Chapter

Adaptive Travel Mode Choice in the Era of Mobility as a Service (MaaS): Literature Review and the Hypermode Mode Choice Paradigm

Stefano de Luca and Margherita Mascia

Abstract

Mobility as a Service (MaaS) is becoming a "fashionable" solution to increase transport users' satisfaction and accessibility, by providing new services obtained by optimally integrating sustainable modes, but also guaranteeing mass transport and less sustainable modes, guaranteeing fast and lean access/egress to the mass transport. In this context, the understanding and prediction of travellers' mode choices is crucial not only for the effective management of multimodal transport networks, but also successful implementation of new transport schemes. Traditional studies on mode choices typically treat travellers' decision-making processes as planned behaviour. However, this approach is now challenged by the widely distributed, multi-sourced, and heterogeneous travel information made available in real time through *information and communication technologies* (ICT), especially in the presence of a variety of available mode options in dense urban areas. Some of the real-time factors that affect mode choices include availability of shared vehicles, real-time passenger information, unexpected disruptions, and weather. These real-time factors are insufficiently captured by existing mode choice models. This chapter aims to propose an introduction to MaaS, a literature review on mode choice paradigms, then it proposes a novel behavioural concept referred to as the hypermode. It will be illustrated a two-level mode choice decision architecture, which captures the influence of real-time events and travellers' adaptive behaviour. A pilot survey shows the relevance of some real-time factors, and corroborates the hypothesized adaptive mode choice behaviour in both recurrent and occasional trip scenarios.

Keywords: Mobility as a Service, mode choice, urban transport, Intelligent transportation systems

1. Introduction

MaaS can be considered as a tool to improve users' mobility and, as stated by [1, 2] "MaaS provides an alternative way to move more people and goods in a way that is faster, cleaner, and less expensive than current options". In particular, also according to [1], "MaaS is a user-centric, intelligent mobility distribution model in which all mobility service providers' offerings are aggregated by a sole mobility provider, the MaaS provider and supplied to users through a single digital platform".

Overall, MaaS application allows to optimize a trip for transit factors such as convenience, carbon emissions, and reliability. In general, the following virtuous impacts may be associated to MaaS concept:

1. reducing car ownership, the use of personally owned modes, car use, energy consumption and pollution;

2. increasing accessibility, equity, welfare;

3. pursuing the system optimum.

Currently, MaaS services have been implemented in several countries such as Germany (MOOVEL, Qixxit, BeMobility, HannoverMobil), Netherlands (Mobility Mixx, NS-Business card, Radiuz Total Mobility), Finland (WHIM, Tuup), Sweden (UBIGO), France (EMMA, Optymod), Austria (Smile, WienMobil lab), USA (SHIFT) and Singapore.

A list of key fundamentals to support such a virtuous MaaS ecosystem is reported by the Maas Alliance, a public-private partnership established in 2015 by the UE encouraging and catalyzing pilot projects. Moreover, several contribution give interesting insights, such as [3, 4].

Importantly, the MaaS Alliance, in the White Paper [5], states that: "due to ecological and capacity advantages, the traditional modes of public transport, like bus, tram and metro/underground, should remain as the backbone of MaaS in urban areas". On the other hand, the integration of traditional modes of public transport with other faster, cheap and continuous services can provide new lifeblood and a new look to public transport and can be the key solution to aid sustainable modes of transport [6].

Unfortunately, if the vision of what MaaS should be is clear, the real challenge is what MaaS could become if its development completely relies on private operators. [7] reported that the main risk of a purely commercial approach to MaaS is to disincentivize sustainable trips, stating that "The success in some markets of new services, including apps for private-hire vehicles and ride-sharing, clearly has the potential to disrupt existing urban mobility services and could also encourage a shift towards car use away from more sustainable modes." Therefore, in the same study it has been concluded that "City and regional authorities need to be involved in the development of policy around MaaS at EU and national level, through new models of governance and with public sector leadership, to avoid environmental, economic and social dysfunctions."

According to the four workshops organized for the MAASiFiE project to define a European 2025 MaaS roadmap, the policy & regulation between public and private participants is seen as the most significant driver for MaaS development [8]. Along the same line, the Maas Alliance recognizes that a limited regulation can compromise the way MaaS applications impact on urban environment and compromise the public interest (e. g. decrease congestion, pollution, etc.).

However, if the problem is clear the solution is not so easy to find. One step forward was taken by the Finnish government adopting in April 2017 the Act on Transport Services (also known as Transport Code), the first known regulatory effort on this matter. However, the Code main aim is to boost the establishment of requirements for MaaS services (integration, interoperability, etc.) and the availability of data [9].

In addition, starting from the vision of how MaaS should work, a great effort need to be used in proposing models and methodologies enabling such working.

MaaS platform should be supported by a simulation environment which, starting from historical and observed data, should be able to reproduce the actual state of the multi-modal transportation system and forecast the future states. This is strictly needed to "offer" updated, reliable and personalized MaaS solutions to the users. Current platforms rely on simplified hypotheses on users' travel behavior models, on transport system simulation models and on the short-midterm traffic forecasting models.

Summarizing, the following drawbacks seem to characterize MaaS implementation:

- MaaS development is mainly driven by private operators; hence, they are mainly developed as business solutions in an open market, where different competitors offer their services, without a clear regulatory framework and without a clear vertical/horizontal integration.

- Uncertainty about the way decision makers and governmental agencies may push towards specific, system-oriented transportation planning strategy due to the lack of a clear regulatory framework.

- MaaS platforms do not rely on consistent and reliable modelling framework able to forecast future system state and consistently modify their offer.

- Existing analyses have not clearly demonstrated the environmental and social sustainability of a MaaS service.

It is, therefore, important to preliminarily define the conceptual framework in which any MasS service should be figure out. To this aim, five pillars can be identified.

i. MaaS service should be an open market but regulated by decision makers/governmental agencies and characterized by a specific and organized regulatory framework;

ii. the traditional modes of public transport, like bus, tram and metro/underground, should remain as the backbone of MaaS in urban areas;

iii. MaaS service should guarantee sustainability and equity and lead toward a car-free transportation system;

iv. MaaS service should offer a smart integration of single-step transport modes offered by different providers;

v. MaaS service should be intrinsically dynamic adapting its characteristics to the day-to-day and the en-route travel needs.

In this context, MaaS requires the ability to model mobility and travel choices. The issue is not trivial especially for travel choices [10]. First, it is necessary to model individual choices, secondly, both predictive and adaptive choices must be considered and third, the intrinsic dynamic of the choice behavior must be explicitly considered.

Indeed, the understanding and quantification of travellers' mode choices is crucial for the prediction and management of multimodal traffic networks, and have become an important field of inquiry in cross-disciplinary research spanning transport engineering, computing, mathematics, psychology, and social and behavioural sciences.

The underlying assumption of most existing studies on travel mode choice is that a traveller chooses a specific mode before commencing his/her trip, which is categorized as planned behaviour. However, some studies have identified and demonstrated the influence of real-time events on mode choices,[1] particularly for travellers using public transport; some examples include real-time passenger information, weather, and transport disruptions [11–13]. These real-time events may lead travellers to assess various modes in an adaptive way to the extent that the aforementioned planned behaviour plays a less significant role in the final outcome of the mode choices.

