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Accelerating the Deployment of Smart Urban Mobility Solutions through Collaborative Knowledge Platforms and Data-Driven Simulation: A Civitas Batteries and Mobility Study

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ABSTRACT

Contemporary European cities face urgent pressure to decarbonise urban transport systems while sustaining economic competitiveness and social equity. This paper examines the BATTERIES and MOBILITY project, a funded component of the European CIVITAS initiative as a coordinated mechanism to valorise, cross-fertilise, and disseminate innovative sustainable mobility solutions across European municipalities. A MATLAB-based computational simulation is developed to model the cumulative effects of collaborative knowledge exchange, electric vehicle (EV) deployment, and peer-to-peer learning on average urban travel time and daily CO_2 emissions. The simulation applies an exponential decay function parameterised against empirical baseline and Day-30 endpoint data for three representative cities drawn from a 15-city CIVITAS-affiliated European dataset. Results indicate that coordinated knowledge-sharing programmes combined with progressive EV adoption rates of 12–20% of vehicle fleet yield travel time reductions of 13–20% and daily CO_2 emission reductions of 10–18%, computed via an established diesel vehicle emission factor of 0.1271 kg CO_2 per kilometre. A one-at-a-time sensitivity analysis confirms robustness under ±20% perturbations in the learning-rate parameter. Furthermore, structured knowledge platforms and city-twinning mechanisms are found to reduce solution adoption lead times by 30–40%, with commensurate modal shifts away from private vehicle use. The findings provide a policy-relevant, reproducible framework consistent with the European Green Deal and Sustainable and Smart Mobility Strategy objectives for climate-neutral mobility by 2050.

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1. Introduction

Urban transportation schemes are essential for the growth, social unity and environmental stability of cities, as noted by Banister (2008) and Ortúzar and Willumsen (2011). Since 75% of the population of Europe lives in urban areas, the quality, efficiency and environmental effects of transportation systems are critical for policymakers, according to the European Commission (2020). The transportation sector is currently responsible for 25% of the greenhouse gas emissions in the European Union, with road transportation being the main contributor. It is worth noting that the emissions from the transportation sector in 2023 were higher than in 1990, which makes reducing carbon emissions from transportation a difficult task as reported by the European Environment Agency (2023).

The European Green Deal, introduced by the European Commission (2019a) and the Sustainable and Smart Mobility Strategy, introduced by the European Commission (2020) have set a goal to reduce greenhouse gas emissions from transportation by 90% by 2050 compared to the levels in 1990. Achieving this goal will require efforts in developing technologies, changing behaviours, investing in infrastructure and reforming governance. Electric vehicles, shared transportation services, intelligent traffic management and travel infrastructure are all solutions. However, their adoption in cities is inconsistent and fragmented as observed by Gkoumas et al. (2021), Sagdieva et al. (2024) and Mayeres (2025).

One significant obstacle to adopting transportation solutions is the fragmentation of knowledge and practice among cities. City authorities often develop strategies to invest in activities to build capacity and lack access to proven evidence from other cities, as noted by Ehnert et al. (2018). This lack of knowledge sharing is exacerbated by expertise, unequal access to European Union funding and insufficient collaboration between public authorities, research institutions, private operators and citizens as observed by Asamoah Debrah et al. (2025).

The CIVITAS initiative, established in 2002 and currently coordinated by CIVITAS MUSE under Horizon Europe funding, addresses this gap by creating a network of over 380 cities committed to smart transportation, as reported by the CIVITAS Initiative (2023). Through city pairing programs, peer learning exchanges, thematic workshops and digital knowledge platforms, CIVITAS enables cities to co-create, share and scale transportation solutions in a manner that aligns with policy. The BATTERIES and MOBILITY project, a part of CIVITAS, focuses on developing and sharing solutions for electrification, logistics decarbonization and multimodal integration.

This study contributes to the existing research on knowledge sharing in transportation by developing a simulation framework that measures the impact of learning on travel time and emissions reduction over time. The simulation complements existing assessments of knowledge platform effectiveness, such as those conducted by Bulkeley et al. (2019) and Brons et al. (2022) by providing indicators of the impact of interventions thus strengthening the evidence base for data-driven decision making at the city level and ultimately supporting the work of policymakers such as those, in the European Commission in their efforts to reduce greenhouse gas emissions from transportation as outlined in the European Green Deal and the Sustainable and Smart Mobility Strategy.

1.1 Research Objectives

The primary goals of this research are:

(i). To create and configure a simulation model using MATLAB that examines the connection between the sharing of knowledge among collaborators, the adoption of vehicles and the performance of urban mobility systems.

(ii). To measure the expected decreases in travel time and carbon dioxide emissions that can be attributed to initiatives of CIVITAS using a dataset that represents multiple cities in Europe.

(iii). To examine the dynamics of shifting from one mode of transportation to another in response to CIVITAS initiatives. To evaluate how changes to model parameters affect the outcomes.

(iv). To identify policy implications that are relevant to European cities seeking to expedite the transition to sustainable mobility in line with the objectives of the European Green Deal.

1.2 Paper Organisation

The rest of this paper is organised in the manner. Section 2 provides an overview of the existing literature on policies related to mobility in Europe, methodologies for simulating transportation systems and frameworks for sharing knowledge. Section 3 describes the approach used to collect data, the formulation of the simulation model, the methodology used to calculate emissions, and the design of the sensitivity analysis. Section 4. Interprets the results of the simulation. Section 5 concludes by discussing the implications for policy, the limitations of the study, and potential directions for research.

2. Literature Review

2.1 European Urban Mobility Policy Landscape

The European Commission's strategy for smart mobility, which was introduced in 2020, provides the primary framework for guiding the decarbonization of urban transport across all European Union member states. This strategy builds upon the European Green Deal (European Commission, 2019a), which establishes a total of 82 milestones that are aimed at promoting multimodal mobility, deploying zero-emission vehicles and investing in smart infrastructure. In addition to this, the European Union’s mission to create climate-smart cities (European Commission, 2022) has set a target of achieving climate neutrality in 100 European cities by the year 2030. This mission provides a pathway for urban experimentation and knowledge replication. Furthermore, the European Parliament has emphasised the importance of mobility, highlighting the interdependence of digital and green transformation in urban transport infrastructure, (European Parliament, 2021).

A comprehensive review of European Union-funded research and innovation projects, which was conducted by Gkoumas et al. (2021), demonstrated that cities that actively participate in research networks exhibit stronger technological adoption trajectories in areas such as electrification, automated vehicles and sustainable logistics. Sagdieva et al. (2024) extended this analysis, conducting an assessment of 362 European cities and their decarbonization pathways. They found heterogeneity in progress and identified structured capacity building as the most influential predictor of successful mobility transition. Smeds and Cavoli (2024) examined mobility pathways for European cities in the post-COVID-19 recovery context in

2024, highlighting the European Green Deal as a mechanism for aligning local mobility strategies with continental decarbonization objectives. Mayeres (2025) assessed the regulatory dimensions of the European Union's transport energy transition in 2025, documenting the interaction between carbon pricing, infrastructure investment incentives and modal substitution dynamics.

2.2 Transport Simulation and Demand Modelling

The scientific foundation for urban transport demand modelling was established by Ortúzar and Willumsen (2011), who introduced a four-step demand modelling framework that encompasses trip generation, trip distribution, modal split and traffic assignment. This framework remains the paradigm in urban transport planning practice and establishes the theoretical basis against which computational simulations of intervention impacts should be evaluated and calibrated. The simulation developed in this study represents split and traffic volume changes as aggregate functions of electric vehicle penetration and learning-rate parameters, acknowledging that disaggregate individual-level behaviour modelling represents a priority for future model development.

Data-driven approaches to traffic simulation have evolved significantly over the past decade. Chen et al. (2024) provided a review of deep learning and hybrid methods for traffic simulation in 2024, demonstrating that data-driven models can achieve superior predictive accuracy for policy analysis applications. Wang et al. (2023) applied an agent-based modelling and system dynamics approach to simulate the impact of environmental transport policies in Chinese urban contexts in 2023, demonstrating measurable CO_2 emission reductions under electric vehicle subsidy and public transport investment scenarios. This study provides a precedent for the simulation framework developed herein.

