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Agent-based modeling in urban human mobility: A systematic review

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A R T I C L E I N F O

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A B S T R A C T

Urban mobility is a complex system influenced by various factors such as infrastructure, technology, and human behavior. Agent-based modeling (ABM) has emerged as a valuable tool for simulating and understanding urban mobility dynamics.

This paper provides a comprehensive review of ABM applications in urban human mobility, offering insights into prevailing trends in this field. The analysis of model scales highlights the predominance of area and city scales, highlighting the need for greater exploration at the intersection, metropolis, and street scales. Furthermore, the examination of technological environments shows a reliance on desktop and laptop computers, complemented by a growing adoption of specialized ABM tools such as SUMO, Anylogic, NetLogo, GAMA, and MATSim.

Additionally, the study correlates ABM objectives with societal needs, revealing areas of alignment and gaps. While competitiveness and smart mobility receive considerable attention, there is a pronounced lack of focus on improving urban accessibility, sustainability, and public health. The analysis underscores the importance of addressing these gaps to ensure that ABM applications contribute effectively to addressing societal challenges.

1. Introduction

Cities, home to over half of the world's population (United Nations Department of Economic and Social Affairs, 2023), face a crucial challenge: urban mobility. The exponential growth of vehicular traffic and the inefficiency of traditional transportation systems give rise to critical issues that negatively impact citizens' quality of life and the planet's sustainability.

Transportation stands as a major contributor to greenhouse gas emissions and local pollutants, directly affecting public health and the environment (Shukla et al., 2022). Vehicular congestion, in particular, significantly worsens air quality, heightening the risk of respiratory and cardiovascular diseases.

Time wasted in traffic results in reduced productivity, increased stress levels, and diminished opportunities for personal and family time. The unchecked expansion of road infrastructures for private transport has contributed to urban fragmentation, the degradation of public spaces, and the loss of green areas. These developments have, thus, limited social interaction, road safety, and urban environmental quality.

Given this scenario, sustainable urban planning requires adopting new mobility models that aim to reduce pollutant emissions, optimize public space usage, and improve citizens' quality of life.

Simulating urban mobility behaviors is a powerful method for evaluating and optimizing the effects of public policies, promoting public transportation, and designing infrastructure for alternative modes of mobility. Within this framework, Agent-Based Models (ABMs) serve as invaluable tools, which, by programming traffic behavior, enable the quantification of the impacts of various urban planning decisions on a given scenario.

This article aims to review recent trends in the literature on Agent-Based Modeling (ABM), focusing on the tools, methodologies, and approaches commonly employed by researchers in the field. This paper is organized into sections that guide the reader through the research process on Agent-Based Modeling (ABM). Following this introduction, the article provides a detailed description of ABM, followed by the search strategy used to gather information and select relevant studies. In the results and analysis section, general data are provided, and the specific objectives of the research are presented. The research questions that frame the study are then introduced, and the subsequent section highlights gaps in the existing literature, identifying areas that require further exploration. Finally, the paper concludes with a summary of key findings and acknowledges those who contributed to the study's development.

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1.1. Agent based modeling (ABM)

Agents originated from research in Artificial Intelligence (AI), particularly from Distributed Artificial Intelligence (DAI). Early AI research often conceptualized agents as specialized programs, although their nature and construction were not detailed (Gómez Sanz, 2002). Currently, no universally accepted definition of an agent exists; however, the definition proposed by (Russell & Norvig, 1995) has gained significant focus within the field. Building on the definitions by (Dorri et al., 2018; Durfee, 2001), the following description is developed:

> An agent is an entity placed within an environment, capable of sensing various parameters to make decisions aligned with its design objectives. It autonomously acts within this environment based on these decisions, aiming to fulfill its goals.

The term *environment* denotes the spatial context within which the agent operates. This environment may manifest as a network in scenarios involving traffic monitoring agents or as software components when the agent oversees their actions (Dorri et al., 2018). The combined use and mutual interaction among autonomous agents constitute a Multi-Agent System or Agent-Based Model. Based on the definition from (Wang & Paranjape, 2014):

> A Multi-Agent System (MAS) generally refers to a body of multiple autonomous agents that interact, cooperate, and negotiate with each other in order to satisfy their design objectives. It provides a way of viewing the world in which an agent system can intuitively represent a real-world situation of interacting entities, and test how complex behaviours may occur.

1.2. Search strategy

The present systematic review has been based on the PRISMA methodology (Page et al., 2021). A series of searches have been conducted in online bibliographic repositories. The following table (see Table 1) presents the questions that will act as the focal point of our research.

- **RQ1.** This question aims to identify the most impactful ABM execution tools in the literature and analyze their evolution over recent years. The answer will provide a clearer understanding of the current context, the usage patterns of each tool, and their respective advantages and limitations.
- **RQ2.** The literature presents a wide range of viewpoints, ideas, and approaches to problem-solving, which can be overwhelming. Therefore, this question aims to quantify the predominant strategies within the field, establishing a framework for addressing the various needs that may arise in the ABM field in urban environments.
- **RQ3.** When proposing a tool as a basis for executing agents, evaluating each option's limitations is essential. Therefore, this question focuses on understanding the scales at which the tools operate and their potential evolution in terms of the number of simulated agents.
- **RQ4.** Finally, it is essential to understand the computational resources involved to assess the computational effort required for an ABM. This will provide insight into the computational powers required to execute ABMs and perform their associated calculations.

Table 1
Raised research questions.

Q. No.	Research Questions
RQ1	Which are the main tools used for agent modeling?
RQ2	Which are the most commonly used strategies?
RQ3	Which scales are being used?
RQ4	Which technological environments are being used?

Building on these research questions, the search filters for the selected information sources are defined. These filters are based on the study's three main pillars: the use of an Agent-Based Model applied to the urban environment and specifically to mobility. The selected keywords for the search criteria are exposed in Fig. 1.

These criteria have been applied in the various selected academic libraries, adapting them to the filtering characteristics of each one, as shown below. For this study, *Scopus*, *SpringerLink*, and *IEEE Xplore* libraries were selected based on different criteria such as thematic parallelism, the scale of the libraries, and their popularity:

- ABS ("MAS" OR "ABM" OR "Multi-Agent Systems" OR "Agent Based Models") AND ABS ("mobility" OR "transport") AND ABS ("urban") on *Scopus*,
- (MAS OR ABM OR Multi-Agent Systems OR Agent Based Models) AND (mobility OR transport) AND urban on *SpringerLink* and
- (("Abstract": MAS) OR ("Abstract": ABM) OR ("Abstract": Multi-Agent Systems) OR ("Abstract": Agent Based Models)) AND (("Abstract": mobility) OR ("Abstract": transport)) AND ("Abstract": urban) on *IEEE Xplore*.

These criteria are supplemented with a temporal filter for publications from 2013 to 2023. Additionally, for *SpringerLink*, a filter by sub-discipline (artificial intelligence) is applied. The temporal filter is intended to focus the search on publications that reflect current trends in tools and methodologies, providing readers with insights into current trends in the use of tools and methodologies.

Based on these search criteria, 541 articles met the original inclusion criteria (212 from *Scopus*, 233 from *SpringerLink*, and 96 from *IEEE Xplore*). The publications were then filtered in phases to ensure all articles included in the analysis were relevant to the study. This methodology involves three manual filtering phases, each progressively more rigorous in evaluating the articles. The filters applied are as follows:

- **Cut 0.** Discard duplicated publications.
- **Cut 1.** Discard by reviewing titles and keywords.
- **Cut 2.** Discard by reviewing the abstract.
- **Cut 3.** Discard after reading the full document.

Likewise, to ensure thematic coherence, the following criteria for discarding publications are established for cuts 1, 2, and 3:

A. **Related to logistics:** Publications focusing on logistics-oriented agent-based models, such as those modeling delivery agents or supply chain operations, are excluded. This exclusion is based on the premise that the behavior of logistics agents may not accurately reflect human behavior in urban settings, which is the primary focus of this review. While logistics play a crucial role in urban environments, the distinct nature of logistics-related behaviors may not align with the broader scope of this study, which aims to understand human-centric mobility patterns and strategies.
B. **Related to non-terrestrial systems:** Publications centered on non-terrestrial systems, such as drones or aerial vehicles, are excluded from consideration. The focus of this review is specifically on mobility within urban environments as experienced by human populations. While advancements in non-terrestrial mobility systems are undoubtedly significant, they operate under different constraints and

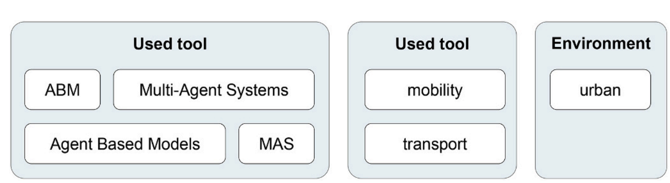

Fig. 1. Keywords considered for systematic search.

dynamics compared to ground-based urban mobility, thus falling outside the scope of this study.

