INTERNATIONAL JOURNAL OF SCIENTIFIC RESEARCH AND INNOVATIVE STUDIES
IJSRIS journal
ISSN: 2820-7157
Advancing Knowledge, Inspiring Innovation
www.ijsrisjournal.com
INDEXED JOURNAL
PEER REVIEWED Rigorous & Transparent
DOI: CROSSREF Member
OPEN ACCESS For Global Visibility
BI-MONTHLY Timely Publication
WIDE READERSHIP High Impact & Visibility
AUTHOR FRIENDLY Fast | Supportive | Reliable

Received Date: February 22, 2026 Accepted Date: March 14, 2026 Published Date: April 02, 2026

Pages from 668 to 674

Artificial Intelligence and Smart Urban Mobility: A Predictive Framework for Sustainable Territorial Development

Ahmed Morachid

LARNED Laboratory, FSJES, University of Hassan II, Casablanca, Morocco, rjmorachid@gmail.com

LICENSE

This article is licensed under the Creative Commons Attribution 4.0 International License (CC BY 4.0).

https://creativecommons.org/licenses/by/4.0/

Crossref doi

PREFIX : 10.63883

IJSRIS JOURNAL

OPEN ACCESS

This is an open access article distributed under the terms of open access.

ABSTRACT

Artificial intelligence (AI) can help territorial authorities anticipate mobility demand, identify infrastructure gaps and compare development scenarios. Its contribution is contingent on reliable data, transparent models and a planning process that treats accessibility, inclusion and environmental performance as outcomes alongside traffic flow. This article develops a predictive framework for sustainable territorial mobility in Rabat, grounded in the mobility and infrastructure findings of a questionnaire-based thesis study (N = 349). The analysis uses the thesis' published descriptive results and measurement diagnostics; it does not train or validate an AI forecasting model. Respondents expressed the strongest concerns about encouragement of alternatives to private cars (41.7% disagreement) and availability of electric-vehicle infrastructure (42.0% disagreement). By comparison, 44.6% agreed that public transport is accessible to all, and 44.0% agreed that traffic policies support flow and safety. These perceptions motivate a four-stage framework: an integrated territorial data foundation; multi-horizon prediction of demand, reliability, access and infrastructure risk; equity- and carbon-aware scenario comparison; and human-authorized planning decisions with public feedback. The proposed validation agenda combines temporal and spatial holdouts, simple statistical baselines, interpretable machine learning, uncertainty calibration and subgroup performance checks. The article's contribution is therefore a thesis-grounded research design

and decision architecture, rather than a claim of demonstrated predictive accuracy. It offers a route for converting residents' reported mobility priorities into measurable, accountable territorial planning questions.

Keywords: artificial intelligence; smart mobility; territorial development; urban transport; accessibility; predictive analytics; Rabat; Morocco

1. INTRODUCTION

Urban mobility is a territorial system: transport networks connect residents to employment, education, health care, public services and social life, while land use and infrastructure shape the journeys people can make. A city may improve average vehicle speed yet leave peripheral neighbourhoods poorly connected. Sustainable mobility planning therefore needs to consider demand, service quality, accessibility, safety, emissions and distributional effects together (European Commission, 2021; ITF, 2023; Ballantyne et al., 2024; UN-Habitat, 2022).

Recent AI research has expanded from traffic-state estimation toward public-transport planning, demand prediction, resource allocation and decision support (Jevinger et al., 2024; Afandizadeh et al., 2024; Shulajkovska et al., 2024). Digital twins and mobility foundation models also point toward integrated, multi-scale representations of urban movement (Shin et al., 2023; Zhou et al., 2024). Yet an algorithm's predictive performance does not itself establish that a transport intervention is socially useful, territorially fair or environmentally sustainable. The planning question is not simply how to predict flow, but how forecasts can help authorities identify unmet needs and compare interventions transparently.

This article develops an AI-enabled predictive framework for the mobility and infrastructure axis of a thesis on intelligent territorial development in Rabat. The study's questionnaire provides evidence about residents' perceptions of current mobility conditions. It does not contain time-stamped traffic counts, geocoded trips, smart-card records or longitudinal service data suitable for training a predictive model. Accordingly, the article reports thesis results as descriptive evidence and proposes the model architecture and validation protocol as future work. It asks: (1) what mobility priorities emerge from the thesis findings; (2) how could AI-based prediction support sustainable territorial decisions; and (3) what data, evaluation and governance safeguards are needed before deployment?

