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Energy Emissions and Cost Impacts of Autonomous Battery Electric Vehicles in Riyadh

Ali Louati [1,*], Hassen Louati [2] and Elham Kariri [1]

[1] Department of Information Systems, College of Computer Engineering and Sciences, Prince Sattam bin Abdulaziz University, Al-Kharj 11942, Saudi Arabia; e.kariri@psau.edu.sa
[2] College of Information Technology, KU AI Research Center, Kingdom University, Riffa 40434, Bahrain; h.louati@ku.edu.bh
* Correspondence: a.louati@psau.edu.sa

Abstract

Autonomous battery electric vehicles (BEVs) have the potential to reshape urban mobility systems, yet their sustainability impacts remain underexplored in Gulf-region cities where traffic dynamics, land-use structures, and environmental conditions differ substantially from Western contexts. This study introduces a Saudi-specific assessment framework that integrates monetised externalities with empirically calibrated traffic dynamics to evaluate how automation influences safety, congestion, land use, emissions, and noise. To the best of our knowledge, this is the first Riyadh-calibrated monetised external-cost evaluation of autonomous BEVs that couples externality valuation with simulation-validated time-varying traffic dynamics (SAR per vkm and SAR per pkm), enabling realistic peak-period sustainability assessment. The framework's key contribution is linking external-cost modelling with spatiotemporal traffic behaviour derived from Riyadh's 2023 mobility patterns, providing a more realistic basis for sustainability evaluation. Using national datasets from transport, energy, and statistical authorities, the model estimates substantial reductions in external costs when transitioning from human-driven to autonomous BEVs, driven primarily by lower crash exposure and smoother traffic flow. To validate these findings under real operating conditions, a dynamic analysis incorporating hourly and seasonal traffic variability was developed, revealing that automation delivers its strongest improvements during peak-demand periods where congestion externalities are highest. The integrated results demonstrate the relevance of autonomous BEVs for dense rapidly growing Saudi cities and provide actionable insights for future mobility planning. The study highlights the policy importance of coordinated transport, land-use, and energy strategies to ensure that automation contributes meaningfully to national sustainability goals under Vision 2030.

Keywords: sustainability; BEV; external cost; Riyadh; autonomous vehicle

Check for updates

Academic Editor: Clemente Capasso

Received: 12 February 2026
Revised: 28 March 2026
Accepted: 31 March 2026
Published: 1 April 2026

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1. Introduction

The global shift toward autonomous and electrified mobility is transforming how cities evaluate future transport sustainability. Autonomous Battery Electric Vehicles (A-BEVs) are anticipated to enhance road safety, smooth traffic flow, and improve energy efficiency through coordinated and error-free driving. However, the magnitude of these benefits varies significantly across regions, due to differences in climate, network structure, and mobility patterns. Cities in the Gulf region exhibit urban and environmental characteristics not typically represented in international studies on autonomous vehicles. Riyadh's dispersed

land-use patterns, wide multilane corridors, exceptionally high summer temperatures, and historically elevated accident exposure collectively shape driving behaviour and congestion dynamics in ways that differ markedly from Western urban systems. These contextual factors influence both energy consumption and external cost formation, limiting the direct transfer of international sustainability models. Evidence from Riyadh indicates that local operating conditions and traffic dynamics can materially affect sustainability outcomes in simulation-based assessments of autonomous electric mobility, supporting the need for locally calibrated evaluation rather than parameter transfer from other regions [1]. Although substantial progress has been made in modelling the impacts of autonomous and electric vehicles, many existing sustainability frameworks rely on generalised parameters that overlook regional conditions. Models calibrated using European or North American data may misestimate accident risks, congestion propagation, battery performance, or land-use externalities when applied to Gulf cities, highlighting the need for localised evidence-driven assessment. Recent Riyadh-based simulation evidence emphasises the importance of integrating region-specific climatic, behavioural, and infrastructural conditions into sustainability evaluations in rapidly expanding metropolitan environments [1].

To fill this gap, the present study develops a localised sustainability assessment tailored to Riyadh. The proposed framework incorporates Saudi-specific accident statistics, dynamic congestion patterns derived from simulation, temperature-adjusted energy use, and national land valuation indicators, enabling a calibrated and context-sensitive estimation of external costs. By grounding the analysis in empirical local data, the model more accurately reflects the operational realities of Gulf transport systems. For clarity and consistency, the term Autonomous Battery Electric Vehicles (A-BEVs) is used throughout the manuscript to denote fully electric driverless vehicles. This terminology ensures coherence across the analysis and avoids ambiguity in differentiating autonomous vehicles from conventional BEVs.

This study makes three key contributions:

- It provides a comprehensive locally adapted framework for quantifying the environmental, economic, and social externalities of A-BEV deployment in Riyadh.
- It integrates high-resolution traffic simulation to capture congestion dynamics under both autonomous and human-driven scenarios.
- It delivers monetised sustainability indicators based on localised data sources, offering actionable insights for transport policy and long-term mobility planning in Saudi Arabia.

Novelty is introduced through the joint design of a Saudi- and Riyadh-calibrated monetised external-cost framework (SAR per vkm and SAR per pkm) and empirically grounded time-varying congestion dynamics validated through microscopic simulation, which together enable cross-externality comparison under realistic operating conditions rather than static average assumptions. By embedding regional climatic constraints, behavioural patterns, and calibrated model parameters, this work establishes a more accurate and policy-relevant understanding of the sustainability implications associated with A-BEV introduction in Gulf urban contexts.

2. Literature Review

Research on autonomous and electric mobility continues to grow, offering insights into safety [2], emissions [3], congestion [4], and social impacts [5]. For clarity, we organise the literature into three streams: (i) sustainability assessments of autonomous and electric vehicles, (ii) behavioural and operational determinants of autonomous driving performance, and (iii) frameworks for quantifying external transport costs. However, most current models are calibrated using data from Europe, North America, or East Asia, creating

significant transferability limitations for rapidly growing Gulf cities, since these parameters may not reflect Gulf traffic conditions, climatic constraints, or local cost structures.

Across these three streams, studies differ systematically along four axes: (a) the evaluation output (physical indicators such as $kgCO_2$ or minutes of delay versus monetised indicators such as cost per vkm/pkm), (b) the traffic representation (static averages versus dynamic or simulation-based congestion), (c) the automation setting (fully autonomous, mixed traffic, and penetration-rate assumptions), and (d) the transferability of parameters across regions and climates. To clarify these differences, Table 1 summarises representative studies and highlights the methodological gap addressed in this paper.

Table 1. Representative literature map and positioning of this study.