C. **Related to robotics:** Publications primarily focused on robotics applications that are not directly related to human mobility are excluded. While autonomous robotics intersect with agent-based modeling in certain contexts, such as fire or traffic assessment drones, this review focuses on human-centric mobility within urban environments. Research solely focused on robotic behaviors or interactions, rather than human-agent interactions, does not align with the objectives of this study.

D. **Applied in areas such as campuses or industrial estates:** Publications centered on agent-based models applied exclusively within controlled environments such as campuses, industrial estates, or closed systems are excluded. While these settings may exhibit some characteristics of urban environments, their dynamics and constraints differ significantly from the complexities of real-world urban contexts. This review aims to capture insights relevant to broader urban mobility patterns and strategies. In Fig. 2 the basic criteria also fall under this label.

E. **Reviews and surveys:** Publications categorized as reviews or surveys, without primary empirical research or real-world application cases, are excluded. While reviews and surveys provide valuable synthesis and analysis of existing literature, this review prioritizes primary research and real-world application cases to derive insights into agent-based modeling approaches in urban mobility.

F. **Unavailability or incomprehension:** Publications that are inaccessible due to unavailability, language barriers, or incomprehensibility, as well as those removed due to plagiarism, are excluded. Ensuring access to and understanding of selected publications is essential for maintaining the integrity and credibility of the review process.

Thus, the analysis is conducted on a total of 154 publications, 387 (71.53 %) having been discarded for failing to meet the established criteria. During this selection process, 517 titles and keywords, 285 abstracts, and 201 publications in their entirety have been read. This rigorous analysis has allowed the extraction of all relevant data to answer the research questions established in Table 1, the justification of which is narrated in Section 1.2.

Fig. 2 describes the articles excluded by each criterion. These are related to the basic criteria as well as those more specific exclusion criteria established earlier. After selecting 154 articles, data relevant to quantifying the characteristics necessary to answer the research questions outlined in Table 1 were extracted.

2. Results and analysis

Since most articles cover more than one ABM tool, the 154 selected articles yielded a total of 258 ABM applications, including testing solutions, generating data, or serving as a solution in itself. Among these cases, 35 (13.57 %) fail to provide any information about the ABM used, 41 (15.89 %) report having developed a custom ABM solution but do not specify details about the tool or language used, and 24 (9.30 %) indicate the use of a simulation tool for traffic behavior without specifying which tool was used.

Because of these gaps and missing data in the literature, the number of “analyzed cases” varies across sections. For each dataset, cases with unspecified data are excluded from the total analyzed.

2.1. General data

Studies of this nature often present general data trends that are interesting to analyze. Regarding the evolution of publications, as can be observed in Fig. 3, there is a clear upward trend overall. However, a noticeable decline in publications occurred during 2016 and 2017, despite the graphical representations for this biennial period not reflecting this decline.

It should be noted that the biennial graphical representations throughout this publication cover the period from 2013 to 2022, excluding data from 2023. This exclusion is due to the timing of the article's writing, as it is prudent to wait until at least mid-year for all publications accepted in 2023 to be recorded in bibliographic systems. Given the incomplete data for 2023, this year has been omitted from the analysis, resulting in a total of 135 publications considered out of the original 154.

As shown in Fig. 4, China has the highest number of publications, followed closely by the United States. After applying data correction based on the population of each country, Fig. 4 also details the regions with the highest publication ratio per 10,000,000 inhabitants. After this correction, it becomes apparent that, despite the lower total number of

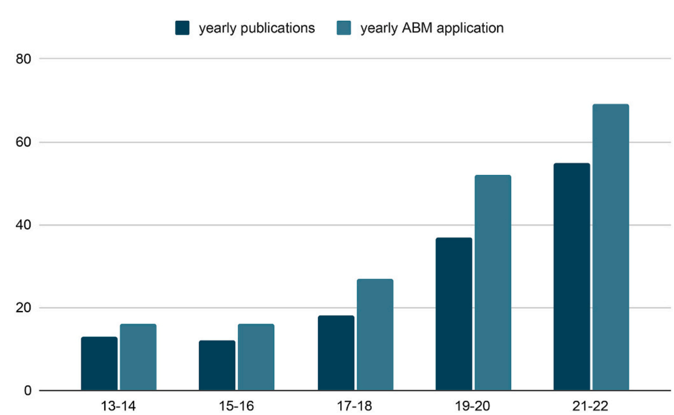

Fig. 3. Temporal evolution of publications and ABM application.

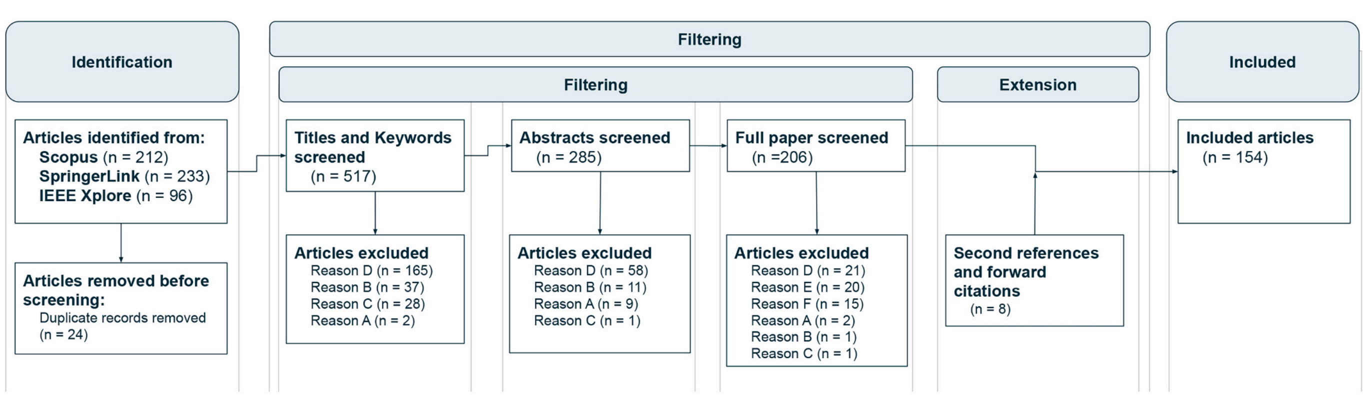

Fig. 2. Development of the publications selection process.

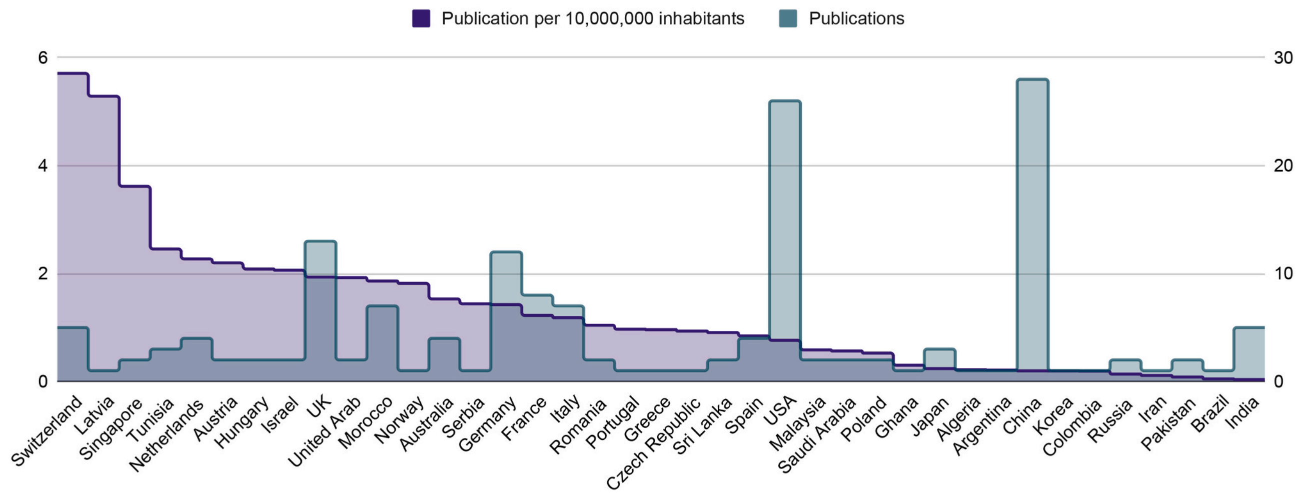

Fig. 4. Publications by region without and with correction per 10 million inhabitants.

publications, interest in applying ABMs to urban environments, particularly in relation to population density, is significantly higher in Europe. Notably, 16 of the top 25 countries contributing to this research are located within this region.

2.2. Research objectives

The objectives of the publications and the ABMs have been collected and presented in Figs. 6 and 7, allowing for the quantification of the main interests described in these research works. It is important to note that not all publications had the same degree of specificity in their targets. For instance, under the label "Upgrade current models," four publications are sub-labeled as "Ridesharing." However, only three include additional subcategories, while one remains labeled only as "Ridesharing."

