



ASSESSMENT OF ELECTRIC MOBILITY TRANSITION IN ETHIOPIA: POLICY, SOCIAL ACCEPTANCE, AND CHARGING LOAD IMPLICATIONS

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Abstract

Ethiopia banned internal combustion engine (ICE) vehicle imports in early 2024, promoting electric vehicles (EVs) and imposing a 15% import duty, compared to 60-100% for ICEs. Within one year, EVs registered in Ethiopia numbered 115,000, with targets of 500,000 by 2030. Despite the rapid rise in registrations, the supporting regulatory, training, supply chain, and grid connection infrastructures lag, creating several challenges and research issues. This study employs a convergent parallel mixed-method design to examine Ethiopia's EV transition through the tripartite themes of policy, social acceptance, and technical specifications. Specifically, the study distributes questionnaires to 422 respondents and conducts 130 semi-structured interviews while analyzing policy documents. Six proxy indicators are normalized to form a Composite Social Acceptance Index (CSAI), ranging from 0 to 100. A Monte Carlo simulation is performed to forecast the hourly load of 50,000, 150,000, and 250,000 EVs in Addis Ababa using 10,000 iterations under three charging demand management scenarios: uncontrolled, off-peak incentives, and smart charging. The identified policy gaps include documentation problems during battery certification, lack of EV-specific insurance, and driver training, while the technical specifications section addresses the charging infrastructure's impact on the grid. The CSAI scores for EV owners and non-owners are 72.3 and 38.4, respectively. The Monte Carlo results show that the peak demand for 250,000 EVs using uncontrolled charging would increase by 9.3%. Off-peak and smart charging incentives would reduce the increase by 35% and 52%, respectively. Overall, this study contributes to a better understanding of EV adoption and demonstrates how the CSAI and Monte Carlo methods could be useful in other data-scarce African countries.

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Keywords: Electric vehicles, Ethiopia, policy gaps, supply chain, social acceptance, charging load forecasting, Monte Carlo simulation, driver training

I. Introduction

Ethiopia faces two critical challenges in terms of imports and air pollution: a five-billion-dollar deficit on annual fuel import payments [IV] and severe smog in Addis Ababa associated with premature deaths [II]. To address the former challenge, the Ethiopian government imposed a complete ICE import ban in early 2024 and a 15% import duty on EVs, compared to 60-100% for ICEs [IX, VII]. Consequently, EVs registered in Ethiopia reached 115,000 within one year, with a target of 500,000 by 2030. Despite the significant mode shift, several gaps have emerged, hindering EV adoption and posing research questions. First, battery certification under UN 38.3 and IEC 62660 creates documentation bottlenecks; second, insurance companies impose ICE-specific terms on 40% of claimants and deny coverage to 30% [XIX]. Third, the Proclamation No. 600/2008 on driver training makes no mention of EVs, and 92% of instructors have no EV-specific training, while 8% have no EVs at their disposal [XI]. Finally, the Ethiopian Electric Utility doesn't have expert training on EV charging load profiles. International studies on EV adoption in developed countries and other African nations are limited to a few articles [I, V, VI, X, XV, XVI].

This study attempts to address the following issues:

- 1) What are the primary gaps in Ethiopia's EV policy?
- 2) What are the EV supply chain bottlenecks in Ethiopia, particularly concerning battery certification?
- 3) What are the EV training and licensing adequacy and challenges?
- 4) What are the EV owners' and non-owners' awareness, willingness to adopt, and perceived affordability?
- 5) Is it possible to develop a Composite Social Acceptance Index (CSAI)?
- 6) What are the characteristics of EV charging demand in Addis Ababa?

By responding to these research questions, the study will produce one of the first comprehensive multi-dimensional assessments, providing a conceptual and methodological basis for similar studies in data-scarce African countries.

II. Methodology

A convergent parallel mixed-method design was chosen, with a pool of quantitative and qualitative data serving as the basis for interpretation [III]. The quantitative component consisted of survey questionnaires administered to 422 respondents and a Monte Carlo simulation involving 10,000 iterations. The qualitative component comprised 130 semi-structured interviews and policy analyses. The study was conducted in Addis Ababa, where over 90% of Ethiopia's EVs are registered, and public charging stations are available.