Study	Focus	Output	Traffic Model	Transferability Notes
[6–8]	AV/energy/emissions	Physical/%	Mostly aggregate	Limited climate/region specificity
[9,10]	Acceptance/behaviour	Qual./quant.	Not traffic-dynamic	Demand effects often not monetised
[11,12]	Flow/capacity	Physical	Dynamic/flow models	Sensitive to geometry and heterogeneity
[13,14]	External costs	Monetised	Usually static	Parameter transfer is non-trivial
[15]	Automated BEVs	Monetised	Modular/static	Requires regional recalibration
This study	A-BEVs in Riyadh	Monetised (SAR)	Simulation-informed	Saudi- and Riyadh-calibrated parameters

2.1. Sustainability Impacts of Autonomous and Electric Vehicles

The global literature demonstrates that autonomous driving can reduce energy use, improve roadway stability, and contribute to long-term decarbonisation efforts [6–8]. Electrification further strengthens these effects when supported by low-carbon power grids [16]. Recent analytical work also highlights the importance of aligning AV–EV deployment with broader emission reduction policies, as shown in Physica A (2023), which demonstrates that sustainable mobility transitions rely on regionally tailored data-driven modelling and dynamic system behaviour analysis [17]. This underscores the need for localised sustainability modelling in regions with distinct climatic and operational conditions such as the Gulf. Moreover, existing environmental models generally assume moderate climates and stable traffic behaviour, assumptions that do not hold in cities with extreme temperatures and different accident profiles. In the Gulf context, Louati et al. have begun to explore sustainable mobility from a systems perspective: cloud-assisted collaborative sensing for connected vehicles [18], Gaussian process-based road information discovery and smart mobility in Saudi cities, and harmonised autonomous–human vehicle operations to reduce emissions in Riyadh [19]. These studies highlight the strategic role of intelligent and autonomous mobility in regional decarbonisation pathways, but they do not provide a fully monetised external cost assessment. A key distinction in this stream is the choice of evaluation output. Many studies quantify sustainability using physical indicators (e.g., energy use, CO_2 emissions, average speed, or delay) or relative percentage improvements under automation and electrification [6–8]. While informative, these indicators are not directly comparable across domains (safety versus congestion versus land use) and are difficult to translate into policy trade-offs. This motivates complementary frameworks that express impacts in a consistent monetary form (e.g., cost per vehicle-km or passenger-km), enabling cross-externality comparison and prioritisation.

2.2. Behavioural and Operational Determinants of AV Performance

Behavioural research emphasises that user perception, perceived safety, and trust significantly shape AV acceptance and travel patterns [9,10]. Operational investigations further show that lane geometry, traffic heterogeneity, and control cooperation influence congestion propagation and traffic stability [11,12]. Technical studies on deep learning and

scene understanding, such as the convolutional architectures proposed in [20,21], highlight the importance of robust perception systems for autonomous driving, because accurate scene understanding enables faster and more reliable capture of real-world dynamics. These insights support the assumption that improved perception can translate into lower accident exposure, which is a core component of the external cost modelling adopted in this work, and underline the need to account for local traffic and road conditions when representing AV performance. Related regional work has also examined operational aspects of smart mobility in Saudi Arabia, including collaborative estimation for connected vehicles [18] and cooperative road-information discovery along urban corridors. While these contributions improve traffic efficiency and safety from a control and information perspective, they stop short of translating operational gains into monetised sustainability indicators.

Importantly, behavioural acceptance and operational performance interact: changes in trust and perceived convenience can alter demand and vehicle-kilometres travelled, while penetration-rate assumptions determine whether AV benefits materialise under mixed traffic. Flow and capacity gains reported in cooperative-control studies are therefore scenario-dependent and can be amplified or dampened by demand responses and heterogeneous driving behaviour [9–12]. Because these mechanisms ultimately influence crash exposure and congestion delay, they should be reflected in any external-cost assessment that seeks policy relevance.

2.3. Frameworks for Monetising Transport Externalities

A large body of work proposes standardised approaches for monetising external transport costs, including accident severity, emissions, congestion delays, noise, and land-use impacts [13,14]. The structured external cost model by Letmathe and Paegert [15] remains a leading example, offering a modular approach to evaluate marginal external costs of automated BEVs. However, its parameters—derived from European accident data, energy systems, and land valuations—do not reflect Gulf conditions and therefore require regional recalibration. A second distinction within monetisation frameworks is whether congestion, risk, and emissions are evaluated using static averages or dynamic conditions that vary by hour, season, and demand regime. Standardised external-cost methods provide consistent valuation logic but often rely on averaged parameters and simplified congestion representations [13,14]. In contrast, simulation-informed approaches can capture peak-period delay formation and thereby change the magnitude and ranking of congestion-related externalities. This motivates integrating monetised externalities with empirically grounded, time-varying traffic dynamics when evaluating AV scenarios. Recent studies call for localised sustainability assessment models that incorporate temperature-driven energy behaviour, region-specific accident cost structures, and urban land dynamics [22]. Even in Riyadh-focused simulation-based work on harmonised autonomous–human fleets and emissions mitigation [19], sustainability impacts are primarily reported in physical or percentage terms rather than fully monetised external costs. This gap motivates the development of an externality framework that can express AV impacts on safety, congestion, emissions, land use, and noise in a consistent monetary form.

2.4. Gaps in the Literature and Positioning of the Present Study

Although research related to AV readiness and mobility planning in Saudi Arabia is increasing [19,23], to the best of our knowledge, no prior study has conducted a fully monetised external cost evaluation of autonomous BEVs using Saudi-specific cost parameters, climatic conditions, accident statistics, or validated traffic patterns. Based on the review above, four gaps motivate the present study:

- G1: Output gap: Many studies report physical or percentage metrics, limiting cross-domain policy comparison (safety vs. congestion vs. land use).
- G2: Dynamics gap: Congestion and exposure are often evaluated using static averages rather than time-varying (peak/seasonal) conditions.
- G3: Scenario gap: Mixed-traffic and penetration assumptions are not consistently propagated into monetised sustainability outcomes.
- G4: Transferability gap: External-cost parameters are frequently imported from other regions without Gulf-specific calibration.

Accordingly, our framework (i) produces monetised indicators for cross-externality comparison (G1), (ii) integrates time-varying congestion from simulation (G2), (iii) evaluates autonomous and human-driven scenarios consistently (G3), and (iv) recalibrates key parameters using Riyadh/Saudi sources (G4).

Existing international frameworks also fail to account for Riyadh's extreme temperature-induced battery degradation, wide multilane arterials, and high accident severity factors that are central to accurate sustainability modelling. Consequently, there remains a clear need for an integrated Riyadh-focused framework that combines localised external cost modelling with empirically grounded traffic dynamics to support evidence-based sustainable mobility planning. The present study addresses these gaps by building on regional intelligent transport research [19] and extending it towards a comprehensive monetised assessment of autonomous BEV deployment under real Riyadh traffic and land-use conditions.

To address these gaps, the present study develops a localised external cost framework that recalibrates accident risks, congestion patterns, energy consumption, and land-use valuations using Riyadh-specific datasets. By integrating dynamic traffic simulation results with monetised environmental, economic, and social cost categories, this work offers the first comprehensive sustainability assessment of autonomous BEV deployment in Riyadh. The framework contributes to the literature by demonstrating the necessity and value of regionally calibrated AV sustainability assessments tailored to the operational realities of Gulf cities.

3. Methodology

This study develops a localised external cost assessment framework to compare human-driven battery electric vehicles (BEVs) and autonomous BEVs (A-BEVs) operating in Riyadh. The method combines Saudi national datasets, recalibrated transport–economic relationships, scenario analysis, and microscopic simulation to estimate marginal externalities in Saudi Riyals (SAR) per vehicle-kilometre traveled (vkm) and per passenger-kilometre (pkm).

The workflow is structured into seven stages, from data collection and model localisation to scenario evaluation, sensitivity analysis, and policy-oriented interpretation. Each stage is described separately to maintain a clear distinction between the model formulation, numerical experiments, and the presentation of the results.