Most publications focus on enhancing existing transportation systems by developing new tools or methodologies to improve transport performance and reduce wait times. In a few cases, solutions are developed to directly assess environmental impact or urban development. Notably, some publications adapt similar methodologies to apply them to the field of epidemiology. Similarly, there is a growing interest among researchers in simulating interconnected networks, underscoring the importance of integrated systems in urban mobility studies.

3. Research questions

As specified in Section 1.2, the present publication aims to answer a series of research questions (see Table 1). The results obtained for each question are presented below.

3.1. Which are the main tools used for agent modeling?

Out of the 154 analyzed publications, 104 different ABM tools were identified, of which 63 % rely on the same five tools:

- **SUMO (26.13 %).** An open-source platform for large-scale traffic simulation. It is used to model and analyze traffic behavior in cities, road networks, and highways (Alhussain, 2021; Appiah-Twum et al., 2019; Chergui & Sayad, 2023; Cruz-Piris et al., 2018; Dai et al., 2019; El-alaouy et al., 2021; Fernandes & Nunes, 2015; Hassan et al., 2023; Kodama et al., 2022; Kovari et al., 2022; Li et al., 2021, 2022; Ma et al., 2023; Medvei et al., 2021; Mittal et al., 2022; Mortazavi Azad & Ramazani, 2023; Patidar et al., 2021; Rakkesh et al., 2015; Soon et al., 2019; Suga et al., 2023; Szoke et al., 2020; Tigga et al., 2022; Wang & Wang, 2023; Withanawasam & Karunananda, 2017; Wu et al., 2020; Xu et al., 2021; Yan et al., 2023; Zhao et al., 2019, 2020).
- **AnyLogic (12.61 %).** A general-purpose modeling and simulation platform that can be used to create a wide range of models, from business system simulations to games and machine learning models (El Ouadi et al., 2022, 2023; Elbanhawy et al., 2013, 2014; ElBanhawy & Dalton, 2013; Gorecki et al., 2022; Morri et al., 2020, 2023; Rahman et al., 2019, 2020; Stevens et al., 2022; Trivedi & Pandey, 2020; Wang et al., 2020, 2022a).
- **NetLogo (9.91 %).** An open-source programming language for complex system simulation. It is easy to learn and use, making it a popular tool for education and research (Adelt et al., 2018; Calabrò et al., 2020, 2023; Chen & Crooks, 2021; Hoffmann et al., 2020; Husarek, Paulus, Metzger, et al., 2021; Husarek, Paulus, & Niessen, 2021; Inturri et al., 2019; Ion et al., 2015; Maggi & Vallino, 2021; Patidar et al., 2021).
- **GAMA (7.21 %).** An open-source agent-based modeling and simulation platform. It is used to create models of complex systems involving the interaction of multiple agents (Chapuis et al., 2022; Grujić et al., 2022; Iskandar et al., 2023; Kaziyeva et al., 2023; López Baeza et al., 2021; Qbouche & Rhoulami, 2022a, 2022b; Yurrita et al., 2021).
- **MATSim (7.21 %).** An open-source software framework for large-scale transport simulation. It is used to model and analyze traffic behavior in cities, road networks, and highways (Beutel et al., 2015; Dingil et al., 2023; Franco et al., 2020; Hackl & Dubernet, 2019; Khaidem et al., 2020; Maciejewski et al., 2016; Rossi et al., 2018; Sana et al., 2014).

The rest of the publications (36.94 %) are based on tools such as *MatLab*, *Repast Simphony*, *VISSIM*, *SimMobility* or *MASON*, or some more specific ones such as *AGlobe*, *JADE* or *FLAME GPU*.

It is noteworthy that out of 154 papers analyzed, 65 (42.21 %)were written by authors who decided to develop their own ABMs (Adelt et al., 2018; Badland et al., 2013; Belkhala et al., 2019; Calabrò et al., 2023; Chapuis et al., 2022; Chen & Crooks, 2021; Chergui & Sayad, 2023; Crooks et al., 2015; Cruz-Piris et al., 2018; Dai et al., 2020; Danassis et al., 2022; de Carvalho & Golpayegani, 2022; Dutta & Nicolas, 2021; Gerostathopoulos & Pournaras, 2019; Gokula Krishnan & Sankar Ram, 2018; Gorecki et al., 2022; Gschwendtner et al., 2023; Hassan et al., 2023; Hofer et al., 2018; Hoffmann et al., 2020; Hu et al., 2016; Husarek, Paulus, Metzger, et al., 2021; Huynh et al., 2015; Ion et al., 2015; Iskandar et al., 2023; Jacob & Roet-Green, 2021; Ji et al., 2023; Kielar & Borrmann, 2018; Ksontini et al., 2015; Kuiper & Wenkstern, 2015; Li et al., 2021, 2023; Liberto et al., 2020; Lim et al., 2018; Louati et al., 2020; Luo et al., 2022; Ma et al., 2023; Manchella et al., 2021; Marczuk et al., 2015; Mohamed et al., 2019; Nahmias-Biran et al., 2022; Pang et al., 2020; Patidar et al., 2021; Pesavento et al., 2020; Rosés et al., 2019; Sassi et al., 2014; Schmedding et al., 2022; Serok & Blumenfeld-Lieberthal, 2015; Shelke et al., 2019; Sur, 2019; Torabi et al., 2018; Wang et al., 2019, 2021; Wu et al., 2020; Xie et al., 2022; Xu et al., 2021; Yan et al., 2023; Yang et al., 2021; Yang, Langellier, et al., 2019; Yong & Li, 2019; Yu et al., 2023; Yurrita et al., 2021; Zhang et al., 2022; Zhao et al., 2020; Züfle et al., 2023). 19 (29.23 %) out of those 65 do not specify the tools or programming languages they are based on (Belkhala et al., 2019; Danassis et al., 2022; de Carvalho & Golpayegani, 2022; Dutta & Nicolas, 2021; Gokula Krishnan & Sankar Ram, 2018; Hofer et al., 2018; Jacob & Roet-Green, 2021; Ji et al., 2023; Ksontini et al., 2015; Kuiper & Wenkstern, 2015; Li et al., 2023; Luo et al., 2022; Manchella et al., 2021; Mohamed et al., 2019; Pang et al., 2020; Sassi et al., 2014; Sur, 2019; Xie et al., 2022; Zhang et al., 2022).

An analysis of the use of ABM tools over time is performed, as shown in Fig. 8. This allows for the observation of the evolution of the previously mentioned tools over the past decade.

Similarly, Fig. 9 shows the programming languages that are most commonly used for configuring the ABMs present in the literature.

3.2. Which are the most commonly used strategies?

It is difficult to quantify such an ambiguous concept as strategy defined by different authors, as it depends on a set of strategic decisions made at various stages of development and is highly related to the scope of application. Therefore, the following strategic points are defined within the ABM design:

- **Origin of data** (Section 3.2.1). The literature reveals multiple strategies and sources for obtaining information. Analyzing their characteristics and recurrent in the literature provides valuable insights into which strategies are more relevant for the project.
- **Application of additional modules** (Section 3.2.2). Many of the analyzed cases are not limited to modeling mobility in the urban system. Some incorporate additional modules to simulate complex disturbances with additional variables, such as weather variability, or to establish more precise patterns using machine learning. Identifying the additional tools, along with their applications, highlights the wide spectrum of opportunities offered by the modeling systems inherent to ABMs.

3.2.1. Data origin

In many situations, the quantity and quality of the data used, as well as the access to it, completely limits the author's ability to make his model. An analysis of the different publications has revealed different trends in the bibliography.

