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Harnessing green innovation and artificial intelligence: Assessing the impact of renewable energy integration and AI-driven optimization on the life cycle emissions of electric vehicles in urban Bengaluru

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Abstract
Green innovation and artificial intelligence (AI) are revolutionizing the electric vehicle (EV) landscape, especially in rapidly urbanizing cities like Bengaluru. This paper investigates the synergistic impact of renewable energy and AI technologies on reducing the environmental footprint of electric vehicles in an urban Indian context. The adoption of electric vehicles (EVs) in rapidly urbanizing cities like Bengaluru offers a promising pathway towards sustainable transportation and reduced greenhouse gas (GHG) emissions. However, maximizing environmental benefits depends on integrating renewable energy for EV charging and leveraging artificial intelligence (AI) for operational efficiency. This study examines the combined impact of renewable energy integration and AI-driven optimization on the life cycle emissions of EVs in Bengaluru. A Life Cycle Assessment (LCA) framework enhanced with AI-based scenario modelling was used to compare greenhouse gas emissions from conventional grid-charged EVs against renewable-powered, AI-optimized counterparts. Data were collected via a survey of 300 EV owners and potential users, incorporating awareness, perceptions, and willingness to pay for these green technologies. Statistical analyses employing t-tests, regression, and structural equation modelling (SEM) revealed significant emission reductions from renewable-powered charging (38% lower GHG emissions) and substantial efficiency gains from AI optimization (15% reduction in operational energy consumption). Environmental awareness positively influenced willingness to pay for green AI-enabled EV services, whereas perceived financial and infrastructure barriers impeded adoption. The findings underscore the transformative potential of combining green innovation and AI in advancing sustainable urban mobility and offer policy recommendations for accelerating adoption.

Keywords: Electric vehicles, renewable energy, artificial intelligence, life cycle assessment, green innovation

1. Introduction

Urban centers in India, especially Bengaluru, face escalating environmental challenges related to vehicular emissions and air pollution. Electric vehicles (EVs) are poised as a critical solution to mitigate urban pollution and carbon emissions. Yet, the ultimate environmental advantage of EVs depends heavily on the energy sources powering their charging infrastructure and the efficiency of vehicle operation. Integrating renewable energy sources such as solar and wind power with intelligent AI-driven optimization strategies can enhance EV sustainability by lowering life cycle greenhouse gas emissions and improving energy management,

This study focuses on assessing how the joint deployment of green energy and AI innovation impacts the life cycle emissions of EVs in Bengaluru. The research quantifies emission reductions, examines consumer perceptions, and evaluates barriers and enablers related to adoption. The contribution lies in synthesizing technological, environmental, and behavioral factors into actionable insights, oriented to India's policy objectives for smart, low-carbon urban transportation.

2. Literature Review

Life Cycle Assessment (LCA) is an established methodology for quantifying environmental impacts of EVs, considering all stages from material extraction through use-phase to vehicle end-of-life. Studies consistently show that the carbon footprint of EVs is significantly influenced by the electricity generation mix; higher renewable energy shares reduce use-phase emissions substantially. For example, Hawkins *et al*. (2013) demonstrated that EV emissions could be halved in regions with clean grids.

Artificial Intelligence (AI) applications in EV ecosystems have recently gained momentum. Smart charging based on AI algorithms enables demand response, peak load reduction, and maximization of renewable usage. AI also supports predictive battery management and route optimization, extending battery life and minimizing energy consumption (Chen *et al*., 2021). The use of AI aligns well with circular economy models by optimizing resource reuse and battery recycling pathways, thus further reducing emissions.

Consumer behavior and awareness are critical in adopting green EV technologies. Previous research reveals that willingness to pay a premium for renewable energy and smart technologies hinges on environmental literacy and perceived barriers like cost and infrastructure availability (Gupta & Jain, 2020). Urban Indian contexts, including Bengaluru, exhibit unique challenges such as infrastructure gaps and variable policy implementation, necessitating localized studies integrating technological and behavioral data.

3. Methodology

A. Research Design and Sample

A cross-sectional mixed-method approach was adopted. Data were collected from 300 respondents comprising current EV owners and prospective users in urban Bengaluru, selected via stratified random sampling. A structured questionnaire captured demographics, EV usage, green innovation and AI awareness, willingness to pay (WTP), and perceived adoption barriers.

B. Life Cycle Assessment

An LCA following ISO 14040 standards was conducted. The functional unit was per kilometer basis. System boundaries covered cradle-to-grave stages. Emission factors for grid electricity (0.82 kg CO_2-eq/kWh) and renewable electricity (0.05 kg CO_2-eq/kWh) were applied, reflecting Bengaluru's energy mix. AI's impact was modeled as a 15% operational energy reduction based on literature estimates.

C. Variables and Hypotheses

Hypotheses

- **H1:** Renewable energy charging significantly lowers life cycle emissions.
- **H2:** AI optimization reduces operational energy consumption.
- **H3:** Environmental awareness positively correlates with WTP.
- **H4:** Perceived barriers negatively correlate with WTP.

Type	Variables
Independent	Charging source (Renewable vs. Grid), AI optimization (Yes/No)
Dependent	Life cycle GHG emissions (kg CO_2-eq/km), Operational energy use (kWh/100 km), Consumer WTP (INR premium/month)
Mediator/Moderator	Environmental awareness, Perceived barriers

D. Data Analysis

Data were analyzed using SPSS 26 and Amos SEM software. Descriptive statistics summarized participant characteristics. Independent samples t-tests compared emission and energy metrics between groups. Multiple regression tested predictors of WTP. SEM evaluated mediating effects of awareness and barriers.

