Hindawi
Journal of Advanced Transportation
Volume 2022, Article ID 7293909, 24 pages
https://doi.org/10.1155/2022/7293909

WILEY | Hindawi

Review Article

Impact of New Mobility Solutions on Travel Behaviour and Its Incorporation into Travel Demand Models

Ada Garus[1,2] **Borja Alonso**[1] **Maria Alonso Raposo**[2] **Biagio Ciuffo**[2] **and Luigi dell'Olio**[1]

[1]*Department of Transportation and Projects and Processes Technology, University of Cantabria, Av. de Los Castros s/n, Cantabria, Santander 39005, Spain*
[2]*European Commission, Joint Research Centre, Via E. Fermi, Ispra 2749–21027, VA, Italy*

Correspondence should be addressed to Ada Garus; ada.garus@ec.europa.eu

Received 8 February 2022; Accepted 22 June 2022; Published 18 July 2022

Academic Editor: Eleonora Papadimitriou

Advancement in the fields of electrification, automation, and digitalisation and emerging social trends are fuelling the transformation of road transport resulting in the introduction of various innovative mobility solutions. Yet the reaction of people to many of the new solutions is still vastly unknown. This creates an unprecedented quandary for transport planners who are requested to design future transport systems and create the related investment plans without fully validated models to base the assessment upon. As some evidence on citizens' behaviour concerning new mobility solutions starts to be progressively made available, first attempts to update the existing models begin to emerge. Nevertheless, a lot more is needed as some of the transpiring mobility solutions have not yet reached the market, making the corresponding behaviour changes imponderable. In this context, the main purpose of this paper is to provide a review on how travel behaviour changes linked to the deployment of new mobility solutions have been considered in travel demand models. The new mobility solutions studied include carsharing, dynamic ridesharing, micromobility sharing services, and personal and shared autonomous vehicles. An overview and comparison of relevant studies implementing activity or trip-based demand models and other methodologies are presented. The analysis shows that the results of the different studies heavily depend on the extent to which behavioural changes are considered. The results of the review thus point to the need for holistic demand models that carefully mimic the urban reality with everything it has to offer and account for the importance of individual traits in the decision-making processes. Such models need an in-depth understanding of the microscopic mechanisms leading to the travel behaviour shifts linked to the most innovative mobility solutions. To achieve this level of detail, mobility living labs and their real-life experiments and experience with citizens, which are flourishing in Europe, are suggested to play a crucial role in the years to come.

1. Introduction

To say that the world has always been evolving is a banality; however, the changes have never been more rapid than nowadays. Globalisation and colossal technological advancements in a plethora of fields have driven us away from the countryside towards densely urban populated areas [1]. Nevertheless, the current rate of urbanization leads to numerous issues in spreading metropolis, such as congestion, air pollution, or an urban sprawl. Given that up to 2050, 68% of global population is said to live in cities [2], we must quickly learn how to tackle and prevent urban problems, which we often do through better city planning and innovation. Regarding innovation, current advancement in the fields of electrification, automation, and digitalisation has allowed for the development of new mobility solutions (NMSs) in the form of public or private transport. As for successful city planning, applied transport modelling has proven to be a suitable instrument supporting planners in their decision-making processes.

Nonetheless, the existing modelling methods are often not agile enough to respond to a quickly updated offer of NMS [3]. Moreover, our mobility preferences and behaviour change once new transport options become available. For instance, Uber, a ride-hailing application that was nonexistent 15 years ago, is claiming to operate 14 million trips each day in more than 700 cities worldwide [4]. Sharing economy solutions bridges the gap between using and owning a vehicle. Electric scooter sharing, a service first introduced in 2017, has a market size estimated at $18.6 billion [5]. Carsharing users are discouraged from buying an additional vehicle [6], whereas bike-sharing market could grow as much as 30% annually in the coming years [7]. Each of the NMS introduced could trigger additional behavioural changes, by extending the offer available to the end user and presenting new usage opportunities.

Nevertheless, transport innovation is not necessarily linked to lowering of negative externalities, either environmental or societal. For instance, dynamic ridesharing or carsharing services could discourage users from frequenting the more sustainable public transport or micromobility resulting in more congestion and higher CO2 emissions. Moreover, NMS such as electric scooter sharing if not managed and used properly could become dangerous not only to its users but also to other vulnerable social groups [8]. European associations that help visually impaired have already started campaigns raising awareness about potential hazards of riding those scooters on pavements and abandoning them blocking tactical paths leading the visually impaired [9–11].

Profitability of those new business models and added technological advancement will result in further update of transport services [3]. It is a major challenge for transport planners who must learn how to respond quicker and more effectively with the aim to lowering the negative externalities caused by the introduction of NMS. Therefore, to ensure that transport models remain useful, not only the supply side of the models needs to be updated. We need to also project the imponderable behaviour changes triggered by the deployment of NMS and represent them in the demand side of the models, to better understand the consequences of innovation deployment.

The well-known transport demand model is often based on a sequential decision-making process of individuals: whether to make a journey, what the destination of the journey should be, the mode of transport to be used, and lastly the route to follow. The sequence is known as a trip-based model (TBM), with steps being trip generation, spatial (or zonal) distribution, modal choice and route choice, or assignment. Over the years, complementary modelling steps have been added to the model (such as time departure model) and a plethora of new techniques for existing modelling steps were developed to improve the overall quality of the methodology. There are numerous methods used to model each step; however, all of TBM results are obtained in aggregated form, often with omission of the personal characteristics that could influence individual's decision-making processes [12].

In response to the limits of an aggregated approach and to denote travel demand more realistically, novel agent-based models and especially activity-based models (ABMs) were developed. ABMs are based on a theory that travel demand derives from people's needs or desires to participate in variety of activities. Some of those could occur at homes, but in many cases, these activities are located outside their homes, resulting in the need to travel [13]. ABMs try to mimic how an analysed population plans and schedules their daily travels. Therefore, those models are based on behavioural theories concerning decision processes about whether to participate in an activity, where to participate in those activities, when to participate in activities, and how to get to these activities. The forecasting of rational decision-making processes incorporated into ABM models is generally done using discrete choice models. These statistical methods are used to recognize factors influencing the decision and assess their impact on the decision-making process [14].

The main purpose of this paper is to comprehensively explore and efficiently present the research field of incorporating travel behaviour changes linked to the deployment of NMS into demand models. Those behavioural changes could be numerous and significantly impact the transportation system as a whole. Nevertheless, they are often omitted by modellers who focus on updating the supply side of models. This overview aims to be useful for the scientific community and urban planners in the development of more accurate demand estimations. The summary of all behavioural changes linked to the NMS that causes them, and a following methodologies for their implementation in demand modelling frameworks is the main contribution of this article in hope of easing the task of representing behavioural shifts more accurately.

The NMS concerned in the paper includes carsharing, dynamic ridesharing, micromobility sharing, and personal and shared autonomous vehicles (all definitions of NMS services are provided in Section 3.2). The authors have decided to consider those NMSs and omit others (such as the hyperloops, urban air mobility, or cable cars), as they are the first modelling results already available for the chosen NMS. Furthermore, only studies that concerned autonomous vehicles (AVs) of level 4 and level 5 of automation according to the SAE were included in the review [15]. The reason is that self-driving cars (either in slightly limited or full capacity) would have the highest influence on travel behaviour changes, freeing the driver from cautiously steering the wheel.

The paper is structured in the following manner. The next section presents the methodology used in the study. Furthermore, third section exemplifies NMS and their impact on travel behaviour in Sections 3.1 and 3.2, overview of applied modelling practices is given in Section 3.3, and a comparison of results is given in Section 3.4. Finally, conclusions and plausible further research steps are described in the fourth section.

2. Methodology

The methodology was set to best fit the research aim. A comparison and analysis of studied papers are presented in the hope of adding value beyond a review. The authors have focused on finding relevant studies with database searches (Scopus and Google Scholar) and so-called backward snowballing, in which references and citations of previously found studies are used to identify additional relevant research. The database queries comprised of combinations of keywords describing the analysed new mobility services and the demand estimation methods or a concrete behaviour change.

Keywords that concerned the NMS were the following: "autonomous vehicles," "automated vehicles," "bike sharing," "carsharing," "dynamic ridesharing," "micromobility sharing," "new mobility services," "ridesharing," and "shared autonomous vehicles." Keywords that concerned the demand estimation methods or the qualitative estimation of implications of travel behaviour changes were the following: "activity-based model," "agent-based model," "car ownership," "demand estimation," "demand modelling," "four step model," "induced demand," "mobility impaired," "parking behaviour," "travel behaviour," and "trip-based model." The keywords were either used standalone or in combination to make sure that found results matched the aim of the search.

The search resulted in plethora of studies; however, only those subject to certain criteria were reviewed for the purpose of this analysis. Following criteria were used while selecting the studies appropriate for the review:

(i) C1: consideration of one or more of the following NMS: AVs of minimum level 4 automation, either private or shared, dynamic ridesharing, carsharing, and micromobility sharing.

(ii) C2: demand estimation based on TBM or ABM or other partial methodology that allows to qualitatively estimate the demand induction due to concrete behaviour change.

(iii) C3: incorporation of behaviour change (studies that assume a full or partial, randomly allocated, coverage of current demand and studies that do not incorporate any other behaviour change are not reviewed).

The relevance of the study was assessed upon examination of title, abstract, and key components and deepened during the full text assessment. The review only considered studies written in English and published in English language journals. The previously described methodology of search for relevant studies is presented in a visual manner in Figure 1.

34 studies were reviewed for the purpose of this analysis. A review study on impact of AVs on transport behaviour and land use has been conducted by Soteropoulos, et al. [16]. Nevertheless, the scope of the studies varies, as this review proposes a categorisation of the behaviour changes caused by NMS, adds on other widely adapted NMS, and reviews other results from the studies apart from behaviour changes, such as environmental or policy implications.

Moreover, it is worth mentioning that the authors decided to omit studies that focused on stated preference survey (SP) development, unless the results were used to estimate and quantify the impacts of behavioural changes for the wider population (to satisfy C2). Excellent reviews of conducted SP experiments concerning AVs and shared autonomous vehicles (SAVs) have already been made by Becker and Axhausen [17] as well as Gkartzonikas and Gkritza [18].

3. Impact of NMS on Travel Behaviour and Its Incorporation into Travel Demand Models

To best understand how NMSs are incorporated into travel demand models, it is worth to look at the key aspects of the studies: location, considered population, objective, and software and data used. The analysis shows that the deployment of NMS is global, and the behavioural changes caused by it in principle are universal, as the reviewed studies were done in Asia, Australia, Europe, and North America.

Moreover, it is worth to look at the population size for each study, to grasp the potential differences in results obtained from studies from variously populated areas. Majority of the studies focus on the current population of analysed areas, although notably some try to project the future population, to better represent the usage of NMSs that are not yet available such as AVs or SAVs. For that case, the studies assume year 2030 [19, 20], although the horizon of adoption and implementations of AVs and SAVs in cities is disputed in literature [21]. Moreover, majority of the studies analyse the entire population of metropolitan areas; however, several studies decided to simulate a fraction of the population for the purpose of lowering the computational costs of the analysis [22–24].

As for the objective of the study, two main goals are identified. Firstly, the study could assess the impact that NMS could have on traffic or other transport externalities, often analysing various policy or adoption scenarios. Secondly, the study could be an implementation framework either for the modelling methodology (TBM or ABM) or for an open-source platform.

The software programs most prominently used across the studies are the agent-based simulation platforms: MatSim, developed at ETH Zurich and TU Berlin, that supports ABM and SimMobility, an activity-based agent model developed at MIT.

As for the used datapoints, the researchers most often used rather traditional datasets and data collection tools for demand modelling (such as census data for the purpose of population synthesis in agent-based model and zonal allocation for TBM and household travel survey or trip diaries to generate the actual demand for trips). Nonetheless, a number of studies opted for a more innovative approach by using data sources that only recently became available such as GPS trace data, smart card data, or NMS statistics [20, 23, 25].