To begin with, there is a percentage of the total cases analyzed (12.34 %) that did not require specific data due to their low complexity regarding agent behavior (Appiah-Twum et al., 2019; Chapuis et al., 2022; Chergui & Sayad, 2023; Cruz-Piris et al., 2018; de Carvalho & Golpayegani, 2022; ElBanhawy et al., 2014; Kodama et al., 2022; Kuiper & Wenkstern, 2015; Louati et al., 2020; Ma et al., 2023; Mittal et al., 2022; Mortazavi Azad & Ramazani, 2023; Suga et al., 2023; Sur, 2019; Tigga et al., 2022; Wu et al., 2020; Xu et al., 2021) or bases of randomness on the behavior of the agents (Amézquita-López et al., 2021; Chen & Crooks, 2021). Concerning the rest of the cases, the percentage distribution, as well as the explanation of the casuistry of each, is described below:

- **Open data (33.12 %).** Most authors consider public sources as an option. We can observe the wide variety of opportunities available, such as data sources developed by regional institutions (Anagnostopoulos et al., 2020; Badland et al., 2013; Crooks et al., 2015; El Ouadi et al., 2022; Franco et al., 2020; Gschwendtner et al., 2023; Hackl & Dubernet, 2019; Inturri et al., 2019; Jacob & Roet-Green, 2021; Kaziyeva et al., 2023; Kim et al., 2022; Ksontini et al., 2015; Li et al., 2023; Morri et al., 2020; Oh et al., 2020; Qbouche & Rhoulami, 2022a, 2022b; Rasca, 2022; Rosés et al., 2019; Schmedding et al., 2022; Skordilis et al., 2022; Wang et al., 2020; Xie et al., 2022; Yang, Langellier, et al., 2019; Yurrita et al., 2021, 2022), works or data sources created by other authors (Ginters et al., n.d.; Calabrò et al., 2020; Danassis et al., 2022; Hofer et al., 2018; Husarek, Paulus, Metzger, et al., 2021; Iskandar et al., 2023; Khaidem et al., 2020; Maggi & Vallino, 2021; Manchella et al., 2021; Martinez et al., 2015; Rossi et al., 2018; Serok & Blumenfeld-Lieberthal, 2015; Stevens et al., 2022; Thompson Sargoni & Manley, 2020; Züfle et al., 2023), or publicly accessible data provided by companies or organization (Chen et al., 2019; Danassis et al., 2022; Dingil et al., 2023; El Ouadi et al., 2022; Franco et al., 2020; Grujić et al., 2022; He et al., 2014; Namoun et al., 2013; Pesavento et al., 2020; Rebollo et al., 2017; Wu et al., 2014; Yu et al., 2023; Zhao et al., 2019).
- **Sensors (21.43 %).** Another widely used option by authors is leveraging sensor technology (Akopov & Beklaryan, 2022; Alhussain, 2021; Belkhala et al., 2019; Crooks et al., 2015; Cruz-Piris et al., 2018; Fernandes & Nunes, 2015; Gokula Krishnan & Sankar Ram, 2018; Hassan et al., 2023; Hu et al., 2016; Ji et al., 2023; Kielar & Borrmann, 2018; Kodama et al., 2022; Li et al., 2021; Liberto et al., 2020; Louati et al., 2020; Luo et al., 2022; Mittal et al., 2022; Namoun et al., 2013, 2014; Rakkesh et al., 2015; Sana et al., 2014; Sassi et al., 2014; Shelke et al., 2019; Soon et al., 2019; Suga et al., 2023; Torabi et al., 2018; Wu et al., 2020; Yan et al., 2023; Yang et al., 2021; Yong & Li, 2019; Yuan & Li, 2023; Zhao et al., 2020; Zia et al., 2016; Züfle et al., 2023). Some of the most interesting cases perform their study or corroboration of the data in-situ (Liberto et al., 2020; Yang et al., 2021), as well as using video systems (Crooks et al., 2015; Kielar & Borrmann, 2018) to determine the state of the traffic.
- **Survey (12.34 %).** In those cases where the necessary data are not yet computed, some researchers advocate extending their field of study to a purely social domain, conducting interviews with the inhabitants of the region (Adelt et al., 2018; Dai et al., 2020; El Ouadi et al., 2023; El-alaouy et al., 2021; Gorecki et al., 2022; Hackl & Dubernet, 2019; Hofer et al., 2018; Huynh et al., 2015; Iskandar et al., 2023; Li et al., 2023; Olszewski et al., 2018; Rahman et al., 2019, 2020; Scott et al., 2016; Vehlken, 2020; Withanawasam & Karunananda, 2017; Yang, van Dam, et al., 2019; Zhang et al., 2022; Züfle et al., 2023).
- **Regional authorities (12.34 %).** Within each territory, different regional institutions have relevant information. Some authors resort directly to them to request information (openly not available) to define the behavior of the agents (Ginters et al., n.d.; Berrada & Poulhès, 2021; Elbanhawy et al., 2013; ElBanhawy & Dalton, 2013; Kaziyeva et al., 2023; Kim et al., 2022; Lu et al., 2022; Morri et al., 2023; Nahmias-Biran et al., 2022; Oh et al., 2020; Qiao et al., 2023; Schmedding et al., 2023; Soon et al., 2019; Torabi et al., 2018; Wang et al., 2022a; Wen et al., 2017; Yang et al., 2021; Yang, van Dam, et al., 2019; Züfle et al., 2023).
- **Census and reports (7.79 %).** In the same way, the use of information obtained through censuses and reports provides authors with the ability to define patterns of behavior or to define those key variables of their models (Calabrò et al., 2023; Dai et al., 2020; El-alaouy et al., 2021; Gorecki et al., 2022; Huynh et al., 2015; Inturri et al., 2019; Iskandar et al., 2023; Pesavento et al., 2020; Qiao et al., 2023; Vehlken, 2020; Wang et al., 2020; Yurrita et al., 2021).
- **Company data (7.79 %).** In this category fall the data obtained from transportation companies (Ahadi et al., 2021; Chen et al., 2019; Maciejewski et al., 2016; Trivedi & Pandey, 2020; Wang et al., 2021), consultancies (López Baeza et al., 2021), telecommunications companies (Franco et al., 2020; Grujić et al., 2022; Zhang et al.,

2022), social networks (Pang et al., 2020) or others (Picasso et al., n.d.; Hao et al., 2022).

- **Synthetic data (5.84 %).** In some cases, due to a lack of information or simply for convenience, data generated by the authors themselves are used, of which 3.25 % are created using software tools (Appiah-Twum et al., 2019; Beutel et al., 2015; Nguyen et al., 2022; Patidar et al., 2021; Rosés et al., 2019), and the remaining 2.60 % are based on the authors' conclusions or knowledge (Chergui & Sayad, 2023; Tigga et al., 2022; Wang & Wang, 2023; Züfle et al., 2023).

The types of data analyzed in the reviewed studies are diverse. Most studies (62.34 %) focus on traffic status, followed by nearly a third (31.82 %) that emphasize agent behavior data. Specific route data is analyzed in 16.88 % of cases, while transportation and mobility infrastructure data appear in 13.64 %, demographics in 7.14 %, service demand in 5.19 %, and environmental data in 3.25 %.

A few cases do not specify their data source (7.4 %) or the type of data used (2.6 %). The origin and typology of the data prove to be a highly interesting characteristic for the authors.

3.2.2. Modules applied

Some authors (55.84 %) consider it relevant for their studies to incorporate additional modules to make their simulation more rigorous and complete. These act as a support, supplement, or as the main point of the study, allowing the analysis of factors adjacent to urban mobility. The typology of modules, as well as the percentage of publications that deal with them, are listed below:

- **Learning module (29.22 %).** A wide variety of solutions that provide the system with learning capabilities fall within this category. Some solutions are based on Machine Learning, such as; Neural Network based systems (Picasso et al., n.d.; Anagnostopoulos et al., 2020; Louati et al., 2020; Mortazavi Azad & Ramazani, 2023), Multi-agent bounded solutions (Hassan et al., 2023; Kovari et al., 2022; Lu et al., 2022; Luo et al., 2022; Wang et al., 2021), Reinforcement Learning based (Chergui & Sayad, 2023; Ji et al., 2023; Khaidem et al., 2020; Rakkesh et al., 2015; Wu et al., 2020; Zhao et al., 2020), Policy Gradient based (Ma et al., 2023; Szoke et al., 2020), QLearning based (Dai et al., 2019; Hassan et al., 2023; Ji et al., 2023; Kodama et al., 2022; Li et al., 2021; Lu et al., 2021; Mortazavi Azad & Ramazani, 2023; Tigga et al., 2022; Torabi et al., 2018; Wang et al., 2021; Wen et al., 2017; Xu et al., 2021; Yan et al., 2023; Yong & Li, 2019), and others (Alhussain, 2021; Danassis et al., 2022; Husarek, Paulus, Metzger, et al., 2021; Kielar & Borrmann, 2018; Li et al., 2022; Skordilis et al., 2022; Sur, 2019; Xu et al., 2021; Yurrita et al., 2022). Approximately 17.78 % of the cases do not specify the type of learning applied, but they do specify that they have used some type of learning tool.
- **Communication module (20.13 %).** The development of communication technologies, as well as intra-vehicular connectivity, is projecting a sense of generalized connectivity that the authors have not neglected. Either they are employing specific tools (such as *NS2* (Shelke et al., 2019), *NS3* (Mittal et al., 2022) or others (Gokula Krishnan & Sankar Ram, 2018; Lu et al., 2021; Rebollo et al., 2017)), or through more generalist tools (such as *MatLab* (Fernandes & Nunes, 2015; Zhu et al., 2021), *Netlogo* (Ion et al., 2015; Patidar et al., 2021) or others (Marczuk et al., 2015; Mittal et al., 2022; Yuan & Li, 2023)), the authors model communication systems to verify the capacity and characteristics of their solutions. It is also remarkable the large number of cases (61.29 %) that do not specify the tool used for such simulation (Akopov & Beklaryan, 2022; Cruz-Piris et al., 2018; Hassan et al., 2023; Hu et al., 2016; Ji et al., 2023; Li et al., 2021; Lim et al., 2018; Lu et al., 2022; Maciejewski et al., 2016; Nahmias-Biran et al., 2022; Oh et al., 2020; Qiao et al., 2023; Rossi et al., 2018; Sana et al., 2014; Tigga et al., 2022; Torabi et al., 2018; Wang et al., 2022a, 2022b; Wu et al., 2020).
- **Environment module (11.04 %).** Considering environmental information has been considered a relevant factor when simulating the behavior of agents in the urban environment. Different authors have added modeling tools to their agent-based models; land-use modeling (Kim et al., 2022; Qbouche & Rhoulami, 2022a), climate modeling (Dai et al., 2020; Li et al., 2023), disease propagation (El-alaouy et al., 2021; Hackl & Dubernet, 2019; Schmedding et al., 2022, 2023), air pollution (Gorecki et al., 2022; Grujić et al., 2022; Wang et al., 2020; Yang, van Dam, et al., 2019; Yu et al., 2023), environmental disasters (Chapuis et al., 2022; Iskandar et al., 2023), macro scale (Stevens et al., 2022), and electricity demand/consumption (Gorecki et al., 2022; Pilo et al., 2021).
- **Optimization module (8.44 %).** The optimization of systems is a topic covered in the literature. Different authors deal with software tools such as *MALLBA* (Kodama et al., 2022; Rakkesh et al., 2015), *PROSA* (Namoun et al., 2013), *EPOS* (Gerostathopoulos & Pournaras, 2019) or *OptQuest* (Rahman et al., 2019), although most of them tend to use algorithms of different types, without specifying a specific tool (Ahadi et al., 2021; Berrada & Poulhès, 2021; Hu et al., 2016; Morri et al., 2023; Pang et al., 2020; Pilo et al., 2021; Sun et al., 2022; Yuan & Li, 2023).
- **Agent behavior module (6.49 %).** Some authors resort to external modules to emulate the behavior of the agents, using different algorithmic tools (Khaidem et al., 2020; Ma et al., 2023; Qbouche & Rhoulami, 2022b; Rosés et al., 2019; Yang, Langellier, et al., 2019; Zia et al., 2016) or specific software (Beutel et al., 2015; Kaziyeva et al., 2023; Li et al., 2022; Nguyen et al., 2022).
- **Graphical interface module (1.95 %).** A small percentage specifies having used some external tool as support for data visualization (Gorecki et al., 2022; Kielar & Borrmann, 2018; Yang et al., 2021).