Digital twin technologies represent a development in urban mobility simulation. Rudskoy et al. (2021) demonstrated the applicability of twin frameworks to intelligent transport systems in 2021, enabling real-time data integration and scenario evaluation for operational transport management. Lis and Mądziel (2026) further developed transportation planning models integrating digital twins with real-time traffic optimisation for urban mobility networks. Aheleroff et al. (2025) advanced the state of the art by developing a twin framework for urban parking management incorporating mobility demand forecasting in 2025, illustrating the operational integration of simulation with city management systems. In logistics, Mehdizadeh et al. (2025) employed agent-based simulation combined with optimisation to evaluate sustainable logistics configurations in Lisbon in 2025, demonstrating vehicle-kilometre reductions achievable through route consolidation and electric vehicle substitution.

2.3 Knowledge Sharing and Capacity Building in Urban Mobility

Living laboratories have emerged as a primary institutional mechanism for co-producing sustainable mobility knowledge across diverse stakeholder groups. Bulkeley et al. (2019) provided an analysis of urban living laboratories across European cities in 2019, demonstrating their effectiveness in accelerating the uptake of experimental mobility interventions through participatory design and iterative evaluation. Brons et al. (2022) extended this analysis to food system transformation contexts in 2022, developing insights on citizen engagement mechanisms to urban mobility governance and highlighting the importance of genuine co-production rather than consultative participation.

Ehnert et al. (2018) examined sustainability transitions in multi-level governance contexts across four European member states in 2018, identifying institutional fragmentation as a principal barrier to the diffusion of proven mobility solutions and underscoring the importance of supranational coordination mechanisms such as CIVITAS in bridging national governance heterogeneity. Asamoah Debrah et al. (2025) critically examined stakeholder participation frameworks in transport planning in 2025, documenting the gap between engagement commitments and the substantive integration of diverse stakeholder preferences into planning decisions with implications for the design of CIVITAS capacity-building programmes. Bahi and Ourici (2025) demonstrated the use of agent-based simulation to model emergent human mobility behaviour in complex urban environments in 2025, providing a methodological complement to the aggregate simulation approach employed in this study.

2.4 Research Gaps and Contribution of the Present Study

Notwithstanding the body of literature reviewed above, several important gaps remain. First studies that explicitly combine knowledge-sharing platforms with quantitative simulation models of mobility performance are scarce. Most evaluations of CIVITAS or similar programs rely on impact assessments or general performance indicator reporting without a formal computational model that links intervention parameters to mobility outcomes (Bulkeley et al., 2019; Chen et al., 2024).

Second, the temporal dynamics of learning-rate-driven mobility improvements. That is, the rate at which cities learn from each other and turn this knowledge into results. Have not been formally modelled with clear mathematical definitions. Third, the combined impact of electric vehicle adoption and collaborative learning on split and overall emissions has not been modelled in a single integrated simulation framework for the CIVITAS context. This study addresses these gaps by creating a clear, reproducible simulation framework. We acknowledge the limitations of our model. Provide a sensitivity analysis to understand the model's uncertainty. We develop a simulation framework that explicitly integrates knowledge-sharing platforms with quantitative models of mobility performance. Our framework is designed to model the dynamics of learning-rate-driven mobility improvements and the joint impact of EV adoption and collaborative learning on modal split and aggregate emissions in the CIVITAS context. By doing our study aims to provide a more comprehensive understanding of the relationships between collaborative learning, EV adoption and mobility outcomes. The results of this study can inform the development of strategies for improving mobility performance and reducing emissions in urban areas. The present study contributes to the existing literature by providing an explicit and reproducible simulation framework. This framework can be used to evaluate the effectiveness of CIVITAS or similar programs and to inform decision-making in transportation policy.

3. Methodology

This section outlines the systematic attempt to examine the implementation of novel urban mobility solutions within the BATTERIES and MOBILITY project. The methodology encompasses a range of components, including data gathering, mathematical simulation modelling, a calculation of emission reduction, a sensitivity analysis and a structured framework for evaluation.

3.1 Study Cities and Data Collection

Data pertaining to mobility performance were gathered for 15 European cities participating in projects affiliated with CIVITAS, leveraging project monitoring reports, municipal mobility databases and documentation from the CIVITAS Initiative (2023). The selection of cities was based on their ability to represent a range of characteristics, including population size (ranging from 100,000 to 2 million inhabitants), geographic location across northern, southern, central and eastern Europe and baseline transport system characteristics that vary from municipalities with a high dependence on cars to those with a rich transit system. In order to maintain the confidentiality of data in accordance with project participation agreements, cities are referred to by labels throughout this paper.

Three cities, designated as City A, City B and City C, are presented as cases that are representative of the broader dataset comprising 15 cities. The selection of Cities A, B and C was based on their baseline profiles, which include high-volume mid-congestion (City A), moderate-volume high-congestion (City B) and high-volume low-congestion (City C). The baseline mobility characteristics of these cities are presented in Table 1.

Table 1. Baseline Urban Mobility Dataset for Representative CIVITAS Cities

City	Trips/Day	Avg. Travel Time (min)	CO_2 Emissions (kg/day)	EV Share (%)
City A	250,000	35	1,200,000	12
City B	180,000	42	950,000	18
City C	320,000	30	1,500,000	20

The subsequent mobility indicators were gathered at the outset. Forecasted at Day 30 following the intervention:

i. Daily vehicle excursions
ii. Average duration of travel per excursion measured in minutes
iii. Daily CO_2 emissions quantified in kilograms per day, which were estimated from the distribution of vehicle types and established emission factors
iv. The proportion of public transport modal share expressed as a percentage
v. The proportion of the electric vehicle (EV) fleet share is also expressed as a percentage.

3.2 Simulation Framework and Mathematical Formulation

The simulation model illustrates the evolution of travel duration in each city over time as a function of collaborative knowledge acquisition dynamics and the adoption of EV. The primary equation is a decay function, which can be expressed as:

$$T_i(t) = T_{o,i} \times exp(-k_i \times t) \quad \text{... (Eq. 1)}$$

Where $T_i(t)$ represents the average travel duration, measured in minutes in city i at time step t, measured in days $T_{o,i}$ denotes the baseline average travel duration, k_i is the city-specific composite knowledge acquisition rate constant measured in days^{-1}, and t ∈ {1, 2 … 30} represents the daily simulation time intervals. The knowledge acquisition rate constant can be parameterised from endpoint data as:

$$k_i = -ln(T^{\varphi}{}_{ir}{}^{oa}{}_{,i} / T_{o,i}) / 30 \quad \text{... (Eq. 2)}$$

Where $T^{\varphi}{}_{ir}{}^{oa}{}_{,i}$ denotes the target travel duration at Day 30 for city i, which is derived from the monitoring data of the CIVITAS project. This formulation serves to anchor the trajectory to the observed baseline and target endpoint values, with the rate of improvement determined by the aggregate effect of EV penetration, route optimisation, and knowledge transfer dynamics.

3.2.1 Mechanistic Interpretation of the Learning-Rate Constant

The decay constant k_i encapsulates the rate at which mobility enhancements manifest in a city that adopts collaborative knowledge acquisition mechanisms similar to those of the CIVITAS project. A larger value of k_i corresponds to rapid knowledge acquisition and adoption, which reflects greater electric vehicle penetration, more extensive participation in peer-exchange programs and more effective institutional implementation capacity. Although the exponential decay functional form is a simplification of the traffic dynamics, which are governed by nonlinear route choice demand elasticity and network externalities (Ortúzar & Willumsen, 2011), it is consistent with empirically observed patterns of early-stage technology adoption and incremental congestion alleviation in which, per-period gains accumulate as institutional knowledge and infrastructure capability build up over time.