Table 1 provides characteristics of all studies that tried to methodologically estimate and represent the behaviour changes linked to deployment of NMS, sorted alphabetically according to the name of first author. For each study information on the location, population size, objective, software and used datapoints.

The remaining parts of this chapter lay out the key takeaways from the comparative review of studies on incorporation of travel behaviour changes linked to deployment of NMS into travel demand estimation. The comparison of reviewed studies is made according to the considered NMS (Section 3.1), incorporated travel

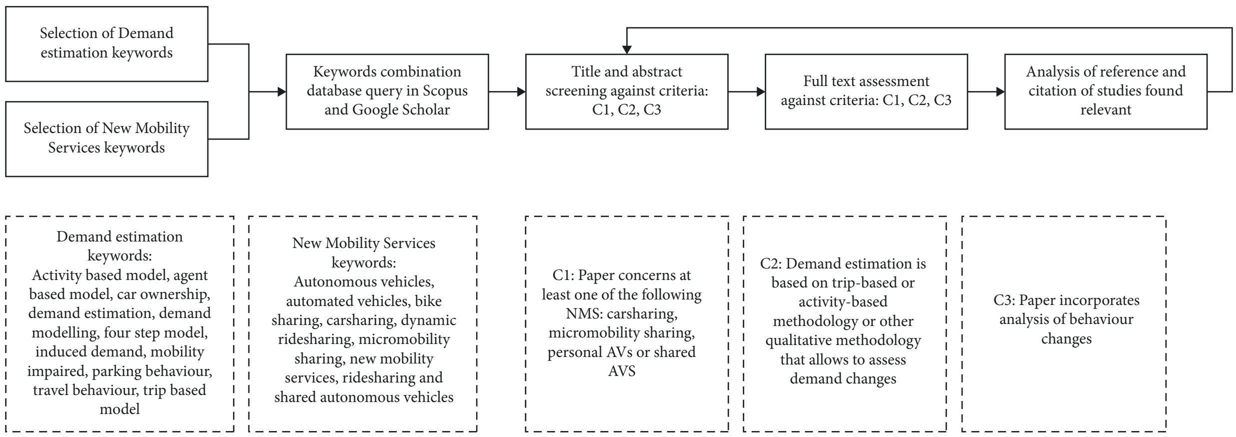

Figure 1: Methodological framework of the search for studies relevant for the analysis.

behaviour changes (Section 3.2), and demand estimation methodologies along with modelling practices and assumptions (Section 3.3) and obtained results (Section 3.4). The studied dimensions were chosen not to be exhaustive but rather to capture how modelling techniques and assumptions are used to represent various behaviour changes and the extent of their impact on the results.

3.1. Review of New Mobility Solutions. Technological and even more so connectivity advancements of the 21st century have brought a paradigm shift to the seemingly stable transport sector. The technological possibilities, guaranteed demand for transport services, and profitable business market have resulted in a plethora of new players and innovators disrupting the market. Upon their arrival, NMS starts to change the demand patterns of individuals, often shifting modal or schedule preferences.

In the majority of the studies, only one NMS is considered, but some of the researchers have considered a mix of available services, most often analysing SAVs and dynamic ridesharing (7) or SAVs and private AVs (3). Most of the studies analysing a single NMS focused on privately owned AVs (8) and SAVs (7), as a potentially disruptive new mean of transport, followed by dynamic ridesharing (6), carsharing (4), and micromobility (2). In Table 2, the reader will find a summary of NMS considered in reviewed studies.

3.1.1. Autonomous Vehicles. AV is a vehicle capable of performing all driving functions under all conditions [21]. Although there is great uncertainty regarding the deployment horizon and market penetration of AVs, the research related to their adoption has been sprouting.

There is already a speculation of plausible market adaptations. Researchers predict that AVs could be privately-owned or shared (SAVs) that are expected to be a taxi-like service allowing users to reserve the vehicle for a single ride. It is also predicted that rides could be private, shared, or the whole service could be handled with higher occupancy vehicles, such as minibuses [54, 55].

The uncertainty of market adoption is also reflected in the analysed studies. Out of 23 studies that included demand estimation for autonomous driving, 10 assumed that AVs would be privately owned and 12 assumed that the vehicles would be a shared fleet. Moreover, the study of Martinez et al. [42] considered two services that SAVs could provide: a taxi-like service and autonomous minibuses on-demand. Another exemplary solution tested only in one study was that analysed by Wen et al. [50] who considered a first and last mile service supplementary to public transport. This non-uniform approach suggests that the future AV deployment strategy is yet to be determined, with researchers analysing how the autonomy of the vehicle will impact the rate and preference towards ownership. Moreover, the implementation strategy for the AVs could vary not only across countries but also across cities, which could incorporate national or regional policies and environmental strategies, as already suggested by review and backcasting studies [21, 56–59].

3.1.2. Carsharing. Carsharing provides its users with access to a fleet of vehicles on an hourly or minutely basis. The service could be twofold: station based or free-floating. Station-based carsharing requires users to pick up a car from the designated station and drop it off, at the same station (round trip), or a different one of the same provider (one-way) [60]. Free-floating carsharing service allows users to book and return a car at any location within the operational area [61]. A substantive amount of research regarding carsharing has already been made. The trends include optimization of the operation of carsharing systems and analysis of successful business models [60], with recent focus on user preferences. The findings of survey-based studies show that carsharing users are often young [62], well-educated [63], environmentally conscious [64], and high-income individuals from high-density areas [65].

As for the reviewed studies, only 4 out of 35 tried to estimate the demand for carsharing under behaviour change assumptions. Nevertheless, carsharing is likely to be replaced by SAVs in the future, which could explain the small interests in including carsharing services in future-oriented demand estimations.

Table 1: Characteristics of reviewed studies.

Reference	Location	Population size	Objective	Software	Demand related data
Azevedo et al. [25]	Singapore, Singapore	4.06 million (m)	Assess the performance of SAVs under various regional transport and service policies.	SimMobility	Land use data: residential building, firm, and school locations and characteristics, household travel survey (2008 and 2012), GPS taxi trace data, public transport smart-card data
Balac et al. [26]	Zurich, Switzerland	1.62 m	Assess the performance of carsharing under various regional transport and service policies.	MatSim	Census and travel diaries
Basu et al. [24]	Singapore, Singapore	351 000 (~10% of Singapore)	Evaluate the impact of SAV introduction on mass transit.	SimMobility	NA
Bischoff et al. [27]	Charlottenburg, Berlin, Germany	37 000	Evaluate the impact of AV parking strategies on waiting times and parking search time.	MatSim	Census and travel diaries
Caggiani et al. [28]	Molfetta, Italy	60 000	Estimate revenues from congestion road tolls to finance a free-floating bike-sharing system along with repositioning.	Matlab	Census
Chen and Kockelman [29]	Grid city based on Austin, USA	2.3 m	Estimate SAV market shares.	MatSim	Census, regional trip data
Chen et al. [30]	Sioux Falls, USA	182 000	Assess the performance of dynamic ridesharing under various regional transport and service policies.	NA	Modified Sioux Falls static OD matrices
Childress et al. [31]	Puget Sound region, USA	4.2 m	Evaluate the impact of AVs on transport system.	Daysim	NA
Ciari et al. [32]	Metropolitan area of Berlin, Germany	4.5 m	Assess the performance of carsharing under various service policies.	MatSim	Census data and on travel diary surveys
Coulombel et al. [33]	Metropolitan area of Paris, France	13.1 m (assumed 8% grow)	Estimate environmental rebound effect linked to dynamic ridesharing.	TransCAD	Regional trip survey (Enquête Globale Transport) and road count data
Dias et al. [34]	NCTCOG area, USA	6.5 m	Develop a framework to represent AVs and their behavioural implications in TBM.	TransCAD	Census and household travel survey
Harper et al. [19]	USA	74 m seniors (2030 estimation) and 20.1 m non-drivers	Estimate increase in travel due to extra activity of mobility impaired in the presence of AVs.	NA	Census and household travel survey
Hebenstreit and Martin [35]	NA	NA	Implement station-based electric and regular bike-sharing systems in MatSim platform.	MatSim	NA
Heilig et al. [36]	Metropolitan area of Stuttgart, Germany	2.5 m	Implement carsharing services in an agent-based model for the first time for a period longer than a day (a week).	mobiTopp	Census and household travel survey
Heilig et al. [37]	Metropolitan area of Stuttgart, Germany	2.3 m	Estimate SAV fleet size necessary to handle projected travel demand.	mobiTopp	Census and household travel survey
Hörl et al. [38]	Sioux Falls, USA	84 110	Assess the performance of SAVs under various regional transport and service policies.	MatSim	Census data and static OD-matrices
Lavieri et al. [39]	Puget Sound region, USA	NA	Estimate adoption rates of personal AVs and SAVs.	NA	Census and household travel survey

Table 1: Continued.

Reference	Location	Population size	Objective	Software	Demand related data
Levin and Boyles [22]	Downtown Austin, USA	NA	Develop a framework to represent AVs and their behavioural implications in TBM.	NA	Household travel survey
Liu et al. [40]	Grid city based on Austin, USA	2.3 m	Evaluate the impact of SAV pricing levels on travel demand.	MatSim	CAMPO's travel demand predictions for 2020. OpenStreetMap (OSM) file
Martínez and Viegas [41]	Metropolitan area of Lisbon, Portugal	2.8 m	Estimation of city impacts related to deployment of two SAV services: taxi-like one and on-demand autonomous minibus.	NA	Census, household travel survey, and travel diaries
Martínez et al. [42]	Metropolitan area of Lisbon, Portugal	2.8 m	Assess the performance of carsharing under various regional transport and service policies.	Aimsun	Census, household travel survey, and travel diaries
Millard-Ball [43]	San Francisco Bay area, USA	NA	Evaluate the impact of personal AV parking strategies on transport system.	SF-CHAMP ABM	SF-CHAMP ABM demand input
Nahmias-Biran et al. [23]	Singapore, Singapore	351,000 (~7% that of Singapore)	Evaluate the impact of SAVs on accessibility levels.	SimMobility	Land use data: residential building, firm, and school locations and characteristics, household Interview travel survey (2012), Uber statistics
Oh et al. [20]	Singapore, Singapore	6.7 m (2030 projected population)	Evaluate the impact of SAV pricing and adoption levels on transport system.	SimMobility	Land use data: residential building, firm, and school locations and characteristics, household Interview travel survey (2012), SP results
Rodier et al. [44]	San Francisco Bay area, USA	883 000	Evaluate the impact of dynamic ridesharing adoption on vehicle miles travelled (VMT).	SF-CHAMP ABM	2000 public use Microdata sample and 2010 census data and 2-day travel diaries
Truong et al. [45]	Victoria, Australia	NA	Estimate additional daily trips generated by closing the gap in travel need at different life stages through AV introduction.	NA	Victorian Integrated Survey of Travel and Activity (VISTA) 2007–2010
Vyas et al. [46]	Metropolitan area of Columbus, USA	2 m	Evaluate the impact of AVs on transport system.	CT-RAMP2	The Columbus ABM demand data
Wadud et al. [47]	NA	NA	Evaluate the impact of SAVs on travel demand and GHG emissions.	NA	Household travel survey
Wang et al. [48]	Yarra Ranges, Australia	158 000	Implement people's preference to their social networks' friends and the flexibility of daily activities to improve the dynamic ridesharing matching.	NA	Census, Victorian Integrated Survey of Travel and Activity (VISTA) 2009–2010
Wang et al. [49]	Yarra Ranges, Australia	158 000	Implement of the flexibility of space and time of daily activities to improve the ridesharing matching.	NA	Census, Victorian Integrated Survey of Travel and Activity (VISTA) 2009–2010
Wen et al. [50]	Major European city	159 000	Develop a framework for the design, simulation, and evaluation of integrated AVs as first and last mile supporters of public transportation.	NA	Census, household travel survey, and travel diary surveys from 2005 to 2014
Yin et al. [51]	Metropolitan area of Paris, France	13.1 m (assumed 8% grow)	Estimate environmental rebound effect linked to dynamic ridesharing.	TransCAD	Regional trip survey (Enquête Globale Transport) and road counts

Table 1: Continued.

