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Applying an ABM-LCA framework for analysing the impacts of shared automated electric vehicles across large-scale scenarios

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A B S T R A C T

Amidst the pressing need for sustainable transportation, Shared Automated Electric Vehicles (SAEVs) emerge as an increasingly explored solution with the potential to revolutionize mobility. Yet, understanding the environmental impacts of operating this mobility solution at different scales remains sparse. This study addresses this by integrating Agent-Based Modelling (ABM) and Life Cycle Assessment (LCA) to assess the environmental impacts of SAEVs at municipal, subregional and regional scales. ABM simulates travellers' behaviour and SAEVs deployment strategies, yielding dynamic patterns along a typical day, while LCA provides a structured framework for assessing the life cycle environmental impacts. This process involves creating an ABM that reflects a representative mobility scenario, and a modified ABM scenario where private car and bus trips are replaced with SAEV services. The analysis extends the different scales, providing both short-term and long-term perspectives on LCA impacts. Findings revealed significant reductions in global warming potential (up to 91%), but challenges include increased operational intensity, human toxicity (up to 240%), and mineral resource scarcity (up to 229%). Vehicle kilometres travelled, and fleet replacement needs are key factors influencing long-term environmental impacts. Larger-scale implementation yields greater environmental benefits compared to smaller-scale deployment.

Introduction

The upcoming evolution of mobility is at the forefront of efforts to address the environmental challenges of the century. As a key economic sector, transportation is closely linked to substantial environmental impacts and is the largest contributor to greenhouse gas (GHG) emissions in the European Union (EU-27), accounting for 25.1 % in 2022 (IEA, 2023a; IPCC, 2023). Despite advances in engine efficiency, the growing adoption of electric vehicles, and the integration of biofuels, emissions from passenger cars and heavy-duty vehicles have continued to rise (IEA., 2023b). This is exemplified by a 5.8 % increase in carbon dioxide (CO_2) emissions from EU-27 passenger cars between 2000 and 2019 (EEA, 2022). These trends underscore the urgent need for systemic changes in mobility to reconcile its environmental footprint with sustainability goals. Thus, conventional road transportation concepts are undergoing a profound shift, led by three key principles: innovation, sustainability, and accessibility. This transition is evident in the emergence of Shared Automated Electric Vehicles (SAEVs), which are nearing technological maturity and proving economically feasible in urban environments (Andorka & Rambow-Hoeschele, 2020; Jager et al., 2017; Vermesan et al., 2021). However, the deployment of SAEVs raises concerns regarding their environmental impact and feasibility, particularly when considering a broader range of sustainability factors, including diverse environmental impact categories and their effectiveness in larger, low-density areas.

Recent studies characterize SAEVs as an effective, comfortable, safe, and affordable mode of transportation (Becker et al., 2020; European Commission, 2019; Greenwald & Kornhauser, 2019; Loeb & Kockelman,

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2019; Meyer et al., 2017; Taiebat & Xu, 2019). While public perception and acceptance will be key in determining SAEVs adoption (e.g. Dichabeng et al., 2021; Miller et al., 2022; Mouratidis, 2022, Patel et al., 2023, Thaithatkul et al., 2024), this mode of transport holds the potential to enhance travel time value and present an opportunity to alleviate the financial strain of owning and maintaining a personal vehicle, enhancing mobility and accessibility for individuals who face transportation challenges due to limited physical access, economic barriers, or other constraints (Dill & McNeil, 2021; Taiebat et al., 2018). However, there is increasing scepticism regarding the assumption that SAEVs will consistently improve welfare. For instance, while SAEVs have shown promise in lowering air pollution and the number of cars required to provide transportation services (Ding et al., 2019), the widespread adoption of SAEVs may lead to intensive vehicle usage (with empty kilometres associated with vehicle relocation), a potential decrease in public transport adhesion, and higher levels of fleet turnover (Axsen & Sovacool, Manders et al., 2020, 2019; Vilaça et al., 2022; Wadud et al., 2016). The aforementioned adaptations largely rely on penetration levels, deployment strategies, and user behaviour, thereby posing significant uncertainty (Ahmed et al., 2023; Arbeláez Vélez, 2024; Axsen and Sovacool, 2019; Garus et al., 2022; Jones and Leibowicz, 2019; Vilaça et al., 2022).

Recognising the limited research and uncertainties surrounding the environmental impact of SAEVs, this paper proposes an approach that integrates Agent-Based Modelling (ABM) with Life Cycle Assessment (LCA) to assess the environmental impacts of SAEVs across municipal, subregional, and regional scales. ABM offers a dynamic perspective by simulating individual behaviour and interactions within a transportation network, providing valuable insights into real-world usage patterns and deployment strategies (Berrada & Leurent, 2017; Huang et al., 2022; Jing et al., 2020; Li et al., 2021, Nguyen et al., 2021). Complementing this with LCA, a well-established and standardised tool for assessing environmental impacts, ensures a comprehensive and holistic view of the environmental implications of SAEVs, considering different aspects of the dynamic information provided by ABM. As observed by Onat and Kucukvar (2022), there is a lack of integrated modelling approaches for life cycle assessment.

This manuscript builds upon a previous proof-of-concept study (Vilaça et al., 2024) that demonstrated the feasibility of coupling an agent-based model with life cycle assessment (LCA) to evaluate SAEVs at a single subregional scale, limited to global warming potential. The current paper significantly expands both the methodological and analytical scope. Specifically, the LCA now includes dynamic modelling of baseline and SAEV scenarios across seven midpoint environmental impact categories, covers three spatial scales (municipal, subregional, and regional), and introduces a structured verification and validation framework to assess behavioural fidelity. This approach is consistent with evidence that effective transport decarbonization requires life–cycle–based regulatory frameworks. Furthermore, the analysis extends to different spatial scales, encompassing not only urban areas but also peripheral regions with low population density and long travel distances. This approach fills a research gap in the existing literature, which predominantly focuses on urban environments, many times only the city centre. By examining shared mobility in areas with varying population densities, we aim to provide a more comprehensive understanding of the potential societal and equity impacts of future massive deployment of SAEVs. The pronounced differences in travel behaviour and transit accessibility across spatial contexts underscore the importance of context-sensitive evaluations.

Recognizing the transformative potential of SAEVs, this study explores extreme scenarios where personal mobility is entirely replaced by this service. While such a scenario may not reflect near-future realities, it serves as a valuable tool to probe the boundaries of system performance and environmental impacts under maximum adoption conditions. Testing extreme cases is a well-established methodology in transportation research, providing insights into the resilience and feasibility of new systems under high-stress conditions (e.g.,Lorig et al., 2023; Martinez & Viegas, 2017; Sopjani et al., 2020). The objectives of this paper are threefold:

1. To assess the operational and environmental viability of SAEVs across different scales: municipal, subregional, and regional.
2. To investigate the potential sustainability benefits and challenges associated with the widespread adoption of SAEVs, including their impacts on global warming potential, particulate matter formation, tropospheric ozone formation, human toxicity, land use, mineral and fossil resource depletion
3. To identify key factors influencing the life cycle environmental performance of SAEVs.

In the next section, we will delve into the literature review, with a focus on the ABM-LCA integration. Section 3 will outline the methodological approach, which is subdivided into the ABM and LCA. The details of input data and case study applications will be examined in Section 4. Section 5 will focus on model verification and validation, including evidence supporting the reliability of the ABM. The results will be presented in Section 6. Finally, Section 7 will conclude with a summary of key findings, contributions, research limitations, and suggestions for future research.

Literature review

LCA offers a comprehensive method for assessing environmental impacts, but it usually depends on predefined assumptions and overlooks the dynamic nature of human decision-making (Gutowski, 2018). As a result, the outcomes may not fully reflect the real-world environmental impacts. One promising approach to obtain closer-to-reality results is through the usage of ABM or other microsimulation approaches which allows for the simulation of individual-level decision-making processes and interactions within complex mobility systems (Francois & Coulombel, 2024; Hicks, 2022). ABM provides valuable insights into the complex decision-making processes underlying transportation choices by simulating individual agents' behaviours and interactions within a larger mobility system. Its importance lies in its ability to capture human behaviour and vehicle deployment strategies, ultimately contributing to a more comprehensive assessment of future mobility scenarios.