3.3. Which scales are being used?

This study quantifies the urban scale using two key metrics: the analyzed environment and the number of simulated agents. Fig. 10 illustrates that 44 % of cases fall under the ambiguous classification of “area,” making it the most common category. This is followed by “city,” which accounts for 34 % of the cases. The remaining scales—“intersection,” “metropolis,” and “street”—are more evenly distributed, representing 12 %, 5.7 %, and 6.3 % of the cases, respectively.

These data can be analyzed in relation to the temporal unit, to evaluate the evolution over recent years, as well as the number of agents involved. This allows for the assessment of potential correlations between urban size and the number of agents to be modeled.

3.4. Which technological environments are being used?

A limited number of authors (16.2 % of the analyzed publications) specify the computational tools used in their ABMs. Because of this, and due to the difficulty of quantifying computational power and computation time (as both depend on several factors), the data obtained are presented in Table A.2, associating these data with the author.

From this table, new data can be extrapolated if we quantify the computing tools within the *desktop computer* (44.0 %) (Chapuis et al., 2022; Franco et al., 2020; Gorecki et al., 2022; Hassan et al., 2023; Huynh et al., 2015; Li et al., 2022; Namoun et al., 2014; Pesavento et al., 2020; Torabi et al., 2018; Wen et al., 2017; Yu et al., 2023), *laptop* (40.0 %) (Ksontini et al., 2015; Lu et al., 2022; Luo et al., 2022; Martinez et al., 2015; Mohamed et al., 2019; Rossi et al., 2018; Wang et al., 2021; Yurrita et al., 2022; Zhao et al., 2019; Zhu et al., 2021), *supercomputer* (12.0 %) (Iskandar et al., 2023; Rahman et al., 2020; Skordilis et al., 2022), and *server* (8.0 %) (Dingil et al., 2023; Namoun et al., 2014) labels; allowing us to evaluate this semi-quantification based on data such as the number of agents to simulate or urban scale.

4. Voids found on literature

After the literature review was conducted, the most common actions for analysis have been identified. However, it is necessary to evaluate the relevance of the reviewed studies, determining if their approaches align with the current needs of society. To do this, the needs and requirements detected by the United Nations (UN) and the European Commission (EC) will be used as a comparative framework.

The UN produces an annual report, assessing progress towards the 17 Sustainable Development Goals (SDGs) (United Nations Department of Economic and Social Affairs, 2023). In this regard, concerning goal number 11, sustainable cities and communities, the report defines various relevant tasks to consider, of which 11.2 is directly related to mobility.

> By 2030, provide access to safe, affordable, accessible, and sustainable transport systems for all, improving road safety, notably by expanding public transport, with special attention to the needs of those in vulnerable situations, women, children, persons with disabilities and older persons. (Sustainable Development Goals, n.d.)

Similarly, the European Commission defines its objectives and needs regarding climate, energy, and mobility principles, within the European Horizon funding program (European Commission, n.d.), Horizon Europe strategic plan (Directorate-General for Research and Innovation (European Commission), 2023) or The New European Innovation Agenda (EUR-Lex, 2022). According to the first one (European Commission, n.d.), 6 quantifiable impacts are listed:

1. Climate sciences and responses for the transformation towards climate neutrality.
2. Cross-sectoral solutions for the climate transition.
3. Sustainable, secure, and competitive energy supply.
4. Efficient, sustainable, and inclusive energy use.
5. Clean and competitive solutions for all transport modes.
6. Safe Resilient Transport and Smart Mobility services for passengers and goods.

Considering the characteristics of both institutions, we can understand that the general vision regarding the challenges and needs society will face in the coming decades considers the following pillars as mainstays:

- **Climate sustainability:** This refers to projects aimed at mitigating the environmental impact of urban mobility systems. These projects may involve reducing greenhouse gas emissions, promoting the use of renewable energy sources in transportation, or implementing measures to adapt to climate change effects such as extreme weather events.
- **Cross-sectoral solutions:** These solutions address the interconnectedness of various urban systems and sectors, recognizing that urban mobility is influenced by and influences factors such as land use, energy consumption, public health, and economic development. For instance, integrating transportation systems with energy grids (vehicle-to-grid), urban infrastructure (vehicle-to-infrastructure), or other sectors like public health can lead to more efficient and sustainable mobility solutions.
- **Accessibility:** These proposals aim to ensure that urban mobility services are accessible to all members of society, including those with mobility restrictions or limited resources. This may involve improving public transportation infrastructure to accommodate people with disabilities, providing affordable transportation options in underserved areas, or implementing policies to promote equitable access to mobility services.
- **Urban health and safety:** Projects in this category focus on enhancing safety measures and promoting public health in urban mobility systems. This includes initiatives to reduce traffic accidents, improve air quality by reducing vehicle emissions, and address public health challenges associated with transportation, such as noise pollution and sedentary lifestyles.
- **Competitiveness:** These proposals aim to enhance the competitiveness of urban areas by improving their transportation systems. This may involve adopting advanced technologies to optimize traffic flow, investing in infrastructure to support economic activities such as freight transportation, or implementing policies to attract businesses and skilled workers by offering efficient and reliable transportation options.
- **Smart Mobility:** This category encompasses initiatives that leverage intelligent systems, IoT (Internet of Things) technologies, and data-driven approaches to optimize urban mobility. Examples include smart traffic management systems that use real-time data to reduce congestion, intelligent transportation systems that provide personalized travel recommendations, and mobility-as-a-service platforms that integrate various modes of transportation into a seamless user experience.

Reassessing the 154 publications initially analyzed under this framework, the authors' objectives are compared with the needs detected by the institutions, resulting in the correlation map depicted in Fig. 13. In this image, it is easy to detect less addressed topics, as well as less common relationships between objectives and needs.

5. Discussion

Analyzing the data obtained by the study (see Fig. 3), it is evident that the application of ABM in urban mobility studies has experienced exponential growth over the last decade. This trend, which gained significant momentum around 2015–2016, may be attributed to several factors, including growing climate interest, exposed in 2016 in the Paris Agreement (United Nations Framework Convention on Climate Change (UNFCCC), 2015) or the development of the 2030 climate targets by the European Union (European Commission, 2014).

The geographical analysis presented in Fig. 5, excluding section (a) due to its evident focus on population within highly productive regions, highlights a notable concentration of interest in Europe, with 16 of the top 25 countries belonging to continental Europe (see Figs. 4 and 5). This shows Europe's growing interest in financing research and development projects related to mobility, 15-min cities, and urban development (European Commission, n.d.; Directorate-General for Research and Innovation (European Commission), 2023; EUR-Lex, 2022). These consistently high values in Europe further support the hypothesis that the Paris Agreement and the 2030 climate targets may have generated an impact in this field. (See Figs. 11 and 12.)

