TRAVEL BEHAVIOUR: STATE-OF-THE-ART, CURRENT AND FUTURE MOBILITY PATTERNS

D3.1

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Executive summary

One of the key objectives of the TANGENT project is to propose advanced techniques for modelling and simulation, optimisation and control that are able to capture the dynamics of traffic and demand and adapt to evolving complex multimodal urban transport settings. In this complex environment, the user plays an important role since their decisions on how they perform their everyday trips are those defining the urban transportation landscape. To this end, it is of utmost importance to understand the people's decision-making process under normal and extreme conditions.

This deliverable aims to, first, identify all relevant factors affecting travel decision-making and, second, to set the framework for an inclusive *mobility data collection plan*. In order to achieve this goal, the international literature consisting of published papers and scientific books is collected and critically analysed based on three major axes:

1. The most relevant approaches to collect data on travellers' decision-making process.
2. The state-of-the-art approaches to analyse and model travel decisions.
3. The most important factors that may affect the decision-making process of travellers with special emphasis on infrastructure- and system-related factors (e.g., the introduction of new services and the occurrence of network disruptions).

Findings on travel data collection reveal that stated preferences (SP) methods are more commonly used for the acquisition of information referring to mobility patterns of travellers. This information includes sociodemographic characteristics, mobility profiles of travellers, their perception towards the system-level attributes and the preferences of respondents between different travel alternatives gathered through specific scenarios. However, revealed preferences (RP) data are more accurate, since the real travel patterns of users are recorded usually through location-based applications. It has been found that when SP and RP methods are combined, the collected data are more representative and result to more accurate analyses.

From a modelling perspective, the literature review revealed that Machine Learning (ML) techniques have been widely used during the last decade for analyses in the travel behaviour and transportation sector. In general, ML techniques may have better predicting accuracy when feeding the model with new and unseen data compared to simple MultiNomial Logit (MNL) models. However, classic MNL models maintain their importance against ML methods due to the concept of interpretability. This term refers to the concept of providing understandable information of the developed models and the interrelations between the variables. Interpretability can be also linked to model's transparency which implies some level of accessibility to the data or algorithm.

For the analysis of the factors that affect the travel behaviour of users, three (3) major categories were considered, namely user-related, trip-related and service-related factors, together with the various choices travellers make before and during a journey. Specifically, three choice dimensions were considered: (i) travel mode (e.g., car, public transport, bicycle), (ii) departure time, and (iii) route choice.

Travel behaviour is multifaceted, and, in the occurrence of extreme disruptions related to the system-level, the usual travel behaviour of users might alter, based on different factors than those affecting one's typical behaviour. Travel behaviour shifts may be caused due to the introduction of new services, Transportation Management Strategies (TMS) measures and the circumstances where non-recurrent events occur (i.e., hazardous events and network disruptions). The review of the literature highlighted the way in which travel-related decisions may alter in case of a system change belonging to one of the three categories of disturbances.

Finally, based on the findings of the aforementioned research and taking into account TANGENT's objectives regarding the collection of travel-related data, the foundations for the mobility data collection plan were set. The data mobility collection plan consists of stated preferences and revealed preferences data. Stated preference data include sociodemographic characteristics of users, their travel patterns for their everyday trips and their perception towards attributes referring to the system, including the acceptance of new services and new traffic management strategies (e.g., pricing). Revealed preferences data include information of the travel behaviour of people under real conditions, which are recorder in real-time and under real conditions. These data refer to trajectories of travellers under system-level disruptions in order to analyse them and identify the travel shifts under the occurrence of such conditions. Literature review has shown that system-level disruptions result to shifts in travel behaviour. However, the real travel patterns of people may differ from what they state in questionnaires. Revealed preferences data will be used to analyze in depth travel patterns and additionally, to identify potential deviations from the stated behaviour.

The results of this deliverable will be further exploited during the project's lifetime to understand and model travel behavior. The identification of factors affecting travel-related choices, and the circumstances under which travel behaviour shifts may occur, would be useful for the development of TANGENT's applications, such as demand modelling and prediction. The mobility data collection plan will be used to efficiently design the data collection process which will include a questionnaire survey and trajectory gathering through Google Timeline.

Key words

Travel behaviour, cognitive factors, affective factors, travel happiness, trip-related factors, service-related factors, travel behaviour shifts, Machine Learning techniques, MNL models, stated preferences data, revealed preferences data

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List of abbreviations and acronyms

Acronym	Meaning
AMoD	Autonomous Mobility on Demand
AV	Autonomous Vehicle
CAVs	Connected and Autonomous Vehicles
CNL model	Cross-Nested Logit model
e-bikes	Electrical bikes
EV	Electric Vehicles
ML	Machine Learning
MNL model	Multinomial Logit model
NL model	Nested Logit model
MoD	Mobility on Demand
PT	Public Transport
RP	Revealed preference
SP	Stated preference
TMS	Transportation Management Strategies

1 Introduction

Decision-making prior to or during travelling incorporates three distinct choices: travel mode, route and time of departure, which are affected by a plethora of factors indicatively including cost, travel time, level of service, etc. The different alternatives that are available for each user's trip are usually evaluated through utility functions. Utility theory assumes that the decision-maker is rational and consistent which means that they will always choose the best alternative (maximum utility) given all the available information (Anderson, 2013). Recent research goes beyond the limits of examining objective/cognitive factors that affect travel-related choices and incorporates additional subjective/affective parameters such as travellers' emotions, feelings, perceptions (Morris & Guerra, 2015) or even happiness (Mantouka et al., 2019). In the era of automation, travel-related decisions become even more complex, since a variety of innovative travel alternatives are available (CAVs, car-sharing, car-pooling, scooters) (Zmud & Sener, 2017). In addition, daily travel-related choices may change in the presence of unexpected events and system disruptions such as extreme weather conditions (Lu et al., 2014) or major transportation service withdrawals (Nguyen-Phuoc et al., 2018b). The field of travel behaviour focuses on understanding and modelling the travel behaviour of transport users. The goal is to describe how individual needs, preferences and sentiments affect travel-related decisions and how mobility patterns change under various system conditions such as the introduction of new services and new travel mode alternatives, or the emergence of network interventions and road pricing policies.

This deliverable aims to review factors affecting travel-related decisions and result in the creation of an extensive list, including users' specific needs, feelings and perceptions. It would also provide critical insights regarding mobility patterns' modifications in the era of multimodal and automated transport services. The identification of all the factors affecting daily travel behaviour will be further exploited to define essential data that should be collected in order to study travel behaviour within the framework of the TANGENT project. All data requirements will be included in an inclusive mobility data collection plan together with some basic guidelines for data collection.

1.1 Attainment of the objectives and explanation of deviations

The specific objectives of the deliverable include first, the identifications of all factors that affect travel decision making under typical and extreme system conditions (adverse weather, service disruptions etc.) and subsequently, the identification of those parameters that affect travel behaviour shifts under various traffic management measures and unexpected events. A thorough review of the literature has resulted in the creation of an exhaustive list of factors that are taken into consideration when users assess their daily trips' travel alternatives. The present deliverable is directly linked to Task 3.1, which aims at examining the factors that affect the travel choices, considering the effect of additional aspects (e.g., events, accidents etc.). In addition, this task focuses on comparison for mobility pattern changes under new traffic circumstances (i.e., capacity changes, strategy prioritization changes and new modes and services emergence).

The objectives related to this deliverable have been achieved in full and as scheduled.

1.2 Intended audience

The research that was conducted and presented in this deliverable was executed within the framework of the TANGENT project. However, the results included in the present deliverable will be available to the whole scientific community, with special interest for for practitioners in the transport and mobility sector, and for postgraduate students in these areas.

1.3 Structure of the deliverable and links with other work packages/deliverables

The present deliverable (D3.1) is directly related to other tasks within work package 3 and consequently their deliverables, and it is also related indirectly to other work packages. More specifically, D3.1 will provide a complete view of the factors that should be taken into consideration when travel behaviour is analysed. The thorough review of the literature will result in critical input for the survey design and the trajectory experiment to be conducted within Task 3.2 and Task 3.4, respectively. Task 3.2 provides the data that will be utilised in the development of D3.2 concerning the travel choice modelling, which will, in turn, provide inputs for work packages 4, 5 and 6, focusing on transport prediction and simulation models, transport network optimization and cooperative traffic management, respectively. Finally, the data produced in Task 3.2 will be used as inputs for the analysis of travel behaviour in Task 3.4 and D3.3.

To serve the purpose of the deliverable, which is to set the framework for the mobility data collection plan by investigating the current and state-of-the-art factors that affect travel behaviour, a structured methodological approach is followed, as shown in Figure 1 in the form of a workflow.

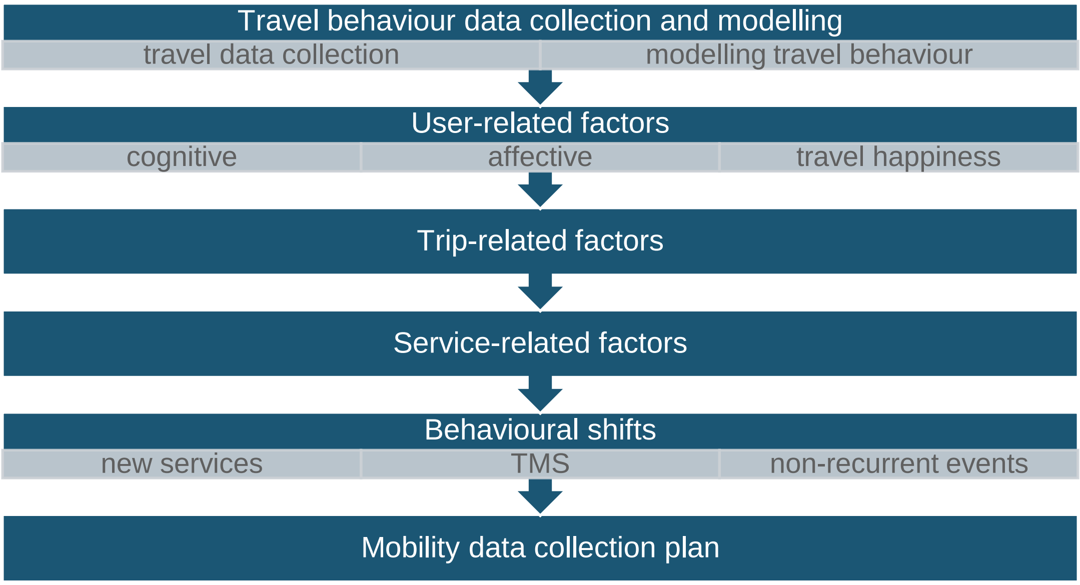

Figure 1: Structure of deliverable

First, a review of the relevant literature is conducted to acquire an understanding of the critical factors that have been researched over the years in relation to travel behaviour. Following, during this review, the factors were categorised with regards to the three dimensions of daily travel decision-making: the user (or traveller), the trip and the system.

The structure of the deliverable is outlined below:

- *Chapter 2* presents the high-level description of the travel behaviour analysis. More specifically, the key principles of travel behaviour, and the basis on which it is analysed, are mentioned. This chapter sets the foundations for the following chapters. Furthermore, the analysis of travel behaviour is briefly mentioned and the concept of interpretability is presented.
- In *Chapter 3* the taxonomy of factors affecting travel behaviour is thoroughly described and includes the user-, trip- and service-related factors.