The ABM methodology has found extensive application in depicting the interplay between supply and demand within transportation systems across various domains, including but not limited to traffic flow analysis, modelling travel behaviour, planning and managing transportation systems, adopting emergent technologies, and examining potential rebound effects (Calabrò et al., 2022; Gurumurthy et al., 2019; Huang et al., 2022; Li et al., 2021; Soteropoulos et al., 2019; Stevens et al., 2022; Sun et al., 2022). Several researchers, including Ciari, Milos, and Axhausen (2016), Jager, Agua, and Lienkamp (2017), Becker, Ciari, and Axhausen (2018), Sheppard et al. (2019) and Wang, Correia, and Lin (2019) have applied ABM to analyse the operational system performance, infrastructure requirements, power grid constraints, and policy assessments related to SAEVs. These studies underscore ABM's effectiveness in simulating real-world mobility scenarios and analyse operational system performance, infrastructure needs, power grid impacts, and policy assessments. For instance, Jager, Agua, and Lienkamp (2017) presented an operational simulation of on-demand SAEVs. They concluded that environmental benefits should only be expected when carpooling is encouraged and the energy supply is sourced from renewable resources, underscoring the importance of simultaneously evaluating both performance and environmental factors. Regarding vehicle performance, SAEVs may require frequent relocation, likely instigating congestion (Bösch et al., 2018). Varying from 5 to 10 min at an urban scale with 95 % of accepted travel demand, average waiting times are a crucial metric for assessing service quality and user satisfaction (Basu et al., 2018; Gurumurthy et al., 2020). Unoccupied repositioning journeys can raise greenhouse gas emissions by 25 % of non-electrified AVs (Lu et al., 2018). However, service levels can worsen due to vehicle electrification and the type of shared system (Vasconcelos et al., 2017; Hyland & Mahmassani, 2020; Vosooghi et al., 2020).

When LCA methods are integrated with ABM, it becomes possible to deepen our comprehension of environmental impacts. This is achieved by revealing how changes in individual behaviour and technology adoption influence environmental outcomes (Alfaro et al., 2010; Micolier et al., 2019). Davis et al. (2009) pioneered this integration within the bioelectricity domain, in a proof-of-concept model. While this coupling has seen widespread application in energy and agriculture, its utilisation in transportation remains limited. Florent and Enrico (2015) integrated ABM into a consequential LCA to analyse mobility-related policies and simulate automobile market dynamics to determine the effects on the economy and environment. Onat et al. (2017) developed an ABM to predict the upcoming market share of electric vehicles in the US, assessing their life-cycle environmental and economic impact. Lu and Hsu (2017) employed an LCA-ABM framework to evaluate the environmental impacts associated with the implementation of a high-speed railway. Recently, Vilaça et al. (2024) introduced a conceptual framework that integrates ABM and LCA for a behaviour-driven SAEV assessment at a large scale. This is the first time that such an integrated approach has been applied for this purpose. This framework demonstrates a significant reduction in daily global warming potential (GWP) without compromising user experience. However, a 30-year perspective, the study projects a 170 % increase in GWP when SAEVs meet all road transport demand in the region. Later, Luo et al., (2024) applied a similar approach to evaluate the environmental impacts of AVs in private use. Their study suggests that AVs may increase the total distance travelled, which, without the promotion of BEVs and increased penetration of renewable energy sources in the power grid, could lead to a substantial increase in fossil fuel consumption.

Despite the growing body of research on SAEVs, significant gaps remain, particularly in comprehensively assessing their life cycle environmental impacts through integrated methodologies like ABM and LCA. Most studies have predominantly focused on market share estimations among different transportation modes or technologies, without fully integrating these approaches to evaluate environmental outcomes in a real-world context (Florent & Enrico, 2015; Lu & Hsu, 2017; Onat et al., 2017). This underscores a critical need for research that, not only bridges these methodological approaches but also applies them to a scalable assessment of SAEVs across multiple scales. Furthermore, this study broadens the analysis beyond typical assessments, encompassing diverse environmental impact categories, namely global warming potential, particulate matter formation, tropospheric ozone formation, human toxicity, land use and mineral and fossil resource depletion. These categories provide a comprehensive framework for understanding the multidisciplinary impacts of transportation systems. By encompassing key areas such as health outcomes, environmental degradation, and economic pressures, they offer a well-rounded perspective on the challenges and trade-offs associated with sustainable transportation. This selection ensures that the analysis captures not only immediate effects, such as air quality and human health risks, but also broader implications for resource use, land management, and long-term ecological sustainability. Investigating these impact categories will deepen our understanding of the environmental, health, and economic implications of SAEVs' implementation, offering crucial insights to guide policy and future research in sustainable transportation.

Methodology

This study proposes a methodology that integrates ABM and LCA to assess the environmental impacts associated with the deployment of SAEVs for door-to-door polled ride-sharing transport. Fig. 1 provides an overview of the methodology structure including the specific tools that have been used for each component.

The methodology comprises a comparative evaluation of the impact of SAEVs before and after substituting them into the representative mobility system, assessing the life cycle implications across various geographic scales - municipal, subregional, and regional. This process entails the construction of an ABM that resembles a common mobility context, alongside a modified ABM scenario wherein private car and bus journeys are substituted with SAEV services.

The ABM models are developed in MATSim (Version 13.0) (Horni et al., 2016). The models serve two purposes: they replicate the dynamics of the representative mobility system and the hypothetical SAEV mobility service, thereby generating datasets for a LCA and essential service performance metrics such as vehicular distance covered,

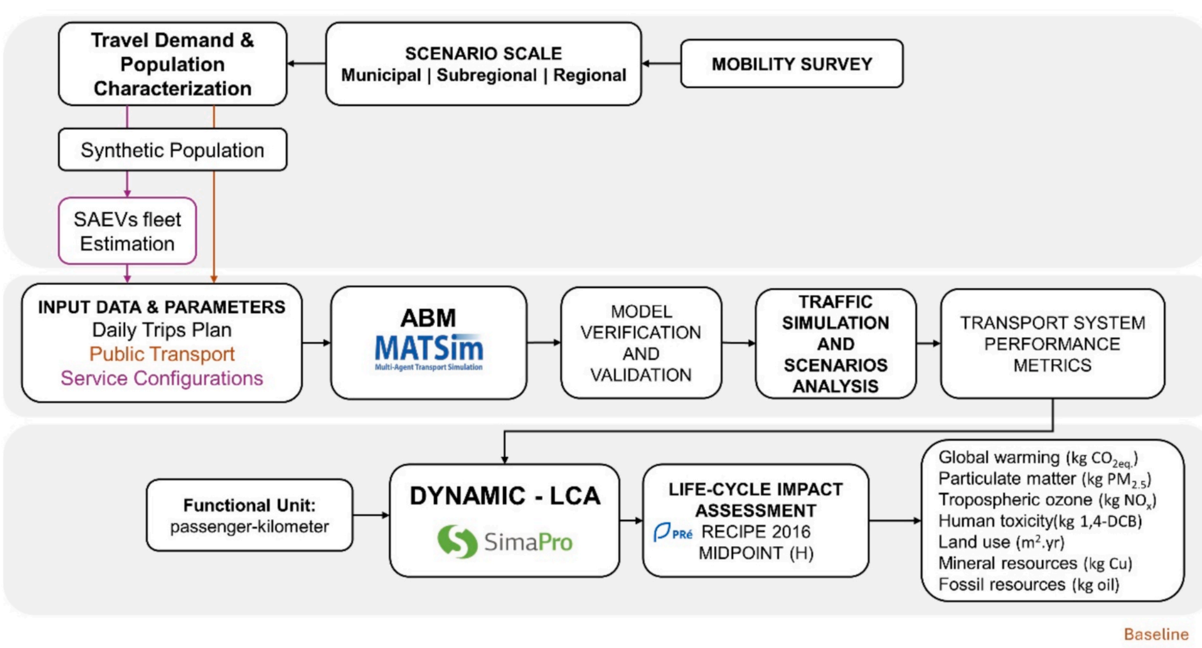

Fig. 1. Methodological framework.

occupancy rates, and daily mobility efficiency at each examined scale. The environmental impact assessment is executed using SimaPro (Version 9.6.0.1), a widely recognised LCA software renowned for its methodical approach to evaluating the environmental performance of products or processes across all life stages (PréConsultants, 2024). Moreover, the ReCiPe 2016 (H) version 1.1 impact assessment method is used, this method aligns with European regulatory frameworks and environmental policies and is widely used in academic research (e.g. Florent & Enrico, 2015; Koroma et al., 2022) due to its detailed categorisation (Huijbregts et al., 2016).

Subsequent sections provide a detailed breakdown of our methodological approach. Section 3.1 explains the ABM simulation, designed in the MATSim simulation platform, and Section 3.2 elaborates on the standardised LCA approach and the environmental impact categories under evaluation.

ABM simulation framework

This study employs MATSim as a simulation platform, to model the behaviour and daily schedules of agents representing the real population of a region. The core concept of MATSim is the simulation of agents and their daily plans, comprising different activities (such as home, work, leisure) and the trips between these locations. These trips can span different modes of transportation, including car, public transport, or taxi. The framework is specially designed to handle large-scale transportation scenarios by simplifying the framework with a queue-based model for network loading and incorporating parallel processing to enhance efficiency (Horni et al., 2016). Essential inputs for initiating MATSim include a synthetic population reflecting the socio-economic attributes, a comprehensive daily activity plan per agent, and transport network attributes with a virtual representation of spatial layout (e.g. residential, commercial, and industrial areas) and available transport services.