Reference	Location	Population size	Objective	Software	Demand related data
Zhang et al. [52]	Metropolitan area of Atlanta, USA	2.1 m of households	Evaluate the impact of AVs on vehicle ownership.	CPLEX optimizer	2011 travel survey data from Atlanta Metropolitan Area and synthesized Atlanta trip profile from the Atlanta ABM
Zhang et al. [53]	Sioux Falls, USA	NA	Evaluate the impact of various AV parking strategies on a transport system.	CPLEX optimizer	Census data and static OD-matrices

Table 2: Classification of reviewed studies according to the considered new mobility services.

Study	Carsharing	Dynamic ridesharing	Micromobility sharing	Private AVs	SAVs
Azevedo et al. [25]		X			X
Balac et al. [26]	X				
Basu et al. [24]		X			X
Bischoff et al. [27]				X	
Caggiani et al. [28]			X		
Chen and Kockelman [29]					X
Chen et al. [30]		X			
Childress et al. [31]				X	X
Ciari et al. [32]	X				
Coulombel et al. [33]		X			
Dias et al. [34]				X	
Harper et al. [19]				X	
Hebenstreit and Martin [35]			X		
Heilig et al. [36]	X				
Heilig et al. [37]		X			X
Hörl et al. [38]					X
Lavieri et al. [39]				X	X
Levin and Boyles [22]				X	
Liu et al. [40]					X
Martínez et al. [42]		X			X
Martínez et al. [42]	X				
Millard-Ball [43]				X	
Nahmias-Biran et al. [23]		X			X
Oh et al. [20]		X			X
Rodier et al. [44]		X			
Truong et al. [45]				X	X
Vyas et al. [46]				X	
Wadud et al. [47]					X
Wang, Winter and Tomko [48]		X			
Wang et al. [49]		X			
Wen et al. [50]		X			X
Yin et al. [51]		X			
Zhang et al. [52]				X	
Zhang et al. [53]				X	

3.1.3. Dynamic Ridesharing. Ridesharing allows users to share a trip with others preventing usage of more than one vehicle to reach a similar destination, whereas dynamic ridesharing is arranged on a per-trip basis, securing flexibility for its users [66]. Incorporation of ridesharing into travel models has mostly focused on optimization of matching algorithm, with randomly generated demand.

Nevertheless, 13 out of 35 reviewed studies tried to estimate the demand for dynamic ridesharing services along with the consideration of its impact on overall demand. As SAV-based services could increase their efficiency by offering shared rides for their users, 7 of the 13 studies considered dynamic ridesharing of SAVs. Moreover, two studies focused on another innovative dynamic ridesharing concept that matches users who live in close proximity or could know each other through social media community [48, 49]. Remaining studies looked at the currently available dynamic ridesharing services, which simply connect the user with the driver.

3.1.4. Micromobility Sharing Systems. Micromobility refers to a variety of small transport modes operating at low speeds, typically below 25 km/h, such as bicycles, electric bicycles, or scooters [67]. In this paper, the authors focus on novel shared micromobility systems and their impact on everyday mobility choices. Research related to micromobility sharing systems has mostly focused on software enhancement, as well as city regulation of those systems [68].

Micromobility is often omitted in transport models, hence representing the smaller interests in demand estimation studies. Out of the 35 reviewed studies, only two looked at the behavioural implications of micromobility and tried to incorporate them into demand estimation methodology [28, 35]. In light of electric micromobility boom as well as regional and urban policy direction towards car-free zones and rising interest in sustainable living trend, more studies should consider this modal choice.

3.2. NMS Impact on Travel Behaviour. Travel demand models try to reproduce the mechanisms influencing travel choices and behaviour of a certain population in response to the transport opportunities available and based on various studied assumptions. The new options that transport innovators propose change our mobility patterns and impact the everyday life in cities. It is crucial for policymakers and regional governors to predict how individuals could behave under various scenarios to best accommodate the needs of citizens. The first step towards that prediction is the understanding of plausible behavioural implication of innovation.

Upon the review of numerous articles that focused on the subject, the authors have classified those changes to be the following: (i) acceptance of longer trips, (ii) change in daily activity timing, (iii) increased number of non-mandatory trips, (iv) increased number of trips of mobility impaired, (v) modal change, (vi) relocation, (vii) shifts in parking habits, and (viii) shifts in vehicle ownership. None of the reviewed studies has considered all of the identified behavioural changes, with study by Vyas et al. [46] omitting just the relocation aspect, and study by Childress et al. considering 5 behavioural shifts [31]. Moreover, the most frequently considered behavioural shift was a modal change with 31 studies incorporating it, followed by the acceptance of longer trips (12 studies), changes in daily activity timing (7 studies), shifts in parking habits (5 studies), increased number of non-mandatory trips (4 studies), increased number of trips of mobility impaired (4 studies), shifts in vehicle ownership (4 studies), and relocation (2 studies). The incorporation of found changes in travel behaviour in the reviewed studies is summarised in Table 3.

3.2.1. Acceptance of Longer Trips. The reduced travel times decrease in perceived value of in-vehicle travel time (VOT) or drop of travel costs, resulting in an increase in accessibility levels and following higher tolerance of travelling. Therefore, certain individuals might decide to travel to areas further away to satisfy the journey purpose, prolonging the trip.

As an AV allows for multitasking, the value of in-vehicle time could be perceived as less burdensome than in other modes resulting in a decrease of VOT [69]. Additionally, it is expected that efficient driving as well as platooning could lead to an increase in road capacity and a decrease in travel times [31]. Moreover, it is expected that automation of vehicles would lead to operational cost reduction [21]. Likewise, the reduced travel time and decrease of VOT could lead to elongation of the trips. A hypothesis confirmed by an experiment tried to capture behaviour changes caused by autonomous driving by giving individuals access to chauffer services [70].

Due to the split of monetary costs between users, dynamic ridesharing is expected to lower the cost of travelling, whereas potential congestion reduction caused by higher vehicle occupancy could shorten travel times. The reduction of costs and potential reduction in travel time will increase the accessibility and possibly encourage people to travel further away and elongate the trips [33].

3.2.2. Change in Daily Activity Timing. The reduction in VOT as well as the decrease of costs could also trigger individuals to tolerate travelling in more congested conditions, altering the schedule of a given individual [31]. Additionally, as users of SAVs and private AVs will not have to worry about finding a parking location for their vehicles and reaching the final destination from it by foot, the daily schedule could change as well, allowing those individuals to leave the households later without risking being late [53]. Therefore, the deployments of AVs, SAVs, and dynamic ridesharing could cause people to change the daily activity timings.

3.2.3. Increased Number of Non-Mandatory Trips. The behavioural studies predict that a decrease in VOT and travel times as well as lower travel costs could also encourage users to participate more often in non-mandatory, leisure activities [31, 33, 70]. Therefore, the deployment of personal AVs as well as SAVs and dynamic ridesharing could result in an increased number of non-mandatory, leisure trips. However, predicted behavioural change is not often considered in the studies, as only 4 studies that analysed AVs, SAVs, or dynamic ridesharing have decided to implement the behavioural change in the demand model.

Nevertheless, the demand estimation studies should look for methodologies to implement the increase in number of non-mandatory trips in their calculations, as the experiments that try to investigate the behaviour changes caused by AVs suggest that individuals will indeed increase the number of their non-mandatory trips. That is because they are willing to use an AV more often than regular car as it allows them to use the vehicle under the influence of alcohol or at night when they would be too tired or sleepy to drive themselves [70].

3.2.4. Increased Number of Trips of Mobility Impaired. Elderly, youth, mobility and visually impaired, and others without a driver's license could use AVs for travelling alone as it does not require driving abilities. Therefore, AVs (as well as SAVs) could increase the number of trips people from those groups generate [45]. The increase of accessibility

Table 3: Classification of reviewed studies according to the considered behavioural changes.

Study	Acceptance of longer trips	Change in daily activity timing	Increased number of non-mandatory trips	Increased number of trips of mobility impaired	Modal change	Relocation	Shifts in vehicle ownership	Shift in parking habits
Azevedo et al. [25]	X	X			X			
Balac et al. [26]					X			
Basu et al. [24]	X	X			X			
Bischoff et al. [27]								X
Caggiani et al. [28]					X			
Chen and Kockelman [29]					X			
Chen et al. [30]					X			
Childress et al. [31]	X	X	X		X		X	
Ciari et al. [32]					X			
Coulombel et al. [33]	X				X	X		
Dias et al. [34]	X		X		X			
Harper et al. [19]				X				
Hebenstreit and Martin [35]					X			
Heilig et al. [36]					X			
Heilig et al. [37]	X				X			
Hörl et al. [38]					X			
Lavieri et al. [39]							X	
Levin and Boyles [22]					X			X
Liu et al. [40]					X			
Martínez et al. [42]					X			
Martínez et al. [42]					X			
Millard-Ball [43]								X
Nahmias-Biran et al. [23]	X	X			X			
Oh et al. [20]	X	X			X			
Rodier et al. [44]					X			
Truong et al. [45]				X	X			
Vyas et al. [46]	X	X	X	X	X		X	X
Wadud et al. [47]			X	X				
Wang et al. [48]	X				X			
Wang et al. [49]	X				X			
Wen et al. [50]					X			
Yin et al. [51]	X				X	X		
Zhang et al. [52]					X		X	
Zhang et al. [53]		X						X

for those individuals is often mentioned as one of the most significant advantages of AVs. Nevertheless, the impact of this increased accessibility on demand estimation is often omitted in the analysis made as of today (only 4 out of 23 studies on AVs decided to fully or partially consider this demand induction in their analysis).

3.2.5. Modal Change. Modal change is the most obvious behaviour change caused by introduction of all considered NMSs. Therefore, majority of the studies reviewed for the purpose of this analysis have introduced it in their models. For this analysis, it is assumed that the modal change behaviour was considered if the study tried to understand the factors that determine the modal choice. If the study did not include any behavioural modal choice model, but rather assumed that the demand would be fully covered by AVs, this review does not consider the study to incorporate modal change as a behavioural change. The same is true for the studies that consider a partial demand covered by AVs but rather than analysing which individuals are prone to shift to other modes draw the sample randomly.

The reduction of VOT, travel costs, and travel times could further influence user preferences towards dynamic ridesharing and AVs resulting in additional modal shifts from more sustainable options such as public transport or micromobility [31]. A similar outcome can be seen with carsharing, as carsharing tends to attract people that use public transport for their commute rather than private car [32, 42].

The observed change in travel behaviour related to the implementation of micromobility sharing system is a modal shift, often on short walking distances [71]. However, bike-sharing can also replace public transport, private car, or taxi [72].

3.2.6. Relocation. A number of studies predict that with the decrease in in-vehicle value of travel time, costs, or travel times, caused by AV deployment and adoption of dynamic ridesharing services, individuals may choose to relocate further from their main activity location, which could potentially result in urban sprawl [25, 33]. Nevertheless, relocation was only considered in two of the reviewed studies, namely, by Coulombel et al. [33] and Yin et al. [51], who tried to assess the environmental rebound effect of dynamic ridesharing services in Paris.

Nevertheless, studies predict that the sprawl and relocation could be stopped if we adopt a shared model of AVs, in which the imbalance between demand and supply of SAVs would result in price increase of services in sprawled-out areas, as more empty rebalancing trips would be needed to fulfil all travel request, increasing the operational costs for the fleet manager [29]. That means that per mile costs in densely populated areas would be lower than in those sprawled [73]. This outcome could stop individuals from relocating, provided that the shared mobility would significantly impact the vehicle ownership rates.