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Purposeful sampling was used to recruit importers, officials, insurers, and instructors, while snowball and convenience sampling techniques were used to target EV owners and non-owners. Table 1 below provides details on the distribution of the sample size among the selected categories.

Six proxy indicators of EV knowledge, willingness to adopt, perceived affordability, trust in battery life, awareness of charging infrastructure, and recommendation intention were used to operationalize EV social acceptance and normalized to form the CSAI (0 – 100). Cronbach's alpha was 0.82, signifying strong internal consistency among the indicators. The sample size was estimated using the Cochran formula at a 95% confidence level and a 5% margin of error, with a minimum of 384 respondents required for the study. To increase the accuracy and reliability of the results, 422 responses were analyzed.

Table 1: Sample distribution

Stakeholder Category	Sample Size
EV Owners	80
Non-EV Drivers (ICE Users)	150
Importers/Dealers	30
Insurance Professionals	30
Transport Officials	40
Driving Instructors	52
Charging Service Providers	40
Total	422

A Monte Carlo simulation developed in Python with 10,000 iterations was employed to forecast hourly charging demand for 50,000, 150,000, and 250,000 EVs, representing 10%, 30%, and 50% of the 2030 target [XIII]. Key input parameters, shown in Table 2, were drawn from a pilot survey of 30 EV owners, Addis Ababa travel data, and the literature [XII]. Three charging strategies were compared: uncontrolled charging with immediate start, off-peak incentives shifting 50% of home charging to 22:00-06:00, and smart charging with centralized load spreading.

Table 2: Simulation input parameters

Parameter	Distribution / Value	Source
Battery Capacity	Uniform (40–100 kWh)	Market Survey
Daily Travel Distance	Triangular (20, 40, 100 km)	Addis Ababa Travel Survey
Home Charging Start Time	Normal ($\mu = 19:00$, $\sigma = 2$ h)	Pilot Survey (n = 30)
Home Charging Share	80% (Fixed)	Literature / Assumption
Charging Efficiency	Uniform (0.85–0.95)	Literature
Energy Consumption	0.20 kWh/km	Literature

II.i. Operationalization, Normalization, and Weighting of CSAI

To evaluate social acceptance across heterogeneous stakeholder cohorts, six proxy indicators (I_1 to I_6) were normalized onto a dimensionless scale of [0, 100]:

II.i.a. Mathematical Normalization Functions:

EV Knowledge (I_1 , discrete score $x \in \{0,1,2,3\}$):

$$I_{1,norm} = \left(\frac{x-0}{3-0} \right) \times 100 = \frac{x}{3} \times 100$$

Likert-Scale Items (I_2 : Willingness to Adopt, I_3 : Perceived Affordability, I_4 : Trust in Battery Life, I_6 : Recommendation Intention; ordinal $x \in \{1,2,3,4,5\}$):

All survey items were positively framed toward EV transition (no reverse coding was required). Transformation to a 0–100 interval was performed via linear min-max rescaled mapping:

$$I_{k,norm} = \left(\frac{x-1}{5-1} \right) \times 100 = \frac{x-1}{4} \times 100 \quad \text{for } k \in \{2,3,4,6\}$$

Charging Infrastructure Awareness (I_5 , binary dichotomous item $x \in \{0,1\}$):

$$I_{5,norm} = x \times 100$$

Missing Data Protocol: Little's Missing Completely at Random (MCAR) test was conducted ($\chi^2=24.18$, $p=0.38$), validating that missing values accounted for less than 1.8% of data points across the sample. Missing values were imputed using multiple imputation by chained equations (MICE) with 10 iterations prior to index normalization and model testing.

II.i.b. Index Aggregation and Weighting Schemes:

The baseline Composite Social Acceptance Index (CSAI) uses an equal-weighting scheme ($w_k = \frac{1}{6} \approx 0.1667$):

$$CSAI = \sum_{k=1}^6 w_k \cdot I_{k,norm}$$

Equal weighting was adopted as the reference approach following OECD composite indicator guidelines to avoid arbitrary normative bias across exploratory domains. To verify robustness against weighting choices, two alternative defensible schemes were tested:

PCA/Factor-Derived Weighting: Weights proportional to indicator variance explained from first-order factor loadings ($(w = [0.12, 0.20, 0.21, 0.20, 0.09, 0.18] = [0.12, 0.20, 0.21, 0.20, 0.09, 0.18])$).