The initial population of agents, representing the initial set of daily plans, is obtained through the generation of synthetic population data based on travel diary data from surveys. The generation of the synthetic population begins with data preprocessing for each individual daily travel plan. Although the specific details of the survey data are proprietary and not publicly accessible, an overview of its key characteristics and the method for generating the synthetic population is provided in Section 4.

To model the replacement of conventional road trips with SAEVs, the Demand-Responsive Transport (DRT) extension developed by Bischoff et al. (2017) was employed. This extension addresses the dynamic vehicle allocation problem by applying a vehicle dispatch algorithm to meet travel demands dynamically based on constraints like capacity, time window, maximum waiting time, and travel time. The primary objective is to maximise a multi-objective function that seeks to balance operational efficiency with service quality. Thus, in cases where multiple vehicles can fulfil the request, the system selects the most suitable. This DRT extension has been used in previous studies such as Bischoff & MacIejewski (2020); Vosooghi et al. (2019, 2020); Zwick et al. (2021).

Life cycle assessment

Aligned with the ISO 14044:2006 framework (ISO 14044, 2006), this research adopts a structured LCA methodology to assess the environmental impacts of integrating SAEVs into a macroscopic road transportation system. Following the framework structure, we aim to compare seven impact categories of a conventional road transportation system against a system that uses SAEVs across three scale levels: municipal, subregional, and regional.

A fleet-based life cycle model encompassing production, usage, maintenance, and final disposal stages is developed. LCA execution utilised the SimaPro software (version 9.6.0.1) together with the Ecoinvent database (version 3.10) (Ecoinvent, 2024; PréConsultants, 2024). Furthermore, ReCiPe 2016 v.1.1 impact assessment method was used to calculate global warming potential, particulate matter formation, ozone formation, human toxicity; land use; and mineral and fossil resources scarcity impact categories (Huijbregts et al., 2016). The method comprises a hierarchist (H) perspective (over a 100-year horizon) which aligns with a predetermined framework for evaluating current technological developments (Huijbregts et al., 2016). This widely applied impact assessment approach, with its midpoint-level characterisation factors, ensures a process of low uncertainty due to the strong correlation between the selected indicators and environmental impacts (Montoya-Torres et al., 2023). Table 1 reviews the description of each environmental impact category and its relevance to the transportation sector.

The environmental and health impacts of transportation systems manifest strongly at the local level, where high concentrations of emissions and infrastructure demands directly affect communities. Global warming potential contributes to localized effects such as the urban heat island phenomenon and increased vulnerability to climate-related disasters like floods and storms. Particulate matter formation ($PM_{2.5}$ and PM_{10}) and tropospheric ozone formation degrade air quality, leading to elevated rates of respiratory and cardiovascular diseases, particularly in urban and high-traffic areas. Human toxicity, through exposure to pollutants such as heavy metals and volatile organic compounds, poses significant health risks, including cancer and neurological damage. Land use changes, driven by transportation infrastructure, result in habitat destruction, loss of green spaces, and ecosystem

Table 1
Environmental Impact Categories Evaluated Using the ReCiPe Midpoint Method (Adapted from (Huijbregts et al., 2016)).

Impact Category	Description	Relevance to the Transportation Sector
Global Warming Potential (kg $CO_{2eq.}$)	Measures the impact of greenhouse gases on global warming, expressed as CO_2 equivalents.	Essential for evaluating the role of vehicle GHG emissions in climate change. Directly reflects sustainability goals in mobility.
Particulate Matter Formation (kg $PM_{2.5}$)	Emissions of particulate matter can affect air quality and cause respiratory issues.	Relevant to assess the contributions of vehicle emissions to air quality (particularly from engine emissions, tire and brake wear). Exposure to particulate matter poses serious health risks, including respiratory and cardiovascular diseases.
Ozone formation (kg NO_x)	Formation of ozone from volatile organic compounds and nitrogen oxides.	Crucial for understanding the transportation impact on urban smog and air pollution, especially in high traffic conditions. It is a harmful pollutant affecting human health and ecosystems.
Human Toxicity (kg 1,4-DCB)	Evaluates harmful effects of released chemical substances.	Vehicle production, maintenance and end-of-life processes can release toxic pollutants, such as benzene and heavy metals, which can cause cancer and neurological disorders.
Land Use (m^2. yr)	Impact on land through occupation or transformation	Affects patterns due to infrastructure development and raw material extraction, leading to habitat destruction and biodiversity loss.
Mineral Resources Scarcity (kg Cu)	Depletion of mineral resources due to extraction and use.	Particularly relevant in the production of electric vehicles, which require significant quantities of rare minerals for batteries.
Fossil Resources Scarcity (kg oil)	Depletion of fossil resources due to extraction and use.	Important for assessing the impact of conventional vehicle fuels.

fragmentation, which reduce biodiversity and urban resilience. Additionally, mineral and fossil resource depletion exert economic stress on communities through increased costs and environmental degradation in resource extraction regions (Kwan & Hashim, 2016; Nieuwenhuijsen, 2016).

Case study: Central region of Portugal

Study area overview and data

The designed methodology is applied to the Coimbra Region in central Portugal (Fig. 2). This region consists of 26 municipalities covering approximately 5900 km^2 and had a resident population of around 601,000, of which 86 % are aged 15 and above (TIS.PT, 2009). This region provides a foundation for exploring transportation dynamics across different spatial scales. Thus, for the study purposes, the region is divided into three levels – municipal, subregional, and regional (see Fig. 2). The population densities at the subregional and municipal levels are estimated to be 1.2 and 3.3 times higher, respectively, than at the regional level (101 inhabitants per km^2) (TIS.PT, 2009). In each scale, it is ensured that all trip origins and destinations fall within their respective geographic boundaries.

Data from a comprehensive mobility survey conducted by an external company (TIS.PT, 2009) form the basis for building the ABM. Despite having been done in 2009 this is still the most accurate data source for characterising the mobility in the region, reporting detailed daily trip information, transport mode options, and satisfaction levels with existing transport modes. In the meantime, the structure of the region did not change significantly neither in terms of population nor regarding transport systems supply. However, the objective is not to replicate the exact current mobility conditions but to develop a mobility system that is representative enough to support the analysis and provide a robust basis for the ABM model. About 13,696 residents were surveyed, contributing to a dataset of 17,760 trips. The survey focused on the population aged 15 or above and included socioeconomic status questions to characterise household transportation behaviour more accurately. The zoning of the geographical area under study (Fig. 2) formed the basis for the survey sample sizing. The adopted zoning has the following general characteristics: the zones are always subsets of municipalities; in the case of the municipality of Coimbra, the zones are sets of statistical sub-sections, generally not respecting administrative boundaries; in the remaining municipalities, the zones consist of one or more administrative boroughs or encompass the entire municipality. The zoning becomes more detailed as closer to the urban area (TIS.PT, 2009).

Mobility patterns in the region indicate an average of 1.5 daily trips per person, primarily dominated by private car usage at 80 %, followed by walking at 10 %, public transport at 8 %, and other less representative modes making up the remaining 2 % (TIS.PT, 2009). Recent studies have indicated minor changes in the modal split: private car usage decreased to 72 %, walking trips increased to 11 %, and PT increased to 16 % (CIM Coimbra, 2016). It is identified in the survey 8518 activities locations. These locations reflect the destination location of a specific trip purpose classified into: work (18 %), home (67 %), health (2 %), education (1 %), services (5 %), shopping (2 %), restaurant (<1%), leisure (2 %), escort (2 %) and other (<1%) (TIS.PT, 2009).