3.2.7. Shift in Parking Habits. The fact that an AV does not require the driver to be present in the car enables new parking options for personal AV users. The reviewed literature suggests that the user could potentially choose one of the following four strategies [22, 43, 46, 74]:

(i) The vehicle could drop off its user and start looking for an available parking spot nearby, relocating if there is a limit on permitted duration of parking.
(ii) The vehicle could drop off its user and park in a dedicated garage area on the outskirts of city or central business district.
(iii) The vehicle could drop off its user and return to the home location to serve other household members or wait for the principal user's orders.
(iv) The vehicle could drop off its owner and start driving in nearby locations until called again by the user, in so called cruising strategy.

The latter three strategies could potentially result in an increase in-vehicle miles travelled (VMT) and CO_2 emissions. Shifts in parking preferences have been the focus of five of the reviewed studies, with three of those placing their solemn focus on investigation of shifts in parking behaviour.

3.2.8. Shifts in Vehicle Ownership. In response to NMS deployment, preferences for vehicle ownership could shift. Researchers agree that vehicle ownership could change as result of carsharing and SAV deployment [6, 39, 63, 75]. Wide availability of mobility as a service in form of SAVs could discourage numerous users from owning a personal AV. SP survey studies have confirmed that in presence of a SAV on-demand service, multivehicle household would be willing to dispose of one or more of their vehicles [76] and that highly educated, young individuals living in dense urban areas are more drawn to SAVs rather than personal AVs [39, 75].

Moreover, surveys conducted among carsharing users prove that access to carsharing services impacts vehicle ownership, as users tend not to buy an additional vehicle [6] or even dispose their old one [63].

3.3. Review of Modelling Practices. Behaviour changes cause a struggle for demand modellers, as the current demand estimation methodologies keep proving to be not agile enough to the changing mobility offer and its implications [3]. Furthermore, the deployment and adoption of NMSs, especially AVs, could mean a major paradigm shift for all transportation and could be a disruptor when it comes to behaviour changes, hence the utmost importance of mirroring the foreseeable behaviour in the demand estimation models.

In this section, the review of modelling techniques and key assumptions used in reviewed studies are presented to the reader. The studies are categorised according to the modelling framework used. The categories stand as ABM (21 studies), TBM (4 studies), and other estimation methods (9 studies).

For each of the categories, the key modelling changes or assumptions that try to incorporate behaviour changes caused by NMS are presented for various parts of the modelling activity.

Thus, TBM is traditionally divided into a four-step modelling sequence (i–iv) with an extra vehicle ownership model (v) and other notable changes:

(i) Trip generation
(ii) Trip distribution
(iii) Modal choice
(iv) Route assignment
(v) AV ownership
(vi) Other changes

Activity-based models are divided into following modelling steps:

(i) Activity scheduling
(ii) Modal choice
(iii) Destination choice
(iv) Time of day choice
(v) AV ownership
(vi) Other changes

As for the demand estimation methodologies outside of the TBM and ABM frameworks, each model is reviewed individually as their approaches often vary.

The key modelling techniques and assumptions used in TBM, ABM, and other identified methodologies that concern behaviour change estimation are presented in Tables 4–6, respectively.

3.3.1. Trip-Based Models. Not many studies have decided to implement the NMS behavioural changes into TBM, as the aggregated nature of those models limits the potential of implementing shared services.

On the trip generation level, the behavioural changes that lead to induced travel demand (such as increase in non-mandatory activities and increased number of non-mandatory trips) are represented. This is reflected in one of the TBM-based reviewed studies, which implemented this behavioural change in the model, through the scenario-based assumption of the increase in number of trips for AV owners [34].

The changes made in trip distribution step of the model could reflect the higher acceptance for longer trips. The implementation of this behaviour change was performed in the reviewed studies, through assuming a lower generalised cost (or time) of travel in the generalised cost origin-destination (OD) matrix [33, 34, 51].

The modal choice level of the model incorporates the modal changes caused by introduction of new services. In the reviewed papers, the researchers have developed either multinomial logit models (MNL) [33, 51] or nested logit models (NL) [22] which allowed to determine the modal choice. Reflection of changes caused by introduced NMS was made through assumed reduction of VOT (for AVs) [34] and assumed lower cost of travel (dynamic ridesharing) [33, 51].

Shifts in vehicle ownership were also analysed in reviewed studies that implemented the TBM. Certain researchers based their studies on the assumption that high-income individuals are more likely to adopt innovation. Based on income classes, the AV availability was assigned to households. The penetration rate was either subject to scenario analysis [22] or assumed [34]. Nevertheless, this approach could be misleading, as the tendency to switch for an innovative solution could be motivated by other factors such as age, costs, or perceived safety and sustainability [77, 78], with SP-based study even concluding that income levels are not significant for the AV adoption [76].

3.3.2. Activity-Based Models. Behaviour changes related to NMS deployment are more often implemented in ABMs, which allow to better represent decisions of individuals based on their socioeconomic profile. A share of reviewed studies was agent-based developed in simulation platforms such as MatSim, SimMobility, or mobiTopp. Agent-based models are used for precision in spatial and temporal representation of the supply side, a key for a faithful representation of shared services. The activity-based model (ABM) is a string of decision-making processes implemented in the form of a series of discrete choice models (typically MNL or NL); therefore, some of the changes implemented (such as decrease of VOT) could be made on all levels of the model with a single assumption.

A small share of researchers have decided to implement changes on the activity scheduling step of the model, which reflect an increased number of non-mandatory trips and increased number of trips of mobility impaired. Implementation of increased number of non-mandatory trips was made through assumed decrease in VOT (in a range from 25 to 50%) [31, 46]. Changes in activity timing, caused by AVs deployment, were implemented analogically.

Increased number of trips of mobility impaired was not studied sufficiently in the ABMs, as only one study decided to consider any changes. Vyas et al. [46] assumed that AVs would be available as a modal choice for children with a scenario-based minimal age requirement. No other demand inductions caused either by additional activity of the elderly or those with no driving license or disabled were considered in the reviewed studies that implemented an ABM.

On the destination choice level of the model, usually a MNL or NL, acceptance of longer trips was considered. Several researchers have decided to implement this behavioural change in their ABMs. For Avs, the implemented changes consisted of assumed VOT reduction (25–50%) with a VOT considered as in regular car [31, 38, 40, 46]. If the utility of the choice was modelled after a taxi service, only a change of cost was assumed (30–40% decrease due to elimination of driver) [20, 23–25, 37].

The modal choice step of the ABM, which incorporated modal changes, was most often modified by the researchers. Nevertheless, the reviewed models often did not consider

Table 4: Modelling techniques used in trip-based models.

Study	Considered NMS	Modelling step	Behaviour change	Modelling practice
Dias et al. [34]	AV	Trip generation	Increased number of non-mandatory trips	Assumed scenario-based 5%/10% increase in number of trips for households owning an AV.
		Trip distribution	Acceptance of longer trips	Reduction of generalised travel cost between zones by 25% for AV owners.
		Modal choice	Modal change	Reduction of VOT for AV owners by 25% as compared to the regular car.
		AV ownership	Shifts in vehicle ownership	Binary logit model based on individuals' household income (survey-based study) with assumed 40% penetration rate.
Levin and Boyles [22]	AV	Modal choice	Modal change and shifts in parking habits	Nested logit model of choice between AV parking nearby, AV repositioning, and transit. Utility functions made of parking fees, fuel costs, and VOT.
		AV ownership	Shifts in vehicle ownership	Scenario analysis of AV availability for five classes of population divided by VOT (1.15$ to 22$).
Coulombel et al. [33] and Yin et al. [51]	Dynamic ridesharing	Trip distribution	Acceptance of longer trips	Assumed lower average travel time due to reduction of congestion.
		Modal choice	Modal change, shifts in parking habits	Multinomial logit model with utility functions of each mode made of VOT and monetary costs. Monetary cost is split evenly between ridesharing users.
		Other changes	Relocation	The potential relocation assessed in a coupled land-use model by incorporating a decrease in average travel time and cost.

socioeconomic attributes and individual preferences as factors that could influence modal shifts. The modal choice is frequently determined by a MNL, following the maximal utility theory, determining the choice based on overall utility of each option. However, utility functions often included only assumed perceived VOT, and monetary cost [29, 38, 40, 46], for which the changes in behaviour were often implemented through assumption of VOT decrease as compared to the regular car (25%–50%). Omitting the importance of individual preferences could be crucial, especially when it comes to unfamiliar modal choices such as AVs.

Alternatively, the utility of the SAV option was modelled as a taxi or as "private car as passenger," by reducing the costs of travel (40–70%) [20, 23–25, 37]. The cost of SAV and AV operation was often assumed as a fraction of taxi service or private car, or subject to scenario analysis. Nevertheless, constant cost assumption could be misrepresentative as SAV services could function, with costs varying based on current supply and demand, whereas the cost of private electric AV operation is also difficult to determine as it highly depends on national energy transformation and electricity mix.

Furthermore, the assumption that VOT is constant for all trip purposes could be misleading, as survey-based studies suggest that it could vary depending on trip purpose, estimating VOT decrease at 30–40% for commuting trips [79] and zero for leisure trips [69]. Only one study implemented a differentiation of VOT subject to the purpose of the trip, claiming VOT to be 100% of wage for business trips and 50% for leisure trips [29]. The variety of perceived value of travel time in different modes was also insufficiently represented as only one study implemented the alteration in value of time in regard to waiting for SAV service or being inside. Hörl et al. [38] assumed that waiting for an AV is twice as valuable as riding inside.

Modal choice for studies focusing on carsharing often incorporated more socioeconomic attributes to utility functions based on survey-based responses—an already available solution for which an adequate SP study could be more straightforward and subject to less bias as it is a mode users could be already familiar with, as opposed to not yet available mobility options like AVs [36, 42]. Moreover, the costs of carsharing were also easier to determine as simply the costs of available services were implemented in the utility functions [26, 32, 36, 42]. The difference in VOT was also exemplified in some of the studies, as the value of access and egress time was modelled as value of walking and value of using the service as value of travelling with regular car [26, 32].

Modal choice in studies that focused on dynamic ridesharing was subject to numerous additional limitations and requirements such as the latest arrival time, the maximum income of users, and departure time and group size [44, 48–50].

Finally, changes in parking habits were studied only in two of the reviewed studies in a modal choice step in NL models, where one of the nests contained various AV parking possibilities [27, 46]. The parking option was determined based on the maximal utility. The utility of parking covered the costs of each parking strategy. The approach, however, could be misleading, as individuals may opt for a given parking strategy for reasons other than financial.

Additionally, a share of studies implemented an assumption of an increase in road capacity, which impacts the utility functions by changing the travel time. Assumptions can vary for different road types and AV market penetration

Table 5: Modelling techniques used in activity-based models.

Study	NMS	Modelling step	Behaviour change	Modelling practice
Azevedo et al. [25]; Basu et al. [24]; and Nahmias-Biran et al. [23]	SAV with ridesharing	Modal choice Destination choice	Modal change Acceptance of longer trips	Change in the utility functions. Utility of SAV based on individual preferences towards taxis with 40% [24, 25] or 33% [23] monetary cost.
Bischoff et al. [27]	AV	Other changes	Shifts in parking habits	Private AVs choose from three parking strategies: parking on a free but time limited parking spot, parking at a garage with unlimited capacity nearby, and cruising in range of 2000 m while waiting for the user. Parking strategy and assumed AV penetration (10% or 20%) are subject to scenario analysis.
Chen and Kockelman [29]	SAVs	Modal choice	Modal change	Modal choice between private vehicle, transit, and SAV determined by MNL model. The utility functions consist of VOT and monetary costs. VOT is assumed to be 50% of hourly wage of modelled individual for personal trips and 100% of hourly wage for business or work trips. VOT in SAV is decreased to 35% of regular private vehicle ride. Monetary costs of SAV subject to scenario analysis: simple distance-based, origin-based, destination-based, and combination of origin and destination pricing. The origin pricing and destination pricing are designed to minimise the empty rides required for relocation.
Childress et al. [31]	AV and SAV	Activity scheduling Modal choice Destination choice Time of day choice AV ownership	Increased number of non-mandatory trips Modal change Acceptance of longer trips Changes in daily activity timing Shifts in vehicle ownership	Three AV scenarios: in all 30% assumed capacity increase and VOT reduced to 65% of regular car for AV owners. In the SAV scenario where all vehicles are shared, the flat cost of travel is assumed at $1.65/mile. Simulated population divided by income. Scenario-based analysis of AV availability. AVs are either available to high-income households (with VOT higher than $24) or a full market penetration is assumed. Last scenario assumes that all vehicles are shared.
Heilig et al. [37]	SAV with ridesharing	Modal choice Destination choice	Modal change Acceptance of longer trips	Mode and destination choices determined in a nested logit model (NL), in which private car is unavailable. The utility of using SAV is modelled as the utility of “private car as a passenger” option with a reduction of monetary costs by 70% per mile.
Hörl et al. [38]	SAV	Modal choice	Modal change	Modal choice based on MNL model in which utility functions consists of VOT and monetary costs. VOT for SAV option modelled at 65% of a private car. Waiting for an AV modelled at twice the VOT of car travel. SAV monetary costs assumed at $0.85/mile.