Policy/Stakeholder-Weighted Scheme: Prioritizing core techno-economic barriers identified during stakeholder qualitative interviews—affordability (0.25), battery trust (0.25), infrastructure awareness (0.20), willingness to adopt (0.15), recommendation intention (0.10), and general knowledge (0.05).

II.i.c. Latent Variable Measurement Model:

Because indicators comprise mixed measurement scales (ordinal 5-point Likert items, discrete counts, and binary items), conventional Pearson covariance-based Factor Analysis was supplemented by a Confirmatory Factor Analysis (CFA) estimated via Diagonally Weighted Least Squares (DWLS / WLSMV) based on a polychoric correlation matrix.

II.ii. Mathematical Formulation of EV Charging Demand and Grid Impact

II.ii.a. Per-Vehicle Energy Consumption and Battery State of Charge

For each simulated vehicle $i \in \{1, 2, \dots, N_{EV}\}$, the net driving energy consumed per day $E_{drive,i}$ depends on the daily travel distance d_i (km) and net traction-specific consumption e_{cons} (kWh/km):

$$E_{drive,i} = d_i \cdot e_{cons} \cdot (1 - \eta_{regen})$$

where η_{regen} represents the fraction of kinetic energy recovered via regenerative braking, fixed at $\eta_{regen} = 0.15$

for standard urban driving cycles in Addis Ababa.

Assuming vehicles start their daily trips at full capacity ($SoC_{max} = 1.0$), the arrival State of Charge $SoC_{arr,i}$ upon returning home is:

$$SoC_{arr,i} = 1 - \frac{E_{drive,i}}{B_i} = 1 - \frac{d_i \cdot e_{cons} \cdot (1 - \eta_{regen})}{B_i}$$

where B_i is the total battery pack capacity drawn from $U(40, 100) kWh$. The required charging energy $E_{req,i}$ to restore the battery to a target state of charge $SoC_{targ} = 1.0$, accounting for internal battery and AC-DC inverter conversion efficiency $\eta_{chg,i} \sim U(0.85, 0.95)$ is modeled as:

$$E_{req,i} = \frac{(SoC_{targ} - SoC_{arr,i}) \cdot B_i}{\eta_{chg,i}} = \frac{d_i \cdot e_{cons} \cdot (1 - \eta_{regen})}{\eta_{chg,i}}$$

Charging losses are defined as $E_{loss,i} = E_{req,i} \times (1 - \eta_{chg,i})$

II.ii.b. Probability Distributions and Temporal Interdependencies

Individual vehicle operational variables are modeled with stochastic dependencies:

Daily Travel Distance (d_i): Sampled from a triangular distribution Triang ($a=20$, $c=40$, $b=100$) km.

Home Arrival Time ($t_{arr,i}$): Sampled from a truncated normal distribution $N(\mu=19:00, \sigma=2.0 \text{ h})$ bounded within $[14:00, 24:00]$.

Next-Day Departure Time ($t_{dep,i}$): Modeled conditional on arrival time:

$$t_{dep,i} = t_{arr,i} + \Delta t_{dwell,i}$$

where dwell time $\Delta t_{dwell,i} \sim N(11.5h, 1.2h)$ with a minimum dwell constraint of 8 hours, yielding typical morning departure times between 06:30 and 08:30.

Charger Rated Power ($P_{rated,i}$): For private home charging (accounting for 80% of total charging sessions), level-2 AC chargers are assigned based on a discrete distribution representative of standard Ethiopian residential connections:

$$P_{rated,i} \in \{3.3kW(30\%), 7.0kW(60\%), 11.0kW(10\%)\}$$

Uncontrolled Charging Duration (τ_i): Determined strictly by energy need and charger power rating:

$$\tau_i = \frac{E_{req,i}}{P_{rated,i} \cdot \eta_{chg,i}}$$

II.ii.c. Charging Management Strategies and Feasibility Constraints

Scenario A: Uncontrolled Charging

Charging starts immediately upon arrival $t_{start,i} = t_{arr,i}$ and proceeds at the maximum continuous rated power until $E_{req,i}$ is fully delivered:

$$P_i(t) = \begin{cases} P_{rated,i}, & \text{for } t_{arr,i} \leq t < t_{arr,i} + \tau_i \\ 0, & \text{otherwise} \end{cases}$$

Scenario B: Off-Peak Shift Intervention

The 50% off-peak incentive program shifts 50% of home-charging vehicles (selected via a Bernoulli trial, $X_i \sim \text{Bernoulli}(0.5)$) from peak evening hours to the overnight window $T_{off} = [22:00, 06:00]$.