- In *Chapter 4,* the travel behaviour shifts are analysed.
- *Chapter 5* presents the mobility data collection plan, based on the aforementioned literature review, including the stated and revealed preferences.
- Finally, in *Chapter 6* the most important findings of the literature are highlighted.

2 Travel behaviour data collection and modelling

The aim of this chapter is to examine the methods by which travel behaviour data is collected and also how this data is being analysed in order to extract useful information. The second sub-section mentions the traditional models and compares them to ML models, the term of interpretability and an estimation of willingness to pay.

2.1 Travel Data Collection

Travel data refers to the information that is necessary in order to sketch the travel behaviour of users and understand their travel preferences and perceptions towards normal conditions or special occasions and policies. This data are collected through stated preferences (SP) and revealed preferences (RP) methods. *SP methods* are widely used in the transportation sector and refer to a set of techniques, which estimate utility functions using individual respondents' statements about their preferences in numerous transport options (e.g., questionnaires, interviews) (Kroes & Sheldon, 1988). SP surveys include data on sociodemographic characteristics, mobility profiles of travellers, their perception towards the system-level attributes and the preferences of respondents in different travel scenarios. Different stated preference methods are available under a wide variety of names; the best-known methods are (Kroes & Sheldon, 1988):

- Conjoint analysis
- Functional measurement
- Trade-off analysis
- The transfer price method.

In Stated Preference surveys, respondents may be also asked to rate, rank or choose between different hypothetical scenarios, that are made up of different attribute combinations, which are usually further analysed to infer how different groups of respondents value different attributes (Politis & Basbas, 2009). The main terminology used in at such scenarios is perfectly illustrated in Figure 2.

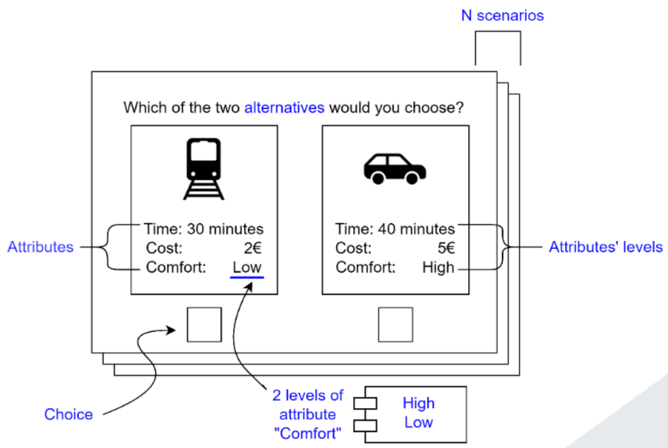

Figure 2: The main aspects of a SP scenario

RP methods include the recording of the real travel behaviour of travellers during real-time conditions and provide more accurate results. Models of travel demand have traditionally been based on data obtained by direct observation of travel behaviour or obtained in surveys asking for actual travel behaviour. RP data are traditionally acquired through travel diaries, where the participants register their trips and their characteristics, as conducted in Di Ciommo et al. (2014). Other ways to acquire such data are with the use of transmitters located on the cars of participants or through applications in smartphones that record the details of each trip (usually location and speed).

Comparing the two methods it is clear that it can be difficult to obtain sufficient variation in the RP data and they cannot be used in a direct way to evaluate demand under conditions which do not yet exist. Furthermore, SP methods are preferred in transport research, since they are easier to control, they are more flexible and they are cheaper to apply (Kroes & Sheldon, 1988). The main drawback of SP methods is that the research is based on the statements that people say during the surveys and these statements may not necessarily correspond to their real behaviour, since it has been observed that people tend to overstate their responses under experimental conditions, which usually leads to misleading estimations of the relative values (Fifer et al., 2014). Evidence has shown that the combined use of RP and SP data for the estimation of attributes usually results in improved statistical precision and in more reasonable parameter values (de Luca & Di Pace, 2015). The key advantages of combining SP and RP data are (Ben-Akiva et al., 1994):

- *Efficiency*: joint estimation of preference (or attribute importance) parameters from all of the available data.
- *Bias limitation*: explicit response models for SP data, which include both preference parameters and bias parameters.
- *Identification*: estimation of preferences for new products or services and for new attributes or attribute levels that are not identifiable from RP data.

2.2 Modelling travel behaviour

When travellers plan a trip, they come across multiple factors that affect their travel decision-making process. The utility function U_j^i evaluates these different factors by determining the importance of each one of them. A widely used formulation of the utility function is presented below (Hess et al., 2007):

$$U_j^i = \sum_{k=1}^{n} \beta_k X_{kj} \qquad (1)$$

where X_{kj} represents both choice makers' (i) characteristics and choice alternatives (j) attributes and βk the corresponding weights. The utility theory takes as precondition that the person who chooses among all different available options, concerning mode choice, route choice and departure time, is rational and consistent. In particular, the decision-maker will always choose the best alternative, with the maximum utility.

2.2.1 Traditional models versus ML models

In the simple MultiNomial Logit (MNL) model, the utility to person *n* from choosing alternative *j* in choice scenario *t* is given by equation (2):

$$U_{njt} = \beta x_{njt} + \varepsilon_{njt} \qquad n = 1, \dots, N; j = 1, \dots, J; t = 1, \dots, T \qquad (2)$$

where x_{njt} is a K-vector of observed attributes of alternative *j*, β is a vector of utility weights (homogenous across users), and ε_{njt} ~ i.d. extreme value is the "idiosyncratic" error (Fiebig et al., 2010).

In the case of travel related choices, MNL models assume that the traveller possesses a utility for each alternative and that they will always adopt the alternative that maximizes the utility given the same circumstances (Hussain et al., 2017). In such a model, a "base" should be defined to indicate the category that is used as the baseline comparison group. The MNL model is a widespread approach to evaluate the effect of explanatory variables on the dependent variable if the latter takes more than two distinct values.

MNL is a category of nested logit (NL) model and it characterizes a partial relaxation of the independence of irrelevant alternatives (IIA) property of the MNL model. NL models are mostly used for models whose subsets of similar alternatives are grouped in hierarchies or nests (Wen & Koppelman, 2001).

As an example, a nested logit model can consist of three-mode choice groups: public transportation modes, private transportation modes, and soft modes and can be calibrated to find coefficients by using standard logit estimation, as shown in Figure 3.

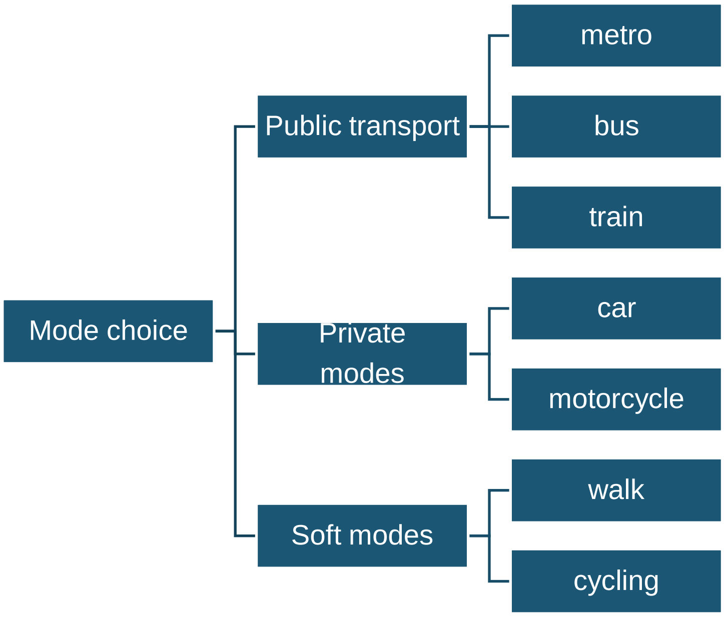

Figure 3: Example of NL model with three-mode choice groups

The hierarchical structure of the NL model is given by equation (3) as follows and it is estimated for each hierarchy (De Cea et al., 1986; de Dios Ortuzar, 1983).

$$P_{ji} = \frac{e^{\beta' s_{ji}}}{\sum_{i=1}^{j} e^{\beta' s_{ji}}} \qquad (3)$$

where:
P_{ji}= is the probability that traveler i chooses alternative j,
β′= is a vector of all estimable coefficients for alternative j,
S_{Ji} = is a vector of all explanatory variables for traveler i.

The MNL model treats all alternatives equally, whereas the nested logit model includes intermediate branches that group alternatives. The MNL models are more widely adopted than the NL models to the paradigm of utility maximization where the MNL model provides a link by which choice probabilities can be estimated given the characteristics of the modes and the traveler (Al-Salih & Esztergár-Kiss, 2021). Cross-nested logit (CNL) models extend and generalize the correlation structure among the alternatives. Instead of each alternative belonging to a single nest in nested logit models, cross-nested models allow alternatives to belong to more than one nest, allowing for a flexible correlation structure.

It has been found that CNL models can better accommodate the similarity among alternatives than the NL model, while keeping a closed-form probability function (Bajwa, 2006).

Departing from the classical utility theory, ML approaches have been gaining a lot of interest over the last decades due to their versatile structures, their inherent complexity, as well as the lack of dependence on fundamental restrictions (e.g., independence of irrelevant alternatives) (Karlaftis & Vlahogianni, 2010). ML models address the problem of mode choice prediction as a classification problem, where a target function *f* is developed through training to map the input space ***X*** to the output ***Y*** (set of choices). Zhao et al. (2018) and Wong & Farooq (2021)compared various ML techniques (Naïve Bayes, Tree-based models, Support Vector Machine, Neural Networks) with MNL for mode choice modelling tasks, concluding that ML and Deep Learning algorithms, may have better predicting accuracy when feeding the model with new and unseen data compared to MNL, but they do not offer a solid interpretation of the phenomenon (Fafoutellis et al., 2021).

2.2.2 A note on interpretability

Understanding how a ML model operates and performs is of utmost importance. The ability to explain the underlying dynamics in a model has been proven critical for the justification of the decisions made based on the results, the improvement of the model and the exploration of new insights from it (Adadi & Berrada, 2018).

According to the ML community, the two approaches that have recently emerged are the *interpretable* ML and the *explainable* (post hoc interpretable) ML (Rudin, 2019). The first is based on the concept that models that are trained and used to generalize on unseen data with ML techniques should be understandable by humans. In general, interpretability can be linked to the model's transparency which implies some level of accessibility to the data or algorithm (Miller, 2019). The second refers to the complex ML models in that the correlation between the inputs and the outputs is estimated after the training of the models with the usage of dedicated tools.

Although the traditional utility theory models have been developed around a well-founded theoretical background in terms of extracting the significant factors that may influence travel-related choices, for ML models, the above task is much more complicated and can be distinguished in the following categories (Molnar, 2019):

1. Model-specific interpretation tools that are limited to specific model classes and deal with weights and structural properties (e.g., the practices followed in linear models)
2. Model-agnostic tools that can be used on any ML model and are applied after the model has been trained (post hoc) and aim to analyse the relationship between feature input and output pairs without considering weights or structural information specific to the model.

In order for a practitioner to efficiently use an interpretable model, it has to meet the following attributes (Doshi-Velez & Kim, 2017):

- Fairness: Predictions are unbiased and do not discriminate against specific groups
- Privacy: Sensitive information on the data is protected.
- Reliability or Robustness: Small changes in the input do not significantly affect the prediction.
- Causality identification: Check that only causal relationships are taken into consideration.
- Trust: Outputs produced by the models are understandable and can be trusted compared to a black box.