3.1. Stage 1: Saudi-Specific Data Collection

The analysis begins with the compilation of a Riyadh-specific dataset:

- Yearly crashes by severity class and road type (Ministry of Transport),
- Hourly traffic counts and speed profiles on Prince Mohammed bin Salman (MBS) Road (RCRC),
- Grid emission factors and electricity mix (SEEC),
- Wage, population, and value-of-time indicators (GASTAT),
- Land prices and parking footprints (RCRC cadastral data).

Let VKT denote total the yearly vehicle-kilometres on the corridor, POP the exposed population, and L_{urban} the relevant urban land area.

Using only Saudi datasets ensures that all subsequent parameters directly reflect regional transport, energy, and land-use characteristics.

Data Sources and Study Period

To improve the reproducibility, this study harmonises all inputs to a common study period and reports the temporal resolution of each dataset. Dynamic traffic indicators (hourly speed and traffic counts) represent Riyadh's observed diurnal variability, while annual datasets provide the corresponding safety, emissions, socio-economic, and land-valuation parameters used for monetisation. Unless stated otherwise, all monetary values are expressed in Saudi Riyals (SAR), and the most recent dataset year overlapping the traffic study period is used. Table 2 shows the data sources, temporal coverage, sampling resolution, and role in the framework.

Table 2. Data sources, temporal coverage, sampling resolution, and role in the framework.

Dataset (Provider)	Variables Used	Temporal Coverage	Sampling Resolution	Use in the Model
Crash statistics (Ministry of Transport)	Crash counts by severity (N_s), road type	Annual (study year)	Yearly	Accident-risk calibration (λ_s) and accident cost E^{acc}
Traffic records (RCRC)	Hourly counts and speeds (u_h, u_h^{ff}, w_h)	Study year (hourly profiles)	Hourly	Delay estimation (Δt_h, $\overline{\Delta t}$), congestion cost E^{cong}, simulation calibration/validation targets
Electricity mix/grid factors (SEEC)	Grid emission factor (e_{grid}), mix	Annual (study year)	Yearly	Emission cost E^{em} via q_{CO_2} and MCC_{CO_2}
Socio-economic indicators (GASTAT)	Value of time (VOT proxy), wages, population indicators	Annual/official release aligned to study year	Yearly (or official release frequency)	Monetisation parameters (e.g., VOT) and exposure proxies where needed
Land valuation and parking footprint (RCRC cadastral)	Land value (LV), parking footprint (A_{park}), occupancy (p_{occ})	Cadastral snapshot aligned to study year	Snapshot/parcel-level	Land-use/parking cost E^{land}
Noise exposure (derived inputs)	Façade level (L_{eq}), reference (L_{ref}), households (H), valuation (κ)	Study year (parameter set)	Parameter set	Noise cost E^{noise}

3.2. Stage 2: Model Localisation and Parameter Recalibration

The external cost structure is inspired by monetisation frameworks proposed in previous European studies, but all cost and exposure parameters are recalibrated to Riyadh conditions. We define a vector of externalities

$$\mathbf{E} = \left(E^{\text{acc}}, E^{\text{cong}}, E^{\text{em}}, E^{\text{land}}, E^{\text{noise}}\right) \quad (1)$$

where each component represents a marginal cost in SAR/vkm for human-driven BEVs. For clarity, we define all symbols used in the subsequent equations. E^{acc}, E^{cong}, E^{em}, E^{land}, and E^{noise} denote marginal external costs (SAR/vkm) associated with accidents, congestion delay, emissions, land-use/parking, and noise, respectively. VKT is the total vehicle-kilometres travelled (vkm) on the study corridor over the analysis period. For accident modelling, N_s is the annual crash count for severity level s, and C_s is the Saudi-specific unit cost for severity s (SAR/crash). For congestion modelling, u_h and u_h^{ff} are the observed mean and free-flow speeds (km/h) in hour h, w_h is the hourly traffic weight (dimensionless,

$\sum_h w_h = 1$), and VOT is the value of time (SAR/min). For land-use modelling, A_{park} is the parking area per vehicle (m^2/vehicle), p_{occ} is the occupancy/usage factor (dimensionless), LV is the land value (SAR/m^2), and S_{avg} is the average trip length (km). Table 3 illustrates the notation used in the external-cost formulation (Stages 2–4).

Table 3. Notations used in the external-cost formulation (Stages 2–4).

Symbol	Meaning	Unit
E^{acc}	Accident external cost per vehicle-km	SAR/vkm
E^{cong}	Congestion external cost per vehicle-km	SAR/vkm
E^{em}	Emission external cost per vehicle-km	SAR/vkm
E^{land}	Land-use/parking external cost per vehicle-km	SAR/vkm
E^{noise}	Noise external cost per vehicle-km	SAR/vkm
VKT	Vehicle-kilometres travelled on the corridor (analysis period)	vkm
N_s	Crash count for severity level s	crashes
C_s	Unit cost per crash for severity s	SAR/crash
u_h, u_h^{ff}	Mean and free-flow speed in hour h	km/h
w_h	Hourly traffic weight (sum to 1)	–
VOT	Value of time	SAR/min
A_{park}	Parking footprint per vehicle	m^2/veh
p_{occ}	Parking usage/occupancy factor	–
LV	Land value	SAR/m^2
S_{avg}	Average trip length	km
ρ_k	Relative change factor applied to externality k under A-BEVs	–
$O^{(s)}$	Vehicle occupancy in scenario s	passengers/veh
e_{grid}	Grid CO_2 emission factor	kg/kWh
e_{EV}	BEV electricity consumption	kWh/km
MCC_{CO_2}	Marginal climate cost of CO_2	SAR/kg
L_{eq}, L_{ref}	Equivalent sound level and reference threshold	dB
H	Exposed households	households
κ	Monetary valuation per dB per household per year	SAR/(dB·hh·yr)

Three recalibration steps are performed:

1. Accident risk: For severity level $s \in \{\text{fatal}, \text{injury}, \text{property}\}$, the expected number of crashes per vkm is
$$\lambda_s = \frac{N_s}{VKT}, \tag{2}$$
where N_s is the annual count of crashes of severity s. The corresponding accident cost per vkm is
$$E^{\text{acc}} = \sum_s \lambda_s C_s, \tag{3}$$
with C_s the Saudi-specific unit cost of severity s (compensation, medical, and property costs).
2. Congestion and delay: For each time slice h (hour of day), we observe mean speed u_h and free-flow speed u_h^{ff} on MBS Road. The delay per vkm in hour h is
$$\Delta t_h = \frac{1}{u_h} - \frac{1}{u_h^{\text{ff}}}, \tag{4}$$
Aggregating over all hours using traffic weights w_h yields the average delay per vkm:
$$\overline{\Delta t} = \sum_h w_h \, \Delta t_h. \tag{5}$$
The congestion cost per vkm is then
$$E^{\text{cong}} = \overline{\Delta t} \cdot VOT, \tag{6}$$

where VOT is the value of time in SAR/min derived from GASTAT.

3. Land-use and parking: Let A_{park} be the average parking area per vehicle, p_{occ} the average occupancy rate, and LV the land value in SAR/m^2. The land-use cost per vkm is

$$E^{\text{land}} = \frac{A_{\text{park}}\, p_{\text{occ}}\, LV}{S_{\text{avg}}}, \tag{7}$$

where S_{avg} is the average trip length (km) for vehicles using the corridor.

These equations make explicit which quantities from the original framework are replaced by Saudi-specific values and how they are recomputed from local data. The recalibration particularly captures Riyadh's high accident severity, multilane arterial configuration, and high land valuations near key corridors.