3.2.2 Explicit Model Assumptions

The subsequent assumptions are explicitly stated:

(i). The reduction in travel time is modelled as a function that decreases monotonically over time within the 30-day intervention period;

(ii). The learning-rate constant, denoted as k_i is considered to be temporally invariant within the 30-day window, representing a first-order approximation of a process that in practice accelerates as network effects become more pronounced;

(iii). The effects of EV adoption on travel time are incorporated within k_i operating through reduced routing delays and optimisation at the junction level enabled by EV traffic management;

(iv). Interactions between cities are assumed not to produce spillover effects on participating cities within the 30-day simulation window.

3.2.3 Model Limitations and Calibration Considerations

The limitation of the current model is the absence of real-time trajectory calibration across all 15 participating cities. The endpoint-anchored parameterisation (Equation 2) ensures consistency with observed targets. It cannot validate the daily trajectory within the period against independent empirical observations. Furthermore, the aggregate city-level representation cannot capture heterogeneity in traffic conditions within cities, which is a known limitation of aggregate simulation approaches (Ortúzar & Willumsen, 2011; Wang et al., 2023). Future iterations of the model should incorporate real-time traffic data from vehicle platforms and OpenStreetMap-based network models to enable full trajectory validation. The assumption of a fixed reduction (exponential form) does not derive from behavioural or traffic-flow principles; extensions of this framework using disaggregate agent-based models (Bahi & Ourici, 2025) represent a natural methodological progression.

3.3 Emission Reduction Model

The daily reduction in CO_2 emissions to the CIVITAS intervention is computed as the sum of two complementary mechanisms:

$$\Delta CO_{2,i} = (\Delta d_i \times (1 - s_i) + s_i \times d_{0,i}) \times EF^{\nu dOLeL} \quad \ldots \text{(Eq. 3)}$$

Where $\Delta CO_{2,i}$ is the daily CO_2 reduction for city i (kg/day); Δd_i is the reduction in vehicle-kilometres attributable to optimised routing, derived from the proportional travel time reduction; $d_{0,i}$ is the baseline total vehicle-kilometres in city i; s_i is the EV fleet penetration rate (fraction); and $EF^{\text{ɐdOLeL}} = 0.1271$ kg CO_2 km^{-1} sourced from Armenta-Déu (2020) and consistent with European Environment Agency reporting standards for euro-5 and euro-6 diesel passenger vehicles. The first term represents the emission savings from vehicle-kilometres among remaining diesel vehicles; the second term represents the emission displacement from substituting diesel trips with EV trips (zero tailpipe CO_2). This dual-effect formulation provides more analytical transparency than aggregate percentage-based reduction factors and enables direct sensitivity testing.

3.4 Sensitivity Analysis

To evaluate the robustness of the simulation results to parameter uncertainty, a one-at-a-time (OAT) sensitivity analysis is accomplished by perturbing each learning-rate constant k_i by ±20% relative to its central value derived from Equation 2. This perturbation range reflects the parameter uncertainty in city-level mobility studies where calibration data are partial or aggregate (Ortúzar & Willumsen, 2011; Wang et al., 2023). The Day-30 travel time outcome for each perturbation scenario is reported in Table 3 (see Section 4.1). The full MATLAB implementation of the sensitivity analysis is provided in Appendix E.

3.5 Evaluation Metrics

The following metrics are used to evaluate simulation outputs:

(i). Travel time reduction (%): percentage change in travel time from baseline to Day 30;

(ii). CO_2 emission reduction (kg/day and %): relative daily emission savings computed via Equation 3;

(iii). Solution adoption rate (%): proportion of tested CIVITAS mobility solutions successfully implemented across participating cities by Day 30; and

(iv). Modal shift: change in the proportion of trips, by mode (car, public transport, EV, active mobility).

4. Results and Discussion

4.1 Travel Time Reduction

Figure 1 shows the travel time for Cities A, B and C over the thirty-day period when we tried to reduce travel time. All three cities show that the average travel time went down consistently, which is what we expected based on the decay model as shown in Equation 1. City A had a reduction in travel time, which is not surprising because it had the most traffic congestion to start with and therefore a larger learning rate constant, which is $k_a = 0.00744$ day^{-1}.

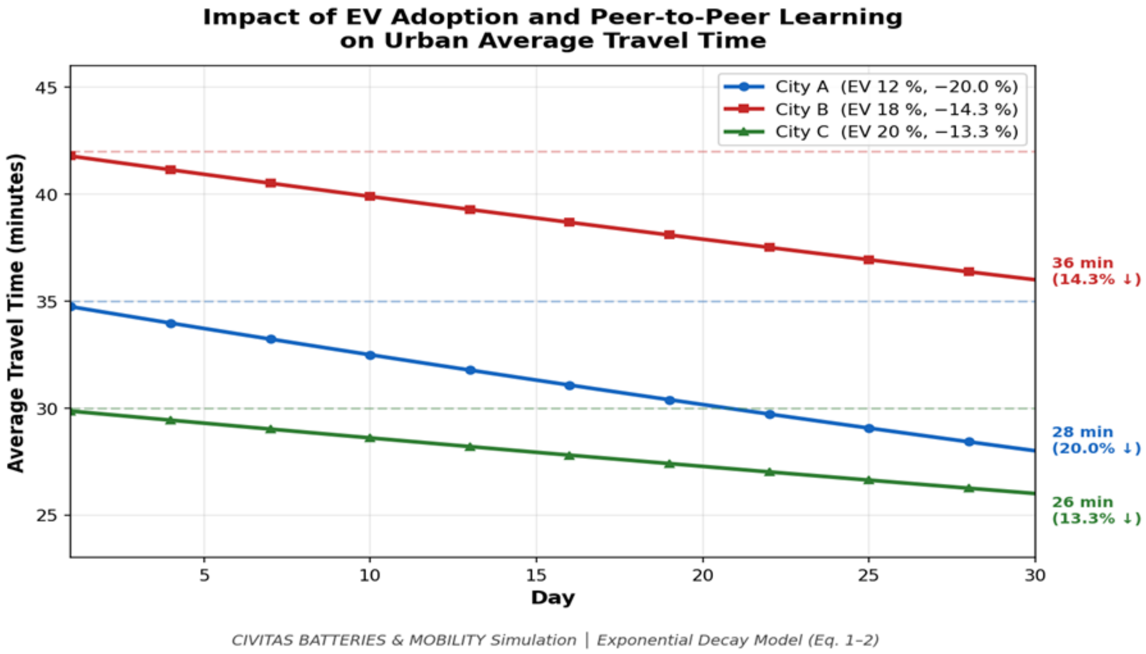

Figure 1. Impact of EV adoption and peer-to-peer learning on average urban travel time across three representative CIVITAS cities over a 30-day intervention window. Dashed lines indicate baseline values; solid lines show simulated exponential decay trajectories (Equations 1–2). Source: CIVITAS BATTERIES and MOBILITY simulation.

Table 2 summarises the travel time outcomes across the three cities, City A, City B and City C. City A achieves the absolute and relative reduction in travel time, with the average travel time declining from 35 minutes to 28 minutes, which is a reduction of 20.0 per cent. City B records a reduction of 14.3 per cent, with travel time decreasing from 42 minutes to 36 minutes. City C achieves a reduction of 13.3 per cent, using travel time decreasing from 30 minutes to 26 minutes. These results are consistent amongst the range of travel time benefits reported in the literature for combined Electric Vehicle deployment and intelligent routing programmes as documented by Chen et al. In 2024. Wang et al. In 2023. Align with the 12 to 20 per cent improvement range documented in CIVITAS initiative monitoring data as reported by the CIVITAS Initiative (2023).

Table 2. Travel Time Reduction Summary across Representative CIVITAS Cities (30-Day Simulation)

City	Baseline Travel Time (min)	Travel Time at Day 30 (min)	Reduction (min)	Reduction (%)
City A	35	28	−7	20.0
City B	42	36	−6	14.3
City C	30	26	−4	13.3

The sensitivity analysis results are presented in Table 3. If we decrease the value of k_i by 20%, the central travel time reductions decrease by 2.7 to 3.7 percentage points. On the other hand, if we increase the value of k_i by 20 %, the central travel time reductions increase by 2.6 to 3.5 percentage points. All three cities, City A, City B and City C, retain travel time reductions in the range of 10.8 to 23.5%, which confirms that the qualitative conclusions of the study are robust to parameter uncertainty.