This chapter aims to give a literature overview of the existing approaches, the aims to propose an adaptive mode choice behaviour paradigm which takes into account real-time events, and provides an empirical validation of this mode choice paradigm. The real-time events include, but not limited to, availability of shared bikes at the docking station, real-time information on bus arrival time, scheduled or unexpected local disruptions, and weather conditions. This research is an important undertaking as it not only identifies a set of new factors that influence mode choices, but also presents a novel framework to study mode choice behaviour. This behavioural paradigm may pose interesting challenges from a modelling perspective and may require an integrated modelling approach for both mode choice and traffic assignment to fully capture the adaptive behaviour. The latter statement stems from the observation that many real-time factors identified above have a dynamic and stochastic nature that is related to the evolution of the system (e.g. the dynamic network loading).

The main contribution made by this paper includes:

- A novel adaptive mode choice behavioural paradigm able to incorporate real-time events (both pre-trip and en-route), which advances state-of-the-art modelling approaches that mostly rely on static attributes and simulate mode choices as planned behaviour.

- A pilot survey that shows the viability and validity of the adaptive mode choice behaviour for real-world scenarios, where a number of mode options and real-time events are defined and combined to analyse user responses under different circumstances.

The rest of this chapter is organized as follows. Section 2 provides an extensive review of state-of-the-art mode choice approaches. In Section 3 the bi-level mode choice behaviour paradigm that explicitly accounts for real-time events is proposed. A real-world scenario pertaining to the hypothesized adaptive behaviour is introduced in Section 4, which also presents the pilot survey study, which assesses the behavioural validity of this new concept at a qualitative level, and discusses the survey results. Section 5 introduces some remarks on the main issues of MAAS and the research perspectives regarding the proposed interpretative hypermode paradigm.

2. Literature review

In general, travel mode choices may be updated between different periods of time (period-to-period) or within the same trip (within-day). In the period-to-period choice process all the available transport modes are considered. Users have the option

[1] Throughout this paper, real-time information is treated as a special case of real-time events.

to choose among the available modes and their decision-making processes converge towards a stable choice that, once reached, can be considered as habitual.

Almost the totality of the existing scientific contributions assume that travellers choose their mode of transport through a one-step decision as a planned behavior, only few exceptions explore the alternatives. In particular, travellers' mode choices are usually reported to be habitual in several travel behaviour studies [14–16]. In general, habits depend on the perception and preference towards a travel mode and it can hardly be modified. As a matter of fact, it is a common approach to investigate and model the habitual behaviour (holding behaviour), and neglect the dynamic element of the choice process. Within this framework, the mode choice analysis may depend on the different interpretative paradigms that can be assumed for modelling travel demand:

a. Trip-based. It implicitly assumes that the choices relating to each origin–destination trip are made independently of the choices for other trips within the same and other journeys.

b. Trip chaining. It assumes that the choices concerning the entire journey influence each other. In this case, the choice of an intermediate destination, if any, takes into account the preceding or following destinations in the trip chain; the choice of transport modes takes into account the whole sequence of trips in the chain, and so on.

c. Activity-based. It analyses transport demand as the outcome of the need to participate in different activities in different places and at different times. It therefore takes into account the relationships among different journeys made by the same person during the day and, in the most general case, between journeys made by the various members of the same household.

The trip-based paradigm is the most widely adopted, and relies on a consolidated theoretical literature [17] and operational literature, which has predominantly investigated mono-modal transport systems competing with each other (e.g. [18–34]).

Minor attention, yet increasing in the last years, has been paid to individuals' preferences in multi-modal networks where different transport modes are integrated and a possible choice alternative is a combination of them (e.g. [22, 35–40]). Nevertheless, it should be noted that most of them consider public or private transport modes separately or, consider integrated transport modes, for instance when combined with park-and-ride. More Recently, [41] attempt to model the full range of choice options in multimodal network settings using a stated preferences approach, and approach the problem as a route choice problem. But they only investigate pre-trip choices.

Trip-chain and activity-based paradigms model pre-trip behaviour in a more realistic behavioural context, hence may allow a better interpretation and simulation of the travellers' mode choices. However, they are usually rather complex for calibration and implementation. Some examples include:

i. mode and departure time [41, 42];

ii. trip chain [42–47]

iii. activity-based [32, 46–50];

Among the pre-trip choice paradigms, pre-trip switching approaches have also been developed to understand and simulate potential modal shift (e.g. [51–56]).

Finally, different attempts have also been made to model an habitual behaviour (holding decision), but taking into account temporal correlation for the same user, thereby showing how tastes can vary for the same traveller using short-term cross-sectional data [57–59].

The pre-trip and habitual choices have been extensively investigated in the literature; however, some scholars have also dealt with the explicit simulation of mode choice dynamics with regard to both short- or long-term scenarios. In particular, [60–63] study short-term mode choice dynamics using discrete choice method and panel data. With regard to long-term mode choice dynamics, [64] investigate commuting behavior within the traditional maximum utility framework, whereas alternative approaches have tried to take into account more complex behavioural determinants and processes such as habits and learning. In particular, [65] derived decision rules based on neural networks to predict activity scheduling and mode choice; [66] developed a computational process model to mimic travel decision-making process; [67] developed an agent-based process to simulate travel behavior in terms of information acquisition, learning, adaptation and decision heuristics. Recently, the Markov chain approach has been fruitfully adopted to model and interpret the decision-making process [32, 68–72].

With regard to the within-day travel mode choice behavior, it can be assumed that a typical traveller chooses a transport mode (or a combination of transport modes) and may change his/her initial choice by switching to other modes before leaving the origin and/or during the trip. Obviously, such behaviour is reasonable only in a multi-modal or inter-modal context. On the one hand not many contributions can be founded in the literature; on the other hand the landscape of available mode options is evolving particularly at the urban level. Multi-modal networks are rapidly growing, and a new generation of mobile, personalised information systems and intelligent transport systems are ready to support this flexible and adaptive behaviour by providing assistance in the planning and implementation of multimodal trips [73].

As a matter of fact, an increasing number of users may reconsider their initial travel choices. However, not many contributions can be found in literature. From a psychological viewpoint, the study undertaken by [74] considers a two-level approach to simulate the mode choice. At the first level (more related to the person) the authors apply the comprehensive action determination model, which assumes that intentional processes, habitual processes, and normative processes lead to a certain level of propensity to use the private car. The second level of choice (more related to the trip) is characterized by situational influences, where trip purpose, disruptions on public transport, and weather are identified as predictors. The authors conclude that the multi-level approach is a promising alternative to conventional models. These insights from the field of psychology are valuable for the correct interpretation of the decision-making processes of travellers, and will be considered in the hypermode approach proposed in this paper.

Different contributions have analysed mode choice as a sort of path choice in a broader context of a multimodal network [49, 75–77], by considering interconnected networks, one for each different transport mode. Such an issue has been addressed in a multi-modal context through the well-established supernetworks [78, 79]. However, such an approach has been mainly adopted/used for modelling elastic demand assignment problems; it is not very flexible to address possible adaptive behaviour.

Contribution by [80] take the mode availability into consideration, but mainly from an assignment perspective as both model the user decision to change mode at each node. In [81] each option (mode and route) is associated with a probability of immediate availability, which is one for private modes and less than one for public transport, the latter being a specific value affected by service frequency. The author therefore revised the transit assignment problem by taking into account mode availability at each node, which represents a decision point for the users. The proposed assignment model entails sequential choices at each intermediate node in the multimodal network and seeks an equilibrium. [80] proposes the strategy of adaptive multimodal least expected time in order to determine the hyperpath associated with the least cost in a multimodal network. In addition to the modes of walking and driving, each public transport line is considered a separate mode. The authors consider a delay associated with the transfer between modes, and model the users' capability to reassess the costs at each node and determinate if switching mode may be a better option. However, the assessment of switching from one mode to another is merely based on time as this is a reasonable assumption for assignment algorithms, but it is not sufficient to capture the decision making process at the mode choice level. Moreover, users are quite reluctant to have too many transfers and reassess all mode options at every en-route node unless a disruption occurs.

