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Agent-based models for simulating e-scooter sharing services: A review and a qualitative assessment

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ABSTRACT

E-scooter sharing services have grown exponentially in many cities of the world within the last 10 years, mainly with the goal to serve first/last mile trips. Compared to other shared mobility modes (e.g., autonomous buses and electric taxis), for which Agent-based Models (ABMs) have been applied in many cases, just a few studies attempted to simulate e-scooter trips. This study aims to bridge the gap between ABMs and e-scooter sharing services by reviewing the existing ABMs and conducting a qualitative assessment. Initially, existing ABMs are described based on ten descriptors. To test suitability of each model for simulating e-scooter sharing services, we developed an evaluation checklist based on empirical findings. The ten criteria refer to the capabilities of each model to (a) adjust in new challenges via an open-source code, (b) model shared mobility modes, (c) perform large scale simulation, (d) describe spatiotemporal variation of demand, (e) simulate bicycle, (f) pedestrian, and (g) mixed traffic (h) consider socio-demographic characteristics, (i) integrate new choice models, and (j) model multimodal trips. Our results reveal the advantages and disadvantages of each model in simulating flexible transport modes and services. We end up with a dilemma or a scalability problem: to model e-scooter riding behavior in link level or e-scooter services in network level. It is concluded that the dual behavior of e-scooter users (pedestrian or vehicle) poses new challenges that can be met through the development of new extensions or hybrid simulation models.

1. Introduction

Micromobility refers to innovative mobility solutions, which contribute to the mitigation of transportation impacts related to car-dominance in urban areas (Oeschger et al., 2020). In the literature micromobility is defined as "*the use of micro-vehicles: vehicles with a mass of no more than 350 kg and a design speed of no higher than 45 km/h.*" (OECD/ITF, 2020).

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The main benefits of micromobility modes are flexibility, quick access from/to public transport terminals, energy efficiency, noise reduction, low demand for parking space and no exhaust pollution (Yanocha and Allan, 2019). According to the taxonomy of SAE International (2019), the main micromobility modes include powered bicycles (or e-bikes), standing scooters (or e-scooters), seated scooters, self-balancing boards (or hoverboards), non-self-balancing boards (or electric skateboards) and skates, while ITDP (2020) enriches the list by adding freight and transit micromobility modes, such as cargo bikes and rickshaws. Focusing on e-scooters, Gössling (2020) described them as equipped electric motors, that move at the same speeds as bicycles, and require about the same or less space for riding and parking. A more refined definition was provided by SAE International (2019): powered standing scooter is a wheeled vehicle that: *"a) has a center column with a handlebar, b) It is controlled by the operator using accelerator/throttle and brakes, c) It has a foot platform for the operator to stand on, d) It is powered partially or fully by a motor, e) It is manufactured primarily for transportation of one person [...], and f) is composed of two or three wheels*".

One of the main attributes of micromobility modes and especially e-scooters is flexibility; yet this attribute has caused noticeable issues in traffic safety and operations as it increases the number of already complex interactions between modes. According to Gössling (2020), e-scooters add extra complexity in an already complicated and dynamic system (i.e., the urban transport system) as they compete over space with pedestrians, cyclists and motorized vehicles. Tuncer et al. (2020) mention that it becomes a challenge to model e-scooters in street space due to their capability to switch from vehicles' roadway to pedestrians' sidewalk. The latter one differentiates e-scooters from e-bikes that rarely run on sidewalks.

Over the last years, e-scooter sharing services have grown exponentially in many cities around the world. In Europe, e-scooters are now considered as an innovative transport strategy to access dense city centers in more than 260 European cities (e.g., Paris, Berlin etc.)[1]. Shared mobility refers to *"the shared use of a vehicle, bicycle or other low-speed travel mode*" (Cohen and Shaheen, 2018). It may be also called "product-service system" as "*it gives access to an asset (an e-scooter) instead of* ownership" (Mount, 2002; Ruhrort, 2020). The majority of e-scooter sharing services are dockless, which means that users are able to rent an available e-scooter from anywhere and leave it within a pre-defined zone (Ruhrort, 2020). To operate effectively, they utilize mobile apps, routing and Global Position Systems (GPS). Recharging of e-scooters constitutes a major task, occasionally performed by freelance "juicers" or "chargers" who are responsible to locate e-scooter that need charging, pick them up and charging these vehicles at home and finally redistribute them at certain locations within the city (Masoud et al., 2019). Definitely, it results in a high-cost process that has a high impact on the financial viability of e-scooter sharing services.

The above issues create a complicated multi-scale problem which has not been addressed entirely when planning transportation systems due to the absence of specialized models to explore the impacts of these new services. Recent studies attempted to understand shared mobility systems and identify some interesting trends by exploring user preferences (Glenn et al., 2020; Sanders et al., 2020; Nikiforiadis et al., 2021), while others used spatial analysis techniques to examine trajectories coming from service operators (McKenzie, 2019; Caspi et al., 2020; Hosseinzadeh et al., 2021; Luo et al., 2021).

Few studies have modeled e-scooter travel patterns or simulated sharing service operations (Cao et al., 2021) as a solution to explore their contribution in sustainable mobility. The calibration of existing open-source microsimulation models, like Simulation of Urban Mobility – SUMO, is an interesting approach to estimate traffic operation impacts (e.g., capacity drop, traffic speeds, etc.) at link level (Christoforou et al., 2020). Yet, these models are not able to give a wider picture on the system impacts of last-mile transport services (e.g., modal shifts, vehicle kilometers, CO_2 emissions, etc.). According to Cohen and Shaheen (2018), these impacts can be grouped into four categories: a) travel behavior, b) environmental, c) land use and d) social effects. In the reviewed literature, Agent-based Models (ABMs) have been utilized simulate operations of shared autonomous vehicles (Bischoff and Maciejewski, 2016; Scheltes and de Almeida Correia, 2017; Bösch, 2018), demand-responsive buses (Bischoff et al., 2016), electric taxis (Bischoff and Maciejewski, 2014), car-pooling (Galland et al., 2014) and bike-sharing systems (Becker et al., 2020) in large-scale. The previously mentioned services as well as shared e-scooters are designed to respond immediately to demand needs that vary over space and time within day. Following a disaggregate approach, ABMs seem to be a unique solution to model demand and supply variations in large transport networks with fine level of detail and examine system impacts looking different perspectives.