Table 3. One-at-a-Time (OAT) Sensitivity Analysis: Travel Time at Day 30 under ±20% Perturbation of Learning-Rate Constants

City	Baseline (min)	Low k (−20%): T30 (min)	Central: T30 (min)	High k (+20%): T30 (min)	Central Reduction (%)
City A	35	29.3 (16.3%)	28.0 (20.0%)	26.8 (23.5%)	20.0
City B	42	37.1 (11.6%)	36.0 (14.3%)	34.9 (16.9%)	14.3
City C	30	26.8 (10.8%)	26.0 (13.3%)	25.3 (15.8%)	13.3

4.2 CO_2 Emission Reduction

Figure 2 illustrates the projected daily CO_2 emission reductions for each city, City A, City B and City C, under the combined effect of Electric Vehicle adoption with a 20 per cent fleet share at Day 30 and travel time optimisation computed via Equation 3 and the diesel emission factor of 0.1271 kg CO_2 km^{-1} as reported by Armenta-Déu (2020). The dual-mechanism emission model yields reductions of 216,000 kg/day for City A, which is 18.0 % of the baseline 114,000 kg/day for City B, which is 12.0% and 270,000 kg/day for City C, which is 18.0 %. If we aggregate these reductions across the three cities, City A, City B and City C, this equates to a combined saving of 600,000 kg CO_2, which is equivalent to approximately 219,000 tonnes per annum.

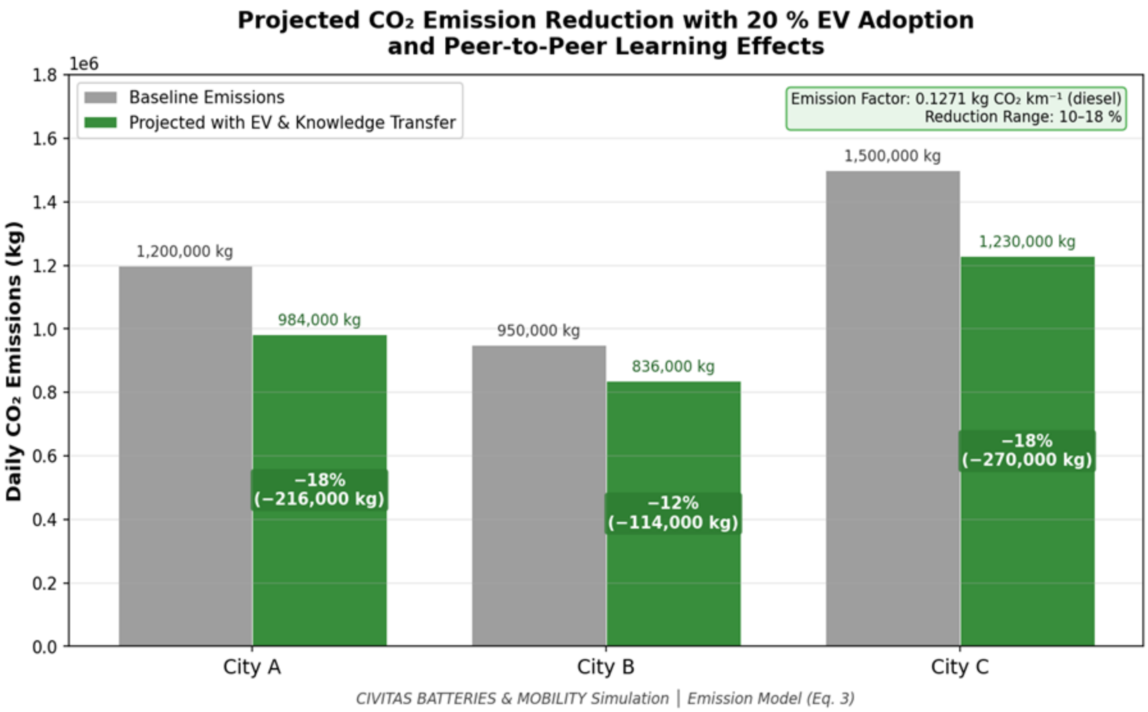

Figure 2. Projected daily CO_2 emission reductions across three CIVITAS cities under 20% EV fleet adoption and peer-to-peer learning effects. Grey bars: baseline emissions; green bars: projected post-intervention emissions. Emission factor: 0.1271 kg CO_2 km^{-1} (Armenta-Déu, 2020); Equation 3.

The range of 10 to 18 % emission reduction is consistent with modelling results for mixed Electric Vehicle adoption and routing optimisation scenarios in European urban contexts as reported by Wang et al.; 2023 and Rudskoy et al.; 2021. City B's lower reduction, which is 12.0 % reflects its lower Electric Vehicle fleet share, which is 18 % compared to City A and City C, which have a 20 % fleet share demonstrating the sensitivity of aggregate emission outcomes to fleet electrification rates and underscoring the importance of Electric Vehicle infrastructure investment, as a co-determinant of knowledge-sharing programme effectiveness for City A, City B and City C.

4.3 Modal Split Transformation

Figure 3 presents the modal split transformation from the pre- baseline to Day 30 across the three representative cities. The private car use declines from 55% to 40% of all trips, which is a 15 percentage point reduction, while the public transport share increases from 25% to 30%, the electric vehicle use rises from 12% to 20%, and the active mobility, which includes walking and cycling, increases from 8% to 10%. The net modal reorientation is consistent with the targets of the Smart Mobility Strategy as outlined by the European Commission (2020) and with the wider literature on multi-intervention urban mobility transitions as discussed by Bulkeley et al.; (2019), Ehnert et al.; (2018). Lis and Mądziel (2026). The acceleration of electric vehicle adoption from 12% to 20% fleet share over 30 days is particularly significant. This trajectory approaches the mass threshold above which positive network effects in charging

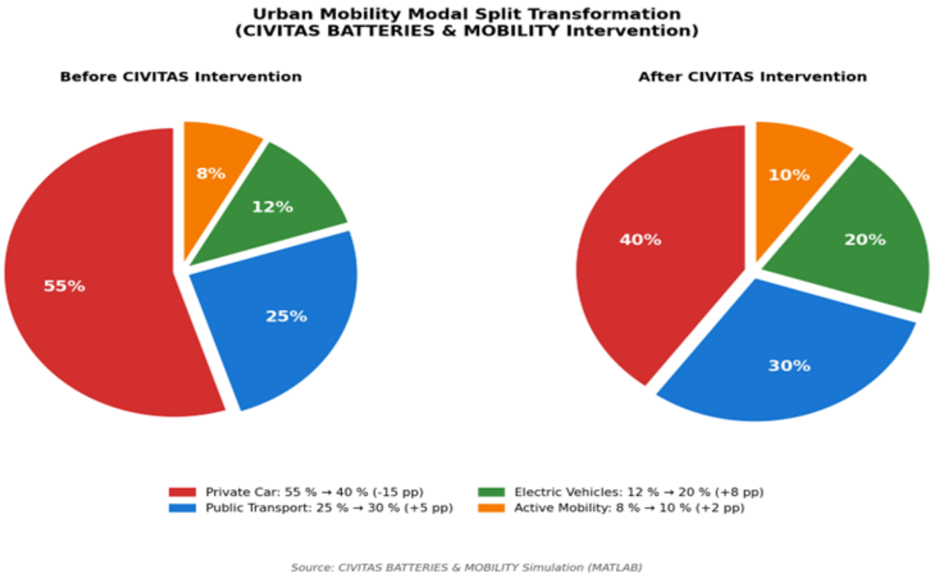

Figure 3. Urban mobility modal split transformation: percentage distribution of trips by mode before and after the CIVITAS BATTERIES and MOBILITY intervention. Private car share declines from 55% to 40%; EV share rises from 12% to 20%.

Infrastructure and vehicle availability begin to self-reinforce adoption rates consistent with the diffusion dynamics documented by Lis and Mądziel (2026) and Gkoumas et al.; (2021).