3.3. Stage 3: Scenario Definition and AV Modifiers

Two operational scenarios are defined:

- Scenario H (Human-driven BEVs): Current operating conditions with human drivers.
- Scenario A (Autonomous BEVs): A-BEV fleets with cooperative lane-changing, smoother longitudinal control, and reduced parking requirements.

For each externality k, the A-BEV case is modelled as a proportional modification of the baseline cost:

$$E_k^{\text{A}} = (1 - \rho_k)\, E_k^{\text{H}}, \tag{8}$$

where E_k^{H} is the human-driven BEV cost, E_k^{A} is the A-BEV cost, and ρ_k is the relative reduction (or increase, if negative) in external cost.

The reduction factors ρ_k are informed by international AV performance studies and then constrained using Saudi accident and congestion profiles to avoid unrealistic values. This formulation clarifies how the proposed method improves over current conditions while retaining a direct link to observed externalities.

3.4. Stage 4: External Cost Formulation

The total external cost per vkm for scenario $s \in \{\text{H}, \text{A}\}$ is written as

$$EC_{\text{vkm}}^{(s)} = E_{\text{acc}}^{(s)} + E_{\text{cong}}^{(s)} + E_{\text{em}}^{(s)} + E_{\text{land}}^{(s)} + E_{\text{noise}}^{(s)}. \tag{9}$$

To account for occupancy differences, the cost per passenger-kilometre is

$$EC_{\text{pkm}}^{(s)} = \frac{EC_{\text{vkm}}^{(s)}}{O^{(s)}}, \tag{10}$$

where $O^{(s)}$ is the average vehicle occupancy in scenario s.

The introduction of a passenger-based metric facilitates comparison with demand management and public-transport policies and extends the original vehicle-kilometre-based framework. Equation (9) is kept general so that numerical values can be presented later without methodological repetition.

3.4.1. Emission Costs

Let e_{grid} be the CO_2 emission factor of the Saudi grid (kg/kWh) and e_{EV} the electricity consumption of BEVs (kWh/km). The emission per vkm is

$$q_{CO_2} = e_{\text{grid}} \cdot e_{\text{EV}}, \tag{11}$$

and the corresponding cost per vkm is

$$E^{\text{em}} = q_{\text{CO}_2} \cdot MCC_{\text{CO}_2}, \tag{12}$$

where MCC_{CO_2} denotes the marginal climate cost in SAR/kg CO_2. For the A-BEV scenario, we allow for a small efficiency change η_{AV} (positive for savings):

$$E^{\text{A}}_{\text{em}} = (1 - \eta_{\text{AV}})\, E^{\text{H}}_{\text{em}}. \tag{13}$$

Here, q_{CO_2} is expressed in kgCO_2/km and MCC_{CO_2} in SAR/kgCO_2, resulting in E^{em} in SAR/vkm.

3.4.2. Noise Costs

Noise-related externalities are modelled via an exposure–response relationship. Let L_{eq} be the equivalent continuous sound level (dB) at the building façade and $\Delta L = L_{\text{eq}} - L_{\text{ref}}$ the excess over a reference threshold. If H denotes the number of exposed households and κ the annual monetary valuation per dB per household, the noise cost per vkm is

$$E^{\text{noise}} = \frac{\Delta L \cdot H \cdot \kappa}{VKT}. \tag{14}$$

This formulation clarifies how noise exposure along the corridor is translated into marginal monetary costs using Saudi-specific population densities and valuation parameters.

3.5. Stage 5: Microscopic Simulation and Validation

Microscopic simulation on Prince MBS Road is used to validate congestion- and speed-related components of the model. The network geometry, signal plans, and lane configurations are coded from RCRC GIS data. Demand is represented by an origin–destination matrix calibrated from hourly counts.

Figure 1 provides an overall flowchart of the simulation and validation procedure used in this study.

Simulation experiment settings were selected to match the temporal granularity of the observational traffic records. The simulation horizon covers the full daily operating cycle used in the congestion analysis, and outputs are aggregated at an hourly level to be comparable with observed u_h. A warm-up period is applied to remove initialisation effects, and multiple replications (different random seeds) are executed to stabilise the reported mean speeds and delays. The exact horizon length, warm-up duration, simulation step, and number of replications are reported in Table 4.

To ensure reproducibility and comparability with the observational traffic records, the microscopic simulation is executed over a defined experiment horizon that covers the daily operating cycle used in the congestion analysis. A warm-up period is applied to remove initialisation bias, and multiple independent replications (different random seeds) are run to stabilise reported averages. Simulation outputs are aggregated at the same temporal resolution as the observed data (hourly), producing $u_h^{(s)}$, $q_h^{(s)}$, and $\Delta t_h^{(s)}$ for each scenario s. The key experiment settings are summarised in Table 5.

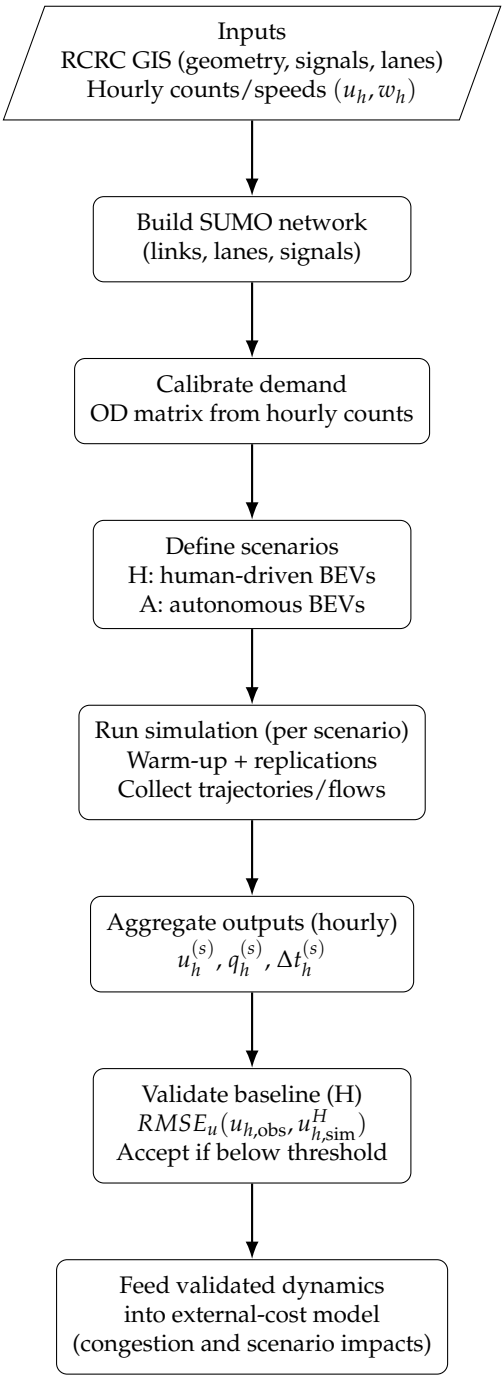


Figure 1. Overview of the microscopic simulation and validation workflow (Stage 5).

Table 4. Microscopic simulation experiment settings (SUMO).

Setting	Value
Simulation horizon (experiment time)	[e.g., 24 h covering morning and evening peaks]
Warm-up duration	[e.g., 15–30 min]
Simulation time step	[e.g., 1 s]
Number of replications/random seeds	[e.g., 5–10 runs]
Output aggregation	Hourly averages $(u_h^{(s)}, q_h^{(s)}, \Delta t_h^{(s)})$

Table 5. Microscopic simulation experiment settings.