In this context, the objective of this study is to assess available ABMs for simulating micromobility sharing services; towards this a methodological approach is built and a set of qualitative criteria are developed. This study contributes to transport modeling research, since it attempts to bridge the gap between ABMs and micromobility sharing services for the first time. Hence, it is first step towards the development of useful models for planning efficient and at the same time sustainable sharing services. The paper is structured as follows: the methodological approach is presented in section 2, and the ABMs are identified and described in section 3. The characteristics of micromobility modes and especially e-scooters with respect to travel behavior of users are explored in section 4, while the assessment based on a set of criteria is performed in section 5. In the last section, recommendations are provided based on the outcomes of the qualitative assessment.

2. Research method

The methodological approach of this study is based on an evaluation checklist. A checklist consists of a set of criteria (or requirements) that should be met by some of the potential problem solutions (Stufflebeam, 2000). Bueno et al. (2015) fol-

[1] New Urban Mobility Alliance (NUMO): Spotlight on Micromobility, website: https://www.numo.global/micromobility

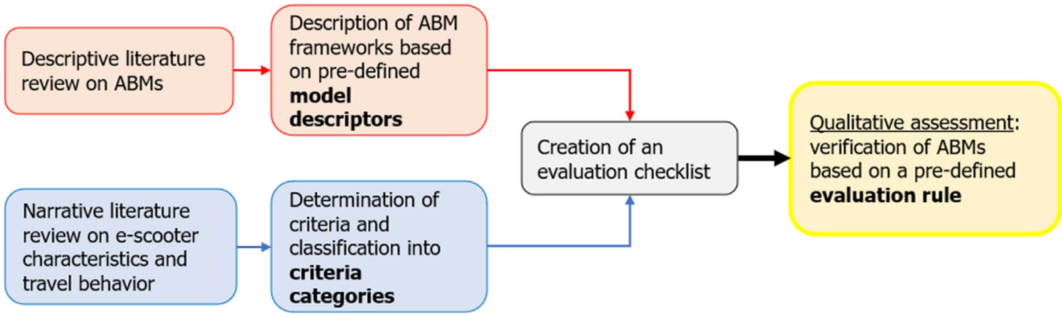

Fig. 1. Methodological flow chart.

lowed a similar methodological approach to discuss the potential of different appraisal methods (e.g., cost-benefit analysis, multicriteria decision making analysis, life-cycle analysis etc.) in the assessment of transport project sustainability. In this study, the potential problem solutions refer to ABMs or simulation models that have been already developed, while the criteria should be related to the challenges posed by e-scooter related services. The methodological framework of this study is presented in Fig. 1.

The first part of the literature review focuses on Agent Based Models that have been used in transport simulation, to define the candidate problem solutions. The study of Kagho et al. (2020) provides an overview of existing ABMs, while Li et al. (2021) reviewed ABMs that have been used to simulate on-demand and urban logistics services. This prior knowledge is utilized to identify the existing ABMs that will be considered in the evaluation. The consequent search strategy focused on identifying and recording the main characteristics and modules of each ABMs. According to Braubach et al. (2008), ABMs can be evaluated based on indicators, such as main functions/modules, usability, operating ability and pragmatics. Similarly, Rousset et al. (2016) proposed five criteria (or model descriptors), to evaluate ABM platforms, including, programming language, agent representation (i.e., as an object or a set of data), agent state, agent behavior, and agent identification algorithms. Synthesizing this information, we propose a set of ten descriptors which are used to present the ABM technical details as well as their capabilities in transport simulation, namely: 1) main developer (the institution or company that developed the model), 2) open-source (yes or no), 3) programming language (JAVA, C++, Python, etc.), 4) simulation scale (microscopic, mesoscopic or macroscopic), 5) traffic simulation method (cellular automata, physical simulation, queue-based etc.), 6) stochasticity in travel behavior (yes or no), 7) simulated traffic modes (cars, bicycles, etc.), 8) main outputs and 9) application cases (local, regional, etc.). At the same time, the level of simulation detail is assessed by considering the model visualization outputs. This initial evaluation of ABMs reveals their suitability of application in micromobility.

The second part of the literature review examines riding and travel behavior of micromobility users. This process does not aim to generalize previous findings but to provide a comprehensive background, so that well-defined criteria can be established (Davis et al., 2014; Paré and Kitsiou, 2017). Therefore, it is a narrative literature review limited to journal articles written in English from 2010 until today, which appear in the SCOPUS database. The total number of reviewed abstracts was 161. Considering the overall methodological framework, selected studies and then criteria can be arranged into three main categories covering multiple perspectives of the problem, namely: general capabilities, traffic simulation and travel behavior simulation. From traffic simulation perspective, empirical findings from five papers are reviewed to define relevant criteria. Speaking for travel behavior of e-scooter riders, this work utilizes survey results from ten studies and spatial analysis outputs from three studies. The criteria related to the general capabilities of a simulation model are set in the end; they are based on the general research questions and scientific recommendations posed in the reviewed studies.

A simple rule that an ABM meets a criterion, when there is at least one case study that performed the required task, is adopted for the purposes of the assessment. If so, the model is verified (i.e., ticked in the checklist), while the approach of each case study is described in text. Case studies can provide some hints in overcoming important challenges posed in the context of micromobility. In the last step, the outcomes of this assessment analysis are summarized.

3. Literature review

In order to better understand the capabilities of models ABM tools and how they can adapt to the distinct driving behavior of e-scouters, we critically analyze the published works with a two-fold aim; first, to provide a taxonomy of the existing ABM traffic simulation models, and, second, to reveal the main differences in travel behavior of micromobility users with respect to other modes of transport.