In conclusion, mode choice behaviour may rely on an extensive scientific literature, but it predominantly deals with habitual behaviour including pre-trip behaviour, pre-trip switching behaviour or travellers' behaviour at specific nodes of the transportation network. Most of the existing efforts have been focused on multi-modal networks in which different transit modes are connected or in which individual transport modes (car, motorbike, cycling) and collective transit modes may interact with each other (Park and Ride). However, the choice contexts are always pre-trip and not much can be found with regard to multimodal contexts in which the transport mode can be changed during the trip (transit alternatives and shared modes). For example, the introduction of shared modes (car/motorbike/bike-sharing) and their integration with the various existing transit systems lead to a significant flexibility that cannot be neglected. Instead, they should be carefully analysed and interpreted with behavioural paradigms that are different from the traditional ones. Furthermore, the literature suggests that weather conditions have the potential to influence mode choices [12, 82], and that there is a lack of comprehensive evaluation of costs, time and service quality in multimodal travel choice [41].

In conclusion, this paper focuses on the decision making process that leads users to take a specific mode in the presence of different mode options and real-time information/events. The proposed novel mode choice paradigm satisfies the following requirements:

- it captures a more realistic mode choice behaviour, which is influenced by real-time events, building on the multi-level approach proposed in the psychology field by [74];
- it is able to subsume planned behaviour as a special case, which addresses travellers whose mode choices are not adaptive; this is particularly true for travellers who use their own vehicles (private cars and bikes);
- it is validated with a pilot study through a preliminary qualitative survey to demonstrate the validity of the approach.

3. The hypermode concept

Currently, mode choice is considered a planned behavior and is embedded within traffic assignment procedures only in a static context [83], which obviously does not capture the influence of any real-time events. With regard to dynamic modelling, mode choice is usually considered a fully pre-trip behavior. This paper investigates an adaptive mode choice behaviour and presents the results of an empirical study undertaken to validate the approach. It focuses on the potential effects of real-time events on both pre-trip and en-route mode choices.

For reason that will become clear below, this adaptive mode choice will be hereafter called "*hypermode*", in analogy to the hyperpath concept proposed for the route choice in transit assignment [84]. The hyperpath approach suggests that travellers first identify a set of attractive lines that connect their origin–destination (O-D) pair; then they choose a specific service according to certain strategies. Such strategies can be based on the minimization of travel time, waiting time, walking distance, or the number of transfers A more complex strategy can also consider the influence of real-time information on path choices [85, 86]. In an analogous way, the hypermode concept stipulates that travellers identify a set of feasible modes for their target trip and may make their final decisions later based on real-time events. These adaptive mode choices have been recently facilitated by the development of Information and Communication Technologies (ICT) such as smartphones, as well as Intelligent Transport Systems (ITS) such as vehicle tracking and prediction. For example, travellers can now make informed mode choices based on estimated time of arrival of buses/trains/trams, or the availability of shared bikes at any given docking station. Such adaptive travel behaviour is suitable for dense urban areas, where plenty of mode options and access points are available to travellers, and walking is always an option especially for short trips. Given that 50% of the trips in urban areas in Europe are shorter than 5 km [87], the hypermode concept enjoys wide empirical support. This extra modelling dimension could lead to a significant yet challenging advancement in the modelling of multimodal transport networks.

This section illustrates this notion by proposing a conceptual analytical framework along with a few examples.

3.1 Decision-making architecture

In this section, we formally introduce the *hypermode* concept, which is analogous to the hyperpath concept proposed for the route choice in public transit assignment [84]. The hyperpath approach suggests that a traveller first identifies a set of attractive lines that connect the origin–destination (O-D) pairs. Then, he/she chooses a specific service according to a certain strategy, which can be based on the minimization of travel/waiting time, amount of walking, or number of transfers. A more sophisticated strategy can also take into account the influence of real-time information on path choices [86]. In an analogous way, the hypermode concept stipulates that travellers identify a set of feasible modes for their target trip and may later make their final decisions based on real-time events. These adaptive mode choices have been recently facilitated by the development of Intelligent Transport Systems (ITS), and Information and Communication Technologies (ICT).

The underpinning decision making process involved in the hypermode concept is articulated in two levels.

1. The user identifies a set of feasible travel modes for the trip, which are accessible at the same physical location or nearby. On this level, the decision making is strategic (i.e. not real-time), and is affected by static characteristics such as user preferences, socio-economic characteristics, average/historical travel times, and financial costs of using different modes.

2. Right before a trip is made, the user evaluates real-time events in order to select a specific mode of transport from the aforementioned feasible set. The real-time event includes but is not limited to: availability of vehicles (relevant to

shared modes), weather conditions (relevant to walking and biking), vehicle arrival time information (relevant to scheduled or unscheduled public transport), and disruption or crowdedness.

This adaptive behaviour can occur at the following different stages of the trip:

- The user has not yet left the origin and has a set of modes in mind that could bring him/her to the destination with acceptable time and cost. Just before leaving the origin the user reassesses these modes based on real-time events such as weather, real-time bus information and so forth, which may influence the user's the final choice of mode within the feasible set.

- The user has just left the origin with a specific mode in mind (e.g. tube). He/she then approaches a tube station and notices a disruption or heavy crowding, hence immediately considers another mode from the feasible set.

- The user has chosen an *access point*, which is a specific location where he/she can access several modes that can all serve the trip. The user approaches the access point and then chooses a specific mode based on a combination of his/her preferences (e.g. first coming/least walking/least transfers) and real-time events.

The extent to which the real-time events affect the mode choices varies among individuals. For example, some users may take their preferred modes in any circumstance. This is particular the case for travellers who use their own vehicles, such as private cars or bikes (cyclists who use their own bikes usually stick to the same mode in case of very adverse weather conditions). Such behaviour is referred to as *planned* in this paper since it is not adaptive, and only involves the first level of the decision making process. Such planned behaviour can be subsumed by the proposed two-level decision making paradigm, as it is a special case with decision parameters on the second level being rigid and non-responsive to real-time events.

3.2 Factors affecting adaptive mode choices

Table 1 illustrates the proposed approach and a non-exhaustive list of factors affecting choice probabilities on the two choice levels.

The realization of a specific mode choice is therefore the consequence of the mode first belonging to the feasible set (choice level 1), and then actually chosen within such set with given real-time events (choice level 2).

Figure 1 illustrates, in further detail, individual components of the decision making processes with inputs and outputs of the two levels of choices.

Any of the traditional mode choice models can be applied to calculate the probability at the first level. Once the probabilities of all possible modes are calculated, the set of feasible modes can be formed, which is a quite standard procedure and thus omitted here. In the second level of the decision making process, the feasible modes are subject to re-interpretation and their probabilities are reassessed based on real-time events. For example, if walking is the preferred mode with the highest probability at the first level, and the weather is rainy in real time, the probability associated with walking decreases.

The whole procedure may be easily formalized in a compact formulation coherent with existing assignment models, thus may be implemented for simulation any transportation system (see technical report [88]).