Moreover, interpretation can be seen as *global*, when the entire behaviour of a model is attempted to be explained or *local* when the focus is on why a prediction for a certain instance is given (Fafoutellis et al., 2021). Some well-known methods for ML interpretability include the Partial dependence plots, the permutation importance and conditional permutation importance, the Individual conditional expectation, the Local surrogate models, the Accumulated Local Effects (ALE) and the SHAP (Molnar 2019).

2.2.3 Estimation of willingness to pay

The MNL family of models are utilized in order to understand the behavioral characteristics of users' travel choices, such as the willingness to pay (WTP). The WTP for each attribute can be computed by the ratio of the emerging coefficient for the specific attribute and the price or cost coefficient. If the attribute examined is the time (e.g. travel time of a transportation mode), WTP is also referred to as the value of time (Brownstone et al., 2003). In particular, the WTP for attribute i is calculated using the following equation:

$$WTP_i = \frac{\beta_i}{\beta_{cost}} \qquad (4),$$

where β_I and β_{cost} are the coefficients of attribute i and cost respectively, and it represents the amount of money one is willing to pay for a desirable change of one unit in attribute *i* or the amount he expects to receive in exchange for an undesirable change of one unit in attribute i. In Machine Learning, the estimation of willingness to pay is not so simple, because the respective models do not incorporate coefficients' estimation (Fafoutellis et al., 2022).

3 A taxonomy of factors affecting travel choices

The aim of the present chapter is to present a taxonomy of factors that affect travel choices. These factors were divided into 3 categories: user-related factors, which include cognitive, affective and travel happiness, trip-related and service-related factors.

Decision-making in the individual trip-making process is linked with a variety of choices that users must make. Users evaluate the different travel choices with respect to primarily three dimensions: mode choice, route choice and departure time choice (Steed & Bhat, 2000), as shown in Figure 4. The environment in which users make these choices is complicated and there are multiple alternative choices. Specifically, a person may choose to travel among a variety of travel modes, such as private car, taxi, public transportation (bus, train, metro) or even walking or cycling or new on-demand and shared mobility concepts (e.g., ride-hailing). Furthermore, they may travel along a number of different routes with the same origin and destination points, perhaps avoiding zones with road pricin. Finally, travellers may choose to leave from their location in many different departure times, avoiding or not the peak hours, or additional travel costs imposed via surge pricing.

In the framework of travel behaviour analysis, several studies have been executed to determine the patterns of users' travel behaviour concerning travel linkages, purpose and the frequencies of travelling (Allahviranioo, 2016). In addition to that, Zhao et al. (2018) investigated the long-term temporal and spatial changes in patterns of public transport users, as far as origin/destination, frequency and time of travel are concerned. Their results revealed that only a minority of the examined users changed their frequency patterns and 28.8% and 44.7% presented an aberration in temporal and spatial dimension, respectively. Other studies examine the patterns that appear in mode choices (Liu et al., 2020; Tirachini & del Río, 2019), route choices (Khoo & Asitha, 2016; Jiwon Kim et al., 2017) and time of departure (Golshani et al., 2018; Thorhauge et al., 2016). The understanding of travel behaviour dynamics and travel-related decisions is of utmost importance since they can provide significant insights for efficient urban planning, mobility management and network optimisation.

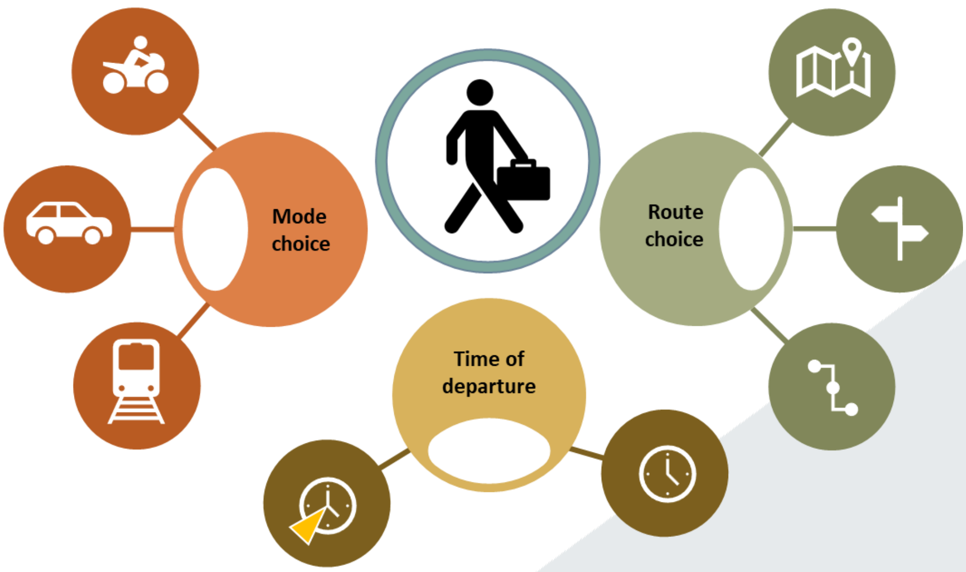

Figure 4: Schematic illustration of travellers' daily choices

Factors that affect travel behaviours and determine the choices that travellers make can be divided into three categories: user-related, trip-related and service-related. User-related factors consist of cognitive (e.g., gender, income) and affective (e.g., previous experiences, value of time) factors, as well as travel happiness. Trip-related factors focus on the attributes that determine each trip (e.g., travel time, travel cost). Finally, service-related factors refer to attributes that specify the services, such as the provided safety or comfort. The aforementioned factors are summarised in Figure 5. The summary of the literature review on factors affecting travel choices can be found in ANNEX.

User-related

- Cognitive (e.g., gender, income)
- Affective (e.g., previous experiences, value of time)
- Travel happiness (e.g., travel satisfaction)

Trip-related

- e.g., travel time, travel cost

Service-related

- e.g., safety, comfort

Figure 5: Categories of factors that affect people's choices

3.1 User-related factors affecting travel behaviour

This chapter analyses the factors affecting travel behaviour, that are traveller-centred and occur under normal network conditions. The three major categories that they can be divided into are cognitive, affective and travel happiness, as shown in
Figure 6. Cognitive factors refer to the common conceptions that are indisputable, whereas affective factors consist of personal perceptions of each individual, involving feelings, emotions and values. Finally, travel happiness is a recently introduced concept in travel behaviour and comes as a broader term that includes travel satisfaction, placing emphasis on the ‘‘generalized’’ emotions travellers experience during their everyday trips (Mantouka et al., 2019). These categories are analysed on the basis of the three pillars of travel behaviour, namely departure time, route and travel mode choices.

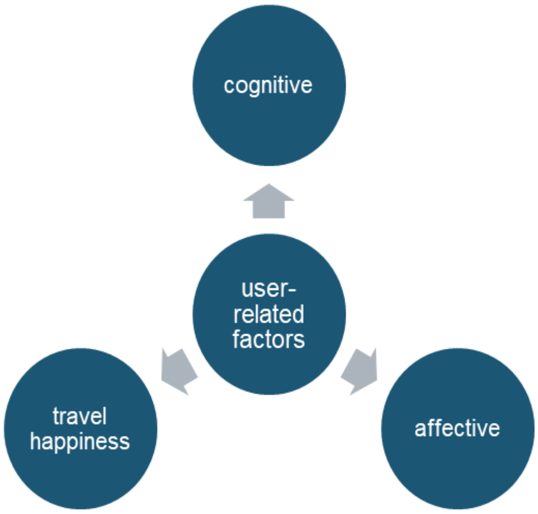

Figure 6: Categories of user-related factors

Table 1 provides a mapping between the most relevant studies with the choices that were investigated and the category of factors that were taken into consideration. It is observed that the majority of literature is focused on the attributes that affect travel mode choice, as shown in Figure 7Figure 7.

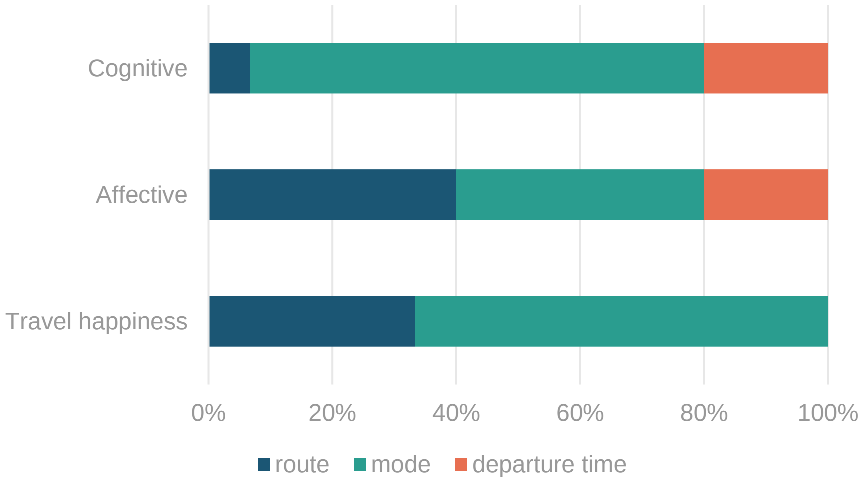

Figure 7: Percentage of papers per travel choices

Authors	Year	Travel choices			Factors		
		route	mode	time of departure	Cognitive	Affective	Travel happiness
Ryley	2006		■		✓		
Beirão & Cabral	2007	■	■				✓
Kumar & Rao	2007		■	■	✓		
Zeid	2009	■	■				✓
Ben-elia et al.	2010			■	✓	✓	
Ettema et al.	2010	■	■				✓
Abou-Zeid et al.	2012		■				✓
De Vos et al.	2012		■		✓		
Saneinejad et al.	2012		■		✓		
Li et al.	2013		■	■	✓		
Prato	2014	■				✓	
Sun et al.	2014	■				✓	
Zanni & Ryley	2015		■		✓		
Böcker et al.	2016		■		✓		
De Vos et al.	2016		■		✓	✓	✓
Charoniti et al.	2017	■			✓		
Jinhee Kim et al.	2017		■			✓	
Alemi et al.	2018		■		✓		
Bödeker et al.	2018		■		✓		
Tirachini & del Río	2019		■		✓		

Table 1: Literature review synopsis on user-related factors affecting travel behaviour
(■: indicates the travel choice that each paper refers to, ✓: indicates the type of factor that each paper refers to)

3.1.1 Cognitive factors

Cognitive factors that affect travel behaviour are in the reasoned dimension and refer to the evaluation of the trip. For further understanding, these factors are completely objective and are publicly accepted. In the context of factors affecting travel choices of travellers, the cognitive ones are thoroughly analysed. Generally, sociodemographic characteristics are the most common cognitive factors.

It is reported that people from young age groups, who are highly educated and have high ***income rates*** are keener on using on-demand ride services (Alemi et al., 2018). According to Tirachini & del Río, (2019), higher household income rates and trips related to leisure are accompanied with a higher probability of a rider travelling frequently and alone by ride-hailing. Respectively, group travelling is observed more often in lower household income rates. Moreover, lower-level employees prefer to walk for work trip when their residential location is close to their workplace (Kumar & Rao, 2004). In addition to that, lower income group prefer the departure time to be before peak, middle income and car users prefer during peak hour, and higher income group (executives) and car owners prefer after peak hour.

Furthermore, ***age*** is also a crucial factor for people when choosing a travel mode (Bödeker et al., 2018; Li et al., 2013). Middle-aged people are keen on utilising soft modes of transport (cycling and walking) compared to younger or older individuals.