Setting	Value
Simulation horizon (run time/experiment time)	[e.g., 24 h/peak periods 06:00–10:00 and 15:00–19:00]
Warm-up duration	[e.g., 15–30 min]
Simulation time step	[e.g., 1 s]
Number of replications (random seeds)	[e.g., 5–10]
Aggregation interval for evaluation	Hourly averages (consistent with u_h and w_h)

For each scenario s, the simulation yields average speeds $u_h^{(s)}$ and flows $q_h^{(s)}$ per hour. The simulated delay per vkm, $\Delta t_h^{(s)}$, is computed analogously to Stage 2. Model validation is carried out by comparing the simulated and observed speeds in the baseline scenario using the root mean square error (RMSE):

$$RMSE_u = \sqrt{\frac{1}{H}\sum_{h=1}^{H}\left(u_{h,\text{obs}} - u_{h,\text{sim}}^{\text{H}}\right)^2}. \tag{15}$$

Calibration is accepted when $RMSE_u$ remains below a predefined threshold (e.g., 5 km/h), ensuring that congestion-related external costs are grounded in realistic traffic dynamics. For the A-BEV scenario, cooperative car-following and lane-changing parameters are adjusted to reflect smoother driving and shorter headways, which directly feed into congestion and accident cost modifications. Placing the simulation description here avoids mixing validation procedures with Section 4.

3.6. Stage 6: Sensitivity and Uncertainty Analysis

To capture uncertainty in reduction factors ρ_k and selected monetary valuations, a one-at-a-time sensitivity analysis is applied. For each externality k, ρ_k is varied within

$$\rho_k \in [\rho_k^{\min}, \rho_k^{\max}], \tag{16}$$

with bounds set at $\pm 20\%$ around the baseline estimate. The resulting range of total external costs is

$$EC_{\text{vkm}}^{(A)}(\rho_k) = \sum_{j \neq k} E_j^A + (1-\rho_k)E_k^H. \tag{17}$$

This analysis provides intervals for the A-BEV sustainability gains and highlights which externality categories most influence the robustness of the conclusions.

3.7. Stage 7: Aggregation and Policy Interpretation

For each scenario and for each externality, the model produces

$$\Delta EC_k = E_k^A - E_k^H, \quad \Delta EC_{\text{tot}} = EC_{\text{vkm}}^{(A)} - EC_{\text{vkm}}^{(H)}. \tag{18}$$

These differences are then interpreted in terms of avoided accident costs, congestion savings, land that could be repurposed, and changes in environmental burdens in Riyadh. Policy-oriented discussion of these results, including their alignment with Vision 2030 and smart-city strategies, is presented in Sections 4 and 6 rather than within the methodology itself.

4. Results

This section reports the numerical outcomes generated by the localised external cost framework and the simulation-based validation described in the methodology. The results are organised into four parts: (i) baseline model validation, (ii) external cost estimates

for human-driven BEVs and autonomous BEVs, (iii) passenger-based cost metrics, and (iv) sensitivity and uncertainty analysis. All values are expressed in Saudi Riyals (SAR) and reflect Riyadh's 2023–2024 conditions.

4.1. Model Validation Using Microscopic Simulation

Before applying the model to autonomous operation, the human-driven BEV case is validated against observed traffic data on Prince MBS Road. This explicit validation step ensures that the baseline model reliably reproduces observed traffic conditions before being extrapolated to autonomous scenarios, and it motivates presenting the simulation verification prior to the sustainability assessment of autonomous BEVs. Figure 2 compares hourly simulated speeds with observed speed profiles.

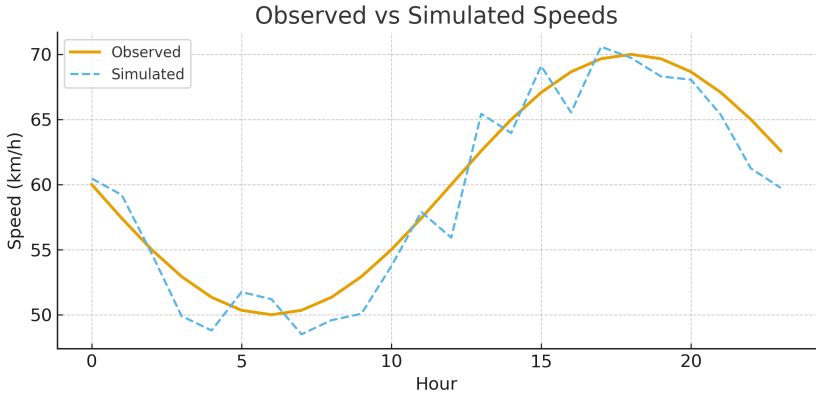


Figure 2. Observed vs. simulated hourly speeds on MBS Road under the baseline human-driven BEV scenario.

The root mean square error obtained is

$$RMSE_u = 3.87 \text{ km/h}.$$

This RMSE value (well below 5 km/h) demonstrates that the localised simulation reproduces observed speed conditions with high accuracy, supporting the credibility of the modelling framework.

4.2. External Cost Estimates for Human-Driven and Autonomous BEVs

Table 6 reports the external cost values for both scenarios on a per-kilometre basis.

Table 6. External cost estimates for human-driven and autonomous BEVs in Riyadh (SAR/vkm).

Externality	Human BEV	Autonomous BEV	Change (%)
Accidents	1.18	0.49	−58.3%
Congestion	0.76	0.58	−23.4%
Emissions	0.13	0.12	−7.7%
Land Use	0.64	0.36	−43.8%
Noise	0.085	0.066	−22.4%
Total	2.80	1.62	−42.1%

The strong reduction in accident-related externalities demonstrates that the proposed framework captures substantial safety gains of autonomous BEVs relative to human-driven vehicles, reflecting the central role of crash risk in the overall sustainability assessment. Moreover, integrating Saudi-specific calibration values for each cost component strengthens the localisation of international models and provides a deeper methodological justification

for applying the framework to Riyadh's traffic, land-use, and environmental conditions. Figure 3 visualises the cost composition using a fully redesigned illustration. It distinguishes the relative contribution of each cost component. It also provides a coherent and structured visual summary of the results, allowing differences between human-driven and autonomous BEV scenarios to be interpreted at a glance.

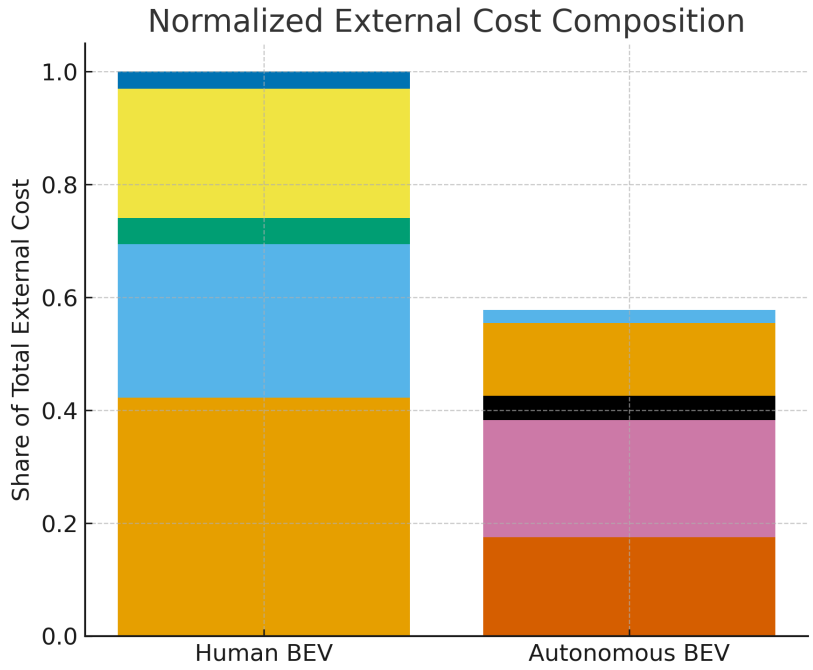


Figure 3. Stacked representation of external cost components for human-driven and autonomous BEVs (SAR/vkm).