Level of choice	Factors affecting choice probability
(1): Feasible set	Probability of each mode to belong to the *feasible mode set* depends on: • Socio-economic characteristics (age, gender, income, etc.) • Health and/or environmental concern • Financial cost • Average travel time • Number of transfers
(2): Final mode choice	Choice probability of a specific *mode* depends on: • Real-time arrival time (bus, train) • Vehicle availability (bike-sharing, car club) • Weather (walking, cycling) • Disruptions and crowdedness (bus/train/tube stations)

Table 1.
The two choice levels and influencing factors in the hypermode approach.

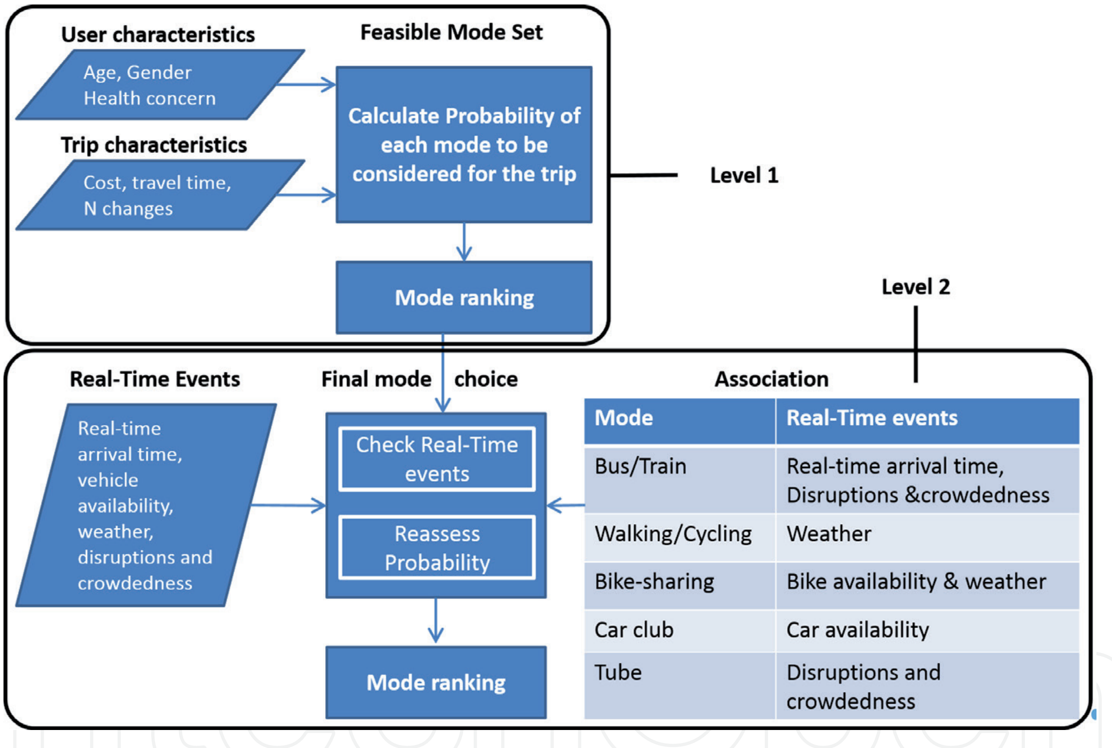

Figure 1.
Flow chart representation of the hypermode concept.

4. Real-world case study

The hypermode concept is illustrated here using a real-world example. The area of interest is part of South Kensington in London.

As shown in **Figure 2**, a traveller starts his trip in O (origin) and wishes to reach the destination D. Before leaving the origin, the user has a set of feasible modes he would consider, namely bus, tube, bike-sharing, and walking, which are all accessible in the vicinity of the origin. These feasible modes are ranked by the user according to his/her own preferences, which are static in nature. For example, the traveller may consider cycling as unsafe, thus bike-sharing may receive a low rank or even is excluded from the feasible set. Moreover, the traveller usually has a

DOI: http://dx.doi.org/10.5772/intechopen.98432

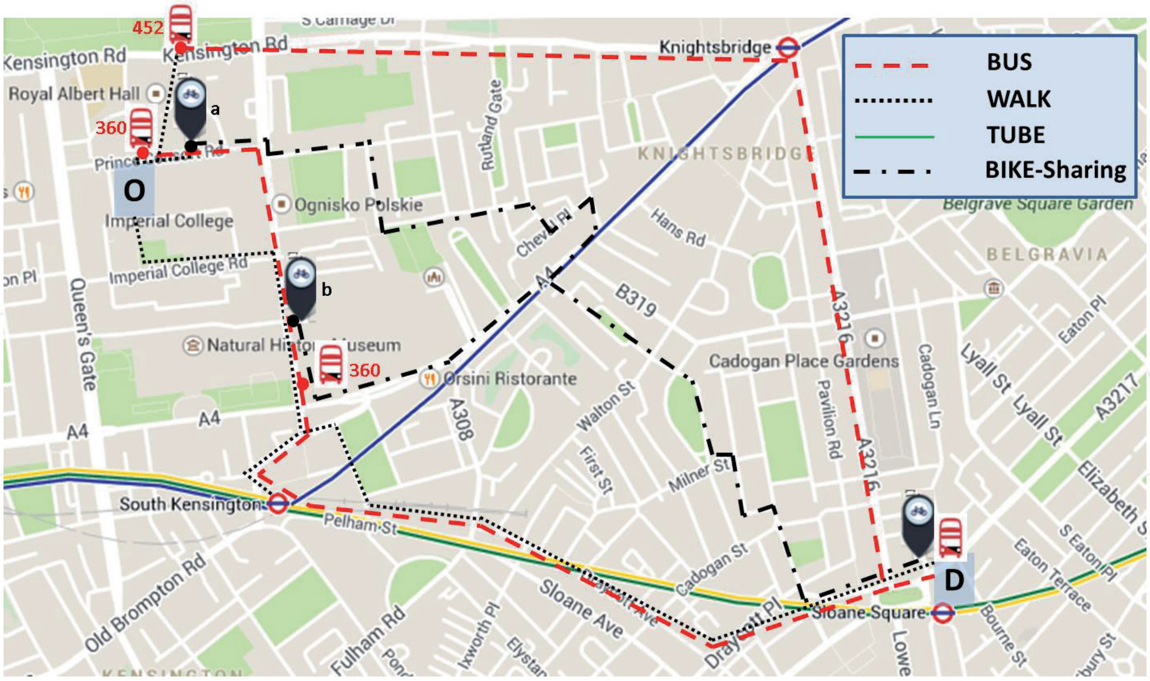

Figure 2.
The study area in South Kensington, with available modes and routes shown.

preferred mode within the feasible set, which is likely to be the one he/she pursues at the first attempt. If this preferred mode is not viable given real-time conditions (e.g. no shared bike is available, or the weather is unsuitable for walking), then the probability of selecting that mode decreases and the user will consider other modes in the feasible set.

Based on **Figure 2**, we describe the following specific scenarios, which are examples of potential adaptive behaviour.

- The user includes walking and bus in his feasible mode set. He prefers to take the no.360 bus at the closest bus stop towards the destination. When he reaches the bus stop, he sees on the digital display board that the next bus will arrive in 10 minutes. Rather than waiting at the bus stop, he switches to walking knowing that the total travel time would be similar (notice that the waking route in this case differs from the one shown in **Figure 2**).

- The user, who eliminates the possibility of walking due to physical conditions, may have bus and tube in his feasible set with bus being the preferred option. Before leaving the origin, he checks his cell phone and finds out the estimated waiting time for the bus is 10 minutes. He then prefers to take the tube at the South Kensington Station instead of waiting for the bus.