3.1. Agent-based models

Over the last decade, traffic operations in large urban areas and road networks have been simulated using ABMs (Kagho et al., 2020). These simulation models have been integrated in existed frameworks to simulate the impacts and the overall system performance of innovative transport modes, such as shared autonomous vehicles, electric taxis demand responsive buses, electric scooters, etc. (Li et al., 2021). Table 1 gives an overview of the investigated ABMs using ten descriptors.

The first agent-based model, which was used for traffic simulation in large-scale road networks and large population, in Portland, US (Simon et al., 1999; Jeihani et al., 2006) and Switzerland (Raney et al., 2003) was TRANSIMS (TRANSportation ANalysis and Simulation System) (Kagho et al., 2020). TRANSIMS can simulate trips of more than 30 million agents using high performance compute clusters with more than 180 TB disk space (Lee et al., 2014). It was developed by the Los Alamos National Laboratory of the US Department of Transportation. It is an open-source microscopic simulation model (developed in C++), which can be used for analytical modeling of travel behavior in metropolitan road networks. Since four-stage models were unable to capture demand and supply variations in space and time occurring within a day, this model aspired to overcome limitations. TRANSIMS model consists of four modules: 1) a population synthesizer, 2) an activity demand generator, 3) an intermodal route planner, and 4) a regional micro-simulator (Guo et al., 2013; Lee et al., 2014). TRANSIMS generates a synthetic population that consists of agents with specific socio-demographic attributes using census data, land uses and the road network. Next, the activity-demand generation function creates trip chains (i.e., activity locations, activity times and travel preferences) in a 24 h-time period for each agent based on a classification tree built from survey trip diary data (Guo et al., 2013; Lee et al., 2014). The intermodal route planner defines time-dependent shortest paths for each simulated trip and finally the regional micro-simulator estimates travel times and traffic delays following a Cellular Automata (CA) approach, in which road links are split into cells of uniform size of 7.5 m, which represent the size of one vehicle plus their required space gaps (Guo et al., 2013). TRANSIMS can provide rich output data consisting of vehicle trajectories, traffic flows in road links, average traffic speeds, vehicle kilometers etc.

NetLogo[2] is a user-friendly multi-agent programming language for building ABMs to simulate complex systems and describe multiparametric natural and social phenomena, such as traffic interactions (Tisue and Wilensky, 2004). It was developed in Northwestern University, USA, and it has been utilized for education and research objectives. NetLogo is an open-source simulation platform written in the JAVA programming language. Users are able to provide instructions to several agents using NetLogo (Han et al., 2015). Four types of agents exist: 1) patches that are stationary agents to describe the two-dimensional space, 2) turtles that are non-stationary agents with specific behavior, 3) links which are used in the description of relationships between agents, and 4) observers who control the agents by collecting data. In traffic simulation, vehicles belong to "turtles" as they are highly autonomous subjects. Their movements in the microscopic simulation environment are described by using acceleration/deceleration and lane changing models. To simulate traffic operations, vehicles' (e.g., speed, direction, ability of deceleration/acceleration etc.) and drivers' characteristics (e.g., intention, reaction time, accepted speed limitation etc.) are taken into account too (Han et al., 2015). Modelers can build traffic simulation models in Netlogo for multiple purposes by programming (i.e., setting rules) the previously mentioned agent types and utilizing its existing knowledge base, i.e., developed functions. A simple grid network can be designed by just choosing the cell (or block) size, while the demand is given by defining the number of simulated vehicles in the beginning of the simulation process (Hayatnagarkar and Murali Krishna, 2016). NetLogo outcomes include the number of stopped vehicles, average speed of vehicles and average wait time of vehicles (Jerry et al., 2015; Hayatnagarkar and Murali Krishna, 2016). Yet, there is a lack of scalability, which hinders the simulation of medium-sized networks using this tool (Auld et al., 2016).

MATSim[3] is an open-source simulation platform, which was developed in JAVA by the Swiss Federal Institute of Technology in Zürich (ETH Zurich) and the Technical University of Berlin (TU Berlin) (Axhausen et al., 2016). MATSim can simulate large and complex networks with numerous agents. MATSim is a mesoscopic simulation model; this contributes to the reduction of computational time when large urban road networks are simulated (Charypar, 2008; Charypar et al., 2009). It is based on a stochastic, co-evolutionary algorithm, which searches for an equilibrium point where the average score of agents' plans cannot further improve (Axhausen et al., 2016). In this simulation loop, there are three basic functions: a) execution of plans, b) scoring, and c) replanning. In the physical simulation (i.e., execution step), MATSim performs queue-based traffic simulation to calculate travel times per trip and consequently per plan; travel times are later imported in scoring functions. The scores are calculated based on a utility function. The utility of one plan is reduced when the activity duration decreases and when the travel time/cost rises (Nagel et al., 2016). In the next step, for a certain percentage of agents, MATSim generates new plans by changing the transport mode, trip route or activity time (Tzouras et al., 2021). At the end, the co-evolutionary algorithm chooses a plan based on predefined strategies, e.g., select the best plan or select a plan based on probabilities from a multinomial logit (MNL) model etc. The outputs of MATSim are modal split, total passenger hours and km per mode, average scores, distribution of trip arrival times and series of events that can be visualized using specialized software (Tzouras et al., 2021) or analyzed for multiple purposes, such as CO2 emmision (Novosel et al., 2015) or spreading of COVID-19 in Berlin[4]. Focusing on the computation efficiency, MATSim needs more than five hours to complete the simulation of the 10% of a metropolitan area population (e.g., Paris, Berlin etc.) (Horl et al., 2019) requiring at least 4 GB RAM and 200 GB free disk space (Rieser et al., 2014).

SimMobility[5] is an alternative solution to simulate more than one day. It is a multi-scale simulation platform that can model multiple interactions appearing in land-uses and transportation. It combines econometric activity-based models with a dynamic traffic assignment (Adnan et al., 2016; Kagho et al., 2020). This simulation platform was developed by the Future Urban Mobility

[2] NETLOGO website: http://ccl.northwestern.edu/netlogo/
[3] MATSim website: https://www.matsim.org/
[4] MATSim Episim: https://github.com/matsim-org/matsim-episim-libs
[5] Mobility Future Collaborative, SimMobility website: https://mfc.mit.edu/simmobility

Table 1
Summary of ABMs.