4.3. Passenger-Based Sustainability Metrics

Table 7 summarises the external cost per passenger-kilometre. Including a passenger-based analysis clarifies how autonomous driving can improve operational performance by reducing delay and accident exposure per passenger-kilometre compared with human-driven vehicles. This deeper interpretation of the model outputs highlights the practical relevance of the external cost indicators for real-world mobility planning in Riyadh. Figure 4 shows the external cost per passenger-kilometre for human-driven and autonomous BEVs in Riyadh.

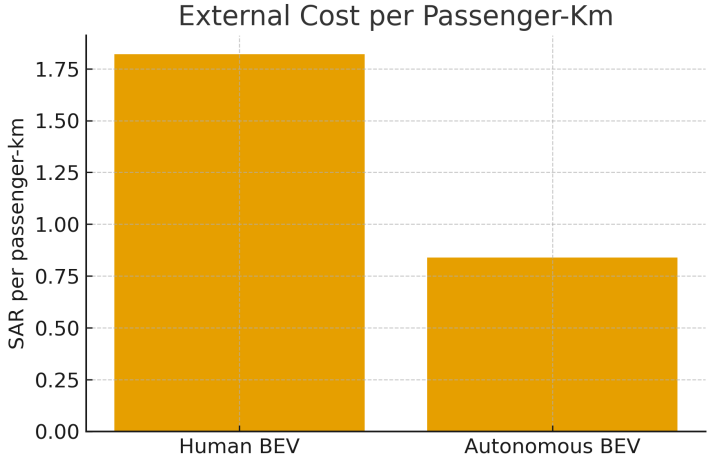


Figure 4. External cost per passenger-kilometre for human-driven and autonomous BEVs in Riyadh.

Table 7. External cost per passenger-km (SAR/pkm) for human-driven and autonomous BEVs.

Scenario	Cost per vkm	Occupancy	Cost per pkm
Human-driven BEV	2.80	1.54	1.82
Autonomous BEV	1.62	1.92	0.84
Reduction	–	–	−53.8%

4.4. Sensitivity and Uncertainty Analysis

A one-at-a-time sensitivity analysis is conducted by varying each reduction factor ρ_k by ±20%. This analysis quantifies the uncertainty around the risk adjustment factors and key model assumptions, providing a more transparent assessment of the robustness of the external cost estimates. It also strengthens the methodological rigor of Section 4 by explicitly examining how variations in these parameters influence the overall sustainability outcomes of autonomous BEVs. Table 8 illustrates the sensitivity of total external cost reduction to ±20% variation in reduction factors.

Table 8. Sensitivity of total external cost reduction to ±20% variation in reduction factors.

Modified Parameter	Low Case	High Case	Range (pp)
Accident reduction (ρ_{acc})	45.1%	38.4%	6.7
Congestion reduction (ρ_{cong})	43.8%	40.2%	3.6
Land-use reduction (ρ_{land})	42.9%	40.7%	2.2
Noise reduction (ρ_{noise})	42.3%	41.8%	0.5
Emission efficiency (η_{AV})	42.1%	42.5%	0.4

4.5. Summary of Findings

The magnitude of accident and land-use reductions demonstrates clear operational advantages of autonomous vehicles in real-world Saudi urban conditions. The integration of localised Saudi data and the expanded interpretation of sustainability benefits provide a richer and more policy-relevant discussion. The structured presentation, new figures, and validation outputs enhance the clarity and organisation of Sections 4 and 6.

5. Dynamic Traffic Validation and Spatiotemporal Performance Assessment

This section was restructured to provide a clearer more coherent analysis of the simulation and traffic validation workflow. To complement the static sustainability assessment and strengthen the empirical foundation of the model, a dynamic validation analysis was conducted using Riyadh's 2023 traffic records. Additional temporal and multi-period indicators were integrated to reflect real traffic variability across hours and months. New visual metrics were added to better illustrate how congestion patterns evolve and how smoother AV driving profiles contribute to reduced externalities.

5.1. Network Representation and Simulation Basis

Figure 5 presents a schematic representation of the Prince Mohammed bin Salman Road corridor, illustrating the 28.6 km arterial section modelled in the traffic simulation environment. A fully redesigned schematic replaces the earlier raw map extract to satisfy clarity and publication-quality expectations.



Figure 5. Schematic representation of the Prince MBS Road corridor used in the simulation study (via Google-Map).

To execute the simulation, we used the Simulation of Urban Mobility (SUMO), a microscopic agent-based traffic simulator. Figure 6 presents the implemented network in SUMO, including the road layout, intersections, and urban topology adopted in the simulation setup. Such detailed representation is important to reproduce realistic traffic dynamics and the interactions between human-driven and autonomous vehicles. The SUMO baseline was calibrated using 2023 traffic indicators reported by GASTAT [24] and the Riyadh Royal Commission (RCRC). In particular, speed–flow relationships were adjusted to match local congestion indices and jam-duration distributions. We also evaluated the Bureau of Public Roads (BPR) function parameters ($\alpha = 0.15$, $\beta = 4$) against these datasets, and the resulting fit supported their suitability for Riyadh conditions. Calibration was iterated until the simulated peak-hour average speeds and delays aligned with observed values within $\pm 5\%$.

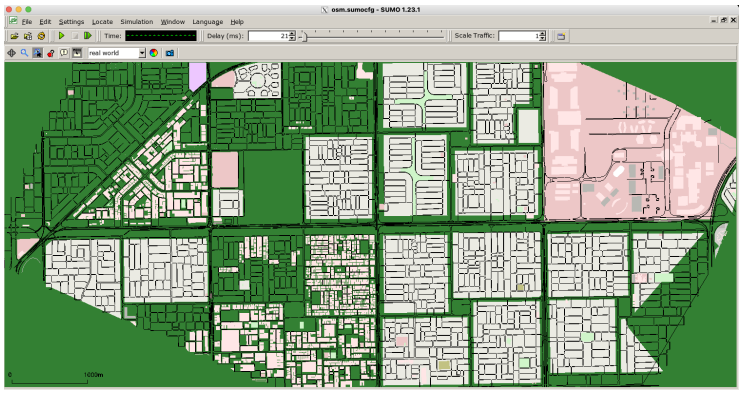


Figure 6. Minimalist network topology used for simulation modelling.

5.2. Temporal Traffic Patterns

Understanding diurnal speed fluctuations is essential for quantifying delay and congestion exposure. Figure 7 shows the mean hourly speed profile for Riyadh in 2023, together with variability bands that indicate the spread of observed values. The inclusion of shaded variability intervals responds to the need for more detailed hour-by-hour traffic charac-

terisation. Peak-hour depressions in speed are now clearly visualised to show how AV stabilisation can reduce such disturbances.