Gender is a critical determinant that affects both the travel mode choice (Li et al., 2013) and the time of departure, when that is close to a peak hour (Ben-elia et al., 2010). Women prefer to walk for active travel, whereas men are more likely to travel by bicycle. Regarding the school pupils, the gender of the student plays an important role and the rate of independent travel as well when choosing the travel mode. As far as departure time is concerned, women present a lower probability to change their departure time in peak hours in comparison to men. Departure time is also influenced by the work time flexibility and time-use constraints that demand specific and inflexible daily plans, such as childcare. However, it seems that people who commute frequently during peak hours are not willing to alter their departure times. Finally, the perceptions of people involved in their willingness to change travel behaviours are determinant for their choices concerning the departure time. High perceived effort is positively associated with peak-hour departure.

Mode choice is also affected by long-term choices, such as ***residential location*** (De Vos et al., 2012; De Vos et al., 2016). It has been found that it constrains their activity and travel patterns in space and time, since it affects the accessibility of possible destinations. For example, in some densely populated areas, it is easier to access facilities and services on foot or bicycle, since the car might be correlated with congestion and parking problems. A great majority of suburban residents use their cars for leisure trips, whereas urban residents present a preference for walking or using public transit. Respectively, people with suburban land-use preferences tend to use their cars more than people with urban land-use preferences. Residential location is also linked with the accessibility to public transport services. In suburban areas public transport is limited. This condition renders the car use necessary. According to Belgiawan et al. (2017) Bus Rapid Transit (BRT) is the most preferred mode for all distance categories as opposed to the car, which is the least one Furthermore, as the number of workers increases in a household, the possibility of people using a bicycle for their trips decreases, whereas the car becomes the most frequent travel mode option. Respectively, ***families*** with children are more likely to use a car compared to one-person families (Ryley, 2006).

When making route-choice decisions with the factors of arrival time being uncertain, Charoniti et al. (2017) found that the ***educational level*** of travellers affects their regret on late expected arrival times. In particular, people with a high educational level present a tendency to regret late arrival. In addition to that, regretting late arrival time is also linked with years of driving experience. Specifically, as the years of experience augment, the regret of late arrival decreases.

3.1.2 Affective factors

Affective factors refer to the emotional factors that each person has and are based on the personal characteristics of people. These factors are affected by perceptions that people have about different matters and previous experiences that have developed their feelings and attitudes.

There are multiple studies that have focused on the affective factors that affect the travel choices of people and it has been found that the ***satisfaction*** of people with the current conditions of cars and public transport plays an important role concerning their willingness to join a car-share organisation (Jinhee Kim et al., 2017). Presently, mobility systems are complementary to car-sharing systems.

Multiple affective attributes are presented in the ***utility and the regret functions*** in route choices (Prato, 2014). Cost of travel in correlation to the distance covered, travel time, number of right and left turns and number of traffic lights were the most significant ones. Results showed that utility was maximised and regret was minimised with routes that cost less, are faster and straighter.

Sun et al. (2014), who investigated the factors affecting route choices, found that although travel time and distance are the main attributes when a driver chooses a route, most of them travel along neither the fastest nor the shortest route. This was further analysed and it was concluded that in relation to region and time period, the ***road preference***, the travel distance and time were the most significant factors.

The ***perception*** towards a mode significantly affects the mode preference of a person (De Vos et al., 2016). It was found that people with a positive stance toward a certain travel mode are more likely to opt that mode. As a result, the way people feel while travelling with a mode affects their decisions when choosing a mode.

Preferred arrival time plays an essential role when people decide what time to depart (Ben-elia et al., 2010). Arrival time is perceived differently by people, since some are more flexible with arrival lateness.

3.1.3 Travel happiness

Travel happiness is a recently introduced notion affecting the travel choices of travellers. It differentiates from the well-known notion of travel satisfaction, since it is based on the fact that travel happiness aims to combine decision utility with the satisfaction from the level of service and enrich with factors which express the perception of the user on the various aspects of their trip. Travel happiness is considered to be an attribute in the continuum of the general decision making in life (including mobility and transport), which may be perceived from two distinct temporal aspects:

i. the medium-term aspect which aggregates the feeling and emotions of users about their mobility patterns, and
ii. the short-term, which encloses the dynamically changing affective factors during travel, which may of course vary in relation to the trip conditions.

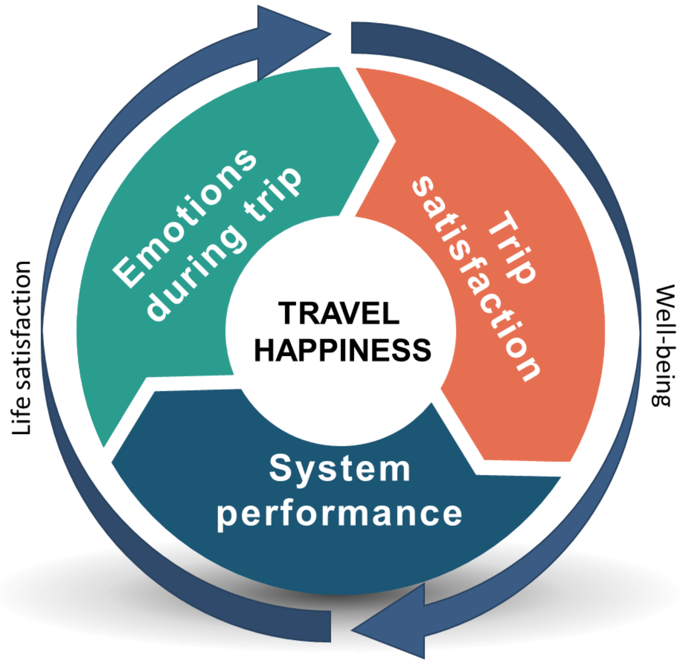

Figure 8: Travel happiness as an aspect of decision-making

Travel satisfaction increases with age and residential neighbourhood (De Vos et al., 2016). It was found that older people present a more positive perception toward trips for all travel modes, with the exception of bicycle trips. Moreover, suburban residents have more positive feelings when travelling in comparison to urban ones. As far as trip-related factors are concerned, longer travel times reduce travel satisfaction, while longer travel distances increase travel satisfaction.

Abou-Zeid et al. (2012) stated that the existence of multiple ***alternatives ways of travelling*** is positively linked with travel satisfaction. However, the number of cars per household member negatively affects the emotions perceived during a car trip.

It has been reported that individuals may experience positive or negative feelings when travelling to a destination (Ettema et al., 2010; Zeid, 2009). As a result, these feelings are taken into consideration during the users' decision-making process regarding the route and mode travel choices. For example, car drivers stuck in traffic can experience stress and impatience (Beirão & Cabral, 2007), whereas many may feel contentment and joy on trips in peaceful environments.

A cross – European survey has investigated the level of travel happiness through the quantification of the level of tolerance in case an unexpected event occurs during a trip and the probability that the traveller assigns to the occurrence of a disruption (Mantouka et al., 2019). Findings revealed that the level of travel happiness a user experiences during their trip is highly related to the aforementioned parameters, which indicates that the level of service (LoS) of the network and the more precisely the perception of the traveller in the LoS is directly related with the emotions of the users.

3.2 Trip-related factors affecting travel behaviour

Travel choices are affected by additional factors that relate to the characteristics of the trips and are dynamic in nature. The literature review was studied again on the basis of the three pillars of travel behaviour, namely departure time, route and travel mode choices. The results of the analysis are briefly presented in Table 2.

Authors	Year	Travel choices		
		route	mode	time of departure
Ettema	2003			■
Müller et al.	2008		■	
Jain et al.	2014		■	
Belgiawan et al.	2017		■	
Charoniti et al.	2017	■		
Vashisth & Aggarwal	2018	■	■	

Table 2: Literature review synopsis on trip-related factors affecting travel behaviour
(■: indicates the travel choice that each paper refers to, ✓: indicates the type of factor that each paper refers to)

As trip-related factors are considered those attributes whose values are different for each trip. Such factors are the purpose of travel, travel time, travel cost, number of transfers, etc. A well-established form of travel cost in the field of travel behaviour is ***travel time***, which consists of in- vehicle time, out-of-vehicle time, walking, and waiting time (Limtanakool et al., 2006). The value of time may vary in relation to the travel mode that is used or even in relation to the trip purpose. Respectively, the ***travel cost*** plays a significant role when an individual decides to use a travel mode (Ghader et al., 2019). Most people prefer lower costs when choosing to use a travel mode for their trip. Furthermore, increase in the ***number of transfers*** for travelling by transit reduces the likelihood of using transit substantially, since travellers will experience longer waiting times, and thus most people prefer alternatives with fewer transfers (Eluru et al., 2012).

The ***time in the day*** and the ***duration*** of the trip affect the departure time (Ettema, 2003). Generally, people, who travel during high peak hours – when there is increased traffic congestion – and also the duration of the trip is longer, are more likely to depart earlier, in order to be at their destination in time.

Regarding the ***elasticity*** of attributes, they found that travel time is elastic for medium and long-distance travel categories, whereas cost is almost inelastic for the car. As far as short-distance travel is concerned the attributes of travel time and cost are nearly inelastic.

The ***purpose of the trip*** is also a factor that affects the route choice of the traveller (Charoniti et al., 2017) and mode choice (Jain et al., 2014; Müller et al., 2008). When people make route-choice decisions with the factors of arrival time being uncertain, those who prefer the usage of public transport present a tendency to regret late arrival. Furthermore, commuters (people travelling for work purposes) have different mode choice preferences than travellers who travel for other purposes, such as leisure and personal purposes. More specifically, motorised modes are being used more commonly by people who go to work or school.

A study examining the factors that influence the school pupils' travel choices (Vashisth & Aggarwal, 2018) revealed that ***safety concerns*** are of great importance. Furthermore, ***the distance*** from school, the ***quality of the pedestrian environment*** and the ***transportation infrastructure*** in the surrounding area of the school are also fundamental factors when school pupils make choices for travelling to/from school.

Weather also determines the mode choice of travellers (Böcker et al., 2016; Saneinejad et al., 2012; Zanni & Ryley, 2015). In particular, during rainy conditions people tend to use the public transport more, instead of the bicycles, whereas the velocity of the wind does not influence the mode preferences. However, rainy weather and higher wind speed have a greater impact on cyclists than pedestrians. It has also been observed that during conditions when there is low visibility (e.g., darkness), car usage is increased causing a decrease in cycling. Lower and higher temperatures negatively affect the usage of bicycles, as opposed to walking and public transport usage, which are preferred during extreme temperatures. Finally, lower temperatures seem to affect more negatively females and younger individuals who use active travel modes.

3.3 Service-related factors affecting travel behaviour

Service-related factors refer to the attributes of the available services that affect the travel-behaviour process of an individual when deciding which service to use when travelling. Studies have identified a number of such factors, which are categorised as *physical* and *perceived* (Mazzulla & Eboli, 2006; Redman et al., 2013):

- Availability (e.g., number of bus or metro stops)
- Accessibility (e.g., distance of bus or metro stops from poles of attractions)
- Reliability (e.g., the time difference between the times in the timetable and the actual arrival time)
- Frequency (e.g., the number of times a service passes through a stop)
- Speed
- Price
- Information provision (e.g., the availability of information at the internet/stops concerning the schedules and the maps, and the explanation of disruptions)
- Ease of transfers/ interchanges
- Vehicle condition
- Comfort on the service

- Convenience
- Safety
- Security
- Aesthetics

Physical attributes consist of factors that the input from users is not necessary for their measurement, and thus assumptions can be made about the impacts on users. The key attributes in this category are availability and accessibility. These terms refer to the ***availability*** of the service within the network; how many access points it has on it and how easy it is for people who live in the suburbs to access the terminals. High rates of ***accessibility*** of services make people more independent and, in some cases, people decide to sell their cars, since public transport fully meets their needs. A study concerning the car-sharing decisions (Jinhee Kim et al., 2017) supports that the availability of shared-car is one of the most determining parameters as to whether someone will choose this mode.