Synthetic population generation

A synthetic population estimation technique was employed to model the demographic distribution across the region. Main variables are obtained from the survey, including person ID, origin and destination coordinates, respective zone ID of those coordinates, travel purpose, mode of transportation, start at home, trip sequence, start time, and coefficient of expansion from sample to population. First, trip sequences are reviewed to ensure the trip plans adhere to the reported sequence. Following that, the 'start at home' parameter, which indicates the origin of each individual's first trip, is processed with two options: 'home' or 'other'. A bank of coordinates is subsequently created from the original data, with each geographical coordinate characterised by zone ID and trip purpose (related to the typology of the facility of origin). This bank is also used to identify locations for the types of activities. Synthetic population generation is then initiated based on a coefficient of expansion, estimated together with the survey which is dependent on the population characteristics in each zone. The coefficient of expansion represents the ratio used to correlate the number of valid survey responses to the corresponding population size within each sample extract, categorized by residential zone, age group, and gender. The synthetic population is reconstructed, and synthetic trips are scaled using this coefficient. For each synthetic individual trip, a random coordinate is selected from the bank of coordinates, ensuring alignment with the reported zone ID and trip purpose. Each coordinate in the bank is associated with multiple purposes and several repetitions, acting as a ponderation for selecting a coordinate. To introduce temporal variability, random deviations of $\pm$ 10 min are applied to the start times of synthetic trips. The randomised coordinates for synthetic trips are selected while retaining the original trip plan structure, maintaining the integrity of the individual's travel patterns. This algorithmic process captures not only structural aspects of travel orders but also introduces stochastic elements for variability. The weighted selection mechanism

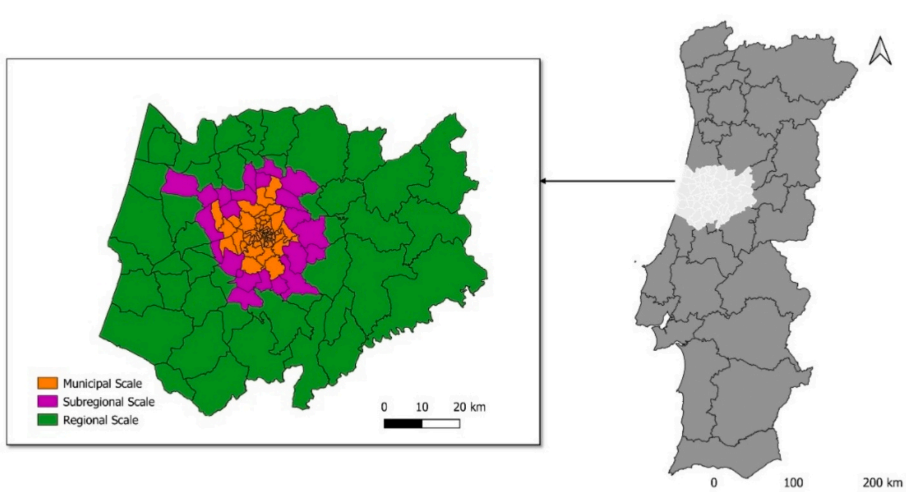

Fig. 2. Coimbra Case Study Location in Central Portugal.

further refines the process, enhancing the representation of diverse travel patterns within the simulated population. Resulting in a total of 615,007 trips within the region, the synthetic trips estimation error varied by scale: −3% at the regional level, −7% at the subregional level, and + 3 % at the municipal level compared to the coefficient of expansion.

Simulation setup

The simulation model uses the Dijkstra algorithm to select the shortest driving path, which is based on minimizing travel time. The simulation model does not incorporate dynamic rerouting. However, this is not expected to significantly affect the results, as the network in our case study has limited alternative route options.

Integration of GTFS files from the SMTUC (Municipal Services of Urban Transport of Coimbra), which operates Coimbra's bus system, and Transdev, the main private transit operator at the regional level, enabled transit route modelling. The GTFS data provided by these two public transport operators was converted into MATSim data format. The municipal services provide 937 transit routes, while combined with Transdev, the regional and subregional scales present 1810 transit routes. Buses in this model are considered to have a capacity of 70 passengers.

Every trip made by bike, on foot, by car, and by PT was modelled. However, for this study, we restrict our analysis to motorised trips (car and PT). A time step of one second was used in the simulated scenarios.

The SAEVs are designed to represent a door-to-door system, offering passengers a service closely resembling private transportation. Each vehicle is configured to carry up to four passengers, a capacity aligning with industry standards such as Uber, and commonly accepted in shared mobility models (Alonso-Mora et al., 2017; Zeng et al., 2020). It is important to emphasise that although the model assumes a maximum capacity of four passengers per SAEV, this does not entail consistent operation at full capacity. The model enables occupancy level variation, reflecting real-world conditions impacted by factors such as time of day, route, and demand fluctuations.

Model execution was computationally demanding, especially at larger geographic scales. All simulations were conducted on a high-performance workstation equipped with 256 GB of RAM and dual processors. Simulation time varied depending on the spatial scale and complexity, ranging from approximately 24 to 168 h per run.

Saevs departure station allocation and fleet distribution strategy

An approach based on the demand density per zone was used to determine the departure stations for the SAEVs fleet to initiate its services. At the municipal scale, where trips are more concentrated, five departure stations were chosen. These stations were distributed across the municipal boundaries, ensuring they were located in areas with sufficient space and covering trips within a short radius of action. For the subregional and regional scales, additional departure points were set based on the zones that accounted for more than 5 % of all departures at each respective scale. At the subregional scale, seven additional stations were added to the existing five municipal points. Similarly, at the regional scale, six additional stations were introduced, including the stations from the municipal and subregional scales. Not diversifying these locations would hinder the vehicles from picking up the passengers at an acceptable waiting time, especially when the day begins. For example, if vehicles are requested at a city that is at more than 30 min travel time distance from the nearest station, and travellers are only willing to wait for 20 min, this would lead to immediately rejected trips. Fig. 3 illustrates the location of the determined departure points.

The fleet of SAEVs was distributed proportionally to the demand for trips at each scale. Within each scale, the vehicles were divided evenly among the departure points except for municipal scale. Specifically, at the municipal scale, the fleet was divided among the five departure stations: the two central stations are assigned 50 % of the fleet allocated to this scale, while the remaining three stations handle the other 50 %. At the subregional scale, 88 % of the fleet was allocated to the five municipal stations, while 12 % was distributed among the seven subregional stations. At the regional scale, 49 % of the fleet was placed at the municipal stations, 7 % at the subregional stations, and the remaining 45 % at the six regional stations. Note that vehicles are not required to return to their starting locations after each service, allowing for flexible routing. We could assume that they will return for spending the night period, but this was not modelled.

Scenarios design

To provide a clear understanding of the different scenarios analysed in this study, Table 2 presents an overview of each scenario and its key characteristics. The explanation behind the selection of the specific scenarios is provided in the next subsections.

Each of the four scenarios (Baseline, Electric Benchmark, SAEVs

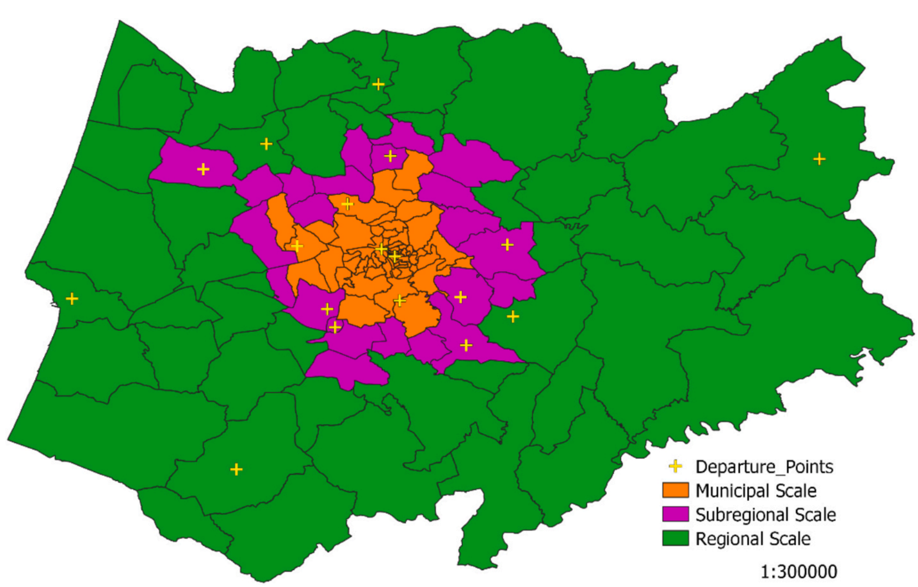

Fig. 3. SAEVs departure stations.

Table 2
Overview of the studied scenarios and description.

Scenario	Description
Baseline	Represent representative mobility conditions, reflecting the characteristics of the average national fleet.
Electric Benchmark	Models the current mobility with an all-electric fleet, maintaining the same operational characteristics as the baseline scenario. This scenario serves as a reference for LCA comparisons.
SAEVs Fleet A	Follows the operational characteristics of shared mobility, where one SAEV replaces five road trips. For environmental assessment, rejected trips are assumed to be fulfilled by private-use electric cars.
SAEVs Fleet B	Follows the operational characteristics of shared mobility, where one SAEV replaces ten road trips. For environmental assessment, rejected trips are assumed to be fulfilled by private-use electric cars.

Fleet A, and SAEVs Fleet B) is considered across the three spatial scales: municipal, subregional, and regional.

In terms of LCA the impact categories are assessed considering two time-frames: the daily impact and a 100-year horizon evaluation. The long-term environmental impact assessment takes into account fleet renewal cycles and their consequent environmental effects. To compute the long-term environmental implications, a scaling factor is applied. This factor accounts for the number of fleet replacements anticipated over 100 years, based on the reference lifetime values for electric vehicles (EVs) and internal combustion engine vehicles (ICEVs). Specifically, these values are 150,000 km for EVs and 250,000 km for ICEVs (Notter et al., 2010; Wernet et al., 2016).