	TRANSIMS	NetLogo	MATSim	SimMobility	Anylogic	POLARIS	SARL
Developed by:	Los Alamos National Laboratory	Northwestern, University	ETH Zurich και TU Berlin	Singapore-MIT Alliance for Research and Technology	Anylogic Company	Argonne National Laboratory	University of Technology of Belfort
Open-source software	yes	yes	yes	yes	no	yes	yes
Programming language	C++	JAVA	JAVA	C++	JAVA	C++	JAVA
Simulation Scale	microscopic	microscopic	mesoscopic	microscopic	microscopic	mesoscopic	microscopic
Traffic simulation method	cellular automata simulation	physical microsimulation	queue-based simulation	physical microsimulation	physical microsimulation (discrete - event modeling)	queue-based simulation	physical microsimulation
Stochasticity in travel behavior	yes	rule-based model	yes	yes	rule-based model	yes	yes
Simulated traffic modes	private cars and transit services	vehicles (e.g., hybrid or electric cars)	private cars, public transport, (electric) taxis and shared mobility services, etc.	private cars, public transport and shared mobility services etc.	private cars, buses, trains, taxis, two-wheelers, cargo bikes, etc.	private cars, public transport and shared autonomous vehicles	private cars, car-pooling services and active modes
Main outputs	vehicle trajectories, traffic flows in road links, average traffic speeds, veh-km etc.	number of stopped vehicles, vehicle speed, average wait time, etc.	modal split, total passenger hours and kilometers per mode, average scores, and series of events, etc.	travel patterns, changes in land-uses, accessibility, vehicle ownership and traffic flows	level of service, travel delays, traffic density, average traffic speeds	travel delays, average speeds per link, traffic flows in links etc.	travel times per agent, traffic loads per link etc.
Application cases	Portland, USA; Switzerland	Luxembourg; Lorraine, France	Zurich, Switzerland, etc.	Singapore	Delft, the Netherlands;	Chicago, USA; Detroit, USA	Flanders, Belgium
Visualization outputs	https://www.youtube.com/watch?v=tR6mXsRh99g&t=2s&ab_channel=ArgonneTRACC	https://www.youtube.com/watch?v=knP7JHR097Q&ab_channel=CamiloTopali	https://www.youtube.com/watch?v=rWTFg1UkZTc&ab_channel=MichaelBalmer	https://www.youtube.com/watch?v=zNyYKlPA5RE&t=397s&ab_channel=TRBVIS,	https://www.youtube.com/watch?v=EHP47tM6ctc&t=913s&ab_channel=AnyLogic,	https://www.youtube.com/watch?v=zjqbLChd5L8&t=182s&ab_channel=ArgonneTRACC,	Buisson et al. (2019)

Research Group of Singapore-MIT Alliance for Research and Technology; it is an open-source simulation model fully implemented in C++ (Azevedo et al., 2017). Therefore, one of the main advantages of SimMobility is its ability to merge different models within the same model framework (Li et al., 2021). Its framework comprises three modules: a) the short-term simulator (within day) which trips are simulated microscopically, b) the mid-term simulator that exports the travelers' behavior and the general mobility patterns, and c) the long-term simulator which predicts the accessibility and the resulting changes in land-uses utilizing econometric models (i.e., housing market models, job location choice model and household vehicle ownership model) (Meng et al., 2019). In the first module, the traffic simulation is performed via an open-source microscopic traffic simulation (MITSIM), which models driving behavior (i.e., car-following, lane changing models, etc.) considering drivers' characteristics (e.g. reaction time) and intersections based on the traffic conflicts technique (i.e., conflict detection and collision avoidance models, etc.) (Azevedo et al., 2017). Compared to other simulation platforms, SimMobility is able to simulate pedestrian crossings movement and freight vehicles (Sakai et al., 2020). In the mid-term, travel decisions (i.e., departure time, mode and route choice) are made based on a sequential application of hierarchical choice models applying a Monte-Carlo simulation approach (Adnan et al., 2016). Travel patterns, changes in land-uses, accessibility, vehicle ownership and data about traffic flows in road links are some of the outputs of SimMobility. The computational time of SimMobility that is required to simulate a large-scale scenario (e.g., Singapore) of around 5.2 million agents exceeds 28 h using a powerful workstation with 32 cores and 125 GB RAM (Oh et al., 2020).

Anylogic[6] is a commercial simulation platform that has been developed by AnyLogic Company in the JAVA programming language, which can perform microscopic agent-based simulation with high level of detail. It uses discrete-event modeling to simulate dynamic systems, such the traffic road network of a city[7]. Each vehicle represents an agent. In Anylogic, agents' behavior is programmed through a set of rules (rule-based model) that are imported by a flowchart (Borshchev, 2014). Anylogic has its own library of predefined algorithms – models, which simulate driving behavior by performing a physical microsimulation. The outputs of Anylogic simulation refer to aggregate results on network performance (e.g., level of service, travel delays, traffic density, average traffic speeds).