- The user has walking, tube and bike-sharing in his feasible set with cycling being the preferred option. He approaches the nearest docking station and cannot find any available bike. In this case he decides to walk or take the tube, depending on which one ranks higher, instead of looking for other docking stations nearby.

- The user has walking and bus in his feasible set, with walking being his preferred option. He is about to leave the origin when it starts raining. He then chooses to take a bus instead.

All of these illustrative examples have one thing in common: The pre-defined feasible modes are re-interpreted and re-ranked with the influence of real-time information, which is dynamic and stochastic in nature. This highlights the key difference between the traditional mode choice model and the adaptive behaviour that we try to demonstrate.

Note that it is possible that the repetitive occurring of a negative real-time event on a day-to-day basis may lead to the exclusion of a mode from the feasible set. For example, if a user constantly finds the bike-sharing station empty, he/she may exclude bike-sharing as one of the feasible modes in his/her planned behaviour. This, however, does not contradict the mode choice behaviour that we propose here. In fact, it still falls within the scope of the proposed two-stage decision-making process, i.e. in the forming of feasible mode choice set (see Level 1 of **Figure 1**). In most cases, the feasible mode set contains more than one element, and the realization of a particular mode choice (or sequence of mode choices) must thus rely on real-time events.

To further support the relevance and likelihood of such adaptive behaviours, we conduct a qualitative survey to validate the behavioural soundness of this subject, as described in Section 4.1.

4.1 Survey study

A pilot survey has been undertaken to explore the validity of the underpinning idea of the proposed hypermode concept. 50 respondents have been interviewed at Imperial College London. The sample includes academic, technicians and administrative staff as well as students, to ensure that behaviour in different user categories is captured. The respondents have been interviewed face-to-face to ensure an in-depth and comprehensive grasp of their decision-making processes.

4.2 Survey design

The respondents were presented with two different scenarios:

SCENARIO 1. The regular commuting trip home from the College at the end of the day, which is a Revealed Preference scenario. The origin is the same for all respondents but the destinations vary, with some at walking distance and others outside of London.

SCENARIO 2. A hypothetical trip from the College to Sloane Square (a shopping destination 2.1 km away from the origin) at the end of the working day. This is a Stated Preference scenario.

In the first scenario the respondent is asked what modes are available for his/her trip. An open question is then asked to describe the decision making process that shortlists the possible mode options or leads to a specific mode choice. Afterwards they are asked if any of the following real-time events may affect their final mode choice:

1. Real-time bus arrival time

2. Bike availability at docking stations for bike-sharing service

3. Disruptions on the tube

4. Weather

5. Other, specify.

If the respondent's explanation of the decision making process at the open question is in line with the adaptive behaviour, as confirmed by answering "yes" to any of the above real-time events (1 to 4), then this user behaviour is related to hypermode.

In the Stated Preference scenario (Scenario 2) the modes available to the user are the same as those shown in **Figure 2** (with possibly different routes and access points), and are associated with given average costs and travel times. The user is asked what would his preferred mode option be in the described scenario. Depending on the preferred mode, a range of real-time events are presented to the respondent, which may lead him/her to reassess the original choice. For example, **Table 2** shows the situation presented to the respondent who selects bus as the preferred mode.

Two different types of trips are considered:

- Leisure (e.g. shopping, visiting friends)
- Important appointment, (on-time arrival is needed)

Since trip purpose is likely to be an influencing factor of mode choice.

Real-time events relevant to other preferred modes are also included in the survey; a few examples are provided below.

- Availability of bike at the docking station if the user chooses bike sharing;
- Wet weather if the user chooses walking;
- Disruptions on the tube once the user reaches the tube station.

The key point for Scenario 2 is to understand if the user would either consider alternative transport modes in a specific situation or stick to the initial mode preference regardless of any real-time events. In the first case the user is associated with the hypermode behaviour. In Scenario 2 both the origin and destination are located in central London, which is not necessary true in Scenario 1. This could have

Preferred mode		**Bus**
Real-time event	You arrive at the bus stop and the information system says that your bus will arrive in 12 minutes.	
Purpose of trip	Leisure (e.g. shopping)	Appointment (on-time arrival is crucial)
What do you do?		
Wait for the bus even if you may arrive later than expected		
Use the 12 minutes for other errands and then go back to the bus stop		
Consider alternative buses		
Consider alternative modes		

Table 2.
Survey scenarios for the bus.

potentially influenced the results as more mode options are available to reach the destinations in Scenario 2, while in the first scenario the users with destination far away may have quite limited mode choices. To avoid potential bias, in Scenario 1 the respondents with destination outside of London are asked to consider the trip from the College to the station in central London from which they take a train; this allows plenty of mode options to be available to all users.

4.3 Survey results

Some characteristics of the sample respondents are reported in **Table 3**.

Table 4 shows the percentages of respondents associated with the hypermode behaviour. We also use the sample size (50) to calculate the 95% binomial proportion confidence interval. Here, the category "Either scenario" accounts for those who show the hypermode behaviour in either Scenarios 1 or 2.

The results of this exploratory survey show that the vast majority of the respondents follow an adaptive behaviour, which is in line with the hypermode concept. In the first scenario, 34% of the respondents consider initially a set of feasible modes for their trips, and their final mode choices are determined/affected by real-time events.

In the second scenario, 86% of the respondents indicate that they would consider alternative modes once adverse real-time events occur. This result refers to the overall responses for the two travel purposes (leisure/appointment) (i.e. respondents who consider alternative modes for at least one of the two travel purposes are associated with hypermode). The analysis of the responses for each travel purpose indicates that:

- [Leisure] 60% of the respondents re-assess the available modes in the presence of adverse real-time events.

- [Appointment] 82% of the respondents re-assess the available modes in the presence of adverse real-time events.

This difference is easily understandable as the urge to reach the destination on time offers another motivation to reconsider other modes and justifies the associated effort.

A more detailed analysis of Scenario 2 identifies the pattern of mode switches under the two different trip purposes. The results are reported in **Table 5**.

Age of respondents		Gender of respondents	
N respondent 18–25	24%	N female respondent	38%
N respondent 26–44	48%	N male respondent	62%
N respondent 45–64	28%		

Table 3.
Age and gender of respondents.

	Scenario 1	Scenario 2	Either scenario
Average percentage	34%	86%	92%
Confidence interval	**[21%, 49%]**	**[73%, 94%]**	**[81%, 98%]**

Table 4.
Survey results with 95% confidence levels for the hypermode behaviour. Sample size: 50.

Mode initially considered	% of switches (Leisure)	% of switches (Appointment)
Walking	50%	41%
Tube	37%	39%
Bus	13%	17%
Bike-sharing	0%	2%
Cycling	0%	0
Taxi	0%	0

Table 5.
Mode switches in Scenario 2.

The adaptive behaviour is more evident in Scenario 2. This may be explained by the fact that the respondents were referring to their regular commuting trip in the first scenario, and were less likely to abandon their preferred mode due to extensive learning of the preferred and alternative modes based on past experience. On the other hand, in the more hypothetical scenario (Scenario 2), the travel environment is new to the commuters, who might be more inclined to consider different modes due to the lack of experience.

The inertia in decision-making may also play a role in the sense that users may be inclined to stick to one specific mode of transport even though it may not appear to be the most rational choice at the moment. This choice behaviour is known as bounded rationality. In the second scenario, despite their familiarity with the area, the users were more prone to consider different modes, as their experience on specific trips is relatively limited. The adaptive behaviour is more evident when on-time arrival at the destination is important.