In Fig. 10, a transformation is shown in these same dates in the analyzed scale, increasing the presence of the city scale compared to the previous period.

In the technical domain, there is a clear decrease in interest in expanding the range of tools and a growing interest in relying on the same five tools: SUMO, Anylogic, Netlogo, GAMA, and MATSim (see Fig. 8). Similarly, the trend in programming languages indicates a decline in interest in JAVA-based tools, and an increased adoption of Python starting in 2015–16. Despite JAVA's superior processing capabilities for agent-based models (or intelligent objects), Python's growing popularity can be attributed to its ease of use and extensive ecosystem of compatible tools (Labanda-Jaramillo et al., 2018). This factor likely contributes to the recent surge in SUMO's adoption.

In terms of data acquisition, most data are obtained from open-access sources or sensorization. However, consulting institutions, organizations, and companies, along with data collected via surveys, are also relevant. There is a rising trend in the use of learning modules, mainly based on Machine Learning, which authors use to model agent behavior or optimize communication and strategy execution to alleviate traffic. Aligned with this trend, there is a significant interest in applying

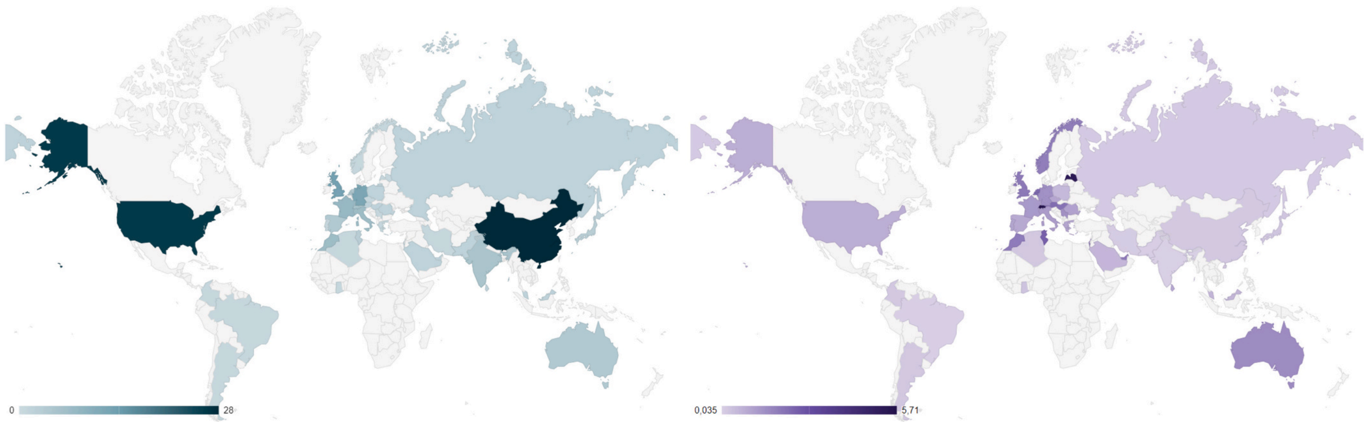

Fig. 5. Publications by region (a) without and (b) with 10,000,000 inhabitants correction.

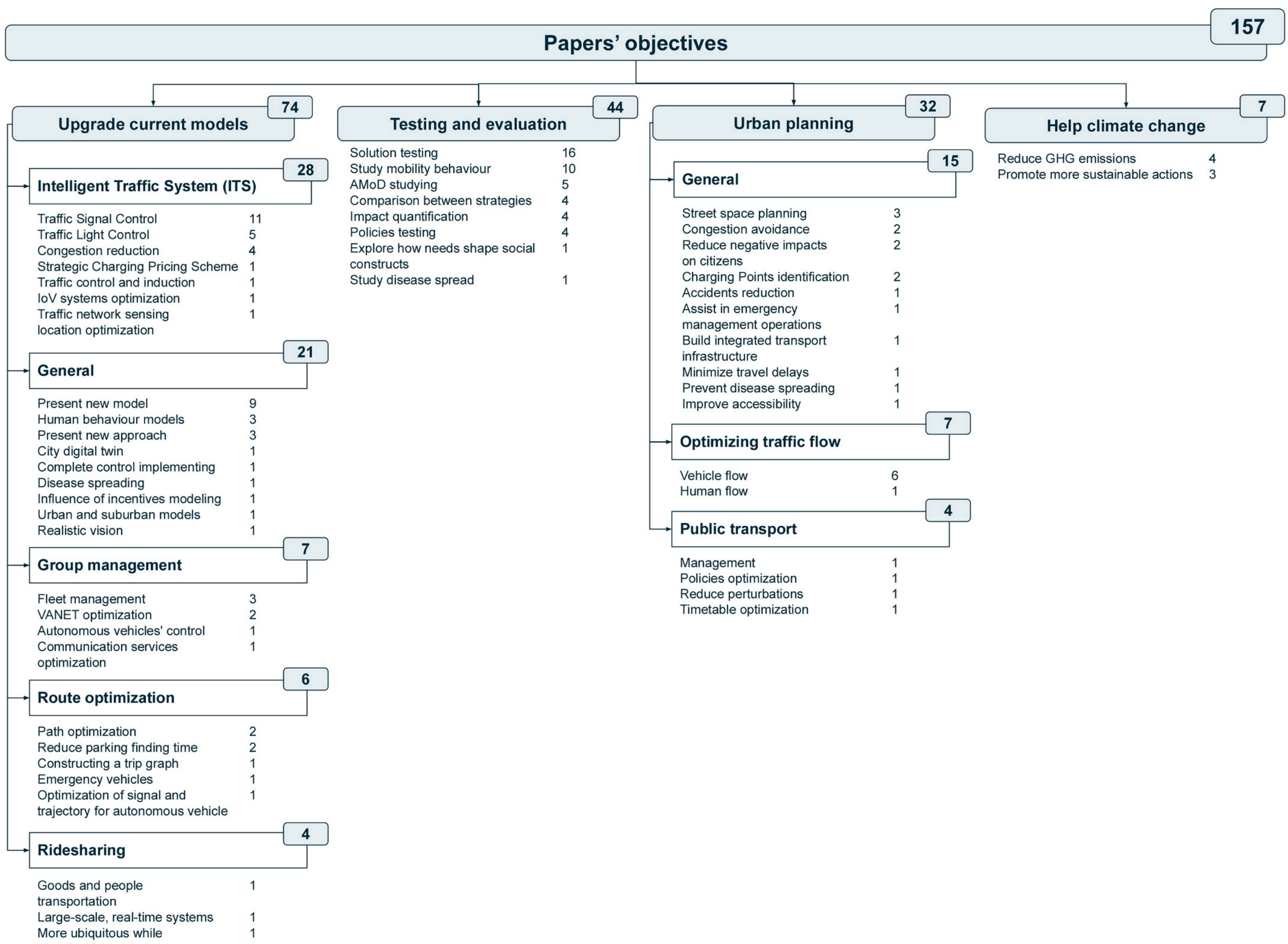

Fig. 6. Main objectives of the analyzed papers.

modules that enable vehicle communication with their surroundings. This includes inter-vehicle communication (V2V), vehicle-to-infrastructure communication (V2I), and integration with cloud-based systems. However, it is noteworthy that few authors allocate significant computational resources to these efforts, demonstrating that this modeling technique is feasible even on laptops.

Finally, in terms of the objectives of the models and publications reviewed, there is a clear focus on competitiveness and competitiveness-enabling solutions, such as efficiency technologies and advances in transportation system intelligence.

This trend is especially notable in contrast to the less frequent focus on ABM studies and models aimed at analyzing key aspects of climate change and quality of life, particularly those addressing accessibility.