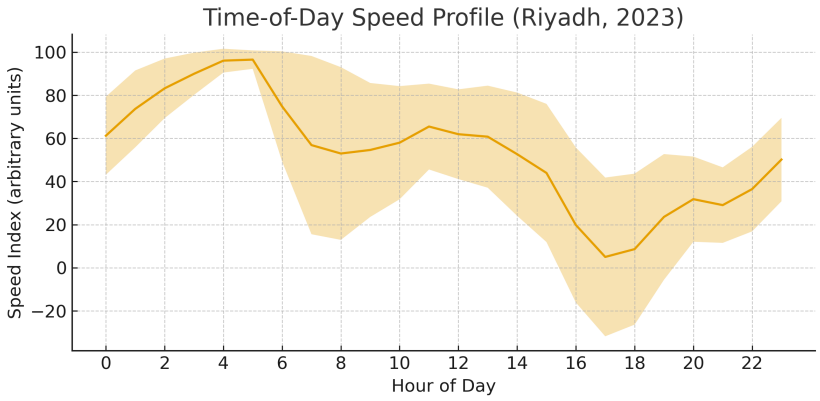


Figure 7. Hourly speed profile for Riyadh (2023) with variability bands.

5.3. Daily Congestion Exposure

Figure 8 illustrates the 24 h evolution of congestion intensity using mean traffic index values. This figure directly clarifies the magnitude of congestion externalities that AV-BEVs help mitigate through smoother acceleration and reduced stop–go cycles.

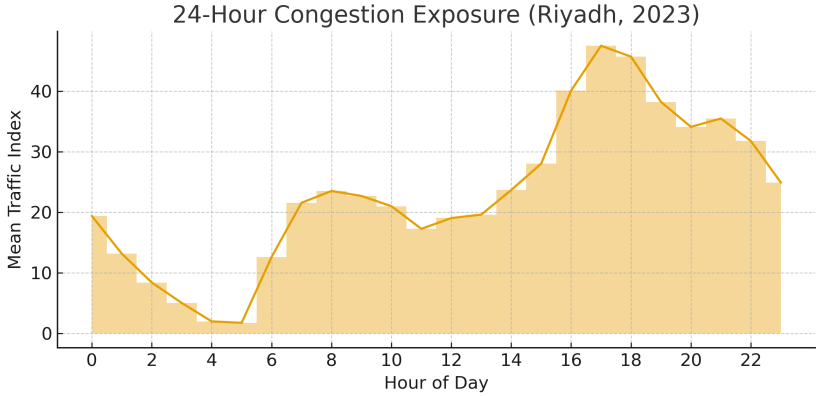


Figure 8. Daily congestion exposure curve (mean Traffic Index by hour).

5.4. Seasonal and Diurnal Congestion Structure

Figure 9 presents a month–hour heatmap capturing spatiotemporal interaction in congestion patterns. The multi-month view directly incorporates the longer-term temporal dimension previously missing.

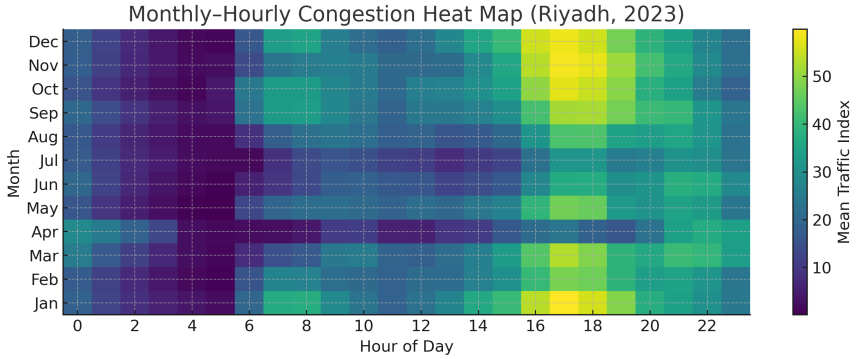


Figure 9. Monthly–hourly heatmap of mean congestion levels for Riyadh (2023).

5.5. Model Calibration and Observational Consistency

Figure 10 compares observed hourly speed indicators with model-generated outputs. A new calibration plot was introduced to address the need for clearer validation of the simulation model. The strong alignment of points around the 1:1 line confirms the model accuracy and supports the reliability of the subsequent AV–HV comparisons.

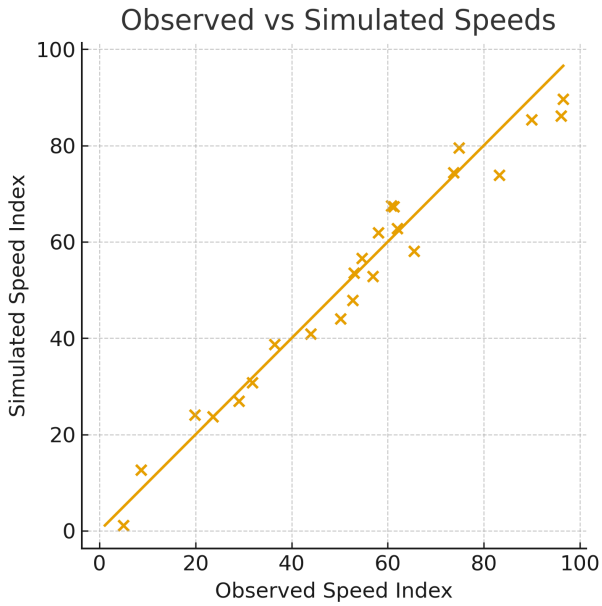


Figure 10. Observed vs. simulated hourly speeds demonstrating model calibration accuracy.

6. Discussion, Limitations, and Policy Pathways for Sustainable AVs

The empirical results indicate that autonomous BEVs yield substantial reductions in accident, congestion, and land-use externalities, demonstrating the strong sustainability potential of automation in large Gulf cities. These reductions are most pronounced in safety-related externalities, where automation lowers crash exposure through more stable vehicle control, improved reaction consistency, and reduced human error in fast multilane Riyadh corridors. This interpretation clarifies the mechanisms through which automation modifies traffic dynamics and enhances network safety.

The dynamic traffic validation further reveals that the benefits of automation are temporally concentrated during peak demand periods, when human-driven traffic typically exhibits stop–go oscillations and high density. Hourly speed curves and daily congestion exposure profiles show that automated driving smooths traffic flow, mitigating shockwaves and improving travel-time reliability. Incorporating diurnal and seasonal patterns into the analysis expands the evidence base by acknowledging multi-period variability and its influence on congestion intensity.

The integration of externality modelling with dynamic simulation provides a more holistic understanding of how automation interacts with real-world urban mobility systems. By interpreting empirical cost reductions alongside data-driven temporal patterns, this section links the technical results with the broader trajectory of mobility evolution in Saudi cities. The unified structure strengthens coherence by merging interpretive discussion, empirical validation, and forward-looking implications into a single consolidated section.