2. CONCEPTUAL BACKGROUND

2.1 Predictive AI for mobility and public transport

Mobility prediction includes tasks with different targets and time horizons: passenger demand by stop or route, traffic speed and travel time, service reliability, transfer demand, infrastructure deterioration and transport-related emissions. Reviews find that machine learning is frequently used for prediction and state estimation in public transport, while deployment depends on access to substantial data about travellers and transport operations (Jevinger et al., 2024; Rocco di Torrepadula et al., 2024). Deep learning can model non-linear temporal and spatial dependencies, but classical statistical models remain important benchmarks and may be preferable where datasets are short or data quality is inconsistent (Afandizadeh et al., 2024; Cheng et al., 2024).

The framework here treats forecasting as one component of a decision-support chain. Candidate methods range from seasonal naïve and ARIMA models to gradient-boosted trees, recurrent networks and spatiotemporal graph models. A method should be selected separately for each prediction target, tested against a transparent baseline and reported with uncertainty. Mobility-as-a-Service and connected data architectures may enable service integration, but they also raise issues of data access, interoperability and digital exclusion (Rouky et al., 2025; Elassy et al., 2024).

2.2 Sustainable mobility as territorial accessibility

A territorial perspective shifts evaluation from movement alone to the opportunities that movement enables. Accessibility can be expressed as the number and diversity of destinations reachable within a reasonable time and cost, subject to the travel needs of different groups. This approach makes it possible to identify mismatches between transport supply and population demand at small-area scales (Ballantyne et al., 2024). It also connects infrastructure investment to the built environment, route planning, service design and maintenance priorities (Jevinger et al., 2024).

AI-supported planning can help compare routes, service frequencies, modal alternatives and land-use scenarios, but the choice of objective matters. If a system optimizes only vehicle throughput, it may overlook walking, cycling, transit access, safety or unequal exposure to pollution. A sustainability objective should therefore include accessibility, service reliability, safety, emissions and distributional indicators in addition to congestion (ITF, 2023; IPCC, 2022; Wang et al., 2024; WHO, 2023).

2.3 Explainability, participation and accountable decision support

Urban planning decisions have public consequences and require reasons that residents and elected officials can inspect. AI-enabled participatory planning literature emphasizes that spatial analytics and AI can inform planning, while identifying limitations around data, communication and democratic decision-making (Du et al., 2024). Decision-support systems can structure priorities and scenario comparisons, but the final choice remains a normative and institutional decision (Shulajkovska et al., 2024). Explainability should consequently expose the data coverage, assumptions, uncertainty and factors affecting a forecast, rather than provide a simplified rationale after the decision has already been made (OECD, 2024; UNESCO, 2021; EEA, 2022).

3. DATA AND METHODS

3.1 Study basis and analytical scope

The empirical basis is the thesis study of territorial development in Rabat. The questionnaire dataset contains 349 respondents overall. The item frequency tables report 348 valid responses and one system-missing response for the mobility items examined here. Since the thesis does not provide a respondent-level file in the materials used for this article, no new statistical tests, subgroup comparisons or predictive estimates were calculated. Percentages below are the thesis' valid percentages, rounded to one decimal place.

The thesis reports a Kaiser–Meyer–Olkin statistic of .829 and a significant Bartlett test for the five-item mobility construct ($\chi^2 = 568.665$, df = 10, $p < .001$), alongside Cronbach's alpha of .818. These are reported as instrument diagnostics from the thesis, not as evidence that an AI model is valid. The thesis also reports a high RMSEA (.251) for its broader confirmatory model. Because this indicates poor global fit, broad structural paths from that model are not used as confirmatory evidence in this article.

3.2 Thesis indicators

Five mobility statements are summarized: public-transport effectiveness and connectivity; encouragement of alternatives to the private car; availability of electric-vehicle infrastructure; traffic policies supporting flow and safety; and accessibility of public transport to all. Infrastructure context is drawn from three additional thesis items on transport maintenance, distribution of public infrastructure and digital infrastructure. The response scale distinguishes disagreement, neutrality, agreement and "do not know."