Table 5 partially illustrates the relevance of users' adaptive behaviour to planning. In particular, it shows the percentage of travellers who abandon their initial (static) mode choice in reaction to real-time events. For example, when there is a interruption/delay of tube service, 39% of travellers will switch to other modes, possibly at nearby access points. Such information is crucial for planning service interruption at tube stations (such as scheduled maintenance or train operation): the planner need to take into account the increase in demand for other modes in the vicinity of the tube station to avoid heavy congestion and/or shortage of supplies.

5. Conclusions

5.1 Remarks on MaaS

Many researchers and stakeholders of the transport sector see Mobility as a Service (MaaS) as the mobility of the future. However, a lot of uncertainty lye under this travel solution. The same first statement is actually uncertain, considering that it depends on MaaS diffusion, which in turn depends on the adopted business model, on its financial convenience and on the membership rate, which in turn depend on what kind of services are offered, their level of service and their price. On the other hand, first MaaS applications have not helped to clarify the financial convenience of a MaaS.

Furthermore, MaaS is also generally associated with many virtuos impacts which can be sinthesized by saying that it goes in the direction of a sustainable mobility, by aiding and supporting intermodality. However, also this statement is not clearly confirmed by the literature. In fact, put different services in the same market place does not suffice to guarantee intermodality: who chooses the service/services to offer to the users? Instead, the literature agrees that if MaaS is developed according to a purely commercial approach, there is a serious risk to dis-incentivize sustainable trips, encouraging instead a shift towards car use. Hence, the literature also agrees on the need of regional authorities to lead MaaS development through new models of governance. However, the way this result can be achieved is not clear.

Consistently with these premises, one of the main necessary research perspective is to investigate and identify possible regulatory frameworks, MaaS schemes and approaches for bidding/tendering the services enabling the public entity to rule the MaaS.

In addition, the way MaaS should work is clear in the literature, but models and methodologies enabling such working are very complex and largely new with respect to the approaches currently used in transportation system modelling.

From the demand side, new approaches are needed to profile users coupling with MaaS requirements and involving also psychological and social science. Moreover, new approaches are needed for the modelling of individual choices, considering the intrinsic dynamicity of the MaaS system and including the effect of service reliability and of the provided information.

From the supply side, new modelling framework are needed to integrate continuous and discontinuous services, to deal with diffused/distributed inter-modality and with dynamically changing conditions and unpredicted temporary disruptions of the service.

5.2 Remarks on the Hypermode paradigm

The widespread of real-time travel information combined with the presence of a variety of travel modes available in dense urban areas could lead travellers to reconsider their planned mode choices based on real-time events, such as real-time passenger information, transport disruptions, overcrowdings, and weather. However, most existing mode choice studies analyse the decision process as planned behaviour, and hence do not capture the influence of these real-time events on mode choices.

This paper aims to address this limitation by presenting an innovative approach to interpret mode choice, which captures an adaptive behaviour of travellers. The underpinning assumption is that the traveller first identifies a set of feasible modes that connect his/her origin to the destination; then he/she evaluates the real-time situation in order to select a specific mode of transport from the feasible set. This novel behaviour paradigm is referred to as hypermode in this paper, in analogous to the hyperpath concept used extensively in transit assignment. A two-level decision-making process is illustrated, which rests on planned and adaptive model choice behaviour, respectively.

A survey has been undertaken to test the proposed approach; it demonstrates the validity of the underlying assumption of hypermode, and serves as a proof of concept. As the next step of this research, we will explore different modelling approaches (e.g. Nested/Mixed Logit and discrete choice model with endogenous attribute threshold/cut-off) along with calibration and validation methods based on a wide variety of data.

For future research, the hypermode concept could be explored alongside dynamic assignment of the multimodal network, which provides feedback to mode choice models in the form of real-time events. For example, the dynamic re-distribution of shared bikes, as a result of multimodal traffic assignment, could affect the availability of bikes at docking stations and hence travellers' mode choices.

Such a feedback mechanism between traffic assignment and model choice presents a research direction not previously investigated, and calls for a more integrated modelling approach driven by the presence of real-time travel information.

IntechOpen

Author details

Stefano de Luca[1*] and Margherita Mascia[2]

1 Department of Civil Engineering, University of Salerno, Salerno, Italy

2 ITS Counsult, Bari, Italy

*Address all correspondence to: sdeluca@unisa.it

References

[1] Kamargianni, M., & Matyas, M. (2017). The business ecosystem of Mobility as a Service. Paper presented at the 96th Transportation Research Board Annual Meeting, Washington DC, USA.

[2] Goodall et al., (2017). The rise of Mobility as a Service: Reshaping how urbanites get around Deloitte University Press (2017)

[3] D.A. Hensher, C. Ho, C. Mulley, J. Nelson, G. Smith, Y. Wong, (2020). Understanding Mobility as a Service (MaaS) - Past, Present and Future, Elsevier Science, UK.

[4] M. Kamargianni, M. Matyas, W. Li, J. Muscat, L. Yfantis, (2018). The MaaS dictionary, Retrieved from University College London's website

[5] MaaS Alliance (2017). White Paper: Guidelines & Recommendations to create the foundations for a thriving MaaS Ecosystem, MaaS Alliance, Brussels (2017)

[6] Kamargianni, M., Li, W., Matyas, M., Schäfer, A., 2016. A Critical Review of New Mobility Services for Urban Transport. Transp. Res. Procedia 14, 3294-3303.

[7] Hoadley (2017). Mobility as a Service: Implications for urban and regional transport, S. Hoadley (Ed.), Discussion paper, POLIS, Brussels, Belgium (2017)

[8] L. Nykänen, J. Eckhardt, A. Aapaoja, J. Sochor, and M. Karlsson. "The European Roadmap 2025 for MaaS". In ICoMaaS 2017 Proceedings, pages 266-279. Tampere University of Technology, Transport Research Center Verne, Finland, 2017

[9] I.C.M. Karlsson, D. Mukhtar, Landgren, G. Smith, T. Koglin, A. Kronsell, E. Lund, *et al. (2020),* Development and implementation of Mobility-as-a-Service – A qualitative study of barriers and enabling factors, Transport. Res. Part A. Pol. Pract., 131 (2020), pp. 283-295.

[10] G. Lyons, P. Hammond, K. Mackay, (2020), The importance of user perspective in the evolution of MaaS Trans. Res. Part A Policy Pract., 131 pp. 20-34

[11] Zhang, M. 2005. "Exploring the relationship between urban form and nonwork travel through time use analysis." Landscape and Urban Planning 73 (1):244-61.

[12] Saneinejad, Sheyda, Matthew J. Roorda, and Christopher Kennedy. 2012. "Modelling the impact of weather conditions on active transportation travel behaviour." Transportation Research Part D: Transport and Environment 17 (2):129-37. doi: http://dx.doi.org/10.1016/j.trd.2011.09.005.

[13] Klöckner, Christian A., and Thomas Friedrichsmeier. 2011. "A multi-level approach to travel mode choice – How person characteristics and situation specific aspects determine car use in a student sample." Transportation Research Part F: Traffic Psychology and Behaviour 14 (4):261-77. Doi: http://dx.doi.org/10.1016/j.trf.2011.01.006.

[14] Pendyala, R., A., Parashar, and G., Muthyalagari. 2000. "Measuring day-to day variability in travel characteristics using GPS data". In: Paper presented at the 79th Annual Meeting of the Transportation Research Board, Washington.