The Planning and Operations Language for Agent-Based Regional Integral Simulation[8] (POLARIS) developed by the Transportation Research and Analysis Computing Center of the Argonne National Laboratory in C++ programming language. It is an open-source model and capable of simulating the population of an entire metropolitan area (e.g., Chicago or Detroit US) in a relatively short computational time (Kagho et al., 2020) through a simulation-oriented memory allocator: the Thread-Caching Malloc (TCMalloc) and a parallel discrete event engine (Auld et al., 2016). POLARIS can simulate 27 million trips in Chicago Metropolitan area in 1.2 hours using two eight core-processors and 64 GB RAM (Auld et al., 2016). POLARIS is a mesoscopic transport simulator (Li et al., 2021) with considerably high level of flexibility, as it allows the introduction of various models – extensions through a system called plug-n-play. The methodological framework of POLARIS consists of two basic components: a) an ABM that completely focuses on the transport network system, and b) a software development kit which facilitate the creation of different simulation scenarios (Auld et al., 2016). It also includes a dynamic activity-based model (i.e. Agent-based Dynamic Activity Planning and Travel Scheduling or ADAPTS) to perform activity planning, scheduling and execution of resulting trips. Therefore, demand generation is not a separate process from traffic simulation in the POLARIS framework (Auld and Mohammadian, 2009). The traffic simulation utilizes Newell's Simplified Kinematic Wave Traffic Flow model to represent traffic flow in road links (Gurumurthy et al., 2020). In essence, it is a queue-based traffic simulation model following a similar approach to MATsim; yet in POLARIS scenarios, Intelligent Transport System (ITS) Infrastructure and traffic management strategies can be introduced. The mode choice is performed by utilizing stochastic modelling (e.g., nested logit), while the user equilibrium traffic assignment model is applied for vehicle routing (Auld et al., 2016). As the other ABMs, POLARIS provide rich disaggregate data, which can be aggregated and statistically analyzed via POLARIS Analyzer. Some of the major outputs are travel delays, average speeds per link, traffic flows in links etc.

Janus[9] is an open-source simulation platform that is fully implemented in SARL, (i.e., a new agent programming language developed in the University of Technology in Belfort, France). For traffic simulation, Janus uses the JaSim library (Galland et al., 2014), which is a physical microsimulation model, capable to simulate the movement of various agents (e.g. pedestrians, cars, bikes, etc.) following the approach "Influence – Reaction". JaSim library consists of various collision-avoidance function that resolves conflicts based also on the perceived safety (i.e., the feeling of safety each synthetic road user). The level of detail is high, allowing the visualization of interactions in a 3D simulation environment. The simulation of travel behavior is performed by using a typical multinomial logistic model that considers the personal characteristics of each individual. The main outputs are travel times per agent, traffic loads per link etc.

3.2. E-scooters, travel behavior and characteristics

E-scooters comprise an innovative mobility solution, that is used as an alternative way to move and access dense urban areas with heavy traffic following a "dual behavior", which sometimes is unsafe (Tuncer et al., 2020). The mean speed of e-scooters varies from 7.9 to 10.0 km/h, while the mean speed of e-bikes exceeds 10.8 km/h in urban areas (Almannaa et al.,

[6] Anylogic discrete event modeling:https://www.anylogic.com/use-of-simulation/discrete-event-simulation/
[7] Anylogic Road Traffic Simulation Software: https://www.anylogic.com/road-traffic/
[8] POLARIS Transportation System Simulation Tool:https://www.anl.gov/es/polaris-transportation-system-simulation-tool
[9] JANUS project website: http://www.sarl.io/runtime/janus/

2021). A spatial analysis of e-scooter trips in Austin, US showed that e-scooter speed increased by 8–9% in cycle lanes and by 5–7% in traffic lanes compared to sidewalks (Zuniga-Garcia et al., 2021). The mean speed of e-scooters on sidewalks was measured to be equal to 5 km/hour, which approximates walking speeds. E-scooter users may make detours in order to follow bikeways, multi-use paths and one-way roads (Zhang et al., 2021). Therefore, travel distance does not seem to be a critical parameter in route selection, unlike other transport modes. On the other hand, perceived comfort and safety is considerably more significant, since e-scooter users experience the lowest comfort level compared to other micromobility modes (Bai et al., 2017). An explanation is that e-scooter users experience higher road vibrations, due to their smaller wheel diameter (Ma et al., 2021). On sidewalks, the frequency of vibrations increases, but this does not impact the driving speed of e-scooters. The low speed of pedestrians plus the complicated interactions occurring on sidewalks lower e-scooters' travel speed. Based on the above, in terms of riding behavior, e-scooters could be classified somewhere between bicycles and walking. Therefore, traffic simulation models, which are already able to simulate bicycle, pedestrian or mixed traffic (see criterion 5, 6 and 7 in Table 2) with fine level of detail, can be adjusted to include e-scooters.

Looking at the characteristics of e-scooter sharing services, Nikiforiadis et al. (2021) reported that elders and low-income travelers are not willing to use them. E-scooters are mainly preferred by males aged between 18 and 54 years old, who do not own a bicycle or a motorcycle and live near city centers. According to Aman et al. (2021), 71% of daily users of e-scooter sharing services are male; yet females seem to be more satisfied by these services. Christoforou et al. (2020) confirmed these findings; e-scooter daily riders are young people (<30 years old) with middle or relatively high income, who feel safe to ride. Environmental values and awareness-knowledge in using flexible transport services are additional parameters that differ among social groups and influence the willingness to use e-scooters (Eccarius and Lu, 2020). Therefore, socio-demographic characteristics should be considered when simulating mode choices, especially for covering first/last mile transportation needs (see criterion 8).

Compared to other transport modes, a considerably high share of e-scooter users ride them "for fun" according to the study of Glenn et al. (2020). This finding is also confirmed by Sanders et al. (2020); their survey results showed that e-scooters are used for entrainment by the 42% of the sample. In addition, several studies, which analyzed spatially e-scooter trips, have observed that the main destination of e-scooter trips are commercial and recreational areas, while the share of e-scooter trips compared to the total ones increased in the weekends (Bakogiannis et al., 2019; McKenzie, 2019; Caspi et al., 2020). Especially the study of McKenzie (2019) has drawn the conclusion that bike-sharing services are more commonly used for travelling to/from work in Washington DC, while shared e-scooters are not. The previous findings underline the significant differences appearing in travel behavior of e-scooter daily users compared to other active modes. There is a need to integrate new choice models in existing simulation models to describe this new travel behavior (see criterion 9).

E-scooters as a first/last-mile transport solution target to the quick transition to/from public transport stations or hubs. However, the spatial analysis on e-scooter trip patterns in Indianapolis, USA performed by Luo et al. (2021) showed that very few e-scooter trips serve the first/last mile connection to bus stops. E-scooters mainly substitute walking trips in areas with low bus coverage, while at same time they compete with bus services in downtown areas. Based on a stated preferences experiment in Singapore Central Area, Cao et al (2021) proved that high level of transit indirectness, high number of transfers and long access/egress walking distance to/from public transport station increases the probability of using shared e-scooters. To maximize service revenues, shared e-scooters should be located either at points far from any transit station or around them. Therefore, e-scooter sharing services should be considered as a major part of a multimodal transport system consisting

Table 2
Development of criteria list.