3.3 Proposed predictive framework

The framework is a conceptual design for a future pilot. It specifies candidate input streams, target variables and evaluation procedures; it does not imply that the requisite operational datasets are currently available or linked. Four connected stages are proposed, with a monitoring loop that returns observed outcomes and citizen priorities to the planning process.

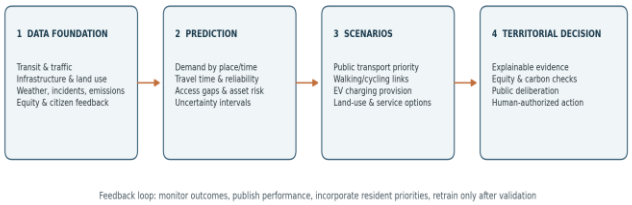

Figure 1: Proposed AI-enabled mobility-to-territorial-decision framework. The architecture is a research proposal, not a deployed system.

3.4 Proposed model targets and validation

A first pilot should select a limited set of forecasts aligned with the data that authorities can lawfully and reliably provide: (a) passenger demand by route, stop and time period; (b) travel time and service reliability by corridor; (c) accessibility to essential destinations by neighbourhood and mode; and (d) infrastructure maintenance priority. Emissions estimates could be added only where vehicle, distance, energy or validated traffic-emission data are available. Each target needs a defined spatial unit, forecast horizon, update frequency and intended planning decision.

Models should be compared with seasonal naïve and ARIMA baselines before testing tree ensembles or spatiotemporal neural networks. Evaluation should use time-ordered holdouts and, where feasible, spatial holdouts to test transfer to locations not used in training. MAE and RMSE can summarize point error; MAPE should be avoided or handled carefully for low/zero demand. Prediction intervals should be evaluated for coverage and width. Performance should also be reported by neighbourhood, mode and population group when lawful, privacy-preserving attributes or defensible area-level proxies are available. A model should not be deployed if the apparent citywide gain conceals systematic error in low-demand, peripheral or underserved areas.

4. RESULTS

4.1 Mobility perceptions in the thesis survey

The two most contested areas are alternatives to private cars and electric-vehicle infrastructure. For the statement that walking, cycling, carpooling and other alternatives are encouraged, 41.7% disagreed, 19.0% were neutral and 34.2% agreed; 5.2% answered "do not know." For the availability of electric-vehicle infrastructure, 42.0% disagreed, 18.7% were neutral and 29.3% agreed, while 10.1% did not know. These results suggest perceived gaps in modal choice and charging provision, although they do not measure objective supply or actual travel behaviour.

Views on public transport are mixed. Agreement that public transport is effective and well connected reached 36.4%, while 28.5% disagreed and 18.7% were neutral; 16.4% did not know. A separate item on universal accessibility received 44.6% agreement and 27.8% disagreement. Traffic-management policies were viewed more positively: 44.0% agreed that policies favor traffic flow and safety, compared with 28.4% disagreement and 23.9% neutrality.

Table 1: Distribution of valid responses across the five thesis mobility items. Disagreement and agreement each combine the two corresponding Likert categories. Percentages are thesis-reported valid percentages and may not total 100.0 because of rounding.

Thesis mobility item	Disagree (%)	Neutral (%)	Agree (%)	Do not know (%)	Valid n
Public transport effective and connected	28.5	18.7	36.4	16.4	348
Alternatives to private car encouraged	41.7	19.0	34.2	5.2	348
EV infrastructure available	42.0	18.7	29.3	10.1	348
Traffic policies support flow and safety	28.4	23.9	44.0	3.7	348
Public transport accessible to all	27.8	20.4	44.6	7.2	348

4.2 Infrastructure context

Infrastructure perceptions reinforce the need to look beyond aggregate mobility averages. In the thesis, 49.1% agreed that transport infrastructure is well maintained, while 27.3% disagreed. For the statement that public infrastructure is accessible and well distributed, 41.1% disagreed and 36.2% agreed. Digital infrastructure received 34.1% agreement and 35.1% disagreement. These different profiles point to distinct planning questions: maintenance, spatial distribution and digital readiness should be measured separately rather than treated as a single "smart infrastructure" score.