Feasibility Check: For a participating vehicle i , if delaying charging start to 22:00 would result in incomplete battery replenishment prior to scheduled departure ($22.0 + \tau_i > t_{dep,i}$), the vehicle is flagged as shift-infeasible.

Infeasibility Handling: Shift-infeasible vehicles fall back to charging immediately upon arrival with power throttle:

$$t_{start,i} = \max(t_{arr,i}, t_{dep,i} - \tau_i)$$

ensuring full delivery of $E_{req,i}$ by departure while minimizing peak coincidence.

Scenario C: Smart Charging Optimization

Smart charging coordinates vehicle charging power profiles $P_i(t)$ through centralized aggregator control to flatten total electrical demand across the 24-hour cycle $T = \{1, 2, \dots, 24\}$:

$$\min_{P_i(t)} \max_{t \in T} \left(P_{baseline}(t) + \sum_{i=1}^{N_{EV}} P_i(t) \right)$$

subject to the following constraints for every vehicle $i \in \{1, \dots, N_{EV}\}$ and time step $t \in \mathcal{T}$:

Power limits & Charger availability:

$$0 \leq P_i(t) \leq P_{rated,i} \times u_i(t), \forall t$$

where $u_i(t) \in \{0,1\}$ is an availability indicator equal to 1 if vehicle i is plugged in at home ($t_{arr,i} \leq t \leq t_{dep,i}$) and 0 otherwise.

Energy delivery requirement:

$$\sum_{t=t_{arr,i}}^{t_{dep,i}} P_i(t) \cdot \eta_{chg,i} \cdot \Delta t = E_{req,i}$$

Where $\Delta t = 1.0h$.

Cumulative energy delivery constraint:

$$\sum_{k=t_{arr,i}}^t P_i(k) \times \eta_{chg,i} \times \Delta t \leq B_i \times (1 - SoC_{arr,i}), \forall t \in [t_{arr,i}, t_{dep,i}]$$

Hourly Grid Aggregation Model:

The aggregate EV charging power demand $P_{EV}(t)$ at hour t across the simulated fleet of size $N_{EV} \in \{50000, 150000, 250000\}$ is calculated as:

$$P_{EV}(t) = \sum_{i=1}^{N_{EV}} P_i(t)$$

The combined hourly system electrical load $P_{total}(t)$ on the Addis Ababa transmission grid is given by:

$$P_{total}(t) = P_{baseline}(t) + P_{EV}(t)$$

Where $P_{baseline}(t)$ represents the empirical hourly utility demand profile of Addis Ababa, peaking at 1,530 MW.

III. Results

The document analysis and interview results identified six policy gaps, as shown in Table 3 below. First, Proclamation No. 600/2008 makes no mention of EVs, and no driving school offers EV-specific training [XI]. Second, customs documentation requires UN 38.3 and IEC 62660 certification, which 93% of importers find challenging, causing an average three-month customs delay [VII]. Third, no battery management guidelines address end-of-life battery management, EV-specific insurance, or software update requirements [XI, XIX]. Fourth, while Directive No. 1034/2024 on EV charging infrastructure sets technical specifications, no formal coordination mechanism exists between the Ethiopian Electric Utility and EV stakeholders [XIV]. Finally, no data privacy regulations ensure the confidentiality of EV telematics data [XVIII].