Additionally, ***reliability*** and ***frequency*** of services are also important physical attributes. These terms refer to how closely the actual service matches the timetable and how often the service operates during a given period of time, respectively. These factors are correlated with the waiting time of the users. Long waiting times due to inconsistency with the timetable or low frequency, render a service less preferred. This also affects the departure time – depending on the preferred mode choice. Moreover, the attribute of ***speed*** affects the decision-making process when using a service. Most people prefer to use services that spend shorter times between specified points. Furthermore, the ***price*** and the provided information of a service are physical characteristics that are widely comprehended. The price refers to the monetary cost of travel and the ***information provision*** concerns the amount of information that is provided to the users on the timetables, the routes, the stops, the interchanges and the announcements in case of delays or disruptions.

In addition to these, the ***ease*** of use when performing a transfer or interaction might greatly influence a traveller's opinion when selecting a service. For example, services that do not require long waiting times or walking distances in these circumstances, are more preferred compared to services that do not have smooth transfers or interactions. The last attribute in the physical category is the physical and mechanical ***condition of the vehicle***. In Parthan & Srinivasan (2013) study, it was found that the most significant variables affecting the mode choice of travellers are comfort in personal vehicles, reliability in Intermediate Public Transport (IPT) and safety in bus.

Regarding the *perceived attributes*, their measurement requires the opinion of users, either directly (Friman et al., 2001) or indirectly (Paulley et al., 2006). Two of the key attributes in this category are comfort and convenience. ***Comfort*** consists of a number of factors that assess how comfortable a journey is. For example, the accessibility to the seats, the level of service overcrowding, the noise levels, the driver handling and the air conditioning constitute the attribute of comfort. ***Convenience*** refers to the simplicity of the service's use and how well it contributes to the ease of mobility. For a better understanding, the introduction of a fleet of new buses, which have more comfortable seats and also have low floor (in order for older people and disabled ones to board on it) increases the level of the service's comfort and convenience and thus, the users' preference for this service.

Furthermore, ***safety*** and ***security*** are also important perceived attributes. These attributes are defined as how safe passengers feel in terms of personal safety. The estimation of the personal safety of a passenger takes into consideration how safe from traffic accidents passengers feel during the journey. It also encompasses the level of safety the passengers feel against crimes.

Finally, the ***aesthetics*** of the service is related to how much the vehicles, stations and waiting areas appeal to users' senses. For example, some travellers might prefer to board on new vehicles, because it appeals to their aesthetics. Relatively, the same applies for the stations and waiting areas of services.

Regardless of the level of safety that passengers feel, they might opt to use a service according to how close the aesthetics of its waiting areas are to theirs.

4 Travel behaviour shifts under system-level disruptions

The aim of this section is to answer the question of how travel behaviour may be affected by any extreme system-level conditions of the transportation system. We assume that travel behaviour shifts may occur in the current reality – during which, and with the development of technology, new services are introduced to the market, TSM measures are applied in order for people to have access to more functional and ecological transportation networks and non-recurrent events happen more frequently than ever. Figure 9 presents the factors causing travel behaviour shifts and which travel choice (mode, route and departure time choice) each one affects. More specifically, the accessibility to new services, such as electrical cars and bikes, AVs and CAVs and AMoD services, may alter people's travel behaviour in terms of their travel mode and route preference. Furthermore, TMS measures, including road pricing in specific time periods during the day or in specific areas, obligate a number of users to change their typical travel behaviour regarding their preferences of travel mode, route and time of departure. Finally, people's travel patterns may change during non-recurrent events, which indicatively include hazards, namely extreme weather conditions and other natural hazards and the COVID-19 pandemic, and perturbations of the road network, such as public transport service disruption, vehicle breakdown and car accidents. Hazardous events most commonly affect travellers' mode, route and departure time choices, whereas network disruptions mostly affect mode and route choices. It is worth mentioning that these disruptions in the system affect trip-related and service-related factors, that were analyzed in previous chapters. In general, travellers must adjust their travel behaviour during system-level disruptions and as a result, they may (Zhu & Levinson, 2012):

- change their normal route because of road and ramp closure or congestion caused by traffic reallocation,
- alter their departure time to avoid congestion,
- satisfy their needs at other destinations,
- consolidate trips,
- switch to alternative travel modes,
- share travel duties among family members.

Travel behaviour is multifaceted and usually studied under typical network conditions. However, in the occurrence of extreme disruptions related to the system-level, the usual travel behaviour of users might alter, based on different factors than those affecting one's typical behaviour. To this end, the international literature on the changes in travel behaviour in the case where disruptions and additional system-level changes occur is collected and analysed. The analysis is conducted again on the basis of the three pillars of travel behaviour, namely departure time, route and travel mode choices.

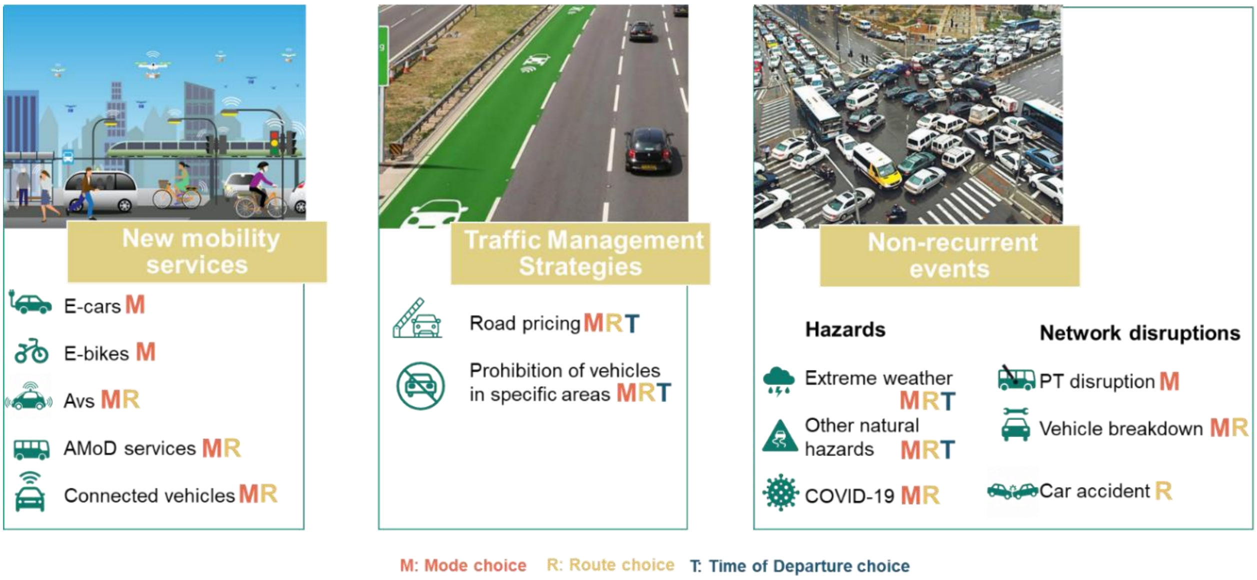

Figure 9: Factors leading to travel behaviour shifts with the travel dimension they affect

4.1 New services

Undoubtedly, in today's reality, in which technology is rapidly evolving and ecological awareness is in the centre of attention, due to climate change, a number of policies are being applied in order to stimulate the adoption of alternative vehicles. Within this framework electrical vehicles and bikes are introduced to the market as well as autonomous vehicles and MoD services, and a large proportion of them substitutes for the usage of conventional cars and other modes of transport. Moreover, CAVs are gradually penetrating urban areas and smart cities. In this section, the impact of these policies at the strategic level is examined.

EVs are novel technology in the transportation sector, and thus multiple studies have examined the acceptability of EVs (De Gennaro et al., 2014; Nordlund et al., 2018). In general, in order to provoke a positive perspective towards the usage of EVs, it is crucial to provide reasonable policy measures. More specifically, policy makers should develop policies that are perceived as just and effective. In this way, policies would be more acceptable to citizens. These policies, focusing on making a more environmentally friendly mode of transport attractive to people, aim to stimulate the purchase and the use of EVs, which would reduce the negative environmental effects of fossil fuel cars. Environmental awareness has a positive influence towards the acceptance of EVs (Barbarossa et al., 2015; Bockarjova & Steg, 2014). As a result, EVs-users, who have a strong environmental awareness, present a higher rate of acceptance towards policies that promote the wider usage of EVs, compared to CVs users. It has been shown that in urban areas EVs are capable of covering a large share of the mobility demand, replacing the usage of CVs. People, who have the flexibility to charge their vehicles whenever it deems necessary, will face no range limitation, and hence it would be easier for them to adopt this alternative mode of transport.

Electric bikes are a major category of EVs and are currently being used in numerous cities around the world. Multiple studies have examined the effects of the usage of e-bikes on travel behaviour (Cairns et al., 2017; Fyhri & Fearnley, 2015; Plazier et al., 2017). Findings show that high rates of e-bikes supply result in higher rates of their usage. In general, e-bikes are being occupied once they are available to the public and are taking a significant share of the CVs used. With the presence of e-bikes, a reduction in the use of PT has also been observed, whereas active modes of transport, such as cycling or walking, have increased. Results from studies indicate that e-bikes are very practical for everyday trips and a big majority of people would like to have access to e-bikes and would use them for their daily commute. Finally, it has been observed that women are more likely to use e-bikes for their daily trips than men. Generally, the main purpose of e-bikes is as a means of transport and as a result, their existence mostly affects the transport policy domain instead of the public health domain.

AVs and AMoD services are becoming more and more acceptable to people (Davidson & Spinoulas, 2015; Fafoutellis et al., 2021). In the near future, autonomous vehicles are expected to be part of transportation networks. Within this new reality, the average speed of vehicles is expected to be lower and as a result, the congestion levels will be increased (Metz, 2018). During the first stage of the implementation of AVs in the traffic, which will have as a priority to follow the speed limits and provide comfort to the travellers, there is going to be a negative effect in the congestion. However, passengers will have the opportunity to focus on personal matters when travelling and take advantage of the travelling time for relaxing or working. As a result, a fall in the usage of PT or active modes of transport is expected to be reduced with the high penetration rate of AVs. The benefits of AVs will be more obvious in later stages, during which they will be able to operate without occupants in a fully automated and connected system (Foteini Orfanou, 2020). In this system, there is going to be instant communication between the vehicles and the infrastructure allowing increased speeds and minimising the spaces between vehicles.

In the study of Minelli et al. (2015), the impacts of CAVs on travel behaviour and mode choice were examined. In a network with vehicles equipped with technology that provides dynamic route guidance using real-time traffic information, travellers can pick the optimal route to save time. For low market penetration rates of CAVs in the network, the use of CAVs is significantly increased, whereas the use of PT is decreased. However, with high market penetration rates of CAVs, the share of CAVs is replaced by all the other modes.