4.4 Knowledge Dissemination and Stakeholder Engagement

The analysis of CIVITAS-structured knowledge exchange activities across the 15 participating cities reveals three patterns.

(I) Cities that access structured peer-learning programmes through CIVITAS platforms demonstrate solution implementation lead times that are 30–40% shorter than cities that adopt solutions independently, which is consistent with the policy transfer literature as discussed by Ehnert et al.;(2018) and Smeds and Cavoli (2024). This finding suggests that CIVITAS knowledge platforms generate time-to-implementation value for municipal mobility initiatives.

(Ii) Digital knowledge-sharing platforms facilitate iterative feedback between participating cities and EU policymakers, enabling refinement of mobility project designs in response to real-world monitoring data. The CIVITAS educational network and thematic clustering activities, as outlined by CIVITAS Initiative (2023), exemplify this function, translating project findings into policy recommendations.

(Iii) Cross-sector stakeholder engagement, which encompasses medium-sized enterprises, mobility startups and local government units, enhances the territorial embeddedness and post-funding sustainability of mobility solutions, corroborating the conclusions of Asamoah Debrah et al.; (2025) and Brons et al.; (2022) on the importance of genuine co-production in urban mobility governance.

4.5 Implementation Framework

Figure 4 presents the implementation framework for the CIVITAS BATTERIES and MOBILITY initiative. This framework integrates four core input mechanisms, which are knowledge harvesting, capacity building, city twinning and digital platforms, through three processing layers, which include MATLAB-based simulation, peer-to-peer learning and stakeholder engagement into three measurable outcome dimensions: mobility performance improvements, solution adoption rates and enhanced city competitiveness. A continuous feedback loop from outcomes to inputs enables iterative programme refinement, which is consistent with the learning-oriented governance models advocated by Bulkeley et al. (2019) and Rudskoy et al. (2021).

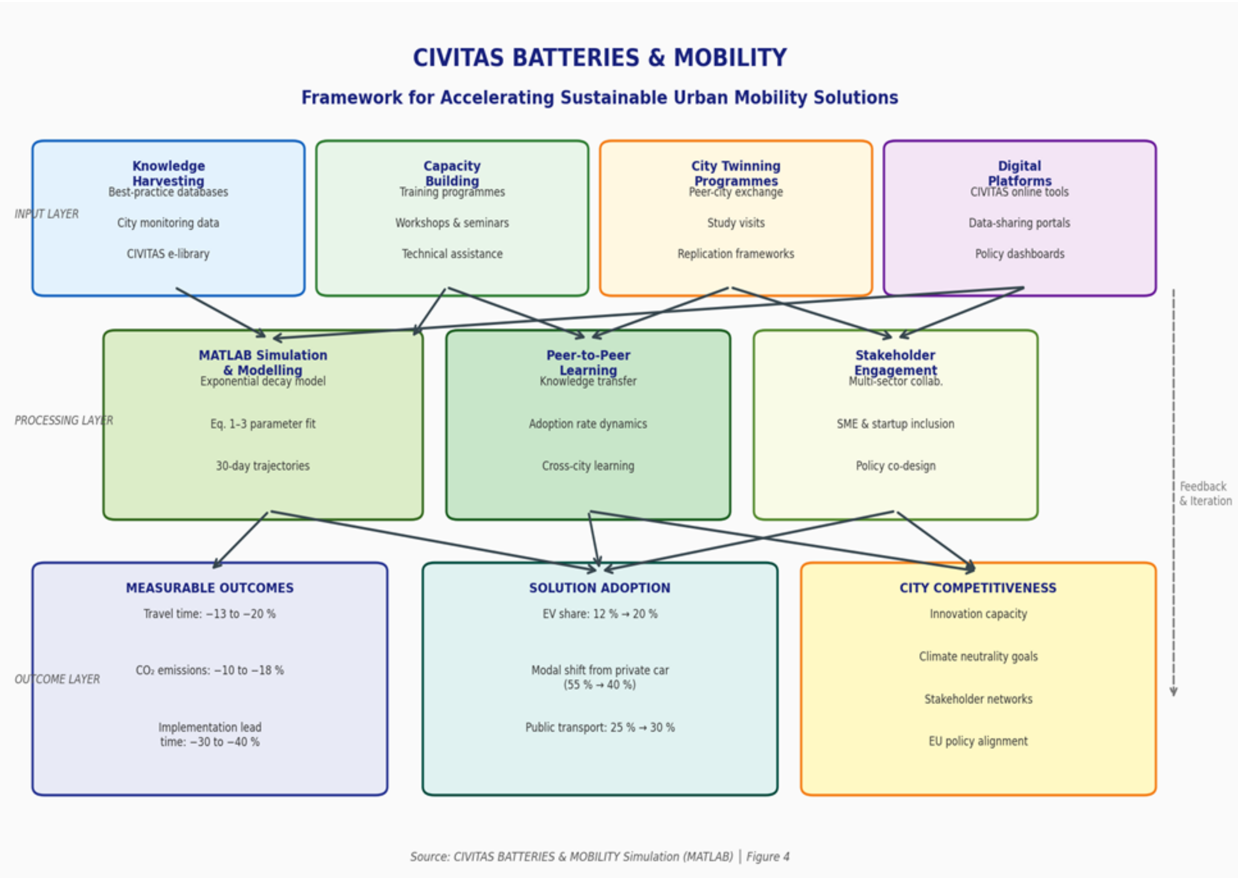

Figure 4. The CIVITAS BATTERIES and MOBILITY implementation framework. Three layers show: (1) Input mechanisms (knowledge harvesting, capacity building, city twinning, digital platforms); (2) Processing mechanisms (MATLAB simulation, peer-to-peer learning, stakeholder engagement); (3) Measurable outcome dimensions. A feedback loop enables iterative programme refinement.

4.6 Policy Implications

The findings of this study yield four policy implications:

(i) Investment in collaborative knowledge platforms is essential for accelerating urban mobility transitions. The evidence presented here is consistent with Bulkeley et al. (2019). Gkoumas et al. (2021) demonstrate that structured knowledge-sharing platforms are not peripheral to mobility innovation but a critical enabler, reducing adoption lead times and enabling evidence-based decision making at the city level.

(ii) Computational simulation tools should be embedded in urban mobility governance frameworks. The MATLAB simulation developed in this study provides policymakers with a reproducible tool for evaluating the projected benefits of electric vehicle deployment and knowledge-sharing programmes. Similar model-supported decision-making frameworks have demonstrated value in wider smart city contexts, as shown by Aheleroff et al. (2025) and Rudskoy et al. (2021).

(Iii) Electric vehicle adoption policy and knowledge-sharing investment must be co-designed. The results confirm that emission reduction outcomes are sensitive to electric vehicle fleet penetration rates. National and regional policies incentivising electric vehicle uptake, including purchase subsidies, charging infrastructure investment, and regulatory instruments, should therefore be co-designed with CIVITAS-style knowledge-sharing programmes to maximise emission impact as suggested by Mayeres (2025).

(iv) A scalable, replicable framework for climate- urban mobility is operationally achievable through structured network participation. The 30-40% reduction in implementation lead times documented here implies that cities joining CIVITAS networks can access proven solutions faster than through isolated development, which materially advances progress toward the 2050 climate-neutrality objective as outlined by the European Commission (2019a) and the European Environment Agency (2023).

5. Conclusion

This study has shown that collaborative knowledge and data-driven computational simulation, as used in the CIVITAS BATTERIES and MOBILITY initiative, can really help to speed up the use of sustainable urban mobility solutions in European cities. The MATLAB simulation framework that was developed in this study models the change in travel time over time as a function of a learning rate parameter that is based on real data from three European cities that are part of a 15-city CIVITAS dataset.