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Table 3: Policy gaps and implications

Domain	Policy Gap	Implication
Battery Certification	No local testing facilities; importers cannot obtain UN/IEC certification documentation locally	93% of importers experience certification delays, with an average holding period of approximately 3 months
EV Insurance	No dedicated EV insurance products; 40% of insurers apply ICE vehicle terms, while 30% decline coverage	Unquantified risk exposure and lack of actuarial data for EVs
Driver Training	Proclamation No. 600/2008 does not include EV-related training requirements	92% of driving instructors lack EV training; no driving school offers EV-specific instruction
Software Updates	Absence of a regulatory framework governing vehicle software and over-the-air updates	EV owners may be unable to receive critical software and safety updates
End of Life Batteries	No Extended Producer Responsibility (EPR) policy or battery recycling requirements	Environmental risks and loss of valuable recoverable materials
Grid Coordination	No formal data-sharing mechanism between Ethiopian Electric Utility (EEU) and EV stakeholders	Uncoordinated charging behavior may threaten grid stability and increase peak demand

Among the 30 importers and dealers interviewed, 93% identified battery certification documentation as the primary challenge during imports. In terms of EV maintenance, 20% have in-house repair capacity, while 7% can perform battery tests and 13% carry out software updates. Few importers (7%) keep spare batteries; hence, owners must wait for several months before their vehicles are repaired. Eighty EV owners expressed a high level of satisfaction with EV safety; however, 25% of them are concerned about battery longevity. On the other hand, the 30 insurance professionals interviewed revealed that 40% apply ICE-specific terms to EVs, while 30% decline coverage. Insurers identified the absence of local data as the primary obstacle to developing EV-specific products; the National Bank of Ethiopia has issued no EV insurance-related directives yet. The 52 driving instructors surveyed identified the following EV driving peculiarities: regenerative braking, silent operation, and charging procedures. Table 4 below provides the summary of the proxy indicators and CSAI scores. Overall, the CSAI was 48.7, with EV owners' CSAI (72.3) being significantly higher than that of non-owners (38.4; $p < 0.001$). Perceived affordability had the lowest mean score (2.5), followed by trust in battery life (2.7). Table 5 below presents the regression results for CSAI. As shown, perceived affordability ($\beta = 0.48$) and battery life ($\beta = 0.44$) had the strongest influence on EV acceptance, surpassing the effect of income ($\beta = 0.41$), age ($\beta = -0.18$), education ($\beta = 0.32$), and awareness

($\beta = 0.38$). Knowing an EV owner increased acceptance by 0.45 standard deviations, on average.

Table 4: Proxy indicators and CSAI scores (0-100 normalized)

Indicator	EV Owners	Non-Owners	All Respondents
EV Knowledge (0–3 Correct Answers)	2.4	1.6	1.9
Willingness to Adopt (1–5)	4.6	3.1	3.6
Perceived Affordability (1–5)	3.2	2.1	2.5
Trust in Battery Life (1–5)	3.5	2.3	2.7
Charging Infrastructure Awareness (%)	85%	18%	40%
Recommendation Intention (1–5)	4.4	2.9	3.4
Composite Social Acceptance Index (CSAI) (0–100)	72.3	38.4	48.7

III.i. Measurement Model Validation and Sensitivity Analysis

Multiple linear regression was performed using SPSS and Python to identify factors influencing CSAI. Statistical significance was evaluated at $p < 0.05$.

The single-factor latent construct for Social Acceptance evaluated via WLSMV demonstrated robust fit across standard structural thresholds: Satorra-Bentler $\chi^2(9)=16.42$ ($p=0.059$); Comparative Fit Index (CFI) = 0.984; Tucker-Lewis Index (TLI) = 0.973; Root Mean Square Error of Approximation RMSEA = 0.044 (90% CI: [0.000, 0.078]); and Standardized Root Mean Square Residual (SRMR) = 0.038. Standardized factor loadings (λ) were statistically significant ($p < 0.001$): $\lambda_{Knowledge} = 0.58$, $\lambda_{Willingness} = 0.81$, $\lambda_{Affordability} = 0.83$, $\lambda_{BatteryTrust} = 0.79$, $\lambda_{InfraAware} = 0.51$, and $\lambda_{Recommend} = 0.76$. Composite Reliability (CR) was 0.86, and Average Variance Extracted (AVE) was 0.52, confirming convergent construct validity. As presented in Table 6, the disparity between EV owners and non-owners remains statistically significant ($p < 0.001$) across all weighting configurations, confirming that the conclusions are not artifacts of the equal-weighting assumption.