The functional unit applied in the performed LCA scenarios is passenger-kilometre (pass.km) travelled, reflecting the current demand for transportation services. For this purpose, passenger counting is conducted using a trip-based counting approach, where each trip segment undertaken by an individual is counted separately. This method ensures accuracy in capturing the performance of the mobility system comparatively across each spatial scale and for both private and public transport. By using passenger-kilometre travelled, the life cycle impact assessment also accounts for possible rejected trips, thereby providing a realistic assessment when compared to shared mobility scenarios.

Baseline scenario

The baseline scenario mirrors the current mobility conditions and the fleet inventory draws from the national fleet composition, with specifics detailed in Table 3, linking to the selected Ecoinvent database sources used for life cycle impact assessment (Ecoinvent, 2024; Emisia, 2022). It classifies passenger vehicles according to fuel type, size segment (small, medium, large), and EURO emissions standards, providing an outline of the conventional vehicle context. In the construction of the life cycle inventory for this analysis, where specific data for newer emissions standards (such as EURO 6) were not available for certain vehicle types, the most recent applicable dataset was employed. In cases where the number of vehicles meeting a specific EURO standard is very low (less than 1 %), these vehicles are grouped into broader emissions categories. To choose a representative EURO standard for each group, we use a weighted average. This average considers not only the proportion of each EURO standard in the national fleet but a proportional weight to the EURO standard immediately before and after it. The analysis adopts a generic model for buses that mirrors the operational characteristics of a typical bus within the representative fleet.

Electric benchmark scenario

In addition to the baseline scenario, a second scenario is run, reflecting the current mobility conditions but assuming a future where all private vehicles are BEV and electric buses. This hypothetical scenario, called 'electric benchmark' scenario, provides a level comparison for assessing the SAEV scenario against a fully electrified current

Table 3
Passenger Car National Fleet Composition and typical bus and selected Ecoinvent database source.

Fuel	Segment	Euro	%	Ecoinvent Database
Petrol	Small	3	12	Transport, passenger car, small size, petrol, EURO 3 {RER}|Cut-off, U
Petrol	Small	4	8	Transport, passenger car, small size, petrol, EURO 4 {RER}|Cut-off, U
Petrol	Small	5;6	15	Transport, passenger car, small size, petrol, EURO 5 {RER}|Cut-off, U
Petrol	Medium	3;4;5;6	3	Transport, passenger car, medium size, petrol, EURO 3 {RER}|Cut-off, U
Petrol	Large[(1)]	3;4;5;6	1	Transport, passenger car, large size, petrol, EURO 4 {RER}|Cut-off, U
Diesel	Small	4	4	Transport, passenger car, small size, diesel, EURO 4 {RER}|Cut-off, U
Diesel	Small	5/6	4	Transport, passenger car, small size, diesel, EURO 5 {RER}|Cut-off, U
Diesel	Medium	3	8	Transport, passenger car, medium size, diesel, EURO 3 {RER}|Cut-off, U
Diesel	Medium	4	14	Transport, passenger car, medium size, diesel, EURO 4 {RER}|Cut-off, U
Diesel	Medium	5;6	24	Transport, passenger car, medium size, diesel, EURO 5 {RER}|Cut-off, U
Diesel	Large	3	2	Transport, passenger car, large size, diesel, EURO 3 {RER}|Cut-off, U
Diesel	Large	4	2	Transport, passenger car, large size, diesel, EURO 4 {RER}|Cut-off, U
Diesel	Large	5;6	2	Transport, passenger car, large size, diesel, EURO 5 {RER}|Cut-off, U
BEV	S/M/L	5;6	1	Transport, passenger car, electric {GLO}| Cut-off, U
Bus	Generic	Generic	-[(2)]	Transport, regular bus {RoW}| transport, regular bus | Cut-off, U

[(1)]Large – SUV – Executive.
[(2)]Directly applied to all the public transit fleet.

mobility system, thus highlighting potential advantages in a future-oriented context.

The Portuguese electricity generation mix from 2020, comprising 33 % natural gas, 26 % hydro, 23 % wind, 7 % biofuels, 4 % coal, 3 %, solar photovoltaic, 2 % oil, and 2 % waste and geothermal is the basis for modelling the energy consumption of EV's use phase (IEA, 2024).

SAEVs scenarios

The determination of the initial SAEVs fleet size was established based on two different scenarios. The first is that one ride-sharing vehicle is on average able to replace 5 private cars (Nenseth et al., 2012; Peer et al., 2024) (designated as Fleet A). The second, in a less conservative approach, is that one ride-sharing vehicle can replace ten private cars (Bischoff & Maciejewski, 2014; Fagnant & Kockelman, 2014; Martinez et al., 2015; Santos & Correia, 2021) (designated as Fleet B). In this study, we expand the scope of these assumptions by considering that all road trips (done by private cars and buses) will be replaced by SAEVs. This is particularly relevant in large-scale, low-density scenarios where public transport often lacks efficiency and frequently operates with low occupancy levels.

In the scenario involving SAEVs, the LCA model is grounded on a BEV model. This base model is enhanced with necessary sensors and subsystems essential for full automation (level 4 or higher) as detailed in prior research by Vilaça et al., (2022). Furthermore, the LCA model incorporates the percentage of kilometres travelled by SAEVs either without passengers or carrying between 1 and 4 passengers, with each passenger assumed to weigh 60 kg (Simons, 2016). Energy consumption during the use phase of SAEVs is modelled based on the Portuguese electricity generation mix from 2020. Trips that could not be accommodated by the SAEVs system were accounted for in the LCA. It is assumed that when a trip cannot be completed by the shared system (rejected trips), a private electric car is used. This ensures that the LCA is comparing the same mobility demand. This approach reflects the anticipated widespread adoption of electric vehicles in a future where SAEVs are common. It can be interpreted in two ways: individuals whose trips are not accommodated by the shared system will use their private electric cars, or from a company perspective, if the service cannot fulfil a request, the company provides an electric car for the individual. The model is designed to minimise rejection trips, which are a by-product of providing a mobility system feasible and attractive to users (i.e. maintaining acceptable waiting times). Above all, the rejection trips represent a small percentage of the overall system impact.

Model verification and validation

To assess the accuracy of the ABM developed for the case study, a multi-step verification process was employed. This process aimed to validate the model's ability to reflect the mobility system by comparing it against established benchmarks from a reference transportation planning study conducted in 2008 (TIS.PT, 2008), and by critically comparing any potential simulation thresholds. The 2008 data was used because it is a high-quality study and one of the few available with such detailed information. For the purpose of this study, it is not crucial that the data reflects the current situation in 2024, rather it should represent realistic mobility patterns in the case study area. Additionally, as the study area has had limited investment in public transportation and maintains a stable population number, it is unlikely that significant changes have occurred since the data was collected.

First, visual inspection of the activity locations represented in the ABM is made. This was conducted to ensure that the model accurately depicted the urban layout and key points of interest as observed in the city's actual environment (Fig. 4). The visual inspection revealed a strong correlation between the model's representation and the actual city layout.

Subsequently, the validation process assessed overall traffic volumes across the urban network. This validation is particularly focused on the city of Coimbra network, as it is the area for which we possess comparative traffic volume data and is less affected by extra-regional trips. A visual verification to compare overall traffic volumes across the network was conducted. This qualitative assessment involved comparing traffic volumes on major links within the city (as counted in the 2009 study) to see if high-traffic volumes were consistent between the ABM and the reference model (VISUM macro model based on the survey and traffic counts).

Following the visual verification, nine specific locations were identified, and absolute traffic volumes (vehicles per day) were compared in both directions of the road (Fig. 5). These locations were strategically chosen based on their importance in terms of traffic flow.

Through the visual comparison, a fair level of consistency between the models has been observed (Fig. 5). Furthermore, the fact that the links with the most significant traffic volumes coincide between the two models, coupled with our comprehensive understanding of the case study area, further strengthens the credibility of the MATSim model. The specific location analysis showed a mean absolute percentage error of −21 %, indicating an underestimation of traffic volumes by MATSim. This deviation is within an acceptable range, given the model's design to exclude traffic not originating within the region. Thus, the observed discrepancy can be rationalised as the model's intentional omission of trips that extend beyond the region of interest.