Category	Criterion	Description	In short
General capabilities	1	The ABM is open source and allows the development - integration of multiple extensions related to e-scooter sharing services	Open-source code
General capabilities	2	The ABM has been utilized by previous studies to simulate shared mobility services (e.g., shared autonomous vehicles, on-demand transport, bike-sharing etc.) and explore their impacts.	Shared mobility simulation
General capabilities	3	The ABM has been used to simulate large-scale transport networks, i.e., a city or a metropolitan area.	Large-scale transport networks
General capabilities	4	The ABM is capable to describe with fine level of detail the spatiotemporal variations of travel demand.	Spatiotemporal demand variations
Traffic simulation	5	The ABM has been used to simulate bicycle traffic in cycle lanes	Bicycle traffic simulation
Traffic simulation	6	The ABM has been used to simulate pedestrian traffic on sidewalks	Pedestrian traffic simulation
Traffic simulation	7	The ABM has been used to simulate mixed traffic operations in traffic lanes or urban roads.	Mixed traffic simulation
Travel behavior simulation	8	The ABM allows the introduction of new discrete choice models, which describe the willingness of travelers to use new transport modes, e.g., e-scooters.	Socio-demographic characteristics
Travel behavior simulation	9	The ABM takes into account socio-demographic characteristics of agents to model travelers' behavior	New discrete choice models
Travel behavior simulation	10	Multimodal trips can be simulated using the methodological framework of this ABM	Multimodal trips simulation

of complex interactions among urban transport modes. As such, ABM aiming to predict the impact of first/last mile solutions (e.g., e-scooter sharing services) should be able to simulate multimodal trips (see criterion 10).

The necessity to develop and integrate multiple extensions to model e-scooter sharing services operations force us to search mainly for open-source simulation platforms which are adjustable to new transport modes and innovative services (see criterion 1). As it has been mentioned, shared e-scooters that appear in cities nowadays belong to the wide spectrum of shared mobility; thus, ABMs that has already been applied to simulate shared mobility operations (e.g., shared autonomous vehicles, on-demand transport, bike-sharing) and explore their impacts seem to be more adjustable to e-scooter case (see criterion 2). In conclusion, the spatiotemporal variations of demand must be predicted with a fine level detail, since they comprise a catalytic parameter which influences the financial sustainability of e-scooter sharing services (see criterion 3 and 4).

4. Assessment and discussion

The evaluation of the general capabilities of each model is presented in Table 3. As can be observed, most of the discussed ABMs are open source; their programming codes are accessible on-line. Anylogic is the only commercial of the examined ABMs, which has been used to simulate and assess the impacts of shared mobility (Scheltes and de Almeida Correia, 2017) and flexible freight transport modes, such as cargo bikes (Salah et al., 2021). Modelers can describe operations of flexible services like on-demand transport by constructing a flow-diagram in a user-friendly simulation environment instead of writing code scripts. Shared mobility services have been simulated using 6 out 7 of the discussed ABMs. The simulation of shared autonomous vehicles has been already performed in MATSim (Bischoff and Maciejewski, 2016; Bösch, 2018), SimMobility (Meng et al., 2020), POLARIS (Gurumurthy et al., 2020), while in JANUS, car-pooling operations have been modelled by Galland et al. (2014). Inturri et al. (2019) followed an alternative approach to plan and design Demand Responsive Shared Transport services in Ragusa Italy, as it utilized a NetLogo GIS Extension. According to Li et al. (2021), MATSim simulation platform has been selected in the 46% of the research studies, which dealt with shared autonomous vehicles and urban logistics.

Large-scale transport networks such as Zurich (Becker et al., 2020) or Berlin (Ziemke et al., 2019a) have been simulated using MATSim, while SimMobility, TRANSIMS and POLARIS has been applied in the metropolitan areas of Singapore (Azevedo et al., 2017), Portland USA (Simon et al., 1999; Jeihani et al., 2006; Lee et al., 2014) and Chicago, USA (Auld et al., 2016), respectively. NetLogo has been used to model traffic operations in Luxembourg (Querini and Benetto, 2014), while JANUS used disaggregate trip demand data from FEATHERS describing the travel demand of the entire Flanders area in Belgium (Galland et al., 2014). The spatiotemporal variations of demand are pre-estimated using activity-based models that are either outside of the simulation loop or integrated within it (e.g., POLARIS, TRANSIMS and SimMobility). The last ABMs are of a multi-scale naturing, allowing impact estimation both in the short and long-term (Adnan et al., 2016; Auld et al., 2016). In Anylogic, travel demand is usually described via an aggregate OD matrix and a trip time distribution (Scheltes and de Almeida Correia, 2017), while in Netlogo, the user only provides the number of simulated vehicles.

Table 4 summarizes the findings of the qualitative assessment of ABMs based on traffic simulation criteria. A large-scale traffic simulation of active modes or micromobility modes using an ABM is still a challenge to overcome for 4 out of 7 ABMs. In MATSim, the interactions between bicycles and motorized traffic have been modeled in the study of Ziemke et al. (2019b), while Agarwal et al. (2020) estimated the impacts of bicycle superhighways using this ABM. Based on the Netlogo simulation platform, an agent-based bicycle traffic model has been developed in Salzburg too (Wallentin and Loidl, 2015). In the SARL platform, Buisson et al. (2013) modeled bicycles and pedestrian movements by developing collision-avoidance mechanisms. The short-term module of SimMobility simulated pedestrians' microscopic movements in simplified way; pedestrian follow a constant speed, while a crossing module controls the pedestrian crosses (Azevedo et al., 2017). Anylogic is capable of modeling pedestrian traffic simulation; for example, Xi and Son (2012) applied a two-level modeling framework to simulate walking behavior in Chigago, USA. NetLogo simulation platform has been used for microscopic modeling of pedestrian movements in crowded road environments, i.e., market streets in Taiwan (Chiou and Bayer, 2021). As for mixed traffic conditions, 3 out of 7 ABMs have been upgraded, so that such conditions can be efficiently simulated. Indeed, Agarwal and Lämmel (2016) improved the queue-based traffic simulation model of MATSim to model seepage behavior, which refers to the condition when smaller vehicles (bikes, e-scooters, etc.) seeps across the available "small" gaps. Sakai et al. (2020) considered interactions between passenger and freight traffic to develop an urban freight simulator using SimMobility. Zhao et al. (2020) verified empirical impedance functions by performing mixed traffic simulations in Anylogic.