Table 5: Multiple Regression results: factors influencing CSAI

Factor	Coefficient (β)	p-value
Age	-0.18	0.02
Education	0.32	<0.001
Income	0.41	<0.001
Knows an EV Owner	0.45	<0.001
Charging Infrastructure Awareness	0.38	<0.001
Trust in Battery Life	0.44	<0.001
Perceived Affordability	0.48	<0.001

Table 6: Sensitivity of CSAI Scores Across Alternative Weighting Schemes

Weighting Scheme	Description / Weight Vector (w_1 to w_6)	EV Owners	Non-Owners	Difference(Δ)	p-value
Baseline (Equal Weights)	$w_k=1/6 \approx 0.1667$	72.3	38.4	+33.9	<0.001
PCA / Factor Loadings	[0.12,0.20,0.21, 0.20,0.09,0.18]	74.1	37.6	+36.5	<0.001
Policy / Techno-Economic	[0.05, 0.15, 0.25, 0.25, 0.20, 0.10]	69.8	36.1	+33.7	<0.001

Table 7 below provides the results of the Monte Carlo simulation for 250,000 EVs (50% of the 2030 target). Using the uncontrolled charging scenario, the peak load would increase by 142 MW, signifying a 9.3% rise. On the other hand, off-peak and smart charging incentives would reduce the increase by 35% and 52%, respectively. Overall, 520 GWh of energy would be required to charge 250,000 EVs, an amount equivalent to 3.5% of Ethiopia's annual electricity consumption of 15,000 GWh.

Table 7: Peak load impact for 250,000 EVs (50% of 2030 target)

Charging Strategy	Peak Load (MW)	Increase over System Peak (1530 MW)	Reduction Compared to Uncontrolled Charging
Uncontrolled Charging	142.0	+9.3%	—
Off-Peak Incentives	92.3	+6.0%	35%
Smart Charging	68.2	+4.5%	52%

IV. Discussion

Ethiopia's 2024 ICE import ban is an innovative leapfrogging strategy that bypasses the need for extensive fossil fuel vehicle infrastructure. However, the analysis revealed several challenges, including the lack of EV-specific insurance, driving schools, and grid coordination mechanisms [VIII]. Indeed, several supply chain problems were reported during the interviews with importers. For example, 93% of them identified certification of batteries under UN 38.3 and IEC 62660 as the main obstacle during imports. Similarly, 40% of insurance professionals apply ICE-specific terms on EV-related claims, while 30% decline to offer coverage. By contrast, the EV owners interviewed identified affordability as the primary barrier during EV adoption, a finding that aligns with studies in developed countries [V, XVI]. According to the regression results, perceived affordability and battery life have the strongest influence on EV social acceptance, surpassing socio-economic factors such as education, income, and age. The CSAI score of 48.7 suggests that Ethiopia is at the early stage of EV adoption [XVII], with only 40% of respondents aware of the existing charging infrastructure and ready to purchase an EV.

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In terms of technical specifications, the study found that uncontrolled charging of 250,000 EVs would increase the evening peak demand by 9.3%. Smart charging could reduce the increase by half, signifying the importance of controlled charging in reducing the burden on the grid [XX]. Since Ethiopia's electricity generation portfolio depends on hydropower, it might be possible to take advantage of the natural load-shifting characteristics of run-of-river plants. For example, EVs could be charged during dry seasons with higher wind speeds and discharged during the wet seasons to stabilize the electricity supply. This ancillary service could become a viable opportunity for Addis Ababa in the next decade.

V. Conclusions

Ethiopia's rapid EV diffusion, driven by ICE import bans, has created several gaps in the supporting infrastructure, notably on the regulatory, training, and technical frontiers. Six major policy gaps, namely, battery certification, insurance, driving schools, software management, end-of-life battery management, and grid coordination, were identified, each posing significant challenges to EV adoption in the country. The social acceptance score was moderate (48.7), with EV owners exhibiting a considerably higher degree of satisfaction than potential buyers. Perceived affordability and trust in battery life emerged as critical areas for awareness and improvement campaigns to promote wider adoption of EVs. Concerning technical specifications, uncontrolled charging of 250,000 EVs would cause a 9.3% rise in peak demand in Addis Ababa. Smart charging, by contrast, has the potential to reduce the increase by 52%. Overall, this study provides a deeper insight into EV adoption in Ethiopia and serves as a starting point for further research in other data-scarce African countries.

Conflict of Interest:

There was no relevant conflict of interest regarding this paper.

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