[15] Gärling, T., and K. Axhausen. 2003. "Introduction: habitual travel choice". Transportation 30:1-11

[16] Gärling, T., and J., Rise. 2002. "Understanding attitude, intention, and

behavior: a common interest to economics and psychology". C.L. Spash, Anders Biel (Eds.), Social Psychology and Economics in Environmental Research, Cambridge University Press.

[17] Cascetta, E. 2009. "Transportation Systems Analysis: Models and Applications". Springer Verlag.

[18] Koppelman, F.S. 1983. "Predicting transit ridership in response to transit service changes". Journal of Transportation Engineering 109(4):548-564.

[19] Bhat, C.R. 1995. "A Heteroscedastic Extreme Value Model of Intercity Mode Choice". Transportation Research Part B 29(6): 471- 483

[20] Bhat, C.R. 2000. "Incorporating Observed and Unobserved Heterogeneity in Urban Work Mode Choice Modeling". Transportation Science 34(2): 228-238

[21] Bhat, C.R, and R., Sardesai. 2006. "The Impact of Stop-Making and Travel Time Reliability on Commute Mode Choice" Transportation Research Part B 40 (9): 709 -730.

[22] Wardman, Mark. 2001. "A review of British evidence on time and service quality valuations". Transportation Research Part E 37:07-128

[23] Cantarella, Giulio Erberto, and S. de Luca. 2005. "Multilayer feedforward networks for transportation mode choice analysis: An analysis and a comparison with random utility models." Transportation Research Part C 13 (2):121-55. Doi: http://dx.doi.org/10.1016/j.trc.2005.04.002.

[24] Hensher, David A., and John M. Rose. 2007. "Development of commuter and non-commuter mode choice models for the assessment of new public transport infrastructure projects: A case study." Transportation Research Part A: Policy and Practice 41 (5):428-43. Doi: http://dx.doi.org/10.1016/j.tra.2006.09.006.

[25] Lo, Hong K., and William H.K. Lam. 2008. "Recent advances in travel choice behavior modeling". Transportmetrica 4(2): 79-81.

[26] Greene, W.H., D.A., Hensher, and J.M., Rose. 2006. "Accounting for heterogeneity in the variance of unobserved effects in mixed logit models". Transportation Research Part B, 40:75-92

[27] Hoogendoorn-Lanser, S., R. Van Nes, S.P. Hoogendoorn, and P. Bovy. 2006. "Home-activity approach to multimodal travel choice modeling". Transportation Research Record 1985: 180-187.

[28] Horeni, O., T.A., Arentze, B., Dellaert, H.J.P., Timmermans. 2008. "Design of a computer-assisted instrument for measuring mental representations underlying joint activity-travel choices". In: Proceedings ISCTSC Conference, Annecy, France.

[29] Walker, J.L. 2011. "Beyond Rationality in Travel Demand Models". ACCESS: the Magazine of UCTC 39: 8-15.

[30] Zhou, Jiangping. 2012. "Sustainable commute in a car-dominant city: Factors affecting alternative mode choices among university students." Transportation Research Part A: Policy and Practice 46 (7):1013-29. doi: http://dx.doi.org/10.1016/j.tra.2012.04.001.

[31] Mercado, Ruben G., A. Paez, S. Farber, M.J. Roorda, and C. Morency. 2012. "Explaining transport mode use of low-income persons for journey to work in urban areas: a case study of Ontario and Quebec". Transportmetrica 8(3): 157-179

[32] Akshay, Vij, A. Carrel, and J. L. Walker. 2013. "Incorporating the influence

of latent modal preferences on travel mode choice behavior". Transportation Research Part A 54: 164-178,

[33] Ermagun, A., R., Taha Hossein Rashidi, and A. Samimi. 2015. "A joint model for mode choice and escort decisions of school trips". Transportmetrica A: Transport Science 11(3).

[34] Cartenì, A., E. Cascetta, S., de Luca. 2015. "A random utility demand model for car park&share services and the pure preference for electric vehicles", Transport Policy, 48(C), pages 49-59

[35] Hensher, Davis. A., and J., King. 2001. "Parking demand and responsiveness to supply, pricing and location in the Sydney central business district". Transportation Research Part A, 35: 177-196.

[36] Cherchi, E., and J. De Dios Ortuzar. 2002. "Mixed RP/SP models incorporating interaction effects: modelling new suburban train services in Cagliari". Transportation 29: 371-395

[37] Espino, R., J. De Dios Ortuzar, and C. Roman. 2007. "Understanding suburban travel demand: flexible modelling with revealed and stated choice data". Transportation Research Part A 41: 899-912

[38] Bos, I.D.M., E., Molin, R.E., van der Heijden, H.J.P., Timmermans. 2007. "Cognition and Relative Importance Underlying Consumer Valuation of Park-and-Ride Facilities". Transportation Research Record, 1835:121-127.

[39] Dell' Olio, L., A., Ibeas, P., Cecín, and F. Dell' Olio. 2011. "Willingness to pay for improving service quality in a multimodal area". Transportation Research Part C 19:060-1070

[40] Abrantes, P., and M. Wardman. 2011. "Meta-analysis of UK values of travel time: an update". Transportation Research Part A 45: 1-17

[41] Arentze, Theo A., and Eric J.E., Molin. 2014. "Travelers' preferences in multimodal networks: Design and results of a comprehensive series of choice experiments". Transportation Research Part A 58:15-28.

[42] Bajwa, Shamas, S., Bekhor, M. Kuwahara, E., Chung. 2008. "Discrete choice modeling of combined mode and departure time". Transportmetrica 4(2).

[43] Bhat, C.R., R., Misra. 2001. "Comprehensive activity travel pattern modeling system for nonworkers with empirical focus on organization of activity episodes". Transportation Research Record 1777:16-24

[44] Wen, C.H., and F.S. Koppelman. 2000. A conceptual and methodological framework for the generation of activity-travel patterns. Transportation 27: 5-23.

[45] Susilo, Yusak O., and R., Kitamura. 2008. "Structural changes in commuters' daily travel: The case of auto and transit commuters in the Osaka metropolitan area of Japan, 1980-2000". Transportation Research Part A 42: 95-115.

[46] Sakano, Ryoichi, and J. Benjamin. 2011. "A structural model of mode-activity choice: The case of commuter rail in a medium-size metropolitan area". Transport Policy 18(2): 434-445,

[47] Ho, Chinh Q., and C. Mulley. 2013. "Multiple purposes at single destination: A key to a better understanding of the relationship between tour complexity and mode choice". Transportation Research Part A 49: 206-219.

[48] Habib, Khandker M. Nurul, and Eric J. Miller. 2009. "Modelling activity generation: a utility-based model for

activity-agenda formation". Transportmetrica 5(1): 3-23.

[49] Zhang, Junyi, and H. Timmermans. 2012. "Activity-travel behaviour analysis for universal mobility design". Transportmetrica 8(3).

[50] Bifulco, G.N., A., Cartenì, A., and A. Papola. 2010. "An activity-based approach for complex travel behaviour modelling" European Transport Research Review 2 (4): 209-221.

[51] Ben-Akiva, Moshe, and T. Morikawa. 1990. Estimation of switching models from revealed preferences and stated intentions, Transportation Research Part A: General, 24(6): 485-495.

[52] Diana, M. 2010. "From mode choice to modal diversion: A new behavioural paradigm and an application to the study of the demand for innovative transport services". Technological Forecasting and Social Change 77(3): 429-441.