4.3 What evidence supports and what it does not

The descriptive results support a prioritization agenda: strengthen multimodal options, assess charging-network coverage, improve public-transport connectivity and test whether infrastructure distribution aligns with population needs. They do not demonstrate that AI will improve these conditions, predict future traffic, reduce emissions or increase accessibility. Those claims require operational data, model validation and evaluation of implemented interventions. The proposed framework translates the survey's reported priorities into testable prediction and planning tasks.

5. DISCUSSION

5.1 From reported perceptions to territorial forecasts

The survey gives planning stakeholders a useful signal about perceived strengths and weaknesses, but perception is not a substitute for a service inventory or observed mobility dataset. In a pilot, the survey should be combined with service schedules, stop and route geometry, actual vehicle locations, ridership counts, road-network attributes, crash and roadwork records, land use and essential destinations. Household or population data can support accessibility and equity analysis. Citizen feedback should be collected in ways that preserve anonymity and include residents who have limited access to digital channels.

Prediction then becomes actionable when tied to a territorial decision. A demand forecast may help adjust service frequency; a travel-time reliability forecast may identify corridor bottlenecks; an accessibility map may reveal neighbourhoods with weak access to schools or health facilities; and an asset-risk model may inform maintenance sequencing. Digital-twin approaches can support scenario simulation, but their usefulness depends on model scope, data coverage and local validation (Yeon et al., 2023; Grotto et al., 2024).

5.2 Equity and sustainability in the objective function

The high disagreement on alternatives to private cars cautions against an AI agenda focused exclusively on road capacity or private-vehicle flow. A sustainable territorial framework should compare interventions by their effects on door-to-door

access, service frequency, transfer burden, safety, affordability and emissions. Results should be disaggregated spatially so that average gains do not obscure losses in peripheral areas or for people with constrained mobility. Work on transport supply-demand indicators and mobility equity shows why both provision and the populations needing access should be considered (Ballantyne et al., 2024; Liu et al., 2024). Traffic forecasting methods should also be assessed against transparent baselines and local operating conditions (Abduljabbar et al., 2025; Attioui & Lahby, 2026).

The relatively low agreement on electric-vehicle infrastructure should also be interpreted in context. Charging stations may support decarbonization, but an EV-only strategy does not resolve access for people who cannot afford a car. Scenario analysis should therefore compare investment in charging with public transport, walking and cycling networks, and integrated service provision. Carbon outcomes require validated activity or energy data rather than a generic AI-generated estimate (Ji et al., 2024; Wang et al., 2024; ITF, 2023).

5.3 Governance safeguards and deployment sequence

A responsible pilot requires data minimization, clear purpose limitation, access controls, retention rules and public documentation. Location traces and ticketing data can reveal sensitive movement patterns, so aggregation and privacy-preserving processing should be considered before analysis. Human planners must review forecasts and record the reasons for accepting, modifying or rejecting recommendations. Public reporting should explain who benefits, where errors concentrate, what uncertainty remains and how residents can challenge or supplement the evidence (OECD, 2024; UNESCO, 2021; EEA, 2022).

A staged deployment is preferable: first establish data inventories and quality controls; next publish baseline accessibility and service indicators; then evaluate forecasts offline using temporal and spatial holdouts; and only after satisfactory validation run a decision-support pilot with planning staff and resident review. Predictions should not trigger automated enforcement or service cuts. Forecasts should be monitored for drift and recalibrated only through documented review. The principle is to use AI to inform a public decision, while leaving the authority and accountability for that decision with the institution.

5.4 Contribution and limitations

The article contributes a thesis-grounded framework that connects residents' reported mobility priorities to measurable prediction targets and territorial planning decisions. The framework brings mobility demand, accessibility, infrastructure, emissions and participation into one decision pathway, while specifying a validation agenda. Its empirical contribution is intentionally bound: the source evidence consists of thesis-reported descriptive frequencies and scale diagnostics. No respondent-level reanalysis was possible, no direct measures of network supply or actual travel were available for this manuscript, and no predictive model was trained. The thesis' high RMSEA for its broader confirmatory model further cautions against treating its structural model as strong validation. Future work should document sampling procedures and field dates, link questionnaire responses to appropriately aggregated spatial indicators, and collect longitudinal transport data before estimating or claiming forecast performance.