Finally, the accuracy of the simulation model in estimating travel distances and times was evaluated. This evaluation began by assessing the estimated distances and travel times of the trips reported in the survey (TIS.PT, 2008) using the Google Distance Matrix API (Google, 2024). A script was developed to convert the coordinates to the WGS84 system, readable by Google Maps. The API requests included departure times and accounted for average traffic conditions to estimate the travel times. This approach was applied to both types of motorised trips: cars and buses. The average travel distances and times obtained from the API for trips by car and bus at three regional scales, weighted by the coefficient of expansion for estimation, were then compared with those simulated by the ABM model. The results indicate that simulated car trip distances vary by no more than 0.5 km on average, while public transport trips vary by up to 1 km. In terms of travel time, on average, the MATSim model slightly underestimates car trips by up to 2 min and PT trips by up to 15 min. The discrepancy, particularly in PT travel times, can be attributed to modelling previous public transport demand with the current PT system, which may cause some differences. Additionally, the routing module aggregates travel time estimations into time bins to keep computational effort feasible. These aggregations can introduce minor inaccuracies as they generalise travel times over periods rather than accounting for exact variations (Horni et al., 2016).

Overall, the integrated ABM framework demonstrates strong contextual fidelity, particularly in replicating spatial mobility patterns and realistic vehicle operations. Nonetheless, limitations should be noted. First, the model validation is constrained by the availability of historical mobility and traffic data; while robust for the purposes of spatial and behavioural benchmarking, these datasets may not fully capture recent or emergent trends. Second, assumptions related to SAEV operations (such as routing logic, passenger acceptance of shared rides, and fixed vehicle capacities) introduce simplifications that could affect the accuracy of trip rejection rates and occupancy estimates. Third,

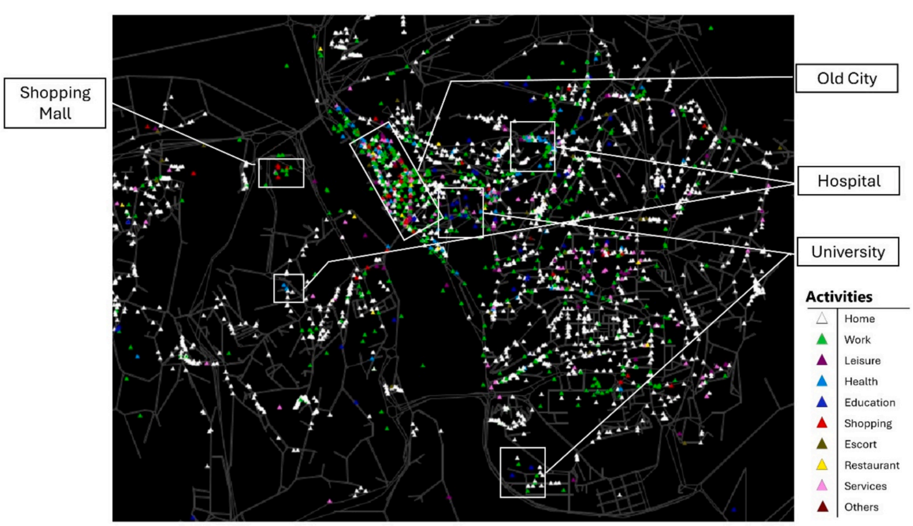

Fig. 4. Visual Representation of Activities Locations within the Urban Environment of the Case Study.

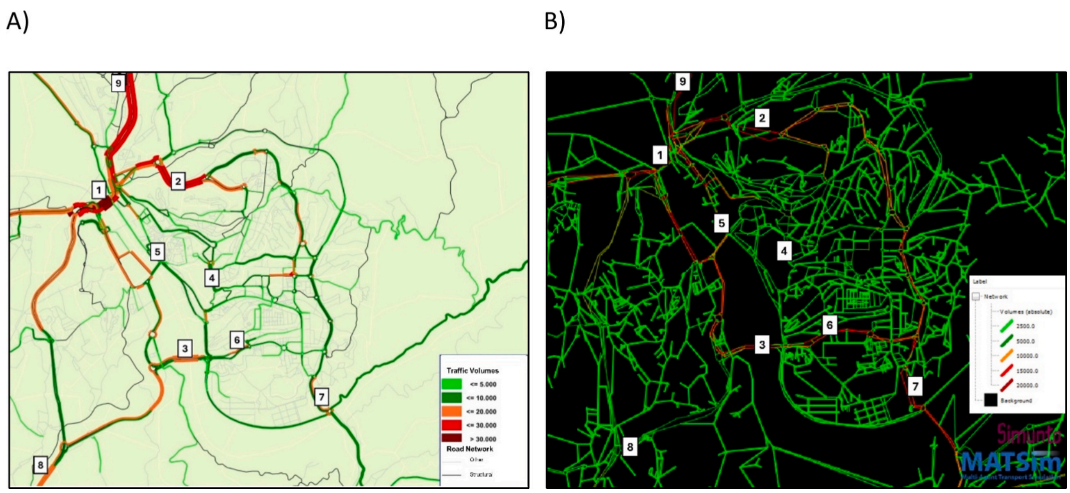

Fig. 5. Comparative analysis of traffic volumes in the urban environment of the case study. A) Reference Transportation Planning Study (adjusted from (TIS.PT, 2008)); B) Developed MATSim model.

while the LCA component uses a well-established impact assessment method (ReCiPe 2016) and high-quality inventory data, there remains uncertainty in long-term projections, particularly for battery degradation, electricity mix evolution, and recycling rates. Despite these limitations, the combination of rigorous simulation design, careful scenario framing, and sensitivity to real-world constraints supports the reliability of the study's core findings.

Results

Table 4 summarises the baseline daily transportation system performance metrics derived from the ABM across the three different geographic scales (review Fig. 2). It details the number of operational vehicles, the average kilometres travelled per vehicle, the number of passengers travelling in both private cars and PT, and the median waiting time for PT. It is important to note, as previously mentioned, that the passenger counts are based on trip occurrences, facilitating a more accurate comparison with public transport and shared mobility metrics. These counts do not represent the total population size but rather the extent of transportation utilisation.

Despite the increase in the total number of private cars with the expansion of the geographic scale, the number of vehicles in movement per km^2 decreases significantly as the scale increases. Specifically, at the municipal level, there are approximately 222 vehicles in movement per km^2. This value reduces to 98 vehicles per km^2 at the subregional level and further decreases to 41 vehicles per km^2 at the regional level. This trend aligns with expectations, as the population density decreases across the geographic areas. Additionally, private cars travelled significantly more distance in regional (+77 %) and subregional (+27 %) scales when compared to the municipal scale. The number of passengers in private cars increased by 28 % at the subregional scale and 237 % at the regional scale, compared to population increases of 23 % at the subregional scale and 189 % at the regional scale. This indicates an increased dependency on private cars as one moves away from the main urban centre in the region, the city of Coimbra.

In terms of PT, the same number of buses is provided for the subregional and regional scales, with differences only observed in the reduction of passengers and fewer kilometres travelled per vehicle. On average, a regional bus travelled 23 km more than a municipal bus. However, the reliance on PT decreases as the geographical scale increases and we move away from the urban centre, with the number of passengers in public transport increasing by only 5 % at the subregional scale and 16 % at the regional scale, which is significantly lower than the population increase.

Table 5 presents the results of the MATSim output metrics when shifting to SAEVs considering fleets A and B. The table also includes the percentage of trip rejections, the median waiting time per passenger and the average level of detour. The detour is defined as the ratio of the actual distance travelled by a passenger to the shortest possible distance if the trip were direct (without detours or shared segments). Thus, the

Table 4
Simulated Baseline Daily Transportation Metrics across Municipal, Subregional, and Regional Scales.

Mode	Metrics	Municipal	Subregional	Regional
Private Cars	Number of Vehicles	66,821	86,972	237,082
	Kilometres per vehicle (km/veh.)	16.2	20.5	28.8
	Number of Passengers	145,292	186,326	490,159
PT Buses	Number of Vehicles used	4,638	5,921	5,921
	Kilometres per vehicle (km/veh.)	66.9	64.7	89.9
	Number of Passengers	43,606	46,184	50,491
	Median Waiting Time (minutes)	6.7	8.2	11.6

Table 5
Simulated Transportation Metrics for SAEVs Scenarios Across Municipal, Subregional, and Regional Scales.

Fleet	Metric (Per Day)	Municipal	Subregional	Regional
A (1 SAEV per 5 trips)	Number of Vehicles	14,292	18,579	48,601
	Kilometres per Vehicle (km/veh.)	41.6	49.5	59.6
	Number of Passengers	149,147	188,659	387,543
	Trip Rejection Rate (%)	14	14	22
	Median Waiting Time (min)	4.1	4.5	5.1
	Detour Level (%)	58	54	49
B (1 SAEV per 10 trips)	Number of Vehicles	7146	9289	24,300
	Kilometres per Vehicle (km/veh.)	76.2	84.7	112.9
	Number of Passengers	131,697	157,430	354,060
	Trip Rejection Rate (%)	22	24	26
	Median Waiting Time (min)	4.5	4.8	5.4
	Detour Level (%)	58	54	49

level of detour represents the increase in travel distance compared to a direct trip.