This orientation responds to a persistent focus on high profitability and technological applicability, often displacing equity and social welfare. This prioritization suggests that projects with direct economic

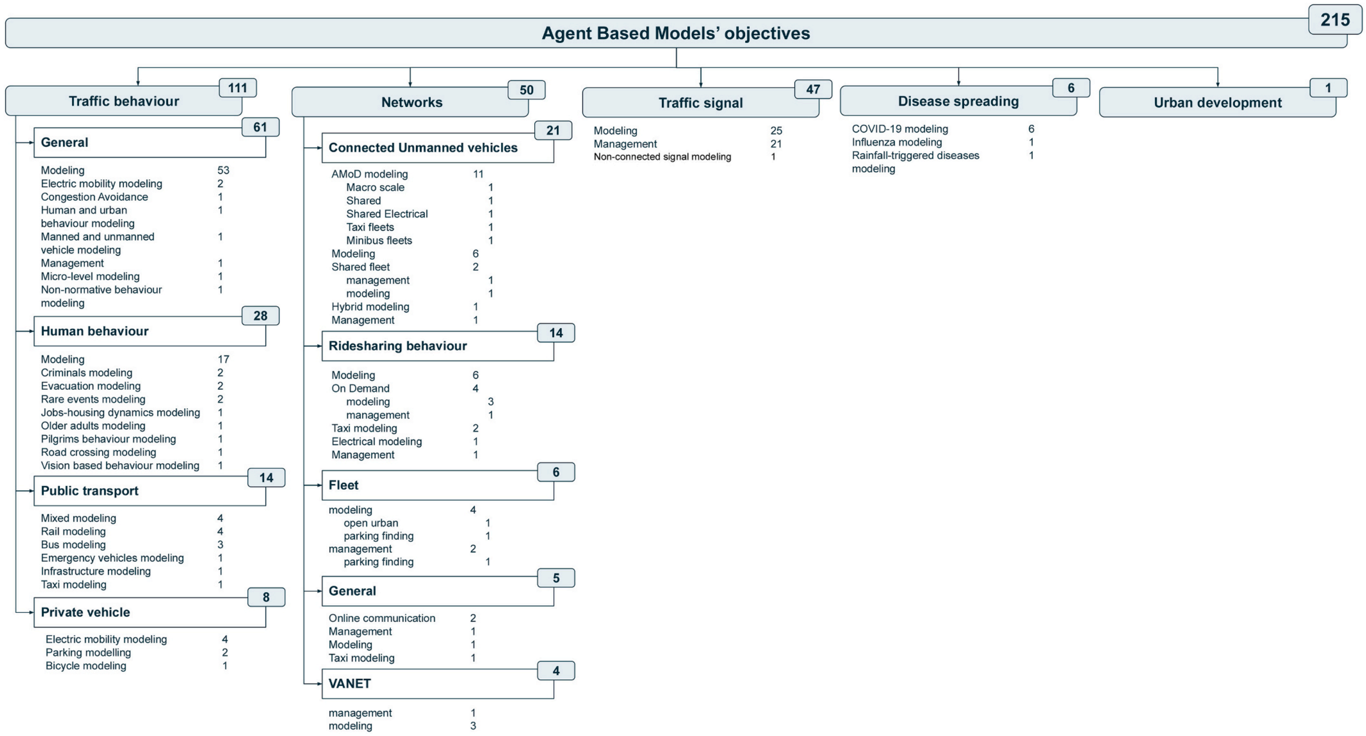

Fig. 7. Main objectives of the analyzed ABMs.

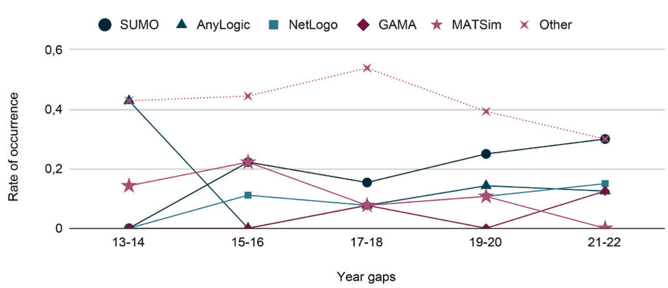

Fig. 8. Biannual evolution of the most used ABM tools.

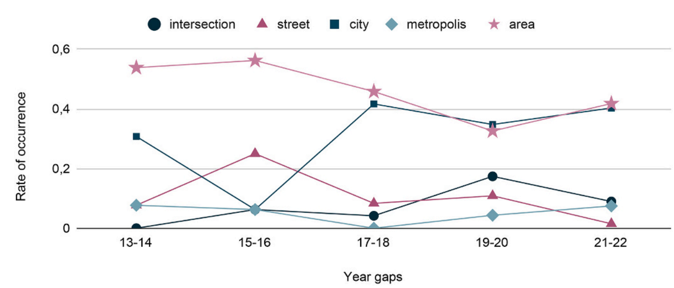

Fig. 10. Yearly distribution of urban scale in the literature.

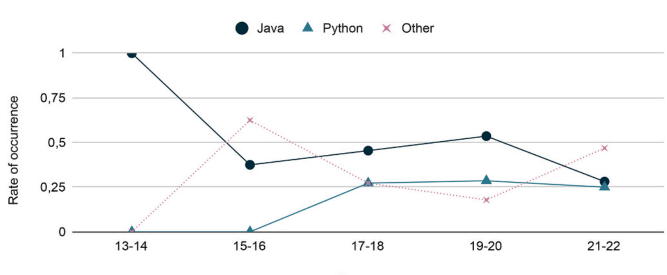

Fig. 9. Biannual evolution of the most used languages for agent management.

impact or with possibilities for advanced technological integration are more attractive for funding and research. However, this trend implies that essential issues such as accessibility, climate sustainability, and urban health are relegated, despite their importance for inclusive and sustainable mobility.

The lack of attention to these areas can have long-term consequences, since transport systems that do not consider accessibility will perpetuate inequalities and contribute to socio-environmental deterioration.

To observe the system as a whole, VOSviewer has been used for constructing and visualizing bibliometric networks (van Eck & Waltman, n.d.), after processing the initial data and standardizing the terminology used to denote the same concepts, the thematic distribution is depicted in Fig. 14.

The clustering in Fig. 14 is represented by colours, revolving around the concept of agent-based modeling (interactive version available on (Divasson-J, n.d.) or extended capture on Fig. A.15). The conceptual diagram presented illustrates the application of ABM in the field of transportation systems. It shows several branches branching off from the central concept of "Agent-Based Modelling (ABM)", each representing a specific area of application within transportation. These branches are further subdivided into smaller branches detailing software tools or terminology relevant to each application.

Taken together, the diagram provides an overview of the potential of ABM to model and simulate various aspects of transportation systems, including traffic simulation, traffic signal control, the impact of events such as COVID-19, the design of ridesharing strategies, the optimization of urban transportation infrastructure, and the management of distribution networks.

6. Conclusions

This study shows the accelerated growth of agent-based modeling

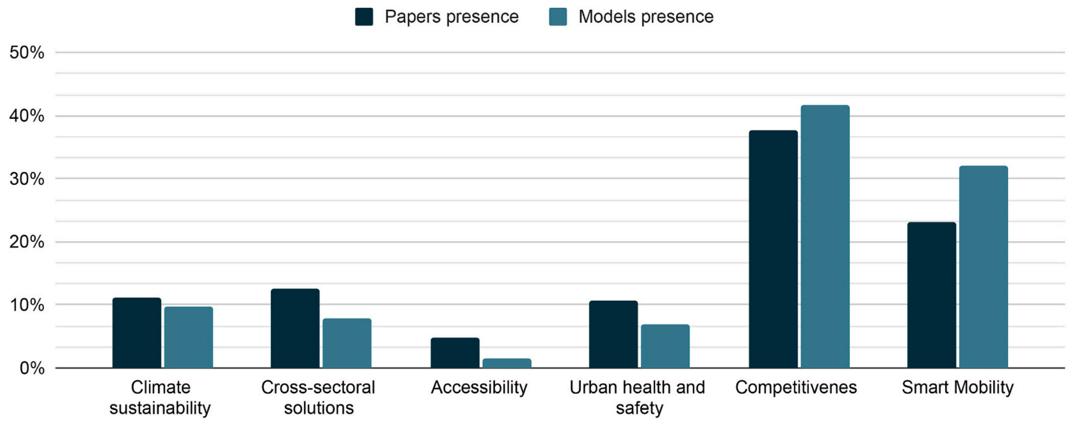

Fig. 13. Sample correlation between authors' objectives and Europe's needs (Heat Map).

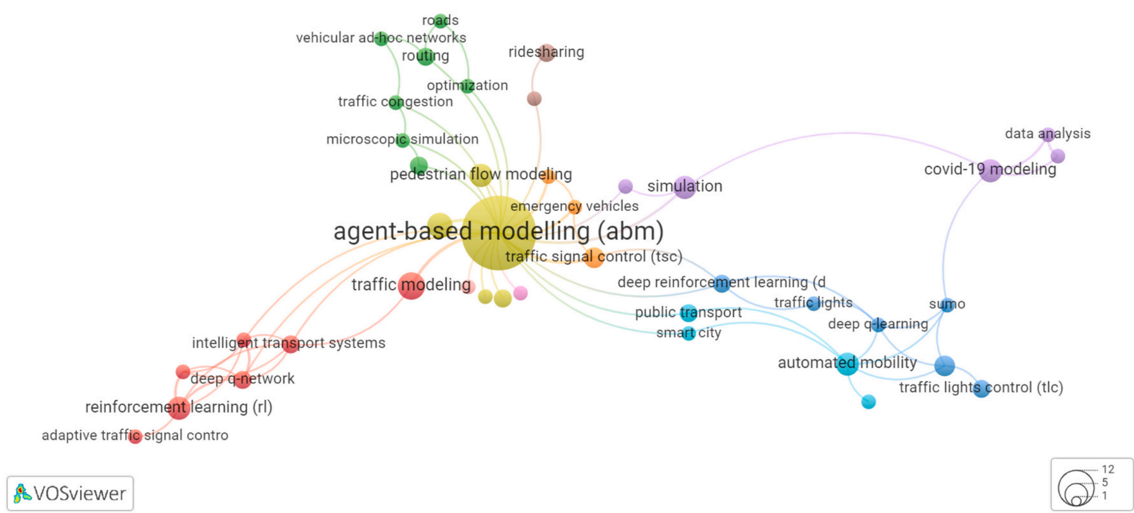

Fig. 14. Causal diagram of keyword occurrence in the literature (simplified).