Personalised services, that address users' expectations for sustainable and cost-efficient mobility, might be implemented in the near future and the innovative concept of transportation. Within this changing transport landscape, commuters, who usually use their car or have a multimodal way of commuting, present a willingness to use the new AMoD services. More specifically, people, who travel every day and their trips mainly include going to/coming from work, find it more important to use a reliable mode for a satisfying cost, competitive to private vehicles' cost (Kuhnimhof & Eisenmann, 2021). Furthermore, users, who have a more flexible schedule, are most likely to accept the concept of sharing their ride. Additionally, it has been found that travellers with different characteristics present different attitudes towards the perspective of negotiating on-board and sharing their ride (Fafoutellis et al., 2021). Specifically, the negotiation system is less acceptable by car-dependent commuters compared to people who use other modes of transport for their daily commuting. Similarly, the non-commuters are in general less likely to negotiate and share their ride compared to commuters. This is because, generally, commuters perform a specific daily trip from their home to their workplace and follow a specific itinerary. As a result, and in order to receive a discount on their total travel cost, they are more likely to show a preference in sharing their ride, since it is easier for them to arrange an AMoD service. On the other hand, non-commuters perform a variety of trips with various origins and destinations and numerous trip purposes and thus, their mobility patterns are more complex and difficult to be optimised in a shared negotiable environment. Finally, travellers who consider the reliability of travel mode as a very important variable in the decision making of mode choice, are more likely to negotiate their travel cost and travel time during their trip.

4.2 Transportation Management Strategies

In this section, the mobility choices of travellers are analysed by examining the travel behaviour shifts as a result of Transportation Management Strategies (TMS) measures in the tactical and strategic phases. More specifically, the way people respond to TMS measures, concerning their travel mode choice, their route choice and their time of departure, is studied. These measures refer to the application of traffic signals, prioritisation or blocking the entrance of vehicles in a specific area either by excluding them completely or by applying tolls for their entry.

The impact of driving restrictions on travel behaviour has preoccupied the scientific community, and thus multiple studies have been conducted in that sector (Baghestani et al., 2020; Cools et al., 2011; Gu et al., 2017). When the policy requires drivers not to use their cars one weekday per week, depending on their plates, a specific day was observed during which there was a higher level of congestion. During these days, limited trip frequencies by non-drivers were observed. However, families that afford to own two or more cars do not experience a change in their schedules, since every day they have access to vehicles that are not prohibited. Furthermore, depending on the distance and the purpose of the trip, people might choose to use their vehicle, despite its prohibition. For example, for short trips, drivers may use their car, since there is a low possibility of being caught. Similarly, when there is an emergency, people may choose to use their car even if it is prohibited with the risk of being caught.

As far as road pricing is concerned, it has been found that the acceptability of a road-pricing policy as a single dimension is not sufficient to entice changes in activity-travel behaviour. More specifically, there is a minimum threshold of road pricing charges, that when it is surpassed, it is sufficient to alter the perspective of a person in order to change their travel behaviour.

Another study examined the effects of road pricing in a specific area through a 3 years natural experiment in Milan, Italy (Gibson & Carnovale, 2015). Most vehicles were required to pay a congestion charge entering a specific area in a specific time slot. The results showed that these measures reduced the traffic and pollution significantly. More specifically, the effect of pricing on traffic depends on the availability of public transportation. It was found that routes without public transit experienced larger traffic changes compared to the ones with public transit. It is suggested that the policy of road pricing works as a substitute to public transit. Furthermore, most drivers might still commute during peak hours and pay the price in the charge area or enter this area during hours when there is a lower charge, but the majority would choose to alter their mode choice, namely switch to PT or carpooling, or even their route by using routes outside of the pricing area. In general, drivers respond with intertemporal substitution toward unpriced times and spatial substitution toward unpriced roads outside the pricing area.

Trips during peak hours cause two major traffic problems. Firstly, high levels of congestion occur on the roads, which cause frustration to drivers and policymakers aim to tackle by applying pricing strategies in specific areas and for peak hours, and secondly, there is also a high demand for PT during peak hours, causing overcrowding, which is necessary to be tackled. As a result, studies also examine the impact of different pricing policies in PT depending on the time (peak and off-peak pricing) (Adnan et al., 2020). It was found that providing discounts in PT ridership during off-peak hours, most car drivers shifted towards PT. Nevertheless, there was a minor impact on road congestion reduction during peak hours. Furthermore, it was indicated that the increase of PT use during A.M. peak was mainly attributed to workers, who generally preferred to shift their evening trip departure time instead of shifting their morning departure times. Additionally, a shift to PT mode from retired individuals and homemakers was observed. Finally, females presented a higher willingness to travel during off-peak hours, during which there was a higher discount on PT ridership, compared to men.

In a study including policy analysis (Parthan & Srinivasan, 2013), it was found that the increase in the fuel price leads to a significant decrease in the use of two-wheeler share and the respective increase distributed among train, bus and Intermediate PT. The share of car and non-motorized use was slightly affected.

4.3 Non-recurrent events

Travel behaviour analysis is an active field of research, especially since travel-related decisions may change in the occurrence of a variety of events and system disruptions. The understanding of the parameters that affect travel decision making during non-typical network conditions, is of great importance both for the efficient planning and management of transport and for improving transport services and system conditions. However, the shifts in users' travel choices, that are examined, occur at the operational level.

4.3.1 Hazards

In this section, the travel behaviour shifts, that occurred as a result of the existence of extreme weather conditions (e.g., flooding) and other extreme physical events (e.g., earthquake) and the pandemic (COVID-19), are analysed. In today's reality, with the climate change resulting in extreme weather conditions and, also, the outburst of COVID-19 pandemic, it is of utmost importance to study the impacts of such events on the transportation sector and specifically on travel behaviour shifts.

Hazardous events, that happen to occur unexpectedly and under specific circumstances, lead to shifts in travel choices of people. Such event is the pandemic of COVID-19, during which travel behaviour was altered completely (Bhaduri et al., 2020; De Vos, 2020; Scorrano & Danielis, 2021; Shakibaei et al., 2021; Yang et al., 2021), not only because citizens were overwhelmed with fear and limited their trips, but also because the governments took strict traffic measures. Travel mode choice is the dimension of travel behaviour mostly affected by such events. PT usage is being reduced, since people recognize the increased risk of transmission, and the measures making protective surgical masks mandatory inside PT have made it less convenient.

The share of PT usage is being replaced by private cars, taxis and ride-sharing services. As a result, the supply of PT changes. Due to the limited demand for PT and the restrictions for less crowded buses and trains, transport operators reduce the frequency and the capacity per vehicle. However, people who do not have the flexibility to change travel mode would prefer travelling during off-peak hours. Furthermore, PT users do not present anymore a precise preferred route for a recurrent trip, and they often use different routes for the same OD (Marra et al., 2022). In general, travel demand is reduced, since telework and remote assistance were implemented for most occupations, while people change their everyday habits and spend more time walking and cycling.

Apart from the aforementioned, changes occur in trip purposes as well. Only necessary trips remained, whereas shopping trips have been reduced to the minimum, since most people preferred online shopping and home delivery. As a result, the number of trips was significantly reduced (Shi et al., 2019).

Travel risk perception is significantly correlated with the possibility of altering travel plans during extreme events, such as pandemics. In particular, travel risk perception decreased with older people, females and lower frequency of trips (Neuburger & Egger, 2021). The destination of the trip also influences the probability of changing the plans. If the destination is characterised by numerous reported COVID-19 cases, people would tend to change their plans. In such cases, travel behaviour gradually returns to the original levels, sometimes leaving residues.

People present a travel behaviour shift also in the framework of extreme weather events. During these occasions, travel behaviour is altered not only because the built environment and the infrastructure might be damaged, but also because people are usually panicking in their effort to stay safe. Multiple studies have examined the travel behaviour adaptation to extreme weather circumstances and natural disasters (Zanni & Ryley, 2015; Zheng et al., 2015), such as flooding (Lu et al., 2014).

People travelling for business purposes are more likely to change their plans during a disruption due to extreme weather conditions, instead of those travelling for personal reasons. However, travellers that do not experience a cancellation or travel on a global level tend not to alter their initial travel plans under these conditions. It is worth mentioning that during extreme natural events that cause significant disruptions to the network (e.g., greater delays, difficulty in accessing the destination point or the public transport infrastructure) travellers change their plans as indicated by transport organisation staff. This could mean leaving at a different time on the same day or even postponing their trip till the next day. Changing the route of the trip is also the case of a shift during extreme weather events. People may adjust their route according to safety in case of such a disruption. Finally, transport organisation staff and communication with family and friends in combination with accessibility to the internet seem to influence the decision-making process when travellers are about to alter their plans under such conditions.

Residents in coastal areas respond differently to flooding and extreme weather compared to those in inland locations, but most people change their travel behaviour under the pressure of flooding events. The key factors that mostly affect travel behaviour choices are road disruption, isolation by flood water and flood frequency. These factors are perceived differently in the two areas mainly because of the fact that people living in the coastal areas feel that the quality of their lives is affected at a higher level. The travel decisions of coastal people are affected mainly by indicators of flooding levels, whereas the decisions of inland people seem to be influenced more by flood frequency and the threat of isolation. Furthermore, coastal residents have experienced more flood conditions over a long time. However, the limited alternative routes and transportation modes in the coastal locations result in decisions that involve the cancellation of trips. Generally, the majority of the people during these conditions have a negative transportation experience and it has been found that people during a flooding prefer to cancel their trips or change their destination. The study of Abad et al. (2020) indicates that the most common type of adaptation during a flood event is changing the departure time and it occurs most frequently during the trip from home to work rather than the opposite.

Earthquakes are also natural hazardous events during and after which travel behaviour is affected (Aghababaei et al., 2020). Trips generated from areas that were impacted by the earthquake tend to take alternative routes and cause increase in flow on these other roads. Furthermore, in the short-term post-disaster situation the trips of heavy vehicles are considerably limited.

During all the hazardous events, travellers experience conditions of emergency evacuations. Studying of route choice decisions under emergency evacuation conditions is crucial (Wang et al., 2017). It was proven that, based on the value of damage concept, during emergency evacuations situations, people are willing to sacrifice travel time in order to gain perceived safety benefits. Furthermore, most evacuees are highly sensitive to the perceived road damage probability and the perceived service level. In general, the values of damage reflect the evacuees' regret aversion psychology. There is also the case that people during such occasions tend to make independent evacuation decisions and not follow the orders from public officials (Pel et al., 2012)

4.3.2 Network disruptions

Travel and transportation disruptions refer to disruptions in the infrastructure and operation of the transport system and can trigger major shifts in the travel choices of users. Disruptions of the network may occur during the existence of major events or even due to PT disruption, vehicle breakdown and road accidents.

Disruptions in PT cause passenger dissatisfaction and also results to travel behaviour shifts. When unexpected transit disruptions occur, a significant percentage of passengers that are affected by this condition choose to alter their travel and either use a taxi or an alternative PT route (Auld et al., 2020; Drabicki et al., 2021). Furthermore, transit riders are more likely to use shuttle service instead of waiting for service restoration, even when there is no difference in the total travel time. On occasions when long-term PT disruptions are planned, everyday commuters are decreased after the reinstatement to usual operation (Eltved et al., 2021). Friman (2004) found that customer satisfaction declined after the frequency of a PT service was increased. This was attributed to disruptions during the implementation of the improvement, causing an increase in negative critical incidents among the customers.