Table 5: Continued.

Study	NMS	Modelling step	Behaviour change	Modelling practice
Liu et al. [40]	SAV	Modal choice	Modal change	Modal choice based on MNL model in which utility functions consists of VOT and monetary costs. In-vehicle VOT for SAV option modelled at 50% of a private car in-vehicle VOT. Waiting for AV modelled at twice the VOT of car travel. Cost of SAV is subject to scenario analysis and consists of distance-based fee of $0.50, $0.75, $1, or $1.25 per mile and a fixed cost of $1, $2, and $3 subject to the starting location of the trip (urban, suburban, and extra urban areas).
Martinez and Viegas [41]	SAV (two services: taxi-like and minibuses)	Modal choice	Modal change	SAVs replace private cars, buses, and taxis which are not available as modal choices. A modal choice determined by a nested logit model along with a series of sequential rules that form a rational decision-making process. Rules concern length of the trip, transit pass ownership, and a number of transfers.
Oh et al. [20]	SAV with ridesharing	Modal choice	Modal change	The alternative specific constants in the utility function and willingness-to-pay for SAV are based on current taxi utilities, tuned so that the proportion of SAV mode shares to rail shares is similar to that predicted by the estimated mode choice model on the weighted stated preference sample under different pricing assumptions. The price of SAV is subject to scenario analysis and studied at 75%, 100%, and 125% fare of a taxi.
		Destination choice	Acceptance of longer trips	
Vyas et al. [46]	AV	Activity scheduling	Increased number of non-mandatory trips, Increased number of trips for mobility impaired	Assumed scenario-based 25%/50% decrease in VOT as compared to a regular car. The mobility impaired are allowed to use the AV if they are a part of a household that owns one. AV availability for children subject to the scenario analysis of age required for a child to use AV by themselves.
		Modal choice	Modal change	NL model to assess modal choice along with parking strategy.
		Destination choice	Acceptance of longer trips	Assumed scenario-based 25%/50% decrease in VOT as compared to a regular car.
		Time of day choice	Changes in daily activity timing	
		Modal choice	Shifts in parking habits	NL model to assess parking behaviour implemented on a modal choice level. Traveller can park an AV in close proximity or send the car back home making it available to other household members.

Table 5: Continued.

Study	NMS	Modelling step	Behaviour change	Modelling practice
Balac et al. [26]	Station-based carsharing	Modal choice	Modal change	Modal choice determined by MNL. The utility functions include the VOT and travel time as well as monetary costs. For carsharing, in-vehicle travel time is modelled as a regular car, and access and egress times are modelled at value of walking time. Monetary costs include fixed rental fee, rental time fee, and distance fee.
Ciari et al. [32]	Free-floating carsharing	Modal choice	Modal change	The utility functions include the VOT and travel time as well as monetary costs. For carsharing, in-vehicle travel time is modelled as a regular car, and access and egress times are modelled at value of walking time. Monetary costs include fixed rental fee, rental time fee, and distance fee. There is a cap on rental time fee to represent available services.
Heilig et al. [36]	Station-based and free-floating carsharing	Modal choice	Modal change	Modal choice determined by MNL based on the results of SP. Carsharing option is available for individuals without private vehicles. The utility functions include socio-demographic variables, land use, travel time, and cost. The cost of carsharing is based on available services: 0.29€ for free-floating service and 2.80€ per hour and 0.23€ per kilometre for station-based service.
Martínez et al. [42]	Station-based carsharing	Modal choice	Modal change	Modal choice determined by MNL based on the results of SP. The utility functions include socio-demographic variables, land use, travel time, and monetary cost. The cost of carsharing is based on available services: 0.29€/min and 0.19€/min when the car is reserved.
Rodier et al. [44]	Dynamic Ridesharing	Modal choice	Modal change	Identification of trips that meet the maximum income and minimum trip length conditions for which ridesharing is a modal option. Ridesharing mode determined upon individual acceptance of departure time flexibility, proximity, and group size.
Chen et al. [30]	Dynamic Ridesharing	Modal choice	Modal change	Agents divided between those with mode set and those with mode choice. Final ridesharing mode choice for flexible agents based on the earliest arrival time at destination.
Wang et al. [49] and Wang et al. [48]	Dynamic Ridesharing	Modal choice Destination choice	Modal change Acceptance of longer trips	The number of shared rides is maximised, subject to time and space limitations and detour tolerance. Priority is given to social network friends. Ridesharing users are changing the destination if a driver is heading for a similar activity location.
Hebenstreit and Martin [35]	Micromobility	Modal choice	Modal change	Modal choice determined by MNL model. The utility of bike-sharing consists of access and egress times as well as the likelihood of finding a bicycle on an origin station and available parking place at the destination station.

Table 6: Modelling techniques used in studies based on other methodologies of demand estimation.

Study	Considered NMS	Behaviour change	Modelling practice
Lavieri et al. [39]	AV, SAV	Shift in vehicle ownership	Multinomial probit kernel for the discrete choices to assess what factors and attributes impact the level of interest of individual in owning AV or using a SAV service. The level of interest was measured at 5-point grading scale.
Truong et al. [45]	AV, SAV	Modal change	Scenario-based analysis. In the first scenario, 10% of public transport trips made by members of households, where there are fewer motor vehicles than people of driving age, are assumed to switch to AVs and 20% of public transport trips by members of no car households are assumed to switch to AVs. Second scenario also introduces an assumption that 10% of travellers switch from walking and cycling to AVs.
		Increased number of trips of mobility impaired	The behaviour of population betweeen 30-65 is assumed to be natural and unchanged. Gaps in travel need for the 12–17 age group and for the 18–24 and 25–29 age groups are measured by the differences between the actual travel need curve and the linear extrapolation of the natural increase trend, and gaps in travel need for the 66–75 and 76+ age groups are measured by the differences between the actual travel need curve and the linear extrapolation of the natural decline trend.
Wadud et al. [47]	SAV	Increased number of non-mandatory trips	Assumed scenario based on 50–80% reduction in VOT and 60–80% reduction in insurance costs, a fraction of operational costs.
		Increased number of trips of mobility impaired	The decline in travel activity between ages 44 and 62 represents the natural rate of decline in travel needs, and that the accelerated decline after age 62 represents travel that is foregone due to impaired driving abilities. The demand that could be filled through automation is calculated as the difference between the actual demand and the linear extrapolation of the age 44–62 trend.
Wen et al. [50]	Public transport compliment with SAV	Modal change	NL model based on the historical observations, simulated level of service, and fare and AV preference assumptions. The fare is estimated based on a similar Uber service with base fare: \$0.83, distance fare: \$0.55/km, and time fare: \$0.11/min. System performance is evaluated and returned to the mode choice in a feedback loop. The level-of-service indicators are service rate, wait time, and detour factor.
Harper et al. [19]	AV	Increased number of trips of mobility impaired	Assumptions: non-drivers travel as much as the drivers within each age group and gender. Elderly drivers without any travel-restrictive medical condition in the youngest elderly cohort (65–74) travel as much as working age adults (19–64) within each gender. Elderly drivers with and without any medical conditions will travel as much as a person 65 years of age within each gender. Working age mobility impaired adult drivers (19–64) will travel as much as working age adults without medical conditions in each gender. Elderly drivers with travel restrictive medical conditions in the youngest elderly cohort (65–74) will travel as much as working age adults within each gender.
Millard-Ball [43]	AV	Shifts in parking habits	Private AV owner can choose from three parking strategies: parking on a free but time limited parking spot and changing a spot after required time, returning home to park, and cruising. The chosen strategy is the one minimising the costs. Cost of the first strategy is modelled as the cost of drive towards a parking location in a free on-street space and return back to the owner. The cost of repositioning is assumed as marginal. In the second strategy, the cost consists of driving home and back to the user. Driving cost of \$0.13/mile is assumed for both strategies. For the cruising strategy, the cost is speed dependent and minimised by finding the routes with lowest travel speeds.

Table 6: Continued.

Study	Considered NMS	Behaviour change	Modelling practice
Zhang et al. [52]	AV	Shift in vehicle ownership	100% of AV market penetration is assumed. The greedy scheduling algorithm is used to minimise AVs needed to satisfy the travel demand of all household members in each household. If there is not enough time to relocate the AV to serve all household trips, the vehicle could not be replaced. Otherwise, if all trips generated by the household could be met with less vehicles, the vehicle ownership of the household is reduced. For households that can reduce vehicle ownership, an optimization mixed-integer programming problem is used to determine the minimum amount of unoccupied VMT generated during AV repositioning process.
Zhang et al. [53]	AV	Change in daily activity timing	Joint equilibrium of AV route parking location choice. The AV users are assumed to omit the walking time for parking location to their activity location, leaving the house later. The assumptions are that for the early arrival commuters, marginal saving in early schedule delay cost is larger than the marginal increase in the cost of self-driving AV to find a parking space.
		Shifts in parking habits	The AVs select an appropriate parking location, which will minimise the total individual travel disutility based on a joint evaluation of distance travelled and cost. In line with the parking choice and the willingness to minimise individual travel disutility, the AV chooses shortest paths with minimal travel time.

or could be constant. However, those assumptions could be optimistic as driving efficiency of AVs could be subject to regional policies for instance in the case of dedicated lanes for platooning [21], a situation not considered in reviewed studies.

3.3.3. Other Methodologies. Although TBM and ABM are used most often for demand modelling, a number of reviewed studies have drawn from other methodologies to estimate the behaviour shifts. Incorporation of those methodologies into TBM or ABM might not be straightforward, either because of aggregation of population (in case of TBM) or because of necessity to include an additional modelling step supported by supplementary assumptions (in case of ABM). The behavioural changes that were studied in methodologies outside of the typical demand estimation were (i) the increased number of trips of mobility impaired, (ii) shifts in parking habits, and (iii) shifts in vehicle ownership.

The studies that focused on estimating the demand induction caused by increase in accessibility for mobility impaired followed a string of assumptions about the needs of travel for three demographic groups, which could potentially have the highest impact: elderly, disabled, and non-drivers. For instance, Harper et al. [19] assumed that non-drivers and disabled would travel as much as their age and gender non-disabled driving counterparts in the population, whereas the elderly were assumed to travel as much as the younger working adults in the population. To better denote the natural demotion of travel needs, Truong et al. [45] following Wadud et al. [47] proposed to analyse the current travel demand for population and assumed that early age increase in travel and late age decrease represent the natural changes in the need to travel. The induction of demand was estimated to be the difference between the natural travelling needs and the current demand. Nevertheless, both approaches neglect the fact that the travelling patterns may change drastically once AVs are introduced, encouraging the population to participate in more leisure, non-mandatory activities, including the mobility impaired.

An assumption that the travel demand will not change was also made by studies trying to assess the future vehicle ownership. Zhang et al. [52] proposed a model that analysed the current travelling patterns of household to see if reduced number of AVs could satisfy the demand by relocating the vehicle between the household members. Nevertheless, the proposed approach ignored the possibility of development of alternative business models and a shift in vehicle ownership towards sharing economy, a factor considered by Lavieri et al. [39] who developed a multinomial probit kernel model based on survey data to assess the future vehicle ownership vs. sharing preferences in the USA.

