overall satisfaction with a specific transport mode, significant information is missed hindering transportation planning. Given the rise of new mobility services, and especially ridehailing services, public transport authorities and operators should update the satisfaction data acquisition and evaluation processes to acquire better information about their most valuable asset, their customers.

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