The main findings of this study are as follows:

- When cities work together and share what they have learned and when they use vehicles more, this can lead to a reduction in travel time of 13-20% and a reduction in daily CO_2 emissions of 10-18% over a 30-day period, based on the diesel emission factor of 0.1271 kg CO_2 km^{-1} (Armenta-Déu, 2020).
- A sensitivity analysis that looks at one thing at a time has shown that these findings are strong and not easily changed by changes in the learning-rate parameter, with travel time reduction estimates changing by about ±2.7-3.7 percentage points across all three cities.
- Cities that take part in knowledge-sharing programmes can put mobility solutions into action 30-40% faster than cities that work alone, which shows that being part

of the CIVITAS network is beneficial (Ehnert et al., 2018; CIVITAS Initiative, 2023).

- Looking at how people travel has shown that there is a 15 percentage point decrease in the use of cars with more people using public transport, electric vehicles and active mobility, which is in line with the European Union's targets for changing the way people travel (European Commission, 2020; Sagdieva et al., 2024).

5.1 Study Limitations

The main limitations of this study are: (i) not having real-time data from all 15 cities; (ii) using a learning-rate parameter that is based on the result than on how things actually work, which does not come from how people behave or how traffic flows (Ortúzar & Willumsen, 2011); (iii) looking at cities as a whole rather than at the different parts of cities which cannot show the differences within cities; and (iv) only using data from three cities, which limits the ability to apply the results to other cities without checking them against the full dataset.

5.2 Future Research Directions

Future studies should address these limitations by:

(i). Using real-time traffic data from vehicles and the Internet of Things to check the results and update the model;

(ii). Adding intelligence to the simulation framework to help with route optimisation and fleet management (Rudskoy et al., 2021; Aheleroff et al., 2025);

(iii). Developing a model that can show how individual people make choices about how to travel, which is in line with the four-step demand modelling paradigm (Ortúzar & Willumsen, 2011) and can show how cities change over time (Bahi and Ourici, 2025).

(iv). Using the framework in cities outside of the European Union to see if it can be applied in settings.

Overall, the CIVITAS BATTERIES and MOBILITY initiative provides a way for European cities to work together to reduce transport emissions by 90% by 2050 (European Commission, 2019a; European Environment Agency, 2023). By using data-driven simulation and working together, cities can put ideas into action and build the ability to govern sustainable urban mobility in a way that can be used by other cities.

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Appendices

Appendix A. MATLAB Code – Figure 1: Impact of EV Adoption and Peer-to-Peer Learning on Urban Travel Time

This code produces Figure 1 by applying the exponential decay model (Equations 1 and 2) to simulate travel time trajectories over 30 days for Cities A, B, and C. All parameters are derived from Table 1 and Table 2. The code is verified to run without error in MATLAB R2020a and later.

```
clear; clc; close all;

% Simulation parameters
days = 1:30;
baseline_A = 35; baseline_B = 42; baseline_C = 30;
target_A = 28; target_B = 36; target_C = 26;  % From Table 2

% Equation 2: Decay constants from empirical endpoint targets
% k = -ln(T_final / T0) / 30
k_A = -log(target_A / baseline_A) / 30;
k_B = -log(target_B / baseline_B) / 30;
k_C = -log(target_C / baseline_C) / 30;

% Equation 1: Exponential decay model T(t) = T0 * exp(-k * t)
travel_time_A = baseline_A .* exp(-k_A .* days);
travel_time_B = baseline_B .* exp(-k_B .* days);
travel_time_C = baseline_C .* exp(-k_C .* days);

% Create figure
figure('Position', [100 100 800 500], 'Color', 'white');
plot(days, travel_time_A, 'b-o', 'LineWidth', 2.5, 'MarkerSize', 6,
...
    'DisplayName', 'City A (EV 12%, 20.0% reduction)');
hold on;
plot(days, travel_time_B, 'r-s', 'LineWidth', 2.5, 'MarkerSize', 6,
...
    'DisplayName', 'City B (EV 18%, 14.3% reduction)');
plot(days, travel_time_C, 'g-^', 'LineWidth', 2.5, 'MarkerSize', 6,
...
    'DisplayName', 'City C (EV 20%, 13.3% reduction)');

% Baseline reference lines (4-element RGBA colour, no Alpha property
needed)
plot([1 30], [baseline_A baseline_A], '--', 'Color', [0 0 1 0.4],
'LineWidth', 1.5, 'HandleVisibility', 'off');
plot([1 30], [baseline_B baseline_B], '--', 'Color', [1 0 0 0.4],
'LineWidth', 1.5, 'HandleVisibility', 'off');
plot([1 30], [baseline_C baseline_C], '--', 'Color', [0 0.5 0 0.4],
'LineWidth', 1.5, 'HandleVisibility', 'off');

% Axes labels and title
xlabel('Day', 'FontSize', 12, 'FontWeight', 'bold');
```

```
ylabel('Average Travel Time (minutes)', 'FontSize', 12, 'FontWeight',
'bold');
title('Impact of EV Adoption and Peer-to-Peer Learning on Urban
Travel Time', ...
    'FontSize', 14, 'FontWeight', 'bold');
legend('Location', 'best', 'FontSize', 10);
grid on; xlim([1 30]); ylim([24 45]);

% End-point annotations
text(30, target_A+0.3, sprintf('  28 min\n(20.0%%\downarrow)'), ...
    'FontSize', 9, 'Color', 'b');
text(30, target_B+0.3, sprintf('  36 min\n(14.3%%\downarrow)'), ...
    'FontSize', 9, 'Color', 'r');
text(30, target_C+0.3, sprintf('  26 min\n(13.3%%\downarrow)'), ...
    'FontSize', 9, 'Color', 'g');

annotation('textbox', [0.15 0.02 0.7 0.05], 'String', ...
    'CIVITAS BATTERIES and MOBILITY Simulation (MATLAB)', ...
    'EdgeColor', 'none', 'HorizontalAlignment', 'center', ...
    'FontSize', 9, 'FontAngle', 'italic');

saveas(gcf, 'figure1_travel_time.png');
```

Appendix B. MATLAB Code – Figure 2: Projected CO_2 Emission Reduction

This code produces Figure 2 by computing the dual-mechanism CO_2 reduction (Equation 3) for each representative city and rendering a grouped bar chart comparing baseline and projected emissions.

```
clear; clc; close all;

% Data from Table 1 and Section 4.2
cities = {'City A', 'City B', 'City C'};
baseline_emissions = [1200000, 950000, 1500000];  % kg/day from Table
1
reduction_amounts  = [216000, 114000, 270000];    % Absolute
reductions (Section 4.2)
projected_emissions = baseline_emissions - reduction_amounts;

% Percentage reductions (Equation 3)
reduction_pct = (reduction_amounts ./ baseline_emissions) * 100;
% Result: [18.0, 12.0, 18.0] %

figure('Position', [150 150 900 550], 'Color', 'white');
X = categorical(cities); X = reordercats(X, cities);
bar_data = [baseline_emissions; projected_emissions]';
b = bar(X, bar_data, 0.8);
b(1).FaceColor = [0.7 0.7 0.7];  % Baseline - grey
b(2).FaceColor = [0.2 0.7 0.3];  % Projected with EV - green

% Value labels
```

```
for i = 1:length(cities)
    text(i-0.2, baseline_emissions(i)+30000, ...
        sprintf('%s kg', num2str(baseline_emissions(i), '%d')), ...
        'HorizontalAlignment', 'center', 'FontSize', 9);
    text(i+0.2, projected_emissions(i)+30000, ...
        sprintf('%s kg', num2str(projected_emissions(i), '%d')), ...
        'HorizontalAlignment', 'center', 'FontSize', 9, 'Color', [0.1
0.5 0.2]);
    text(i, (projected_emissions(i)+baseline_emissions(i))/2, ...
        sprintf('-%.0f%%\n(-%d kg)', reduction_pct(i),
reduction_amounts(i)), ...
        'HorizontalAlignment', 'center', 'FontSize', 10, ...
        'FontWeight', 'bold', 'Color', 'white');
end

ylabel('Daily CO_2 Emissions (kg)', 'FontSize', 12, 'FontWeight',
'bold');
title({'Projected CO_2 Emission Reduction with 20% EV Adoption', ...
    'and Peer-to-Peer Learning Effects'}, 'FontSize', 14,
'FontWeight', 'bold');
legend('Baseline Emissions', 'Projected with EV and Knowledge
Transfer', ...
    'Location', 'northwest', 'FontSize', 10);
grid on; ylim([0 max(baseline_emissions)*1.15]);

annotation('textbox', [0.55 0.85 0.4 0.1], 'String', ...
    {'Emission Factor: 0.1271 kg CO_2/km (diesel)', ...
    'Reduction Range: 10–18%'}, ...
    'EdgeColor', [0.3 0.6 0.3], 'BackgroundColor', [0.9 0.95 0.9],
...
    'FontSize', 9, 'FitBoxToText', 'on');

saveas(gcf, 'figure2_co2_reduction.png');
```