Regarding the travel behavior related criteria (see Table 5), multi-scale ABMs, such as TRANSIMS, SimMobility and POLARIS, take into account socio-demographic characteristics of travelers to predict travel behavior in the mid or long-term; trips chains are constructed and preferable transport modes are determined per agent (Lee et al., 2010; Auld et al., 2016; Meng et al., 2019). In addition, these simulation platforms allow the introduction of new discrete choice models to model shifts in travel behavior. For example, Lee et al. (2010) assessed pricing schemes of high occupancy lanes by importing new choice models in TRANSIMS, while Adnan et al. (2016) used SimMobility and choice models to examine the changes in travel behavior because of public transport pricing changes. The introduction of discrete choice models in MATSim is still a point for further research, since MATSim is based on a co-evolutionary algorithm which seeks system equilibrium points (Tzouras et al., 2021). Hörl et al. (2018) have attempted to relax this heavily random process by developing algorithms to bridge the gap between MATSim and behavioral models. These models can consider socio-demographic characteristics, that each synthetic traveler has, to predict mode or route choices only in the short-term (within day) (Hörl and Balac, 2021). Fur-

Table 3
Qualitative assessment of ABMs – General Capabilities.

	TRANSIMS	NetLogo	MATSim	SimMobility	Anylogic	POLARIS	SARL
Criterion 1: Open-source code	✔ https://code.google.com/archive/p/transims/	✔ https://github.com/NetLogo/NetLogo	✔ https://github.com/matsim-org/matsim-code-examples	✔ https://github.com/smart-fm/simmobility-prod		✔ https://github.com/anl-polaris/anl-polaris.github.io	✔ https://github.com/janus-project/janus-project.github.io
Criterion 2: Shared mobility simulation		✔ e.g. demand responsive shared transport (Inturri et al., 2019)	✔ e.g. ride-hailing services (Bischoff et al., 2018) shared autonomous vehicles (Bischoff and Maciejewski, 2016; Bösch, 2018)	✔ e.g. automated mobility on demand (Meng et al., 2019)	✔ e.g. automated last-mile transport in Delft, the Netherlands (Scheltes and de Almeida Correia, 2017), shared cargo-bikes (Salah et al., 2021)	✔ e.g. shared autonomous vehicles (Gurumurthy et al., 2020)	✔ e.g. car-pooling (Galland et al., 2014)
Criterion 3: Large-scale transport networks	✔ e.g. Portland, USA (Simon et al., 1999; Jeihani et al., 2006; Lee et al., 2014)	✔ e.g. Luxembrourg and Lorraine, France (Querini and Benetto, 2014)	✔ e.g, Berlin, Germany (Ziemke, Kaddoura, *et al.*, 2019), Zurich, Germany (Becker et al., 2020) etc.	✔ e.g. Singapore (Azevedo et al., 2017; Meng et al., 2019)		✔ e.g. Chigago, USA (Auld et al., 2016; Gurumurthy et al., 2020)	✔ e.g. Flanders, Belgium (Galland et al., 2014)
Criterion 4: Spatiotemporal variations of demand	✔ it can simulate travel behavior of each agent in a 24-hour period (Lee et al., 2014)		✔ by combining activity-based models with MATSim, e.g.: mobiTopp (Briem et al., 2019), UrbanSim (Zhuge et al., 2019) or equasim pipeline (Hörl and Balac, 2021)	✔ it is a multi-scale simulation model; it can describe demand in the short-term, mid-term and long-term (Adnan et al., 2016)		✔ activity-based demand model is one of the basic components of POLARIS (Auld et al., 2016)	✔ by integrating activity-based models, e.g. FEATHERS (Galland et al., 2014)

Table 4
Qualitative assessment of ABMs –Traffic Simulation Criteria.

	TRANSIMS	NetLogo	MATSim	SimMobility	Anylogic	POLARIS	SARL
Criterion 5: Bicycle traffic simulation		✓ Wallentin and Loidl (2015) developed an agent-based bicycle traffic model for Salzburg City	✓ Ziemke et al. (2019) modelled interactions between bicycles and motorized traffic; Agarwal et al. (2020) estimated the impacts bicycle superhighways				✓ Buisson et al. (2013) developed collision avoidance mechanisms to simulate pedestrian and bicycle traffic.
Criterion 6. Pedestrian traffic simulation		✓ Netlogo platfom has been used for microscopic modeling of pedestrian movements in a market street (Chiou and Bayer, 2021)		✓ SimMobility can model pedestrian crossings (Azevedo et al., 2017).	✓ Xi and Son (2012) developed an pedestrian simulation model		✓ Buisson et al. (2013) developed collision avoidance mechanisms to simulate pedestrian and bicycle traffic.
Criterion 7: Mixed traffic simulation			✓ the study of Agarwal and Lämmel (2016) modelled seepage behavior of smaller vehicles in mixed-traffic conditions	✓ the study of Sakai et al. (2020) modelled interactions between passenger and freight traffic	✓ the study of Zhao et al. (2020) utilized it to verify an improved impedance function for road with mixed traffic		

Table 5
Qualitative assessment of ABMs –Travel Behavior Simulation Criteria.