6. RESEARCH PROPOSITIONS FOR A FUTURE PILOT

P1. Integrating operational public-transport, road-network and land-use data will improve short-horizon demand and reliability forecasts relative to seasonal naïve and ARIMA baselines, subject to adequate data quality and temporal coverage.

P2. Adding neighbourhood-level population and destination accessibility features will improve the territorial usefulness of predictions by identifying gaps that are not visible in network-wide averages.

P3. Scenario ranking that jointly considers accessibility, safety, emissions and distributional effects will produce different planning priorities from traffic-flow-only optimization.

P4. Human review and accessible public explanation will improve the legitimacy and practical interpretability of AI-supported mobility planning, provided that residents can influence problem framing and evaluation.

CONCLUSION

The Rabat thesis findings identify practical mobility priorities: respondents most often expressed concern about encouragement of alternatives to private cars and the availability of electric-vehicle infrastructure, while views on transit accessibility and traffic policy were more favorable but not unanimous. These findings justify a predictive research agenda, not a claim that AI has already solved or forecast the city's mobility challenges. The proposed framework links an integrated data foundation to prediction, sustainability-oriented scenario comparison and accountable territorial

decisions. Its next step is an operational pilot with transparent baselines, spatially and temporally valid testing, uncertainty reporting and equity checks. AI can support sustainable territorial development when its forecasts answer clear public questions and remain open to human judgment and citizen scrutiny.

REFERENCES

Abduljabbar, R., Dia, H., & Liyanage, S. (2025). Machine learning traffic flow prediction models for smart and sustainable traffic management. Infrastructures, 10(7), 155. https://doi.org/10.3390/infrastructures10070155

Afandizadeh, S., Abdolahi, S., & Mirzahossein, H. (2024). Deep learning algorithms for traffic forecasting: A comprehensive review and comparison with classical ones. Journal of Advanced Transportation, 2024, 9981657. https://doi.org/10.1155/2024/9981657

Attioui, M., & Lahby, M. (2026). Sustainable traffic congestion forecasting through lightweight explainable AI and TinyML edge deployment: A Casablanca case study. Sustainability, 18(9), 4439. https://doi.org/10.3390/su18094439

Ballantyne, P., Filomena, G., Rowe, F., & Singleton, A. (2024). Developing two-dimensional indicators of transport demand and supply to promote sustainable transportation equity. Computers, Environment and Urban Systems, 113, 102179. https://doi.org/10.1016/j.compenvurbsys.2024.102179

Cheng, L., Lei, D., & Tao, S. (2024). Recent advances in deep learning for traffic probabilistic prediction. Transport Reviews, 44(6), 1129–1135. https://doi.org/10.1080/01441647.2024.2408840

Du, J., Ye, X., Jankowski, P., Sanchez, T. W., & Mai, G. (2024). Artificial intelligence enabled participatory planning: A review. International Journal of Urban Sciences, 28(2), 183–210. https://doi.org/10.1080/12265934.2023.2262427

Elassy, M., Al-Hattab, M., Takruri, M., & Badawi, S. (2024). Intelligent transportation systems for sustainable smart cities. Transportation Engineering, 16, 100252. https://doi.org/10.1016/j.treng.2024.100252

European Commission. (2021). The new EU urban mobility framework (COM/2021/811 final). https://transport.ec.europa.eu/transport-themes/urban-transport/sustainable-urban-mobility_en

European Commission. (2020). Sustainable and smart mobility strategy—Putting European transport on track for the future (COM/2020/789 final). https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52020DC0789

European Environment Agency. (2022). Transport and environment report 2022: Digitalisation in the mobility system. EEA. https://www.eea.europa.eu/publications/transport-and-environment-report-2022

Grotto, A., Casas Fonseca, P., Zubaryeva, A., & Sparber, W. (2024). Formalizing sustainable urban mobility management: An innovative approach with digital twin and integrated modeling. Logistics, 8(4), 117. https://doi.org/10.3390/logistics8040117