Several studies have examined the effects of public transport disruption on travel behaviour in rural areas (Papangelis et al., 2013, 2016) as well as the respective effects in urban areas (Nguyen-Phuoc et al., 2018a). It has been observed that travellers in rural areas adapt to such disturbances either by altering their travel choices temporarily or by changing their travel plans on a permanent level. According to the purpose of the trip and its importance, most travellers may change the mode or route option for their trip. For disturbances that occur on a frequent basis users may adopt new habits customised in these events. An example of this can be the allocation of their departure time or the avoidance of social arrangements on the day of the travel. However, disturbances that may occur frequently and have a significant effect on the users' travel plan may lead to a more drastic course of action, namely buying a car or relocating, in order to have a more convenient trip. These shifts in decisions are also based on the residential area of the user, the social norms and the personal attributes. Specifically, the availability of transport modes and the information during the disruption may affect each person differently. Individual's social network is crucial during disruptions, since through them it is possible to raise awareness of the dynamic system. Additionally, previous experience in a similar condition plays an important role in the decision-making process. Specifically, past successful actions usually result in considering them as future options in analogous situations. Overall, the population in rural areas is more prepared to adjust to the consequences of network disruptions than those in urban areas.

The majority of people in urban areas, when public transport is unavailable, are likely to shift to cars. The most related factors that seem to influence this decision of users are context-related and refer to the travel distance, time and cost. More specifically, for individuals, whose trip distance is longer than a typical walking or bicycling distance, the option of taking a private car is the only way for accessing their destination. Travel time affects the decision of travellers in the same way. If there is no flexibility in arrival time, during the disruption of a public transport service, most people would shift to the fastest transport mode, which usually is the private car. However, in some cases, the fastest travel mode might be the bicycle, if the travel distance allows it. Travel cost has also a crucial role in opting for an alternative transport mode. For individuals who do not have access to a private car, because they do not own one or the family car is not available, taxi is the least preferred travel mode due to the high cost. Instead, they tend to ask friends or relatives for car-pooling as they can share the expenses. Finally, the purpose of the trip plays an important role in these situations, since many users might cancel their trip if it is not of high importance, when the public transport ceases.

5 Mobility Data Collection Plan

The findings from the literature review presented in the previous chapters will set the foundations for designing the mobility data collection plan and assessing the critical factors that should be collected. In order to collect the mobility data from users, two types of travel-related data collection methods will be designed and executed within the framework of Task 3.2: stated preferences (SP) and revealed preferences (RP) method. Combining the data exported from the two methods, the actual market behaviour can be represented more realistically (J. Cairns & Grieve, 2021).

This chapter outlines the data that should be collected from the two methods. Information regarding the two travel-related data collection methods (i.e., SP and RP), that will be used in the TANGENT project, are presented. SP survey and mobility tracking will be leveraged in order to capture behavioural evolution in macro level (perceived mode's utility) and micro level (short term deviations from basic mobility patterns due to externalities). The aim of Task 3.2 is to reveal the current travel patterns of users and also how these patterns will be altered with the introduction of new services, the capacity restrictions and the alteration of strategic goals. The strategic goals will be focused on promoting a shift to PT and overall, towards a sustainable transportation system in terms of social, environmental and climate impacts.

5.1 Stated preferences

According to the aforementioned, the information that is required to be extracted from the survey is presented in Table 3 and includes *sociodemographic characteristics, users' mobility profile and their perception towards system-related attributes*, and the travel choices that are affected by these factors. Furthermore, the survey will also include a section with dedicated scenarios. The aim of the SP survey is to capture the travel choices, patterns and perceptions of users and also, associate them with their sociodemographic characteristics.

When designing questionnaires that will be distributed to different countries it is of utmost importance to pay close attention to the country-specific factors and take into consideration the differences that exist in the social environment and the transportation network of each country. For example, regarding the sociodemographic characteristics the minimum wage varies across the European countries. Furthermore, each country's transportation system offers a specific set of alternatives when it comes to available travel modes and in addition, the same travel mode may be considered worst in terms of level of service in different countries.

Finally, in the hypothetical scenarios that will be included in the SP survey, respondents will be asked for preference statements about them. The sensitivity of choices to system changes and other critical factors (cost, time and value of time) is usually examined through dedicated hypothetical scenarios that stem from a variety of methods including full factorial design and fractional factorial design (Cascetta, 2001; Eboli & Mazzulla, 2008). In the Tangent project, these scenarios are strongly related to the services and functionalities introduced in WP4,5 and will be co-created in order to be aligned with the objectives of the project.

Factor	Description	Type of measurement	Travel choices: route	Travel choices: mode	Travel choices: time of departure
Sociodemographic characteristics					
Age	The age range of the traveller	6 categories			■
Gender	The gender range of the traveller	2 categories (male/female)	■	■	■
Income	The income of the traveller	3 categories		■	
Occupation	The occupation of the traveller	6 categories		■	■
Education level	Level of education	4 categories		■	
Mobility profile					
Residential area	The residential area of the traveller	2 categories (center/non-center)		■	■
Peak hour trips	Time of the traveller' trips	2 categories (peak/off-peak trips)	■	■	■
Travel mode	The usual travel mode of the traveller for their everyday trips	5 categories		■	
Trip purpose	The usual purpose of the traveller's trip	4 categories		■	■
Flexibility of departure time	If the traveller has flexibility in their departure time and if yes, the time range of it	4 categories			■
Travel cost	The average cost of the traveller's trip	4 categories	■	■	
Perception towards system-related attributes					
Availability	The significance of a service's availability, when choosing a travel mode	5 categories		■	
Frequency	The significance of a service's frequency, when choosing a travel mode	5 categories		■	
Affected by disruptions	The significance of the effect of a disruption on a service, when choosing a travel mode	5 categories		■	

Table 3: Factors from SP survey

5.2 Revealed preferences

The method of SP surveys is the most common way of collecting data. However, the responses do not always correspond to the real travel behaviour, since these data represent only the aggregated information. In order to extract the actual mobility pattern of travellers, we will collect RP data, that are recorded in real time and can reveal the travel behaviour of people under real conditions. These data include the *trajectories of travellers during periods of system-level disruptions* and will be acquired using Google's Timeline functionalities. The information that will be collected for each trace is presented in Table 4. Using the extracted data an in-depth analysis will be conducted in order to identify the shifts in travel behaviour under the conditions of system-level disruptions. The disruptions, under which the travel behaviour will be examined, will be defined from the use-cases analysed in WP1.

Type	Description
user id	the user identification code
timestamp	the date and time of day that each trace was recorded
location tag	the location tag of each place (e.g., “home”, “work”)
sequence of activities	the sequence of the activities (e.g., home→work→home)
duration of activities	the duration of the activities
travel time	the duration of each trip
distance travelled	the distance travelled for each trip
travel mode	the travel mode that was used for each trip

Table 4: RP data for each trace

The aforementioned information is crucial for the mobility pattern recognition of each traveller. The data concerning the specific day and time of the day, the duration of the activities, the travel time and distance, are important to understand the mobility pattern of users. That is completed with the identification of the location tag of each place, the sequence of activities and the travel mode that each traveller uses for their trip.

6 Conclusions

The aim of the present report is first, to identify all relevant factors affecting travel decision-making and, second, to set the framework for an inclusive mobility data collection plan. For achieving these goals, we have studied the international literature and assessed:

1. The most relevant approaches to collect data on travellers' decision-making process.
2. The state-of-the-art approaches to analyse and model travel decisions.
3. The most important factors that may affect the decision-making process of travellers with emphasis to infrastructure or system related factors (e.g., the introduction of new services and the occurrence of network disruptions).

Findings on data collection reveal that, although stated preferences methods are more commonly used when they are combined with revealed preferences methods, the collected data are more representative and result in more accurate analysis.

From a modelling perspective, the literature review revealed that ML techniques have been widely used during the last decade for analyses in the travel behaviour and transportation sector. In general, ML techniques may have better predicting accuracy when feeding the model with new and unseen data compared to simple MultiNomial Logit (MNL) models. The importance of these techniques is linked with the concept of interpretability. This term refers to the concept of providing understandable information about the developed models.

The review of the literature resulted in the identification of factors that affect the travel behaviour following a taxonomy in 3 major categories: user-related, trip-related and service-related factors. In addition, we identified the various choices travellers make before and during a journey. Specifically, three choice dimensions are considered: (i) travel mode (e.g., car, public transport, bicycle), (ii) departure time, and (iii) route choice. The analysis was conducted on the basis of these three pillars of travel behaviour and the results are summarized in

and

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Factors	Travel choices		
	route	mode	time of departure
Cognitive factors			
Income	-	Higher income → on demand services	Higher income → after peak hour
Age	-	Middle-aged → soft modes	-
Gender	-	Women → active modes	Men → likely to change their departure time in peak hours

Fixed Schedules	-	-	Work-time → stick to the same departure time
Residential location	-	Urban → active modes, PT Suburban → car	-
Number of people in household	-	Large number → car	-
Educational level	-	-	High educational level → regret late arrival
Weather	-	Rain → car	-
Affective factors and travel happiness			
Satisfaction	-	Lower satisfaction of car/PT → car-sharing	-
Travel cost	Cost when opting a route	-	-
Travel time	Travel time when opting a route	-	-
Number of turns	Less turns → preferred route	-	-
Travel distance	Distance of a route	-	-
Road preference	Personal preferences for opting a route	-	-
Perception	-	Perception towards a mode	-
Preferred arrival time	-	-	Flexible with arrival lateness
Trip-related factors			
Travel time	-	-	Long trips → earlier departure time
Accessibility to PT	-	High PT accessibility renders that mode preferred	-
Purpose of the trip	-	Commuters → motorised modes	-
Safety concerns	Safer routes are preferred	Safer modes are preferred	Departure times in the dark are avoided
Transportation infrastructure	-	Good transportation infrastructure renders the involved modes preferred	-

Table 5: Set of user- and trip-related factors and their effect on each travel choice

Physical factors	Perceived factors
Availability/Accessibility/Reliability	Comfort on the service
Frequency	Convenience
Speed	Safety

Physical factors	Perceived factors
Price	Security
Information provision	Aesthetics
Ease of transfers/ interchanges	
Vehicle condition	

Table 6: Service-related factors affecting travel behaviour

Regarding the *user-related factors*, they consist of cognitive factors, affective factors and travel happiness. The first category includes traditional factors, such as sociodemographic characteristics, as well as other predetermined factors, like car ownership. Results have shown that men are more likely to change their departure time in peak hours than women. Furthermore, this category also refers to factors that are objective and unanimously accepted. For example, it has been found that when the weather is rainy, people prefer to use public transportation instead of active travel modes (e.g., bicycle, walking). Apart from the conventional factors, there are travel happiness and affective factors that affect people's travel choices. These attributes take into account the emotions of people and their personal perspectives that seem to affect more their choices. For example, past negative experiences of someone that used a public transport service might be a limiting factor for the person to use it again.

As far as *trip-related factors* are concerned, they refer to the objective characteristics of a trip, such as travel time and cost. It has been found that the purpose of the trip plays an important role when people are choosing a mode of transport. More specifically, motorised travel modes are being used more commonly by people who go to work than those who travel for leisure.

In addition to the aforementioned, service-related factors may affect the decision of a user to choose to use a service. These factors refer to physical attributes of the service, such as availability, frequency, speed and price, and perceived attributes, such as comfort, safety and aesthetics. For example, the availability of a service and the perceived security while riding it are attributes that people might take into account when opting to use a service (e.g., public transport, taxi).