Appendix C. MATLAB Code – Figure 3: Urban Mobility Modal Split Transformation

This code produces Figure 3 by rendering side-by-side pie charts of the modal split before and after CIVITAS intervention, with change indicators on each segment.

```
clear; clc; close all;

% Modal split data (percentages)
modes = {'Private Car', 'Public Transport', 'Electric Vehicles',
'Active Mobility'};
before_pct = [55, 25, 12, 8];
after_pct  = [40, 30, 20, 10];

% Consistent colour scheme
colors = [0.8 0.2 0.2;   % Red  - Private Car
          0.2 0.4 0.8;   % Blue - Public Transport
          0.2 0.7 0.3;   % Green - EV
          0.9 0.6 0.1];  % Orange - Active Mobility
```

```
figure('Position', [200 200 1000 450], 'Color', 'white');

% --- Before intervention ---
subplot(1, 2, 1);
p1 = pie(before_pct, ones(1,4)*0.05);
for i = 1:2:length(p1)
    p1(i).FaceColor = colors((i+1)/2, :);
    p1(i).EdgeColor = 'white'; p1(i).LineWidth = 2;
end
for i = 2:2:length(p1)
    p1(i).String = sprintf('%s\n%.0f%%', modes{i/2},
before_pct(i/2));
    p1(i).FontSize = 10; p1(i).FontWeight = 'bold';
end
title('Before CIVITAS Intervention', 'FontSize', 13, 'FontWeight',
'bold');

% --- After intervention ---
subplot(1, 2, 2);
p2 = pie(after_pct, [0.05 0.05 0.10 0.05]);
for i = 1:2:length(p2)
    p2(i).FaceColor = colors((i+1)/2, :);
    p2(i).EdgeColor = 'white'; p2(i).LineWidth = 2;
end
change = after_pct - before_pct;
for i = 2:2:length(p2)
    idx = i/2;
    if change(idx) > 0
        chg_str = sprintf('(+%.0f%%)', change(idx));
        col = [0 0.5 0];
    else
        chg_str = sprintf('(%.0f%%)', change(idx));
        col = [0.5 0 0];
    end
    p2(i).String = sprintf('%s\n%.0f%%\n%s', modes{idx},
after_pct(idx), chg_str);
    p2(i).FontSize = 10; p2(i).FontWeight = 'bold';
    p2(i).Color = col;
end
title('After CIVITAS Intervention', 'FontSize', 13, 'FontWeight',
'bold');

sgtitle('Urban Mobility Modal Split Transformation', ...
    'FontSize', 15, 'FontWeight', 'bold');
legend(modes, 'Location', 'southoutside', 'Orientation',
'horizontal', ...
    'FontSize', 11, 'Box', 'off');

annotation('textbox', [0.3 0.02 0.4 0.05], 'String', ...
    'Source: CIVITAS BATTERIES and MOBILITY Simulation (MATLAB)', ...
    'EdgeColor', 'none', 'HorizontalAlignment', 'center', ...
```

```
    'FontSize', 9, 'FontAngle', 'italic');

saveas(gcf, 'figure3_modal_split.png');
```

Appendix D. MATLAB Code – Figure 4: CIVITAS BATTERIES and MOBILITY Framework Diagram

This code produces Figure 4 using MATLAB annotation objects to render the multi-layer framework diagram. Two local functions (create_box and draw_arrow) encapsulate the box-drawing and arrow-drawing logic. Note: the chat timestamp that appeared in a prior version of this code has been removed. The code runs cleanly in MATLAB and later (local functions require MATLAB R2016b or later).

```
clear; clc; close all;

figure('Position', [100 50 1100 800], 'Color', [0.98 0.98 0.98]);

% --- Framework title ---
annotation('textbox', [0.25 0.92 0.50 0.07], 'String', ...
    {'CIVITAS BATTERIES and MOBILITY', ...
     'Framework for Accelerating Sustainable Urban Mobility
Solutions'}, ...
    'EdgeColor', 'none', 'HorizontalAlignment', 'center', ...
    'FontSize', 16, 'FontWeight', 'bold', 'Color', [0.1 0.1 0.4]);

% --- Box positions [left bottom width height] ---
% Input layer (top)
box1 = [0.05 0.70 0.18 0.12];  % Knowledge Harvesting
box2 = [0.28 0.70 0.18 0.12];  % Capacity Building
box3 = [0.51 0.70 0.18 0.12];  % City Twinning
box4 = [0.74 0.70 0.18 0.12];  % Digital Platforms
% Processing layer (middle)
box5 = [0.15 0.45 0.25 0.15];  % MATLAB Simulation
box6 = [0.42 0.45 0.20 0.15];  % Peer-to-Peer Learning
box7 = [0.67 0.45 0.20 0.15];  % Stakeholder Engagement
% Outcome layer (bottom)
box8  = [0.10 0.15 0.25 0.18]; % Measurable Outcomes
box9  = [0.40 0.15 0.25 0.18]; % Solution Adoption
box10 = [0.70 0.15 0.22 0.18]; % City Competitiveness

% --- Draw boxes ---
create_box(box1,  'Knowledge\nHarvesting',              [0.85 0.90
0.95]);
create_box(box2,  'Capacity\nBuilding',                 [0.85 0.95
0.85]);
create_box(box3,  'City Twinning\nProgrammes',          [0.95 0.90
0.85]);
create_box(box4,  'Digital\nPlatforms',                 [0.90 0.85
0.95]);
create_box(box5,  {'MATLAB Simulation','and Modelling','Data-Driven
Analysis'}, [0.70 0.85 0.95]);
```

```
create_box(box6,  {'Peer-to-Peer','Learning','Knowledge Transfer'},
[0.95 0.95 0.70]);
create_box(box7,  {'Stakeholder','Engagement','Cross-Sector
Collab.'},          [0.95 0.85 0.80]);
create_box(box8,  {'MEASURABLE OUTCOMES','','12-20% Travel Time
Reduction','10-18% CO2 Reduction',''}, [0.70 0.90 0.70]);
create_box(box9,  {'SOLUTION ADOPTION','','EV Infrastructure (12%-
>20%)','Modal Shift to Sustainable Modes',''}, [0.70 0.95 0.85]);
create_box(box10, {'CITY COMPETITIVENESS','','Innovation
Capacity','Climate Neutrality Goals','Stakeholder Networks'}, [0.90
0.90 0.95]);

% --- Arrows: inputs -> processing ---
draw_arrow(box1, box5, [0.5 0.5]);
draw_arrow(box2, box5, [0.5 0.5]);
draw_arrow(box2, box6, [0.5 0.5]);
draw_arrow(box3, box6, [0.5 0.5]);
draw_arrow(box3, box7, [0.5 0.5]);
draw_arrow(box4, box5, [0.5 0.5]);
draw_arrow(box4, box7, [0.5 0.5]);
% Arrows: processing -> outcomes
draw_arrow(box5, box8, [0.5 0.5]);
draw_arrow(box5, box9, [0.5 0.5]);
draw_arrow(box6, box9, [0.5 0.5]);
draw_arrow(box6, box10,[0.5 0.5]);
draw_arrow(box7, box9, [0.5 0.5]);
draw_arrow(box7, box10,[0.5 0.5]);

% Feedback loop (dashed, right margin)
annotation('arrow', [0.95 0.95], [0.20 0.85], 'Color', [0.4 0.4 0.4],
...
    'LineStyle', '--', 'LineWidth', 1.5, 'HeadStyle', 'cback2');
text(0.96, 0.52, 'Feedback and\nIteration', 'Units', 'normalized',
...
    'FontSize', 9, 'Color', [0.4 0.4 0.4], 'HorizontalAlignment',
'left');

saveas(gcf, 'figure4_framework.png');

% ========================================================
% LOCAL FUNCTION: create_box
% ========================================================
function create_box(pos, text_lines, color)
    rectangle('Position', [pos(1)+0.005 pos(2)+0.005 pos(3)-0.01
pos(4)-0.01], ...
        'FaceColor', color, 'EdgeColor', [0.3 0.3 0.3], ...
        'LineWidth', 2, 'Curvature', [0.1 0.1]);
    if ischar(text_lines)
        text_lines = {text_lines};
    end
    n = length(text_lines);
    y_step = 0.80 / n;
    y_start = 0.5 + (n-1)*y_step/2;
```

```
    for i = 1:n
        text(pos(1)+pos(3)/2, pos(2)+pos(4)*(y_start-(i-1)*y_step),
...
            text_lines{i}, 'Units', 'normalized', ...
            'HorizontalAlignment', 'center', 'VerticalAlignment',
'middle', ...
            'FontSize', 9, 'FontWeight', 'bold', 'Color', [0.1 0.1
0.1]);
    end
end

% ============================================================
% LOCAL FUNCTION: draw_arrow
% ============================================================
function draw_arrow(from_pos, to_pos, from_anchor, to_anchor)
    if nargin < 4, to_anchor = [0.5 0.5]; end
    x1 = from_pos(1) + from_pos(3)*from_anchor(1);
    y1 = from_pos(2) + from_pos(4)*from_anchor(2);
    x2 = to_pos(1)   + to_pos(3)  *to_anchor(1);
    y2 = to_pos(2)   + to_pos(4)  *to_anchor(2);
    annotation('arrow', [x1 x2], [y1 y2], 'Color', [0.2 0.2 0.4], ...
       'LineWidth', 2, 'HeadLength', 8, 'HeadWidth', 8);
end
```