Intergovernmental Panel on Climate Change. (2022). Transport. In Climate change 2022: Mitigation of climate change (AR6 WGIII, Chapter 10). Cambridge University Press. https://doi.org/10.1017/9781009157926.012

International Transport Forum. (2023). ITF transport outlook 2023. OECD Publishing. https://doi.org/10.1787/b6cc9ad5-en

International Transport Forum. (2021). Travel transitions: How transport planners and policy makers can respond to shifting mobility trends. OECD Publishing. https://www.itf-oecd.org/travel-transitions

Jevinger, Å., Zhao, C., Persson, J. A., & Davidsson, P. (2024). Artificial intelligence for improving public transport: A mapping study. Public Transport, 16, 99–158. https://doi.org/10.1007/s12469-023-00334-7

Ji, T., Li, K., Sun, Q., & Duan, Z. (2024). Urban transport emission prediction analysis through machine learning and deep learning techniques. Transportation Research Part D: Transport and Environment, 135, 104389. https://doi.org/10.1016/j.trd.2024.104389

Liu, J., Wen, X., & Jian, S. (2024). Toward better equity: Analyzing travel patterns through a neural network approach in mobility-as-a-service. Transport Policy, 153, 110–126. https://doi.org/10.1016/j.tranpol.2024.05.018

OECD. (2024). Governing with artificial intelligence: The state of play and way forward in core government functions. OECD Publishing. https://doi.org/10.1787/26324bc2-en

Rocco di Torrepadula, F., Di Martino, S., Mazzocca, N., & Sannino, P. (2024). A reference architecture for data-driven intelligent public transportation systems. IEEE Open Journal

of Intelligent Transportation Systems, 5, 469–482. https://doi.org/10.1109/OJITS.2024.3441048

Rocco di Torrepadula, F., Napolitano, E. V., Di Martino, S., & Mazzocca, N. (2024). Machine learning for public transportation demand prediction: A systematic literature review. Engineering Applications of Artificial Intelligence, 137, 109166. https://doi.org/10.1016/j.engappai.2024.109166

Rouky, N., Benmoussa, O., Fri, M., Abourraja, M. N., & Ben-Bouazza, F.-E. (2025). Artificial intelligence applications for smart and sustainable mobility as a service concept: A systematic literature review. Future Transportation, 5(3), 122. https://doi.org/10.3390/futuretransp5030122

Shulajkovska, M., Smerkol, M., Noveski, G., Bohanec, M., & Gams, M. (2024). Artificial intelligence-based decision support system for sustainable urban mobility. Electronics, 13(18), 3655. https://doi.org/10.3390/electronics13183655

UN-Habitat. (2022). World cities report 2022: Envisaging the future of cities. United Nations Human Settlements Programme. https://unhabitat.org/wcr/

UNESCO. (2021). Recommendation on the ethics of artificial intelligence. UNESCO. https://unesdoc.unesco.org/ark:/48223/pf0000381137

United Nations. (2021). Sustainable transport, sustainable development: Interagency report for second Global Sustainable Transport Conference. United Nations. https://sdgs.un.org/publications/sustainable-transport-sustainable-development-28633

Wang, H., Wang, X., Yin, Y., Deng, X., & Umair, M. (2024). Evaluation of urban transportation carbon footprint Artificial intelligence-based solution. Transportation Research Part D: Transport and Environment, 136, 104406. https://doi.org/10.1016/j.trd.2024.104406

World Bank. (2023). Urban mobility and accessibility: A sourcebook for policy makers. World Bank. https://openknowledge.worldbank.org/

World Health Organization. (2023). Global status report on road safety 2023. WHO. https://www.who.int/publications/i/item/9789240086517

Yeon, H., Eom, T., Jang, K., & Yeo, J. (2023). DTUMOS, digital twin for large-scale urban mobility operating system. Scientific Reports, 13, 5154. https://doi.org/10.1038/s41598-023-32326-9

Zhou, Z., Gu, Z., Qu, X., Liu, P., Liu, Z., & Yu, W. (2024). Urban mobility foundation model: A literature review and hierarchical perspective. Transportation Research Part E: Logistics and Transportation Review, 192, 103795. https://doi.org/10.1016/j.tre.2024.103795