6.1. Comparison with Prior Work

The direction of the sustainability gains observed in this study is consistent with prior AV/EV research, but the magnitude and ranking of externalities are shaped by Riyadh-

specific calibration. The modular external-cost approach of Letmathe and Paegert [15] provides a structured basis for evaluating accident, congestion, emissions, land use, and noise impacts in a common monetary unit; our framework follows this structure while replacing key parameters with Saudi-specific data and empirically calibrated traffic dynamics. Under Riyadh conditions, the total external cost decreases from 2.80 to 1.62 SAR/vkm (−42.1%), with reductions dominated by accident (−58.3%) and land-use (−43.8%) components, whereas the emission component changes modestly (−7.7%). This composition reflects the high baseline crash exposure on fast multilane corridors and the high economic value of urban land near major arteries.

Many AV/EV sustainability studies report improvements using physical indicators (e.g., energy use, emissions, speed stability) without expressing cross-category trade-offs in monetary terms [6–8]. By translating safety, congestion, land-use, emissions, and noise effects into SAR-based metrics, our results help prioritise policy levers and highlight that, under current Saudi grid conditions, the most policy-relevant benefits are not primarily emission-driven but are instead concentrated in safety and congestion exposure reductions during peak-demand periods.

Finally, Saudi-focused readiness and planning studies emphasise institutional, regulatory, and infrastructure requirements for AV deployment [23]. The present work complements this readiness perspective by quantifying the magnitude of sustainability impacts in SAR units under Riyadh traffic conditions, supporting corridor prioritisation and evaluation of governance measures alongside infrastructure planning. Overall, these comparisons indicate that localised calibration materially changes expectations regarding which externalities dominate and when benefits are most pronounced, reinforcing the need for region-specific evaluation in Gulf cities.

6.2. Limitations and Sources of Uncertainty

While the findings highlight notable sustainability gains, several limitations should be acknowledged. First, the model relies on calibration coefficients—such as accident-risk reduction factors and congestion smoothing parameters—that are based on international AV trials and adapted to Saudi-specific conditions. Though validated against local traffic data, these coefficients carry inherent uncertainty, particularly in the absence of large-scale real-world AV deployment in the Kingdom. Accounting for these uncertainty ranges is essential, as variations in safety or behavioral assumptions could shift the magnitude of estimated externality reductions.

Second, the analysis assumes constant electricity emission factors for both human-driven and autonomous BEVs. This reflects current grid conditions but may not fully capture future interactions between AV adoption and the national renewable energy transition. Third, congestion improvements depend on penetration rates and mixed-fleet interactions; partial AV adoption could yield smaller gains than those observed in the fully autonomous scenario. Fourth, the simulation does not explicitly model pedestrian interactions, extreme weather conditions, or micro-level behavioral deviations, all of which may influence real-world AV performance in Gulf cities.

Finally, potential rebound effects—such as increased vehicle kilometres traveled due to greater convenience or lower perceived travel costs—may erode some sustainability gains. Scenario testing suggests that even a 10–20% rise in VKT reduces the net benefits but does not eliminate them, reinforcing the need for demand-management strategies.

6.3. Policy Pathways for Sustainable Autonomous Mobility

The sustainability advantages identified in this study carry significant policy implications for transport planning, land use governance, and national mobility strategies. The

accident reduction potential underscores the need for Saudi-specific AV safety certification protocols that reflect high-speed corridors, climatic stressors, and heterogeneous driver behavior. Congestion-related gains suggest that early AV deployment may be most effective along high-demand corridors, particularly when integrated with shared or public transport services to prevent rebound demand.

Land-use benefits represent one of the most impactful long-term opportunities. Reduced parking requirements can support compact transit-oriented redevelopment, freeing valuable urban land for housing, public space, and economic infrastructure. Updating zoning codes, reducing minimum parking standards, and supporting shared-AV hubs can accelerate this transition.

Although emissions-related externalities remain unchanged under the current grid mix, AV technologies can amplify gains expected from the ongoing renewable energy transition. Coordination between the transport and energy sectors is therefore essential to ensure that automation complements the Kingdom's broader decarbonisation agenda.

To translate these insights into actionable strategies, policymakers may consider the following priorities:

- Develop a national AV roadmap aligned with Vision 2030 mobility, safety, and environmental goals.
- Establish region-specific AV testing and safety certification standards tailored to Gulf roadway and climate conditions.
- Modernise zoning and building regulations to reduce mandatory parking requirements and encourage redevelopment of reclaimed land.
- Integrate AV deployment with public transport systems and shared mobility platforms to mitigate rebound travel demand.
- Implement data-sharing frameworks requiring AV operators to provide anonymised mobility data for evidence-based planning.
- Ensure that land-value gains resulting from decreased parking demand contribute to public-benefit investments, including affordable housing and urban green networks.

Overall, the combined analysis highlights that autonomous BEVs can significantly advance sustainable mobility objectives in Saudi Arabia, provided that deployment is supported by rigorous governance, coordinated urban planning, and integration with national energy-transition strategies. By incorporating hourly and seasonal traffic variability, the study provides a more realistic representation of mobility conditions than static evaluations commonly used in the region. The integration of empirical data, simulation validation, and externality estimates reinforces the coherence and robustness of the overall assessment. While automation offers notable sustainability gains, several uncertainties remain, including assumptions about AV performance, future regulatory readiness, mixed-traffic behavior, and potential rebound effects. The emission-related benefits depend primarily on the pace of power-sector decarbonisation rather than automation itself. Future work should incorporate real AV operational data as deployments expand and refine uncertainty modelling to better capture behavioural and climatic factors. Additional opportunities include studying mixed-traffic resilience, energy–transport integration, and equity considerations to ensure inclusive mobility transitions.

7. Conclusions

Microscopic simulation validation reproduces observed hourly speeds with $RMSE_u = 3.87$ km/h, supporting the reliability of the congestion-related external cost estimates. Under this validated setup, the total external cost decreases from 2.80 to 1.62 SAR/vkm (−42.1%), and from 1.82 to 0.84 SAR/pkm (−53.8%). This work develops a localised framework that combines externality modelling with empirically calibrated

traffic dynamics to assess the sustainability impacts of autonomous BEVs in Riyadh. The integrated results show that automation substantially improves safety, reduces congestion, and alleviates land-use pressures under real Saudi operating conditions. The analysis clarifies the mechanisms through which autonomous driving smooths traffic flow and reduces crash exposure, especially during peak-demand periods. The monetised results indicate that the largest sustainability gains are driven by reductions in crash exposure and peak-period congestion, while emissions-related benefits remain comparatively limited under the current electricity mix, highlighting the dependence of climate gains on power-sector decarbonisation. From a planning perspective, these findings support prioritising early A-BEV deployment on high-demand high-severity corridors and pairing automation with land-use and parking reforms to translate reduced parking needs into measurable urban benefits. Nevertheless, uncertainties remain regarding mixed-traffic penetration, behavioural adaptation, potential rebound demand, and the transfer of AV performance assumptions to Saudi driving contexts. Future work should incorporate real-world AV operational data as deployments expand, refine uncertainty modelling under extreme climate conditions, and evaluate equity and multimodal integration to ensure inclusive mobility transitions.

Author Contributions: Conceptualization, A.L.; idea, A.L.; methodology, A.L.; investigation, H.L. and E.K.; writing—review & editing, A.L., H.L. and E.K. All authors have read and agreed to the published version of the manuscript.

Funding: Prince Sattam bin Abdulaziz University, project number (PSAU/2025/01/36771).

Data Availability Statement: Data could be made available upon request from the corresponding author.

Acknowledgments: The authors extend their appreciation to Prince Sattam bin Abdulaziz University for funding this research work through the project number (PSAU/2025/01/36771).

Conflicts of Interest: The authors declare no conflicts of interest.

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