		Climate sustainability	Cross-sectoral solutions	Accessibility	Urban health and safety	Competitivenes	Smart Mobility
PAPER	Upgrade current models	6,55%	7,74%	3,57%	8,93%	44,64%	28,57%
	Testing and evaluation	16,67%	19,05%	5,95%	14,29%	27,38%	16,67%
	Urban planning	6,38%	19,15%	8,51%	12,77%	38,30%	14,89%
	Help climate change	58,33%	8,33%	0,00%	0,00%	8,33%	25,00%
SUM PAPER		11,25%	12,54%	4,82%	10,61%	37,62%	23,15%

Fig. 11. Sample correlation between papers' objectives and Europe's needs (Heat Map).

		Climate sustainability	Cross-sectoral solutions	Accessibility	Urban health and safety	Competitivenes	Smart Mobility
ABM	Traffic behaviour	13,82%	9,76%	1,63%	5,69%	43,09%	26,02%
	Networks	0,00%	8,57%	5,71%	2,86%	40,00%	42,86%
	Traffic signal	10,00%	0,00%	0,00%	5,00%	44,00%	41,00%
	Disease spreading	0,00%	37,50%	0,00%	37,50%	25,00%	0,00%
	Urban development	0,00%	100,00%	0,00%	0,00%	0,00%	0,00%
SUM ABM		9,82%	8,00%	1,45%	6,91%	41,82%	32,00%

Fig. 12. Sample correlation between ABM's objectives and Europe's needs (Heat Map).

(ABM) in urban mobility research over the last decade, driven by increased environmental awareness and climate goals, such as the Paris Agreement and the European Union's 2030 objectives. This trend particularly stands out in Europe, where there is a growing focus on sustainable mobility solutions and urban development models like the "15-min city," which have fueled research investment. Since 2015, there has been a notable shift in studies towards analyzing mobility at a more urban level, reflecting the importance of addressing mobility challenges at the city scale. At the same time, there has been a consolidation in the use of established modeling tools and a shift in preference towards Python over JAVA, probably due to its flexibility and ease of use, which facilitate access to a wider range of compatible tools. This shift has been key to implementing machine learning modules that model agent behaviors and optimize traffic strategies more effectively.

As for the objectives of the studies, most focus on improving efficiency and competitiveness, as well as applying advanced technological solutions, in tune with economic growth goals. However, this trend has also neglected fundamental areas such as accessibility, environmental sustainability and urban health, aspects that are critical for quality of life and social inclusion in cities. This narrow focus could lead to long-term socio-environmental challenges, as mobility systems that do not consider accessibility and equity can deepen inequalities and affect the quality of life in cities.

In this context, it is essential to promote interest and participation in accessibility and climate adaptation issues, incorporating more diverse perspectives on mobility patterns. This includes projects that analyze reduced mobility (Elorriaga et al., 2017), as well as special attention to disadvantaged socio-demographic groups (Saitec, 2023; V2G Quests Project, 2023).

CRediT authorship contribution statement

A. Divasson-J.: Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ana M. Macarulla:** Writing – review & editing, Supervision. **J. Ignacio Garcia:** Writing – review & editing, Supervision. **Cruz E. Borges:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: A. Divasson-J. reports financial support was provided by University of Deusto DeustoTech. If there are other authors, they 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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Appendix A. Graphics and pictures

The following appendix presents all the figures referenced throughout the text, as well as any additional ones that may serve as support for the reader.

Table A.2
Technological environment and simulation time.

Author	Technological Environment	Simulation Time
(Zhao et al., 2019)	Cambridge High-Performance Computing (HPC), utilizing 32 cores	22 mins
(Hassan et al., 2023)	128GB RAM and Nvidia GeForce RTX 4080 GPU on Ubuntu	
(Li et al., 2022)	AMD Ryzen7 4800 U CPU	
(Rahman et al., 2020)	Windows a core i3 processor,1.9 GHz CPU 4 GB RAM	75 mins
(Gorecki et al., 2022)	Traditional computer	4 h
(Iskandar et al., 2023)	Debian Linux Intel Xeon 2.2 and 3 GHz RAM 192 GB per node	360 h
(Chapuis et al., 2022)	Laptop with an Intel Core i7–7700HQ CPU (2.80GHz)	40 seg
(Franco et al., 2020)	40 CPUS 200 GB of RAM	1.5 days
(Dingil et al., 2023)	Windows 10, 16 GB of RAM, and i7-118G7	2 days
(Rossi et al., 2018)	Intel Core i7–5960, 64 GB RAM	0.5 seg
(Torabi et al., 2018)	Intel Core i7 X980 CPU (3.33 GHz), 6.00 GB, 64-bit Windows 8	
(Wang et al., 2021)	Single core of AMD Ryzen 74800H with Radeon Graphics 2.90 GHz	
(Yu et al., 2023)	Windows 10 Pro Intel Xeon W-2123 3.60GHz CPU 32GB RAM	
(Pesavento et al., 2020)	Windows 6 CPUs at 4.0 GHz and 64 GB of RAM	
(Huynh et al., 2015)	Intel Core i5–4570 with 16 GB of RAM	1.5 h
(Ksontini et al., 2015)	Dual-core 2.5 GHz Intel Core i5 CPU 4GB RAM	
(Mohamed et al., 2019)	Intel Core i3-370M Processor 2.40 GHz 4 GB	
(Luo et al., 2022)	NVIDIA 2080Ti GPUs	
(Dutta & Nicolas, 2021)		2.32 s
(Skordilis et al., 2022)	NREL's supercomputer, Eagle, a single CPU node with 36 cores	
(Yurrita et al., 2022)	Intel Core i7–8565 CPU 1.8 GHz	102 mins
(Martinez et al., 2015)	64-bit Windows 7 with 16-GB RAM and i7 CPU	
(Namoun et al., 2014)	64-bit Windows 7 3.1 GHz Intel Core i5 processor 4GB	
(Namoun et al., 2014)	Ubuntu Virtual Machine (VM) 2.7 GHz AMD Opteron processor 2GB	
(Lu et al., 2022)	4 cores Intel Core i7 and 8 GB memory	
(Wen et al., 2017)	2.7 GHz Intel Core i5 and 8 GB	
(Zhu et al., 2021)	Core i5-6300HQ, 2.30 GHz and 8 GB RAM	10 mins

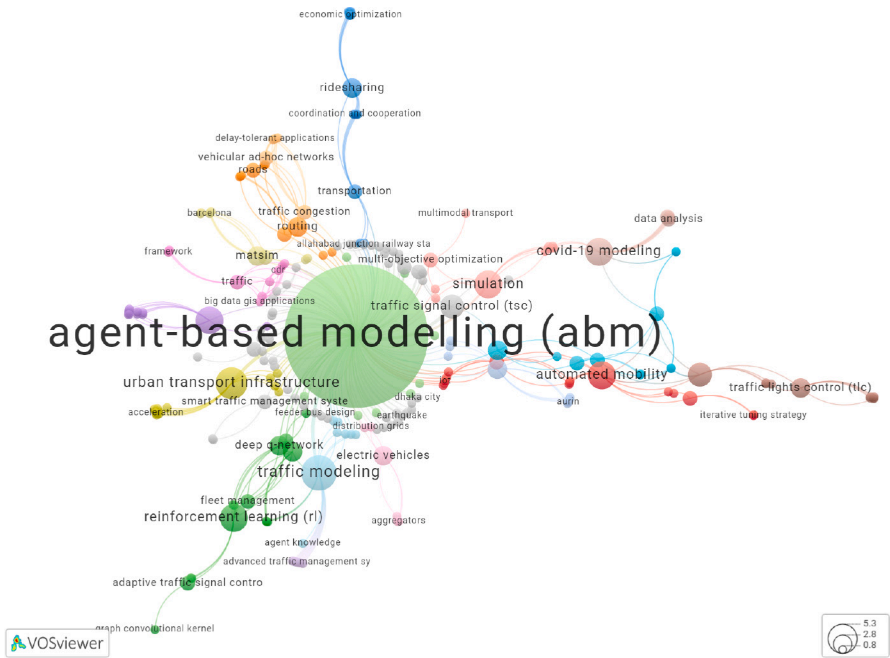

Fig. A.15. Causal diagram of keyword occurrence in the literature (full map).

Data availability

Data will be made available on request.

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