Apart from the conventional factors that affect users' travel behaviour, elements from the new reality are causing travel behaviour shifts. In particular, the introduction of new services, such as electrical, autonomous and connected vehicles and AMoD services, motivates people to adopt a more environmentally friendly travel behaviour. Additionally, TMS measures are affecting the travel behaviour of users in the three dimensions of route, mode and departure time choices. More specifically, pricing road strategies that are implemented in specific areas and time zones aiming at reducing congestion and emissions in the network, are prompting users to switch to other modes of transport that are not so expensive to use in the preferred area. Respectively, others may opt to use a different route or depart at a different time in order to avoid entering the area and paying a fee. Finally, non-recurrent events, that have occurred during the previous years, obligate users to alter their usual travel behaviour and adapt to the conditions. For example, because of hazardous events, such as extreme weather conditions or the COVID-19 pandemic, people change their travel patterns – temporarily or for a longer period – in order to stay safe and follow the regulations. Finally, network disruptions that occur unexpectedly, such as the disruption of a PT service, affect users' travel choices. Depending on the purpose of the trip and its importance, most travellers may change the mode or route option for their trip. The above conclusions are summarized in the table below:

Factors	Travel choices		
	route	mode	time of departure
New mobility services			
E-vehicles	-	Switch to e-vehicles	-
Autonomous vehicles (Avs)	-	Switch to AVs	-
AMoD Services	-	Switch to AMoD services	-
Connected autonomous vehicles (CAVs)	Provide dynamic route guidance	Switch to CAVs	-
Traffic Management Strategies (TMS)			
Road pricing	Alter route to avoid pricing area	Switch to other mode to avoid pricing area	Adapt departure time to avoid high fees
Prohibition of vehicles in specific areas	Alter route to avoid prohibition of vehicles in areas	Switch to other mode to approach specific area	Adapt departure time to avoid prohibition of vehicles in areas
Non-recurrent events – Hazards			
Extreme weather	Choose a safer/without-congestion route	Switch to other available mode	Adapt departure time to avoid dangerous causes from extreme weather
Other natural hazards	Choose a safer/without-congestion route	Switch to other available mode	Adapt departure time to avoid dangerous causes from natural hazards
COVID-19	Choose faster routes	Switch to modes, that are not crowded	-
Non-recurrent events – Network disruptions			
Public transport disruption	-	Switch to other available mode	-
Vehicle breakdown	Alter route to avoid congestion	Switch to other available mode	-
Car accident	Alter route to avoid congestion	-	-

Table 7: Factors leading to travel behaviour shift

Finally, the data mobility collection plan was presented, which consists of SP and RP data. SP data include sociodemographic characteristics of users, their travel patterns for their everyday trips, and their preference in dedicated scenarios. RP data includes information on the travel behaviour of people under system-level disruptions, aiming to identify the travel behaviour shifts under these conditions. RP data consists of information regarding the trajectories of travellers, such as the location tag, the travel mode and the travel time and distance of each trace, in order to recognize the mobility pattern of each user. It should be noted that the disruptions, under which the travel behaviour will be examined, will be defined from the use-cases analysed in WP1. Expecting to have access to a large amount of data produced by the SP and RP methods, data-driven approaches will be followed. However, emphasis should be given to the theoretical framework.

7 ANNEX

Authors	Year	Travel choices			Factors				Country		Type of experiment				Duration of experiment	Sample size	Methods	Accuracy
		route	mode	departure time	User-related	Trip-related	Service-related	Travel behaviour shifts	Europe	Other	survey	experiment	travel diaries	interviews				
Steed & Bhat	2000			•	•					USA	•					44 414	MNL	
Friman et al.	2001		•				•											
Ettema	2003			•	•	•			the Netherlands				•			79		
Friman	2004		•					Network disruption	Sweden		•					1048/ 1261	Statistical Analysis	
Ryley	2006		•		•				Scotland		•				1 year	4016	Cluster Analysis	
Mazzulla & Eboli	2006		•				•		Italy					•		382	Statistical Analysis	
Paulley et al.	2006		•				•											
Beirão & Cabral	2007	•	•		•				Portugal					•		24	Qualitative Analysis (grounded theory)	
Kumar & Rao	2007		•	•	•					India	•					1750	MNL	
M•ller et al.	2008		•			•			Germany		•					4700	MNL	Accuracy = 81%
Zeid	2009	•	•		•													
Ben-elia et al.	2010			•	•				the Netherlands			•			13 weeks	10315	MNL, Logit mixture, LC	
Ettema et al.	2010	•	•		•													
Cools et al.	2011	•	•	•				TMS	Belgium		•					300	two-stage hierarchical model	explained variance: 74%
Zheng et al.	2011							Flooding		Australia	•				8 weeks	550	Random-effects ordered logit	
Abou-Zeid et al.	2012		•		•													
De Vos et al.	2012		•		•													
Saneinejad et al.	2012		•		•					Canada	•				6 months		MNL	Accuracy = 59%
Pel et al.	2012	•	•	•				Evacuations										
Zhu & Levinson	2012	•	•	•				Network disruption										
Li et al.	2013		•	•	•					China	•					5632	Binomial, MNL	Accuracy (Binomial) = 81.9%-84.4%, Accuracy (MNL) = 70.4%-74%
Redman et al.	2013		•				•											

Parthan & Srinivasan	2013		•					TMS		India				•		967	RUM-MNL, RDM, RRM-MNL, CDR-MNL	R^2(RUM-MNL) =0.491, R^2(RDM)=0.491, R^2(RRM-MNL) =0.492, R^2(CDR-MNL) =0.497
Papangelis et al.	2013	•	•					Network disruption	UK					•		158		
Prato	2014	•			•				Italy		•					575	MNL, RRM, RUM	Adj. R^2 (RRM)=0.1869-0.1890, Adj. R^2 (RUM)=0.1872-0.1908
Sun et al.	2014	•			•					China		•					Linear Regression, Mix Logit	Adj. R^2(linear)=0.004-0.016, Adj. R^2 (mix logit) =0.009-0.023
Jain et al.	2014		•			•				India	•				6 months	385	Analytical Hierarchy Process	
De Gennaro et al.	2014		•					E-vehicles	Italy			•			1 month	28000	Statistical Analysis	
Bockarjova & Steg	2014		•					E-vehicles	the Netherlands		•				1 month	2974	Regression analysis	Adj. R^2 = 0.249-0.337
Lu et al.	2014	•	•	•				Flooding		Bangladesh	•				4 months	998	MNL	
Khoo & Asitha	2015	•			•					Malaysia	•				3 months	1000	Bivariate Model	Log likelihood at convergence = -15,403
Zanni & Ryley	2015		•		•				UK		•				6 months	740	Multivariate Analysis	R^2=0.196-0.273
Barbarossa et al.	2015		•					E-vehicles	Denmark, Belgium, Italy		•					2005	SEM (CFA), multi-group analysis	RMSEA(CFA) < .08, RMSEA (multi-group) = .05
Fyhri & Fearnley	2015		•					E-bikes			•		•		6 months	5462 (s), 66 (exp.)	Statistical analysis	
Davidson & Spinoulas	2015		•					AMoD				•						
Minelli et al.	2015		•					CAVs		Canada		•					MNL	McFadden R^2 = 0.256
Gibson & Carnovale	2015	•	•					TMS	Italy			•			4 years		Linear Model	R2=0.785-0.900
Allahviranloo	2016	•	•	•	•					USA			•		1 year	26269	Clustering/Classification, MVP, SVM, 'Adaboosting' algorithm	Accuracy = 80.3%
Thorhauge et al.	2016			•	•				Denmark		•					286	SEM, DCM, HCM	R^2=0.352-0.362
Böcker et al.	2016		•		•				the Netherlands		•				7 months	945	SEM, Regression Model	R^2=0.125-0.692, RMSEA=0.009
De Vos et al.	2016		•		•				Belgium		•				2 months	1720	Linear Regression	Adj. R^2 (RRM)=0.06-0.30
Papangelis et al.	2016	•	•	•				Network disruption	UK					•	5 months	66		
Kim et al.	2017	•			•					Australia		•			6 months	813593	OLS, Quantile Regression	

Charoniti et al.	2017	•			•	•			the Netherlands		•					693	ML, LCM, RRM	R^2=0.2673-0.3351
Kim et al.	2017		•		•		•		the Netherlands		•					995	MIMIC, RRM, HCM	
Belgiawan et al.	2017		•			•				Indonesia	•				4 days	526	MNL (RUM), RRM	R^2(MNL)=0.73-0.091, R^2(RRM)=0.073-0.090
Cairns et al.	2017		•					E-bikes	UK		•	•		•	8 weeks	609 (s), 80 (exp.), 80 (int.)	Statistical Analysis, Qualitative Analysis	
Plazier et al.	2017		•					E-bikes	the Netherlands			•		•	2 weeks	24 (1,090 trips)	Statistical Analysis, Qualitative Analysis	
Gu et al.	2017	•	•					TMS		Beijing			•			253584		
Wang et al.	2017	•						Evacuations		China	•					531	RRM, RUM	R^2(RRM) 0.787 R^2 (RUM)=0.643
Golshani et al.	2018			•	•					USA	•				13 months	9450	MNL, NN, IM, JCM	(NN)=87.20%, (IM)=63.92%, (JCM)=77.77%
Alemi et al.	2018		•		•						•					1975		
Bödeker et al.	2018		•		•													
Vashisth & Aggarwal	2018	•	•			•				India	•					300	MNL	R^2(McFadden)=0.549, R^2(Cox and Snell)=0.532, R^2(Nagelkerke)=0.71
Nordlund et al.	2018		•					E-vehicles	Sweden		•					1200	Statistical Analysis, Multiple-group Analysis	RMSEA = 0.053
Nguyen-Phuoc et al.	2018		•					Network disruption		Australia				•	3 months	30	Qualitative Analysis	
Tirachini & del Rio	2019		•		•					Chile	•				2 months	1529	Statistical Analysis	
Shi et al.	2019							COVID-19										
Liu et al.	2020		•		•					China	•	•			7 months	152	MNL	Accuracy = 84.2%
Baghestani et al.	2020		•	•				TMS		USA		•						
Adnan et al.	2020		•	•				TMS		Singapore		•					Hierarchical Discrete Choice Models - Monte-Carlo Simulation	
Bhaduri et al.	2020							COVID-19		India	•				3 weeks	498	MDCEV	
De Vos	2020		•	•				COVID-19										
Abad et al.	2020			•				Flooding		Philippines	•				2 months	716	Chi-square Analysis, Binary Logit Model	Pearson χ^2 = 26.2, R^2 = 0.126-0.416
Aghababaei et al.	2020	•						Earthquake		New Zealand		•						
Auld et al.	2020	•	•					Network disruption		USA	•				3 months	659	Statistical Analysis	
Fafoutellis et al.	2021		•					AMoD	Greece		•				2 months	1600	Bayesian Classifier, RF, Gradient boosting machine, Ensemble learning	NBC = 62% RF = 82% GBM = 78% EL = 78%
Shakibaei et al.	2021							COVID-19										

Yang et al.	2021		•					COVID-19		China				•	3 months	33		
Scorrano & Danielis	2021							COVID-19	Italy		•		•		5 months	315	MNL, RPL	Adj. R^2 (MNL)=0.27, Adj. R^2 (RPL)=0.34
Neuburger & Egger	2021			•				COVID-19	Austria, Germany, Switzerland		•				-	1370	Cluster Analysis	
Drabicki et al.	2021	•	•					Network disruption	Poland		•				6 months	450	Statistical Analysis, Chi-square Analysis	χ^2 = 20.25
Eltved et al.	2021		•					Network disruption	Denmark			•				395875	Cluster Analysis	
Marra et al.	2022							COVID-19	Switzerland		•		•		22 days/5 months	172/48	Mixed Logit Model	Adj. R^2 = 0.7

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