Researchers that chose to look beyond the TBM or ABM methodologies also focused on assessing the future shifts in parking habits caused by vehicle automation. The studies followed an assumption that users would choose the most cost-effective parking strategy. The costs were modelled as operational driving costs (distance based) and an assumed parking fee [43, 53]. Moreover, Zhang et al. [53] tried to analyse the changes in daily activity timings caused by the fact that AV can drop off its user in front of the activity location, and no extra time is needed for egress or looking for a parking spot. Nevertheless, the adopted cost minimising approach ignores entirely the personal preferences for parking, as users might prefer to make the vehicle available to other household members or otherwise would prefer it to keep it parked nearby because of environmental concerns or other factors.

3.4. Review of Results and Impact of NMS on Mobility. This section provides a wider look at the results that reviewed studies presented. The purposes of reviewed studies varied; therefore, their outcomes are often incomparable, although there are linkages between the results. For this study, the results were divided into four categories: regional traffic implications, user preferences, findings related to NMS market potential, and environmental implications.

3.4.1. Regional Traffic Implications. Reviewed studies tried to assess the impact of NMS on urban congestion, which is a major transport negative externality in numerous urban areas. The researchers assessed that dynamic ridesharing could lower traffic volumes during peak hours by more than 20% [33, 51], whereas deployment of AVs could result in an increase in congestion of up to 28% [20, 24]. Furthermore, due to the variety of assumptions and selective behaviour change incorporation, the results tend to contradict one another. For instance, Dias et al. [34] predicted 2% increase in average speeds, while Levin and Boyles [22] argued that the average speeds would in fact decrease. Chen and Kockelman [29] stated that increase in VHT is expected in networks with high transit usage and a decrease in networks with high private vehicle usage. Nevertheless, despite congestion implications, the cost and VOT reduction of travelling would result in higher accessibility levels.

Number of trips could also be used as a proxy for congestion implications of AV deployment, but the results are found to be similarly contradictory suggesting 46% decrease [37] or stability [25] or 2.7% increase. Those differences are a result of distinctive assumptions in regard to the future AV adoption strategies and levels as well as selective and various behaviour change implementations. For instance, Heilig et al. assumed that the cost of the SAV would be 70% lower than a passenger vehicle, while Azevedo et al. opted for a 40% reduction compared to a taxi. Low cost of SAV service assumed by Heilig could therefore result in numerous agents to opt out of public transport or walking towards SAV, which in turn results in higher congestion.

Analysts, who tried to assess the demand induction caused by accessibility gains for mobility impaired, agree that the AV deployment will result in increased number of trips, with Truong et al. [45] expecting 4.14% increase in number of trips caused by higher activity of the elderly, whereas Harper et al. [19] predicted that 9% non-drivers could increase VMT by 9% while elderly drivers and those with medical conditions could increase VMT by 2.2% and 2.6%, respectively.

Most often, the estimation of regional traffic implications of introduction of NMS is reflected through an analysis of VMT. The analysed studies state that ridesharing could decrease VMT by 19% [44]. Papers that study the impact of AVs on VMT have contradictory results. Martinez and Viegas [41] state that if private cars, buses, and taxis were replaced by SAVs, with the possibility of ridesharing, VMT could decrease by 30%, whereas other studies that incorporate additional behavioural shifts implicate that VMT would increase by 3–20% [31, 34, 46] with two studies indicating a 60% rise [47], also due to repositioning and empty rides of SAVs [38]. Basu et al. [24] tried to analyse how the VMT of SAV services is distributed coming to a conclusion that 60% of total VMT is spent while travelling with a passenger, 35% while going for pick-up or parking, and 5% for empty vehicle cruising. Visibly, the VMT is higher in the studies that considered numerous behavioural changes and assumed a lower VOT for SAVs (Table 5), resulting in a higher uptake of a service.

Nevertheless, the findings of all those studies heavily depend on the extent to which behavioural changes were implemented, thus making their results incomparable and partial.

3.4.2. Regional Policy Implications. Effective policies towards new solutions could alter the behaviour of individuals, serving the vision of policymakers. Therefore, a number of reviewed studies have also assessed various policy measures aimed at transport management and VMT reduction. Vyas et al. [46] predicted that increasing parking costs could result in as high as 15% increase in empty AV trips. Bischoff and Maciejewski [74] also studied the implications of parking policies predicting that with 10 and 20% AV penetration, the average time needed to find a parking spot will decrease by 5 to 15% if AVs park on regular spots, 9% to 16% if AVs use garage, and 6 and 20% if the AVs are cruising. Parking strategies were also assessed by Millard-Ball [43] who estimated that free on-street parking with repositioning is preferred by 13% of users, typically for long stays, returning home is adopted by 8% of users, mainly by individuals who live close to the centre, and 40% of users would adopt cruising which is the cheapest option.

Oh et al. [20] tried to assess the impact of a different policy measure in presence of SAV service introduction—capping the vehicle population, which resulted in a 4% decrease in VMT. The regional policy driven results did not only focus on AV and SAV deployment, as Balac et al. [26] claim that carsharing is used three times more often provided one-way trips are allowed.

3.4.3. User Preferences. In terms of user preferences, reviewed studies most often focus on the modal shifts. Introduction of AVs and SAVs could have the largest impact on the change of modal preferences, with studies predicting that around 80% of public transport trips could be replaced by SAV [25, 38] and more than 60% by AVs [22]. Oh et al. [20] suggested a more conservative number claiming that 24.8% of public transport users and 75% of taxi users would opt for SAVs in the future. Basu et al. [24] second the claim stating that taxi users would benefit from lower cost of SAV services. Certain reviewed studies also point to the decrease in walking, claiming that 57% of walking trips could be replaced by SAVs [38]. Nevertheless, those results could vary according to the length of the trip, as some researchers predict that even with SAV services widely available, walking and cycling could be the preferred mode on short trips under 2 km [37]. The variety of the resulted impact on the user preferences is a result of various VOT, cost, and behavioural shift assumptions, with studies that assume lower monetary costs and higher VOT reduction, obtaining higher SAV market uptake.

It would seem that unrestricted introduction of SAV services could lead to a significant cannibalization of public transport. Nevertheless, reviewed studies also point at the reduction of private car usage with Chen and Kockelman [29] claiming that 90% of SAV trips were previously handled by private cars and Oh et al. [20] identifying that 20.2% SAV users previously chose their private cars. The difference could be caused by varied assumption of the cost of SAV used by Chen and Kockelman [29] which made the SAV trips more accessible to all income groups basing the price on agents' income with simultaneous decrease in VOT spent in the SAV. Moreover, SAVs do not necessarily have to replace the public transport services, but could rather complement them and serve as first and last mile support, as proven by Wen et al. [50] who found that SAVs with public transport connection could replace 43% of park and ride trips and 10% of car trips.

Introduction of AVs and SAVs will also highly impact the vehicle ownership preferences, with claims that younger and highly educated individuals living in urban areas are more inclined to own AV or use SAV services [39]. Moreover, if the current demand was not subject to changes, automation of vehicles could result in 9.5% decrease in ownership, as one vehicle could be shared by couple of household members with self-relocation. Besides, with 15 minutes permissible delay, the vehicle ownership declines even further (by 12.3%) [52].

The results also unravel the usage preferences for carsharing, suggesting that various types of carsharing are used for different purposes, free floating carsharing used more often by young users [42] and commuters and station-based carsharing used for leisure purposes [32]. Studies that predict modal shifts changes caused by carsharing indicate that 26%–30% of car users, 23% of bike users, 22%–32% of public transport users, and 17% of walking trips could switch to carsharing [32, 42]. Moreover, the results of analysis of Heilig et al. [36] prove that carsharing is used provided the optimization of fleet size and operation.

Dynamic ridesharing preference results prove that a rise in user trust could be a major enabler for the adoption of technology, as users prefer to rideshare with someone form their social network circle [48].

3.4.4. NMS Market Potential and Management. The studies that looked at the market potential of NMS focused on predicting the market penetration of SAV services. Depending on the assumptions on VOT implications, model of costs and fares used in the study, and fleet size, the results varied, estimating the SAV penetration anywhere from 5.8% to 43% [20, 29, 38, 41]. Moreover, results of Oh et al. [20] suggest that the achievable sharing rate of SAV rides could be significant with 65% of trips shared, which potentially could alleviate negative externalities of transport. The sharing rate, however, could be subject to location of SAV implementation with various preferences across the continents.

Moreover, a couple of reviewed studies looked at the fleet management and profitability. Wen et al. [50] have found that economy of scale relation between the fleet size and demand for the service. Nevertheless, Chen and Kockelman [29] who examined the relationship between the profitability for the fleet manager and the fare levels claim that it is more appealing to businesses to target the high income earners, whose VOT is more substantial and would be willing to pay more for the ability to multitask during the commute. The study also proved that zone-dependent fares could be a tool used for rebalancing of the fleet, minimising the empty rides and possibly limiting the urban sprawl.

3.4.5. Environmental Implications. Environmental implications of NMS introduction were not the major concern of the majority of the studies, as only two studies focused on AVs and two studies performed by fellows from the same research group focusing on dynamic ridesharing reported any environment related results. All those studies report a positive environmental effect of the innovation introduction and adoption, through CO2 emission reduction. Nevertheless, Coulombel et al. [33] claim that the reduction could be three times as high if not for the following behavioural implications of dynamic ridesharing introduction, while Wadud et al. [47] claim that a shift from privately owned, privately used vehicles to SAVs might decrease energy, vehicle travel, and emissions in several ways, either through more efficient driving and platooning or through pooling the rides in higher than 5 occupancy vehicles.

The extent to which substantial behaviour changes related to AV introduction will have on CO_2 emissions (so called rebound effect) has not yet been assessed according to the knowledge of the authors; however, in light of findings provided by Coulombel et al. [33] that indicate the rates of the rebound effect, such study needs to be conducted, as our hopes for achieving more sustainable transportation with AVs could be premature.

4. Conclusions and Further Research

This paper is a systematic review of studies that incorporated behaviour changes caused by deployment of new mobility services. The study summarised and categorised the behaviour changes caused by the introduction of NMS as well as reviewed a variety of applied modelling practices and assumptions from existing studies. Additionally, the paper provides an overview of results that the studies obtained, underlining the impact and importance of adequate behavioural modelling. The authors believe that this review will prove to be useful to the scientific community and transport modellers as an exhaustive and easy to navigate content repository and field summary.

The representation of behavioural shifts gains importance especially in light of arising long-lasting paradigm shift caused by COVID-19 pandemic we are currently experiencing. The pandemic could result in significant long-term travel behaviour changes, caused by a shift towards teleworking or avoidance of transit that requires contact with strangers. Nevertheless, as the consequences of the pandemic are yet to be determined, the travel behaviour changes caused by it are omitted in the paper, although they should not be recognized as irrelevant.

The analysis highlights that all NMS could alter behaviour by extending the offer of available transport modes, shifting the modal choices of individuals. Nevertheless, the ability to let go off the wheel in the AVs could be truly revolutionary. The autonomy means lower travel costs not only for private vehicles but also for ride-hailing services, as well as overall increase in road capacity, introduction of new parking strategies, ability to multitask in the vehicle, and potential harvest of users currently not able to drive a conventional vehicle. Innovations that lower travel costs—autonomous vehicles and dynamic ridesharing—have the highest potential impact on travel behaviour, encouraging users to participate in additional activities or to accept destinations further away either in the short or long term, possibly leading to relocation. Finally, NMSs that offer fully available vehicle replacement services such as carsharing or SAVs could also alter the vehicle ownership rates. For the purpose of this article, categorisation and summary of behaviour changes caused by deployment of NMS were made, and its summary is presented in Figure 2.