For fleet A, the reduction of fleet size by 5 times results in daily kilometres travelled per SAEV being 1.6, 1.4, and 1.1 times higher than private cars at the municipal, subregional, and regional scales, respectively. With a tenfold reduction in fleet size in fleet B, the vehicle usage intensity is more pronounced. Compared to private vehicles in the baseline scenario, SAEVs travel 3.7 times more kilometres at the municipal scale, 3.1 times more at the subregional scale, and 2.9 times more at the regional scale. The reduction between regional and municipal levels is due to the fact that in the latter scale, many trips are done without detouring and a larger distance, connecting different subcities with the main one of Coimbra in the centre.

The trip rejection rate increases as the geographic scale enlarges for both fleets. In fleet A, rejection rates range from 14 % to 22 %, while in fleet B, it ranges from 22 % to 26 %.

Regarding user experience, the median waiting time for SAEVs across all scenarios varies from 4.1 to 5.4 min, which is 3 to 8 min less compared to PT. The waiting time for passengers increases slightly as the geographic scale expands due to longer distances and increased travel times within larger areas. Furthermore, waiting times are higher in fleet configurations where each SAEV is responsible for replacing 10 trips (Fleet B) compared to configurations where 1 SAEV replaces 5 trips (Fleet A). This is because the higher demand on each SAEV in the former configuration results in more operational constraints and longer waiting times for passengers. Additionally, the level of detour is highest at the municipal scale, where vehicles travel 58 % more than the direct route. The higher detour level at the municipal scale reflects the higher density of pick-up and drop-off points in urban areas, which requires more frequent stops and route adjustments for ride-sharing.

The following figures present the LCA results considering two approaches: daily impact (Fig. 6) and a 100-year perspective (Fig. 7). The heat-tables display the impact values (numbers annotated within each cell) and use colour intensity to represent the normalised values within each impact category. Columns represent Baseline, Electric Benchmark, Fleet A, and Fleet B scenarios for each geographic scale. To enhance clarity, normalisation and the associated colour scale are applied independently to each set of four columns, corresponding to the respective geographic scale section. Darker shades indicate higher normalised values relative to the maximum value within each row, facilitating the comparison of environmental impacts. Categories include GWP (kg CO_2 eq), Ozone formation (kg NOx eq), Fine particulate matter formation (kg PM2.5 eq), Human carcinogenic toxicity (kg 1,4-DCB eq), Human non-carcinogenic toxicity (kg 1,4-DCB eq), Land use (m^2.yr crop eq), Mineral resource scarcity (kg Cu eq), and Fossil resource scarcity (kg oil eq). Values in the figures should be analysed by impact category (i.e., by row) since each impact category follows different units and scales.

In terms of daily LCA impacts (Fig. 6), the electric benchmark demonstrates clear advantages at the municipal and subregional scales, whereas the baseline scenario proves more favourable at the regional scale. At the municipal scale, five out of eight daily impact categories at SAEVs scenarios reveal increases compared to the baseline scenario. Focusing on the impact categories benefiting from this transition, the GWP shows a potential reduction of 15 % (fleet A) and 35 % (fleet B); fine particulate matter formation decreases by 3 % (fleet A) and 26 % (fleet B); and fossil resource scarcity presents reductions of 18 % (fleet A) and 37 % (fleet B).

At subregional scale, the GWP shows a potential reduction of 40 % (fleet A) and 61 % (fleet B); ozone formation presents a decrease of 9 % (fleet A) and 41 % (fleet B); fine particulate matter presents a reduction of 32 % (fleet A) and 55 % (fleet B); and fossil resource scarcity is reduced by 42 % (fleet A) and 62 % (fleet B). The remaining impact categories, however, worsen with this transition.

Across all three geographical scales, the impact categories that consistently show increased negative impacts are human toxicity (both carcinogenic and non-carcinogenic) and mineral resource scarcity. This highlights the importance of a balanced and comprehensive approach when considering the adoption of SAEVs, ensuring that improvements in some areas do not lead to significant detriments in others.

Daily impacts are influenced mostly by operational efficiency, so the fleet size, increase in vehicle kilometres travelled, and rejection rates have a significant influence on these results. Despite efforts to maintain a smaller rejection rate, the impact of these trips is substantial, representing around 78–86 % of the impact in Fleet A and 73–78 % in Fleet B.

The long-term LCA impacts were analyzed, considering the number of fleet replacements and maintenance needed for both the baseline,

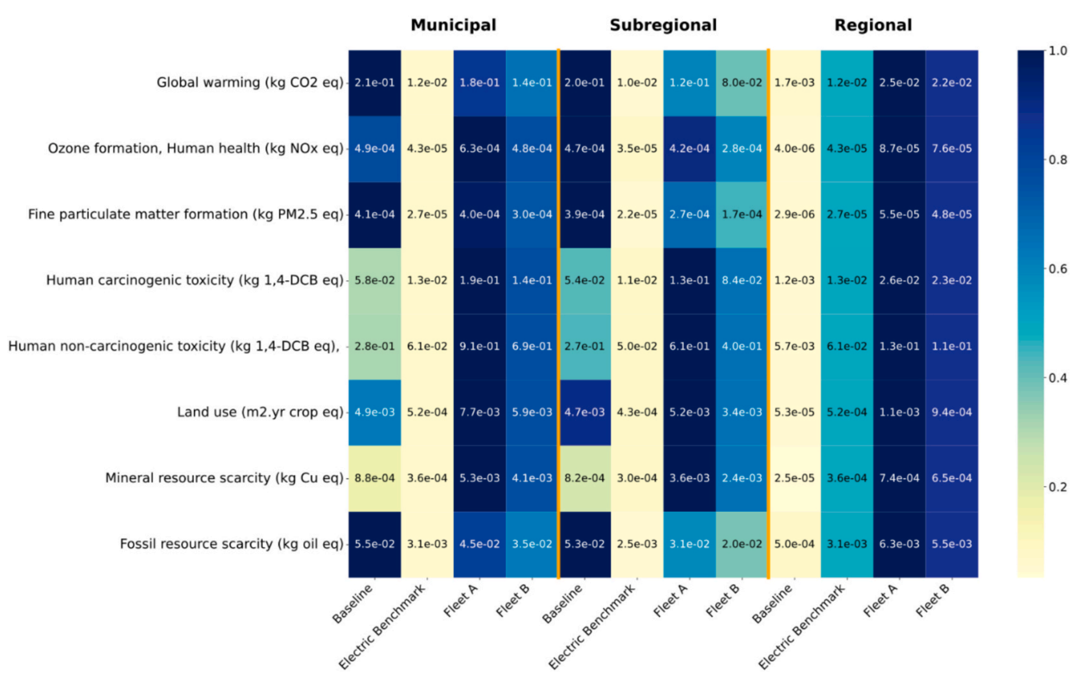

Fig. 6. Comparative Environmental Impact of Baseline and SAEVs scenarios across different geographic scales. Daily Impact, Values per passenger kilometre (pass.km).