	TRANSIMS	NetLogo	MATSim	SimMobility	Anylogic	POLARIS	SARL
Criterion 8: Socio-demographic characteristics	✓ Lee et al. (2014) considered socio-demographic characteristics of synthetic travellers, e.g. gender, age, etc to simulate travel behavior		✓ sociodemographic attributes per synthetic traveler can be imported in MATSim (Hörl and Balac, 2021)	✓ socio-demographic characteristics are considered to predict long-term mobility choices (Meng et al., 2019)		✓ travelers characteristics are the main inputs in route - mode choice process (Auld et al., 2016)	✓ user characteristics are used to match car-pooling trips and negotiotion activity (Galland et al., 2014)
Criterion 9: New discrete choice models	✓ Lee et al. (2014) implemented new choice models related to value pricing of high occupancy toll lanes		✓ extensions to implement discrete choice models in MATSim have been developed (Hörl et al., 2018)	✓ Adnan et al. (2016) calibrated choice models to examine the impacts of time-based pricing strategies in public transport		✓ POLARIS is based on mode and route choice models (Auld et al., 2016)	
Criterion 10: Multimodal trips			✓ multimodal trips are simulated in MATSim Open-Berlin Scenario (Ziemke, Kaddoura, *et al.*, 2019)	✓ Azevedo et al. (2016) simulated trips that contained transfers from private vehicle to on-demand autonomous vehicles.			

thermore, multinomial logit model have been introduced in agent-based modeling using SARL-Janus to match car-pooling trips and in negations among users (Galland et al., 2014). Finally, MATSim and SimMobility are able to simulate multimodal trips. Indeed, a scenario developed by Azevedo et al. (2016) in Singapore contained transfers from private vehicles to shared autonomous ones, while the MATSim Open-Berlin Scenario considers plans that combine walking with public transport modes. (Ziemke et al., 2019a).

Overall, SimMobility and MATsim meet 9 out of 10 criteria, respectively. SimMobility is able to perform multi-scale simulations, which is the main advantage of this model. Yet, MATSim have been used in a plethora of cases by upgrading simulation functions. NetLogo and Anylogic meet 6 and 5 criteria respectively. They provide user-friendly interfaces to model complicated interactions occurring in the link level; yet at network level their capabilities seem limited. There are no studies that attempted to model active modes using TRANSIMS or POLARIS. Finally, the Janus have been used to model car-pooling service operations and so far, this methodological framework has not been adjusted to other type of services.

A limitation of the present assessment is that it did not consider hybrid forms of simulation, by combining two or more simulation models with different scale (Lämmel et al., 2016). Taking into account the limitations of the examined ABMs, a hybrid model would yield interesting solutions, as it will give the chance to explore the impacts of e-scooter sharing services both in network and link level.

5. Conclusions

This study evaluated the suitability of existing ABMs to simulate e-scooters sharing services, using proper criteria set in an evaluation checklist. It was realized that the dual and unsafe riding behavior of e-scooter users, the unwillingness of some socio-demographic groups to use e-scooters due to traffic safety issues and operational challenges of shared mobility services create a complicated simulation environment. As e-scooters may become an integral part of future urban transport systems, the utilization of ABMs to simulate this reality and estimate system impacts is more than ever necessary.

Most of the examined ABM can describe in detail the spatiotemporal variations of demand in an urban area, which comprise a determinant factor for the design of economic sustainable e-scooter sharing services. However, the level of detail differs among examined ABMs. Multi-scale ABMs like SimMobility and POLARIS can predict the spatial changes in demand both in the short (within day) and long term (in 10 years); but as it was noted, these have not been used in modeling bicycle or pedestrian traffic in link level. On the contrary, models that execute physical microsimulation like Anylogic include already in their libraries functions that can describe pedestrian movements (i.e., social-force modeling, pedestrian crossings) and mixed traffic operations. Yet, these models are not able to simulate large-scale networks, as it would result in a tremendous increase of required resources and computational time. The trade-off between computational time and level of simulation detail has already been mentioned in previous studies (Charypar, 2008; Charypar et al., 2009; Waraich et al., 2015; Cao et al., 2019). In e-scooters, this trade-off can be translated to a dilemma: to model e-scooter riding behavior and its interactions with other road users in link level or to predict long-term travel behavior changes due to the introduction of micromobility services. Consequently, this choice depends solely on the scope of each study.

Another fact that should be considered is that e-scooter sharing services comprise a first/last-mile transport solution from/to public transport stops. The interactions with public transport modes occurring within the service operational area is an interesting research topic that has already examined in some recent studies by conducting questionnaire surveys (Glenn et al., 2020; Sanders et al., 2020; Nikiforiadis et al., 2021). Simulation data would contribute to the discussion regarding whether e-scooter compete public transport modes and local bus routes especially. Typical utility variables like travel time or travel cost, may not be enough to describe mode and route choices. ABMs that already use econometric models (i.e., SimMobility, POLARIS) are capable to consider more subjective variables, which are related to the socio-demographic attributes of each agent.

This study attempted to conceptually bridge the gap between micromobility and ABM by performing a qualitative assessment. Yet algorithmic-wise there are still points that are not analyzed in depth and require further research. The development of algorithms that can simulate mixed traffic operations both in microscopic and macroscopic scale is still a great challenge that requires further research and new innovations. Empirical data can be utilized not only to further explore safety issues in mixed traffic conditions but to calibrate and validate mesoscopic or microscopic models. New extensions that are under development or hybrid simulation models aspire to solve some of the scalability problem.

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CRediT authorship contribution statement

Panagiotis G. Tzouras: Methodology, Investigation, Formal analysis, Visualization, Writing – original draft. **Lambros Mitropoulos:** Conceptualization, Methodology, Investigation, Formal analysis. **Eirini Stavropoulou:** Investigation, Formal analysis, Visualization. **Eleni Antoniou:** Investigation, Formal analysis, Visualization. **Katerina Koliou:** Investigation, Formal analysis, Visualization. **Christos Karolemeas:** Project administration. **Antonis Karaloulis:** Investigation. **Konstantinos Mitropoulos:** Investigation. **Marilena Tarousi:** Investigation. **Eleni I. Vlahogianni:** Supervision, Writing – review & editing. **Konstantinos Kepaptsoglou:** Methodology, Supervision, Writing – review & editing.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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