The analysed studies have mostly focused on assessing one of the considered NMSs, the majority of which investigated AVs either private or shared (with potential possibility to share a ride in some cases). Limiting the analysis to one innovation could bring insights into its impact on the urban area, and it does not however reflect the actual state of modern and future cities, where all innovations are mixed and available at the same time. To better represent the urban environment and provide a more realistic assessment, further research should include a variety of NMSs to choose from. Those could include privately owned AVs and SAVs with the opportunity to share a ride. Additionally, it is crucial to adequately represent privately owned and shared micromobility, which are gaining importance in urban areas which aim to limit private car dependency. Of the NMS considered in this paper, carsharing services could be omitted as the service could be replaced by SAVs in the future.

The behaviour changes linked to the deployment of NMS are often modelled as a fraction of followed demand estimation framework—TBM or ABM. However, ABMs are more widely used because of their disaggregation which allows to better represent individual preferences. The behaviour changes linked to AVs are most often implemented in scenario-based analysis that follows assumptions on future travel costs and decrease in VOT linked to the possibility to multitask in the vehicle. The said assumptions are changing the utilities of new options and therefore the behaviour of modelled subjects that seek utility maximisation. Nevertheless, the used utility functions that consist of assumed VOT and costs often omit important individual traits, lifestyle choices, and personal preferences which could heavily impact future decisions about NMS usage. Ideally, each step of the model (each discrete choice model) could consider socioeconomic attributes as well as user preferences to better mimic the individual, plausible human behaviour, contributing to a more adequate representation of the entire demand estimation.

This could be achieved by using data coming from stated preferences experiments that gather respondents' choices, socioeconomic information, and lifestyle traits, such as environmental concern and internal innovativeness of individuals, through specifically altered revealed preference questions. However, stated preference experiments often lead to biased results, especially when the choices are strictly hypothetical because the analysed services are not yet ready for implementation, and respondents do not have any experience with them. Alternatively, the studies that focus on NMS still in development and testing phases could harvest user data and feedback from living labs, in which users are able to experience and co-create the innovative solutions in realistic environments. Acknowledging the importance of testing the interaction between people and NMS, of involving citizens in the co-design of future cities and of providing innovation players with safe as well as defined environments to test their behavioural assumptions, living labs are currently flourishing in Europe. They therefore promise to play an important role in shaping the future of European cities [80]. Both qualitative and quantitative experimental data collected from living labs could indeed be used coupled with data analytic techniques, such as machine learning, to predict the demand to better represent individual preferences for innovation lowering the risk of unrealistic results.

The methodologies from outside the TBM and ABM focus on behavioural changes linked to deployment of AVs, which are often omitted in TBM and ABM framework—shifts in vehicle ownership, shifts in parking habits, and increased number of trips of mobility impaired. The proposed approaches use available data on vehicle ownership, parking costs, and travel gaps to predict the future behaviour. Nevertheless, those studies do not take into account remaining behaviour changes analysed in ABMs and TBMs that could heavily impact the results. Future studies could strive to implement those already proposed frameworks into an ABM to achieve a fully comprehensive study that would predict the results of NMS most realistically.

The remaining NMSs are also incorporated within the ABM and TBM framework. The implementation is often more adequate and concerns the impact of individual characteristics, as the researchers did not need to assume the costs of services which are already available and were more willing to use stated preference experiments with a known service. Nevertheless, the reviewed studies often decide to omit some of the behavioural changes, which could result in misleading results and misguide the policymakers in their decisions. In future studies, researchers could strive to represent all the identified behavioural changes caused by NMS to avoid the risk of omitting significant rebound effects caused by changing everyday mobility patterns.

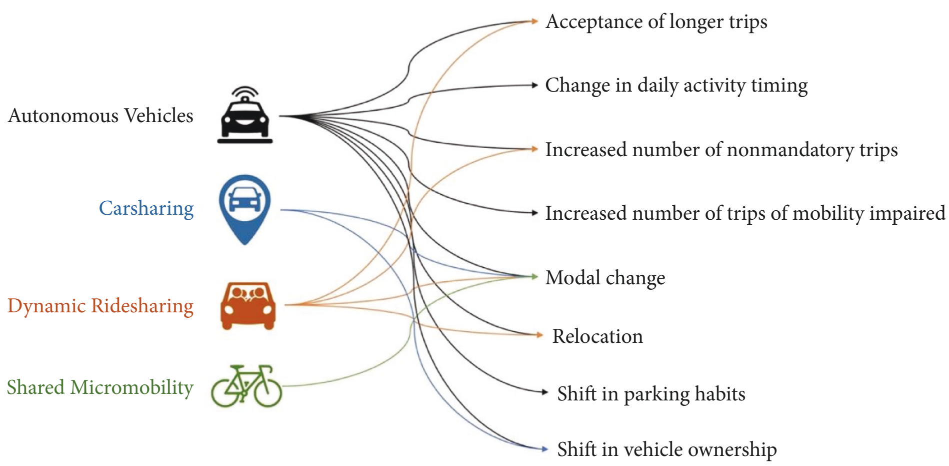

Figure 2: Summary of impact of NMS on travel behaviour.

Even though certain studies already start to implement scenario-based analysis of regional policies concerning parking and limiting the overall number of vehicles, much more could be done in the field. Further studies could consider simulating dedicated platooning lanes, super-blocks, car restricted zones, or tradable credit schemes used for mobility management. Provided sufficient data are available, the studies could be developed correspondingly for various countries or density areas (urban, rural, etc.) to assess the influence of regional, national, or geographical factors that also impact the demand for transport services. Comparison of scenarios of plausible policy developments in a given area would be of utmost importance to policymakers that often struggle to identify the effect of their policies in light of innovation deployment.

Finally, not many of the reviewed studies report results of environmental impact of NMS deployment, with only two studies focusing on the rebound effect of dynamic ride-sharing. Research conducted by Coulombel et al. [33] suggests that rebound effects caused by behavioural shifts could lower the benefits of innovation deployment to one third of its potential. In light of current environmental focus of numerous urban areas, there is an arising need of impact assessment of NMS deployment on transport environmental externalities such as energy consumption, CO2 emission, or air quality. Furthermore, an understanding of how each identified and studied behaviour change, caused by deployment of AVs and SAVs, contributes to environmental factors could be of utmost importance for regional and national policymakers aiming at achieving greener and more sustainable regions.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

Ada Garus was responsible for conceptualization, investigation, visualization, original draft preparation, and review and editing. Borja Alonso Oreña, María Alonso Raposo, Biagio Ciuffo, and Luigi dell'Olio were responsible for conceptualization, original draft preparation, and review and editing.

References

[1] World Bank, *Urban Population (% of Total Population)*, 2022, https://data.worldbank.org/topic/urban-development.

[2] The world city, *The World's Cities in 2018*, 2018, https://www.un.org/en/events/citiesday/assets/pdf/the_worlds_cities_in_2018_data_booklet.pdf.

[3] C. Antoniou, E. Chaniotakis, and D. Efthymiou, "Demand for Emerging Transportation Systems Modeling Adoption, Satisfaction, and Mobility Patterns Constantinos," in *Constantinos Antoniou, Emmanouil Chaniotakis, and Dimitrios Efthymiou*, Elsevier, 2019.

[4] Uber, *Company Information | Uber Newsroom*, 2018, https://www.uber.com/newsroom/company-info/.

[5] Electric Scooters, *Electric Scooters Market Size | E-Scooters Industry Report, 2030'*, 2020, https://www.grandviewresearch.com/industry-analysis/electric-scooters-market.

[6] S. Le Vine, Le Scott, and J. Polak, "The impact of free-floating carsharing on car ownership: early-stage findings from london," *Transport Policy*, vol. 75, no. March, pp. 119–127, 2019.

[7] Bike Share, *Bike Share | Cycling Industries Europe - the Voice of Cycling Businesses in Europe*, 2019, https://cyclingindustries.com/what-we-do/bike-share.

[8] A. Garus, B. Alonso, M. A. Raposo et al., "Last-mile delivery by automated droids. Sustainability assessment on a real-world case study," *Sustainable Cities and Society*, vol. 79, no. January, Article ID 103728, 2022.

[9] E. Blind Union, *Poland - Electric Scooters May Be Dangerous for the Visually Impaired*, 2019, http://www.euroblind.org/newsletter/2019/june/en/poland-electric-scooters-may-be-dangerous-visually-impaired.

[10] L. P. Kaelbling, M. L. Littman, and A. W Moore, "Reinforcement learning: a survey," *Journal of Artificial Intelligence Research*, vol. 4, no. January 2014, pp. 237–285, 1996.

[11] S. Radio, *'Sweden's Electric Scooter Surge Making the Visually Impaired Afraid to Go Out - Radio Sweden'*, 2019, https://sverigesradio.se/artikel/7279972.

[12] R. Cordera, Á. Ibeas, L. dell'Olio et al., "Models for simulating the transport system," in *Land Use–Transport Interaction Models*, pp. 155–175, CRC Press, 2019.

[13] J. de D. Ortúzar and L. G. Willumsen, "Modelling transport," *Modelling Transport*, 2011.

[14] The Second Strategic Highway Research Program, *Activity-Based Travel Demand Models A Primer*, 2015.

[15] Sae International, "Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles," *SAE International*, vol. 4970, no. 724, pp. 1–5, 2018.

[16] A. Soteropoulos, M. Berger, and F. Ciari, "Impacts of automated vehicles on travel behaviour and land use: an international review of modelling studies," *Transport Reviews*, vol. 39, no. 1, pp. 29–49, 2019.

[17] F. Becker and K. W. Axhausen, "Literature review on surveys investigating the acceptance of automated vehicles," *Transportation*, vol. 44, no. 6, pp. 1293–1306, 2017.

[18] C. Gkartzonikas and K. Gkritza, "What have we learned? A review of stated preference and choice studies on autonomous vehicles," *Transportation Research Part C: Emerging Technologies*, vol. 98, pp. 323–337, 2019.

[19] C. D. Harper, C. T. Hendrickson, S. Mangones, and C. Samaras, *Estimating Potential Increases in Travel with Autonomous Vehicles for the Non-driving, Elderly and People with Travel-Restrictive Medical Conditions*, 2016.

[20] S. Oh, R. Seshadri, C. L. Azevedo, N. Kumar, K. Basak, and M. Ben-Akiva, "Assessing the impacts of automated mobility-on-demand through agent-based simulation: a study of Singapore," *Transportation Research Part A: Policy and Practice*, vol. 138, no. August, pp. 367–388, 2020.

[21] T. A. Litman, *'Developing Indicators for Comprehensive and Sustainable Transport Planning'. Transportation Research Record*, www.vtpi.orgInfo@vtpi.org, 2017.

[22] M. W. Levin and S. D. Boyles, "Effects of autonomous vehicle ownership on trip, mode, and route choice," *Transportation Research Record*, vol. 2493, no. 1, pp. 29–38, 2015.

[23] B. Nahmias-Biran, B. Hen, B. Jimi, N. Kumar, C. Lima Azevedo, and M. Ben-Akiva, "Evaluating the impacts of shared automated mobility on-demand services: an activity-based accessibility approach," *Transportation*, vol. 48, no. 4, pp. 1613–1638, 2020.

[24] R. Basu, A. Araldo, A. P. Akkinepally et al., "Automated mobility-on-demand vs. Mass transit: a multi-modal activity-driven agent-based simulation approach," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2672, no. 8, pp. 608–618, 2018.

[25] C. L. Azevedo, C. Lima, S. Raveau et al., "Microsimulation of demand and supply of autonomous mobility on demand," *Transportation Research Record*, vol. 2564, no. 1, pp. 21–30, 2016.

[26] M. Balac, F. Ciari, and K. W. Axhausen, "Carsharing demand estimation: Zurich, Switzerland, area case study," *Transportation Research Record*, vol. 2563, no. 1, pp. 10–18, 2016.

[27] J. Bischoff, M. Maciejewski, T. Schlenther, and K. Nagel, "Autonomous vehicles and their impact on parking search," *IEEE Intelligent Transportation Systems Magazine*, vol. 11, no. 4, pp. 19–27, 2019.