[53] Chen,C.F., and Wei-Hsiang Chao. 2011. "Habitual or reasoned? Using the theory of planned behavior, technology acceptance model, and habit to examine switching intentions toward public transit". Transportation Research Part F 14(2): 128-137,

[54] Idris, Ahmed Osman, K. M. N. Habib, and A. Shalaby. 2015. "An investigation on the performances of mode shift models in transit ridership forecasting" Transportation Research Part A 78: 551-565,

[55] de Luca, S., and R. Di Pace. 2015. "Modelling users' behaviour in inter-urban carsharing program: A stated preference approach". Transportation Research Part A 71:59-76

[56] Li, Yeun-Touh, Jan-Dirk, Schmöcker, and S.Fujii. 2015. "Demand adaptation towards new transport modes: the case of high-speed rail in Taiwan". Transportmetrica B: Transport Dynamics 3(1): 27-43

[57] Hess, S., K.E., and Train, K.E. 2011. Recovery of inter-and intra-personal heterogeneity using mixed logit models. Transportation Research Part B 45(7): 973-990.

[58] Cherchi, E., and C.A., Guevara. 2012. "A monte carlo experiment to analyze the curse of dimensionality in estimating random coefficients models with a full variance-covariance matrix". Transportation Research Part B 46(2): 321-332.

[59] Kitamura, R. 1990. "Panel analysis in transportation planning: an overview" Transportation Research Part A 24(6): 401-415.

[60] Pas, E.I., F.S., Koppelman. 1987. "An examination of the determinants of day-to-day variability in individuals' urban travel behavior", Transportation 14(1): 3-20.

[61] Cirillo, C., and K.W., Axhausen. 2002. "Mode Choice of Complex Tours: A Panel Analysis". ETH, Eidgenössische Technische Hochschule Zürich, Institut für Verkehrsplanung, Transporttechnik, Strassen-und Eisenbahnbau IVT.

[62] Ramadurai, G., and K.K, Srinivasan. 2006. "Dynamics and variability in within-day mode choice decisions: role of state dependence, habit persistence, and unobserved heterogeneity". Transportation Research Records 1977(1): 43-52

[63] Cirillo, C., and K.W., Axhausen. 2010. "Dynamic model of activity-type choice and scheduling". Transportation 37(1): 15-38.

[64] Srinivasan, K.K., and P., Bhargavi. 2007. "Longer-term changes in mode choice decisions in Chennai: a comparison between cross-sectional

and dynamic models". Transportation 34(3): 55-374.

[65] Pendyala, R., R. Kitamura, and D., Prasuna Reddy. 1998. "Application of an activity-based travel-demand model incorporating a rule-based algorithm". Environmental Planning B 25: 753-772.

[66] Arentze, Theo A., H.J., Timmermans. 2004. "A learning-based transportation oriented simulation system". Transportation Research Part B 38 (7): 613-633.

[67] Xiong, C., and L., Zhang. 2013. "Positive model of departure time choice under road pricing and uncertainty". Transportation Research Records 2345(1): 117-125.

[68] Goulias, K.G. 1999. "Longitudinal analysis of activity and travel pattern dynamics using generalized mixed markov latent class models". Transportation Research Part B 33(8): 535-558.

[69] Ben-Akiva, Moshe. 2010. Planning and Action in a Model of Choice. Choice Modelling: The State-of-the-Art and the State-of-Practice. Emerald, Bingley.

[70] Choudhury, C.F., M. Ben-Akiva, and M., Abou-Zeid. 2010. "Dynamic latent plan models". Journal of Choice Modelling 3(2):50-70.

[71] Xiao, Fu, W.H.K. Lam, and Q. Meng. 2014. "Modelling impacts of adverse weather conditions on activity–travel pattern scheduling in multi-modal transit networks". Transportmetrica B: Transport Dynamics, 2(2):151-167

[72] Xiong, C., and L. Zhang. 2015. "Dynamic travel mode searching and switching analysis considering hidden modal preference and behavioral decision processes". Transportation, 42(6): 985-1002

[73] Zhang, Junyi, T. Arentze, and H., Timmermans. 2012. "A Multimodal transport network model for advanced traveler information system". Journal of Ubiquitous Systems & Pervasive Networks, 4 (1): 21-27.

[74] Klöckner, C.A., Friedrichsmeier, T. (2011). A multilevel approach to travel mode choice—how person characteristics and situation specific aspects determine car use in a student sample, Transportation Research Part F: Traffic Psychology and Behaviour, 14 (2011), pp. 261-277

[75] Rehrl, K., S. Bruntsch, and H. J. Mentz. 2007. "Assisting multimodal travelers: design and prototypical implementation of a personal travel companion". IEEE Transactions on Intelligent Transport Systems 8 (1): 31-4

[76] Zografos, K.G., and K.N., Androutsopoulus. 2009. "Algorithms for Itinerary Planning in Multimodal Transportation Networks". IEEE Transactions on Intelligent Transport Systems, 9(1):75-184

[77] Yin, M., and M. Griss. 2005. "SCATEAgent: context-aware software agents for multi-modal travel". Applications of agent technology in traffic and transportation. Whitestein Series in Software Agent Technologies and Autonomic, Computing: 69-84.

[78] Sheffi, Yosef. 1985. "Urban Transportation Networks: Equilibrium Analysis with Mathematical Programming Methods". Prentice Hall.

[79] Liao, F., T.A. Arentze, and H.J.P. Timmermans. 2011. "Application of supernetworks in modeling activity-travel behaviour". Science and Technology 33:279-286

[80] Opasanon, Sathaporn, and Elise Miller-Hooks. 2001. "LEAST EXPECTED TIME HYPERPATHS IN STOCHASTIC, TIME-VARYING MULTIMODAL NETWORKS." Transportation Research Record 1771 (1):89-96. doi: 10.3141/1771-12.

[81] Leurent, Fabien. 2013. “On modal availability, travel strategies and traffic equilibrium on a multimodal network.” In hal.archives-ouvertes.fr

[82] Sabir M., Koetse M. J., and P. Rietveld. 2009. “The Impact of Weather Conditions on Mode Choice: Empirical Evidence for the Netherlands.” In Proceedings of the 17th Annual conference EAERE, June 2009, Amsterdam.

[83] Cantarella, G.E., A., Cartenì; and S., de Luca. 2015. “Stochastic equilibrium assignment with variable demand: theoretical and implementation issues” EUROPEAN JOURNAL OF OPERATIONAL RESEARCH 241(2): 330-347

[84] Nguyen, S., and S. Pallottino. 1988. “Equilibrium traffic assignment for large scale transit networks.” European Journal of Operational Research 37 (2):176-86. doi: http://dx.doi.org/10.1016/0377-2217(88)90327-X.

[85] Cats, O., H.N., Koutsopoulos, W., Burghout, and T. Toledo. 2012. “Effect of Real-Time Transit Information on Dynamic Path Choice of Passengers”.

[86] Trozzi, Valentina, Guido Gentile, Michael Bell, and Ioannis Kaparias. 2013. “Dynamic User Equilibrium in Public Transport Networks with Passenger Congestion and Hyperpaths.” Procedia - Social and Behavioral Sciences 80 (0):427-54. doi:http://dx.doi.org/10.1016/j.sbspro.2013.05.024.

[87] The European Commission, DG XI — Environment. 1999. “Cycling: the way ahead for towns and cities.”

[88] Mascia, M., Han, K. (2015). “The Hypermode concept”, Internal report, Imperial College London.