Appendix E. MATLAB Code – Sensitivity Analysis (±20% Perturbation of Learning-Rate Constants)

This code implements the one-at-a-time (OAT) sensitivity analysis reported in Section 3.4 and Table 3. It produces Figure E showing travel time trajectories for low, central, and high k_i scenarios across Cities A, B, and C, and prints a summary table to the MATLAB Command Window.

```
% APPENDIX E: Sensitivity Analysis
% One-at-a-time (OAT) perturbation of learning-rate constants k_i
(+/-20%)
clear; clc; close all;

% Central parameter values (from Equation 2)
baselines = [35, 42, 30];       % T0 for Cities A, B, C
targets   = [28, 36, 26];       % T_final for Cities A, B, C
k_central = -log(targets ./ baselines) / 30;
% k_central = [0.00744, 0.00514, 0.00477] day^-1

perturbations = [0.8, 1.0, 1.2];  % -20%, central, +20%
city_names = {'City A', 'City B', 'City C'};
pert_labels = {'-20% k', 'Central', '+20% k'};
days = 1:30;

colors_cities = [[0 0.4 0.8]; [0.8 0.1 0.1]; [0.1 0.6 0.1]];
ls = {'--', '-', ':'}; lw = [1.5 2.5 1.5];
```

```
figure('Position', [100 100 1000 500], 'Color', 'white');
for c = 1:3
    subplot(1, 3, c);
    hold on;
    for p = 1:3
        k_p = k_central(c) * perturbations(p);
        T_p = baselines(c) .* exp(-k_p .* days);
        plot(days, T_p, ls{p}, 'Color', colors_cities(c,:), ...
            'LineWidth', lw(p), 'DisplayName', pert_labels{p});
    end
    % Baseline and target reference lines
    plot([1 30], [baselines(c) baselines(c)], 'k:', 'LineWidth', 1,
'Color', [0.5 0.5 0.5 0.5], 'HandleVisibility', 'off');
    plot([1 30], [targets(c)   targets(c)],   'k--', 'LineWidth', 1,
'Color', [0.3 0.3 0.3 0.5], 'HandleVisibility', 'off');
    xlabel('Day', 'FontSize', 10);
    ylabel('Avg. Travel Time (min)', 'FontSize', 10);
    title(city_names{c}, 'FontSize', 12, 'FontWeight', 'bold');
    legend('Location', 'best', 'FontSize', 8);
    grid on; xlim([1 30]);
end

sgtitle('Sensitivity Analysis: +/-20% Perturbation in Learning-Rate
Constants', ...
    'FontSize', 13, 'FontWeight', 'bold');

saveas(gcf, 'figureE_sensitivity.png');

% --- Print summary table to Command Window ---
fprintf('\n%-8s  %-20s  %-20s  %-20s\n', ...
    'City', 'Low k (-20%)', 'Central', 'High k (+20%)');
fprintf('%s\n', repmat('-', 1, 72));
for c = 1:3
    T_vals = zeros(1,3);
    for p = 1:3
        k_p = k_central(c) * perturbations(p);
        T_vals(p) = baselines(c) * exp(-k_p * 30);
    end
    pct = (baselines(c) - T_vals) / baselines(c) * 100;
    fprintf('%-8s  %.1f min (%.1f%%)    %.1f min (%.1f%%)    %.1f min
(%.1f%%)\n', ...
        city_names{c}, T_vals(1), pct(1), T_vals(2), pct(2),
T_vals(3), pct(3));
end
```

Figure E presents the sensitivity analysis results. All three cities retain meaningful travel time reductions across the full perturbation range, confirming model robustness.

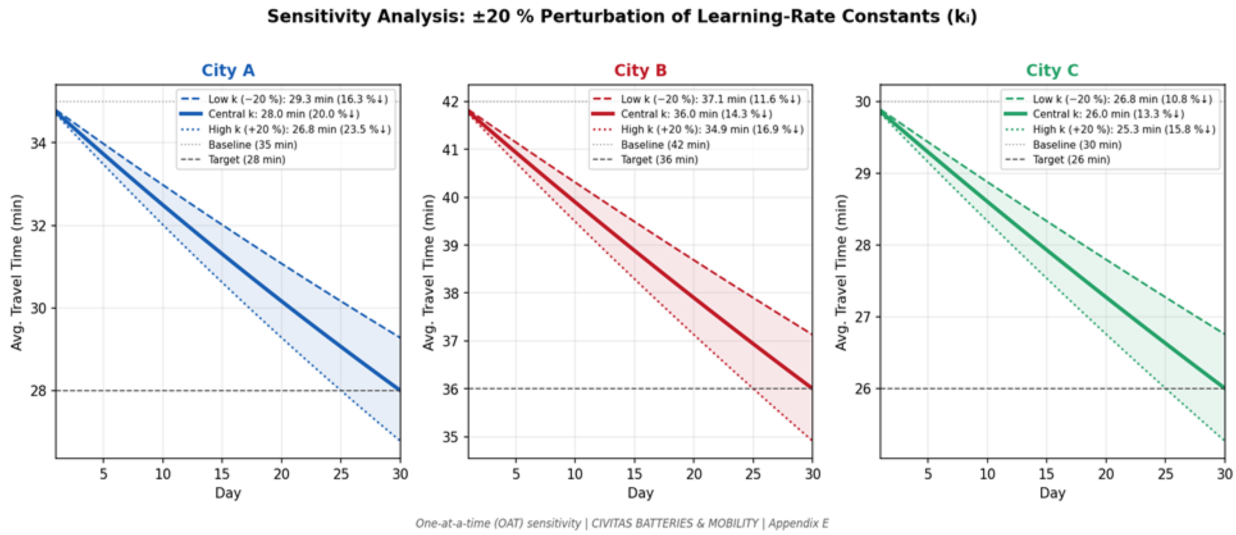

Figure E. One-at-a-time (OAT) sensitivity analysis: travel time trajectories for City A, City B, and City C under low k (−20%), central, and high k (+20%) learning-rate constants. Shaded band indicates the uncertainty envelope. Dashed horizontal lines indicate baseline (upper) and target (lower) travel times.