[28] L. Caggiani, R. Camporeale, and M. Ottomanelli, "Planning and design of equitable free-floating bike-sharing systems implementing a road pricing strategy," *Journal of Advanced Transportation*, vol. 2017, pp. 3182387–18, 2017.

[29] T. D. Chen and K. M. Kockelman, "Management of a shared autonomous electric vehicle fleet: implications of pricing schemes," *Transportation Research Record*, vol. 2572, no. 1, pp. 37–46, 2016.

[30] Z. Chen, X. C. Liu, and R. Wei, "Agent-based approach to analyzing the effects of dynamic ridesharing in a multimodal network," *Computers, Environment and Urban Systems*, vol. 74, no. March, pp. 126–135, 2019.

[31] S. Childress, B. Nichols, B. Charlton, and S. Coe, "Using an activity-based model to explore the potential impacts of automated vehicles," *Transportation Research Record*, vol. 2493, no. 1, pp. 99–106, 2015.

[32] F. Ciari, B. Bock, and M. Balmer, "Modeling station-based and free-floating carsharing demand: test case study for Berlin," *Transportation Research Record*, vol. 2416, no. 1, pp. 37–47, 2014.

[33] N. Coulombel, V. Boutueil, L. Liu, V. Viguié, and B. Yin, "Substantial rebound effects in urban ridesharing: simulating travel decisions in Paris, France," *Transportation Research Part D: Transport and Environment 71*, pp. 110–126, 2019.

[34] F. F. Dias, G. S. Nair, N. Ruíz-Juri, C. R. Bhat, and A. Mirzaei, *'Incorporating Autonomous Vehicles in the Traditional Four-step Model'. Transportation Research Record*, Journal of the Transportation Research Board, June, Article ID 036119812092254, 2020.

[35] C. Hebenstreit and F. Martin, "A dynamic bike sharing module for agent-based transport simulation, within multimodal context," in *Procedia Computer Science*, vol. 130, pp. 65–72, Elsevier B.V, 2018.

[36] M. Heilig, N. Mallig, O. Schröder, M. Kagerbauer, and P. Vortisch, "Implementation of free-floating and station-based carsharing in an agent-based travel demand model," *Travel Behaviour and Society*, vol. 12, pp. 151–158, 2018.

[37] M. Heilig, Tim Hilgert, N. Mallig, M. Kagerbauer, and P. Vortisch, "Potentials of autonomous vehicles in a changing private transportation system - a case study in the stuttgart region," in *Transportation Research Procedia*, vol. 26, pp. 13–21, Elsevier B.V, 2017.

[38] S. Hörl, E. Alexander, and K. W. Axhausen, *Simulation of Autonomous Taxis in a Multi-Modal Traffic Scenario with Dynamic Demand*, 2016.

[39] P. S. Lavieri, V. M. Garikapati, C. R. Bhat et al. "Modeling individual preferences for ownership and sharing of autonomous vehicle technologies," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2665, pp. 1–10, 2017.

[40] J. Liu, K. M. Kockelman, M. Kockelman et al., "Tracking a system of shared autonomous vehicles across the austin, Texas network using agent-based simulation," *Transportation*, vol. 44, no. 6, pp. 1261–1278, 2017.

[41] L. M. Martinez and J. M. Viegas, "Assessing the impacts of deploying a shared self-driving urban mobility system: an agent-based model applied to the city of lisbon, Portugal," *International Journal of Transportation Science and Technology*, vol. 6, no. 1, pp. 13–27, 2017.

[42] L. M. Martínez, M. Mendes Lopes, G. H. Correia, F. Moura, and M. Mendes Lopes, "Insights into carsharing demand dynamics: outputs of an agent-based model application to lisbon, Portugal," *International Journal of Sustainable Transportation*, vol. 11, no. 2, pp. 148–159, 2017.

[43] A. Millard-Ball, "The autonomous vehicle parking problem," *Transport Policy*, vol. 75, no. March, pp. 99–108, 2019.

[44] C. Rodier, F. Alemi, and D. Smith, "Dynamic ridesharing: exploration of potential for reduction in vehicle miles traveled," *Transportation Research Record*, vol. 2542, no. 1, pp. 120–126, 2016.

[45] L. T. Truong, C. De Gruyter, G. Currie, and A. Delbosc, "Estimating the trip generation impacts of autonomous vehicles on car travel in victoria, Australia," *Transportation*, vol. 44, no. 6, pp. 1279–1292, 2017.
[46] G. Vyas, P. Famili, P. Vovsha et al., "Incorporating features of autonomous vehicles in activity-based travel demand model for columbus, OH," *Transportation*, vol. 46, no. 6, pp. 2081–2102, 2019.
[47] Z. Wadud, D. MacKenzie, and P. Leiby, "Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles," *Transportation Research Part A: Policy and Practice*, vol. 86, pp. 1–18, 2016.
[48] Y. Wang, S. Winter, and M. Tomko, "Collaborative activity-based ridesharing," *Journal of Transport Geography*, vol. 72, no. September, pp. 131–138, 2018.
[49] Y. Wang, R. Kutadinata, and S. Winter, "'Activity-Based ridesharing: increasing flexibility by time geography'. GIS," *Proceedings of the ACM International Symposium on Advances in Geographic Information Systems*, 2016.
[50] J. Wen, Yu X. Chen, N. Nassir, and J. Zhao, "Transit-oriented autonomous vehicle operation with integrated demand-supply interaction," *Transportation Research Part C: Emerging Technologies*, vol. 97, no. December, pp. 216–234, 2018.
[51] B. Yin, L. Liu, N. Coulombel, and V. Viguié, "Appraising the environmental benefits of ride-sharing: the Paris region case study," *Journal of Cleaner Production*, vol. 177, pp. 888–898, 2018.
[52] W. Zhang, S. Guhathakurta, and E. B. Khalil, "The impact of private autonomous vehicles on vehicle ownership and unoccupied VMT generation," *Transportation Research Part C: Emerging Technologies*, vol. 90, no. May, pp. 156–165, 2018.
[53] X. Zhang, W. Liu, and S. T. Waller, "A network traffic assignment model for autonomous vehicles with parking choices," *Computer-Aided Civil and Infrastructure Engineering*, vol. 34, no. 12, pp. 1100–1118, 2019.
[54] M. Maurer, B. Lenz, J. Christian Gerdes, and W. Hermann, "Autonomous driving technical, legal and social aspects," *IT - Information Technology*, vol. 57, 2015.
[55] N. Masoud and R. Jayakrishnan, "Autonomous or driver-less vehicles: implementation strategies and operational concerns," *Transportation Research Part E: Logistics and Transportation Review*, vol. 108, no. December, pp. 179–194, 2017.
[56] E. Papa and A. Ferreira, "Sustainable accessibility and the implementation of automated vehicles: identifying critical decisions," *Urban Science*, vol. 2, no. 1, p. 5, 2018.
[57] D. Stead and B. Vaddadi, "Automated vehicles and how they may affect urban form: a review of recent scenario studies," *Cities*, vol. 92, no. January, pp. 125–133, 2019.
[58] E. González-González, S. Nogués, and D. Stead, "Parking futures: preparing European cities for the advent of automated vehicles," *Land Use Policy*, vol. 91, no. May 2019, Article ID 104010, 2020.
[59] A. Alessandrini, A. Campagna, P. D. Site, F. Filippi, and L. Persia, "Automated vehicles and the rethinking of mobility and cities," *Transportation Research Procedia*, vol. 5, pp. 145–160, 2015.
[60] K. Münzel, W. Boon, K. Frenken, and T. Vaskelainen, "Carsharing business models in Germany: characteristics, success and future prospects," *Information Systems and e-Business Management*, vol. 16, no. 2, pp. 271–291, 2018.
[61] K. Kortum, R. Schönduwe, B. Stolte, and B. Bock, "Free-floating carsharing: city-specific growth rates and success factors," in *Transportation Research Procedia*, vol. 19, pp. 328–340, Elsevier B.V, 2016.
[62] H. Becker, F. Ciari, and K. W. Axhausen, "Comparing car-sharing schemes in Switzerland: user groups and usage patterns," *Transportation Research Part A: Policy and Practice*, vol. 97, pp. 17–29, 2017.
[63] S. Shaheen, E. Martin, and A. Bansal, "Peer-to-peer (P2P) carsharing: understanding early markets, social dynamics, and behavioral impacts," 2018.
[64] C. Costain, C. Ardron, and K. N. Habib, "Synopsis of users' behaviour of a carsharing Program: a case study in toronto," *Transportation Research Part A: Policy and Practice*, vol. 46, no. 3, pp. 421–434, 2012.
[65] F. F. Dias, P. S. Lavieri, S. Astroza, R. M. Pendyala, C. R. Bhat, and C. R. Bhat, "A behavioral choice model of the use of car-sharing and ride-sourcing services," *Transportation*, vol. 44, no. 6, pp. 1307–1323, 2017.
[66] A. Levofsky and G.. Allen, *ORGANIZED Dynamic Ride Sharing: The Potential Environmental Benefits and the Opportunity for Advancing*, 2001.
[67] Itdp, *The Electric Assist: FOR MORE LIVABLE CITIES the ELECTRIC ASSIST: People for Bikes*, 2019.
[68] D. Lo, C. Mintrom, K. Robinson, and T. Ryan, *Micromobility: The Influence of Regulation on Travel Mode Choice*, New Zealand Geographer, 2020.
[69] V. Kolarova, F. Steck, and F. J. Bahamonde-Birke, "Assessing the effect of autonomous driving on value of travel time savings: a comparison between current and future preferences," *Transportation Research Part A: Policy and Practice*, vol. 129, pp. 155–169, 2019.
[70] M. Harb, Yu Xiao, G. Circella, P. L. Mokhtarian, and J. L. Walker, "Projecting travelers into a world of self-driving vehicles: estimating travel behavior implications via a naturalistic experiment," *Transportation*, vol. 45, no. 6, pp. 1671–1685, 2018.
[71] D. Efthymiou, C. Antoniou, and P. Waddell, "Factors affecting the adoption of vehicle sharing systems by young drivers," *Transport Policy*, vol. 29, no. September, pp. 64–73, 2013.
[72] S. Shaheen, E. Martin, and A. Cohen, "Public bikesharing and modal shift behavior: a comparative study of early bikesharing systems in North America," *International Journal of Transportation*, vol. 1, no. 1, pp. 35–54, 2013.
[73] W. Gruel and J. M. Stanford, "Assessing the long-term effects of autonomous vehicles: a speculative approach," *Transportation Research Procedia*, vol. 13, pp. 18–29, 2016.
[74] J. Bischoff and M. Maciejewski, "Simulation of city-wide replacement of private cars with autonomous taxis in Berlin," in *Procedia Computer Science*, vol. 83, pp. 237–244, Elsevier B.V, 2016.
[75] Y. Jiang, J. Zhang, Y. Wang, and W. Wang, "Capturing ownership behavior of autonomous vehicles in Japan based on a stated preference survey and a mixed logit model with repeated choices," *International Journal of Sustainable Transportation*, vol. 13, no. 10, pp. 788–801, 2019.
[76] N. Menon, N. Barbour, Yu Zhang, A. R. Pinjari, and F. Mannering, "Shared autonomous vehicles and their potential impacts on household vehicle ownership: an exploratory empirical assessment," *International Journal of Sustainable Transportation*, vol. 13, no. 2, pp. 111–122, 2019.
[77] Eccad, *Expectations and Concerns of Connected and Automated Driving*, 2020.

[78] T. Litman, "Autonomous vehicle implementation predictions: implications for transport planning," *Transportation Research Board Annual Meeting*, vol. 42, no. 5 June 2020, pp. 1–39, 2020.

[79] F. Steck, V. Kolarova, F. Bahamonde-Birke, S. Trommer, and B. Lenz, "How autonomous driving may affect the value of travel time savings for commuting," *Transportation Research Record*, vol. 2672, no. 46, pp. 11–20, 2018.

[80] R. Alonso, Maria, A. Mourtzouchou et al., *JRC Future Mobility Solutions Living Lab (FMS-Lab): Conceptual Framework*, State of Play and Way Forward, 2021.