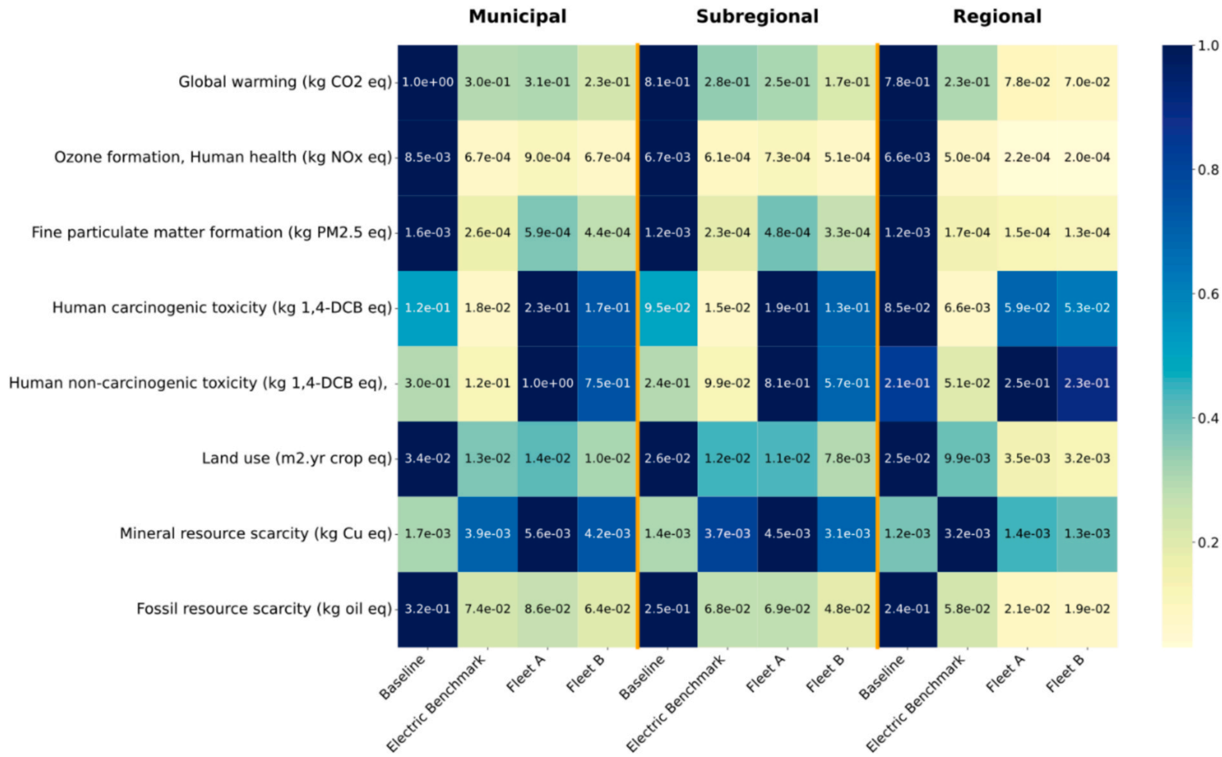

Fig. 7. Comparative Environmental Impact of Baseline and SAEVs scenarios across different geographic scales – 100-Years Perspective, Values per passenger kilometre (pass.km).

electric benchmark, and SAEVs scenarios over a 100-year period (Fig. 7). It is important to note that this analysis does not account for the potential evolution of vehicle efficiency over the years. The difference between the daily impact analysis and this long-term perspective lies in the normalization of impacts, particularly concerning the need for fleet replacements. Over the 100-year timeframe, the replacement and maintenance cycles significantly influence the overall environmental impacts, highlighting the importance of durability and operational intensity in determining long-term sustainability outcomes.

In the long-term perspective, it becomes evident the potential of SAEVs to reduce most of the impact categories at every scale compared to the baseline scenario. However, there are notable increases in human toxicity and mineral resource scarcity impacts. For instance, human carcinogenic toxicity reveals a potential increase of up to 99 % for fleet A and 45 % for fleet B, whereas the regional scale observes a reduction of 31 % (fleet A) and 38 % (fleet B). Human non-carcinogenic toxicity shows increases in SAEVs scenarios across all scales and fleet configurations, with increases reaching up to 240 % for fleet A at the municipal scale. Mineral resource scarcity with an impact that can increase up to 229 % for fleet A at the subregional scale.

The impacts of the SAEVs at fleet A configuration are close to those of the electric benchmark. This similarity suggests that the environmental benefits of shared automated mobility may not be significantly higher than those achieved by simply transitioning to an electric vehicle fleet.

The need for fleet replacement is a crucial factor in the long-term environmental impact of SAEVs. With more vehicles, Fleet A benefits from less frequent replacements (10–12 replacements over 100 years, depending on the geographic scale). In contrast, Fleet B, with fewer vehicles but higher utilisation rates, requires more frequent replacements (19 to 23 over 100 years). Despite this increased frequency of replacements, Fleet B still presents better overall environmental performance than Fleet A. The reduced number of vehicles in Fleet B effectively compensates for the higher replacement frequency, resulting in overall better environmental outcomes.

Considering the differences between geographical scales, larger scales tend to be more favourable in most cases when looking at long-term impacts. This indicates that implementing SAEVs on a larger scale could amplify the environmental benefits. This occurs because, even under higher-intensity usage and consequently facing higher replacement rates, their ability to dynamically adjust to demand still allows them to transport more passengers efficiently compared to, for example, traditional buses, reducing detour levels and the inefficiency of empty trips.

Conclusions and future work

This study aimed to assess the environmental impacts of transitioning from conventional road transportation systems to Shared Autonomous Electric Vehicles (SAEVs) across various geographic scales. By integrating Agent-Based Modeling (ABM) with Life Cycle Assessment (LCA), we compared seven impact categories of both systems at municipal, subregional, and regional levels.

Our findings reveal that the adoption of SAEVs presents promising opportunities to reduce the number of vehicles, generally improve user experience (with median waiting times 3–8 min shorter than public transport), and partially enhance environmental sustainability. However, the transition introduces challenges such as increased operational intensity (resulting in 30–60 additional kilometres travelled per vehicle per day), trip rejection rates, and the complexity of interpreting future environmental trade-offs.

From an environmental perspective, transitioning to SAEVs offers substantial reductions in several environmental impact categories, such as global warming potential, ozone formation, particulate matter formation, land use, and fossil resource scarcity. However, these benefits come with significant increases in human toxicity (both carcinogenic and non-carcinogenic) and mineral resource scarcity. Over the long term, human toxicity could increase by up to 99 % for carcinogenic and 240 % for non-carcinogenic effects, while mineral resource scarcity may rise by as much as 229 %. This suggests that focusing solely on global warming emissions may introduce bias into life cycle assessments.

Human toxicity impacts can lead to a decline in human health, which can be difficult to trace to its source due to long-term exposure. Similarly, the scarcity of mineral resources can drive up system costs, creating economic disadvantages and supply chain vulnerabilities. While addressing global warming remains critical, comprehensively addressing human toxicity and mineral resource depletion is equally imperative for achieving overall environmental sustainability. This aligns with evidence suggesting that transportation decarbonization requires a lifecycle-based regulatory approach (Xue et al., 2023). Accordingly, extended-producer-responsibility schemes, mandatory recycled content thresholds for battery packs, and transparent diligence requirements for critical-mineral supply chains should be integrated into AEV deployment strategies.

Our analysis indicates that the need for fleet replacement significantly influences long-term impacts. High operational intensity, reflected in the number of kilometres travelled per vehicle, exacerbates the intensity of fleet replacement. To mitigate this, stakeholders must consider the trade-offs between reducing trip rejection rates and managing fleet sizes. Excessive efforts to reduce rejection rates by increasing fleet size can lead to increased kilometres travelled per vehicle, adversely affecting environmental outcomes.

This finding highlights that SAEVs can be effectively implemented on a large scale to maximise environmental benefits. Nevertheless, parallel investments in renewable-generation capacity and smart-charging infrastructure are essential to ensure that upstream power-sector emissions do not erode tail-pipe gains, especially under high-penetration scenarios.

This research makes several novel contributions. First, it introduces an integrated ABM-LCA framework that enables the simultaneous assessment of operational performance and environmental impact of SAEV systems. Second, it quantifies trade-offs across multiple environmental categories, offering researchers new insights into the spatial and systemic implications of SAEV deployment. For policymakers, the results show that fleet operational efficiency alone does not ensure environmental benefits; life cycle considerations must be embedded into deployment strategies. The analysis also identifies critical trade-offs (particularly in toxicity and resource scarcity) that require careful management, highlighting the need for policies on battery and electric powertrain chemistry and technologies, as well as the importance of clear recycling measures. Finally, the study underscores the potential of equitable SAEV deployment in low-density regions, highlighting its role in supporting transport inclusivity alongside sustainability.

While the findings of this study offer valuable insights, it is important to state some limitations. First, the model does not account for potential shifts in population distribution patterns, which could significantly impact transportation needs and preferences. Additionally, our model lacks mechanisms to predict mode choices it varies from the current mobility scenario to an extreme scenario where most demand is satisfied by SAEVs. These static assumptions limit the ability to capture variability in user preferences and operational factors. Additionally, future research should incorporate structured feedback from stakeholders to validate model assumptions and ensure practical relevance. Stakeholder engagement through focus groups, expert interviews, or participatory scenario design could enhance the credibility and applicability of the findings, and help align technological pathways with user expectations, regulatory feasibility, and local planning contexts.

Future research should address these limitations to provide a more comprehensive understanding of the impacts of SAEVs. Linking discrete–choice travel–demand models to agent–based simulations, coupling power–system optimisation with vehicle–to–grid scenarios, and using mixed–methods to reveal distributional effects across income, gender, and ability will build a stronger evidence base for holistic policy. Cross–disciplinary collaboration can translate that evidence into test–bed regulations that foster innovation, protect the environment, and advance social justice.

CRediT authorship contribution statement

Mariana Vilaça: Conceptualization, Formal analysis, Methodology, Software, Validation, Writing – original draft. **Gonçalo Homem de Almeida Correia:** Writing – review & editing, Validation, Supervision, Conceptualization. **Margarida C. Coelho:** Writing – review & editing, Validation, Supervision, Project administration, Funding acquisition, Conceptualization.

Declaration of competing 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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Data availability

The survey data that has been used in this study is proprietary and cannot be publicly shared. The code developed for both data processing and agent-based modeling will be made available upon request.

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