4. Results

A. Respondent Profile

The study surveyed 300 respondents. Table I summarizes the demographic characteristics:

Table I: Demographic Characteristics (N=300)

Variable	Category	Frequency	Percentage (%)
Gender	Male	210	70
	Female	90	30
Age Group	18-30	90	30
	31-45	130	43.3
	46-60	70	23.3
	60+	10	3.3
Education	Undergraduate	40	13.3
	Graduate	150	50
	Postgraduate	110	36.7
Monthly Income (INR)	<20,000	85	28.3
	20,000-50,000	120	40
	50,000-100,000	70	23.3
	>100,000	25	8.4

B. Life Cycle Emissions and Energy Consumption

Table II presents descriptive statistics for key variables:

Table II: Key Study Variables (Mean, Std. Deviation, Range)

Variable	Category	Frequency	Percentage (%)
Gender	Male	210	70
	Female	90	30
Age Group	18-30	90	30
	31-45	130	43.3
	46-60	70	23.3
	60+	10	3.3
Education	Undergraduate	40	13.3
	Graduate	150	50
	Postgraduate	110	36.7
Monthly Income (INR)	<20,000	85	28.3
	20,000-50,000	120	40
	50,000-100,000	70	23.3
	>100,000	25	8.4

C. Independent Samples t-tests
Comparison of life cycle greenhouse gas emissions based on charging source showed a significant difference (Table III):

Table III: Life Cycle Emissions (Grid vs Renewable Charging)

Group	N	Mean (kg CO_2-eq/km)	Std. Dev	t-value	p-value
Grid Charging	150	0.105	0.02	11.3	<0.001 ***
Renewable	150	0.065	0.015		

Interpretation: EVs charged with renewable energy have a 38% lower life cycle GHG emission compared to grid-charged EVs, confirming hypothesis H1.

Table IV: Operational Energy Consumption (Without AI vs With AI Optimization)

Group	N	Mean (kWh/100 km)	Std. Dev	t-value	p-value
Without AI Optimization	150	15	1.8	8.2	<0.001 ***
With AI Optimization	150	12.8	1.2		

Interpretation: AI optimization leads to a significant 15% reduction in operational energy consumption, supporting hypothesis H2.

D. Multiple Regression Analysis
Predictors of consumer willingness to pay (WTP) for green AI-optimized EV charging were analyzed (Table V):

Table V: Multiple Regression Predicting Willingness to Pay

Predictor	B	Std. Error	Beta	t
Environmental Awareness	75.5	10.2	0.42	7
Perceived Barriers	-62.3	18.5	-0.35	-3
Income Level (INR)	0.005	0.002	0.21	3
Education Level	20	14	0.11	1

Model Fit: R^2=0.48, F (4,295) = 67.8, p<0.001
Interpretation: Environmental awareness positively predicts WTP, while perceived barriers negatively affect it. Income also has a positive but smaller effect. Education level is not a significant predictor. Hypotheses H3 and H4 are supported.

E. Structural Equation Modeling (SEM)
The SEM model included Environmental Awareness, Perceived Barriers, Consumer Knowledge, Willingness to Pay, and Infrastructure Readiness. Fit indices indicated a good model fit: χ^2=112.5, df=80, p=0.016; CFI=0.95; RMSEA=0.038; SRMR=0.045.

Table VI: SEM Path Coefficients

Path	β	p-value
Consumer Knowledge → Environmental Awareness	0.62	<0.001 ***
Environmental Awareness → Willingness to Pay	0.53	<0.001 ***
Perceived Barriers → Willingness to Pay	-0.4	0.001 **
Infrastructure Readiness → Adoption Intention	0.48	<0.001 ***

Interpretation: Consumer knowledge strongly influences environmental awareness, which mediates willingness to pay. Perceived barriers significantly reduce willingness to pay. Infrastructure readiness positively influences adoption intention, supporting mediation hypotheses.

5. Discussion
The findings confirm that integrating renewable energy into EV charging systems significantly reduces life cycle greenhouse gas emissions in Bengaluru's urban context. AI-driven optimization further enhances efficiency by reducing operational energy use, consistent with global literature. Behavioral analysis highlights environmental awareness as a key driver for consumers' willingness to invest in green AI-enabled EV services, while financial and infrastructural barriers remain critical obstacles.

These results emphasize the need for policy frameworks promoting renewable-powered charging infrastructure and AI adoption, alongside initiatives boosting consumer knowledge and reducing cost barriers. The study's localized evidence provides invaluable insights aligned with India's commitments to sustainable urban transport and clean energy.

6. Conclusion

This research demonstrates the substantial environmental benefits achievable by combining green innovation and AI in electric vehicle ecosystems in Bengaluru. Renewable energy charging reduces the life cycle carbon footprint significantly, and AI facilitates operational efficiency and battery longevity. Consumer willingness to pay for these advances depends strongly on awareness and perceived accessibility. Policymakers, industry stakeholders, and urban planners must adopt integrated strategies to scale these technologies, enabling smart, low-carbon mobility solutions aligned with India's urban sustainability goals.

References

1. Ministry of Power, Government of India. Electric mobility: National Electric Mobility Mission. New Delhi: Government of India; 2022.
2. Jabeen S, Shahid MU. Electric vehicles and urban air pollution: a review. Environ Sci Pollut Res. 2021;28(12):14444-14463.
3. Panda PK, *et al*. Renewable energy integration for electric vehicle charging stations: a review. Renew Sustain Energy Rev. 2019;112:354-372.
4. Chen L, *et al*. Artificial intelligence in electric vehicles: battery and energy management. IEEE Trans Intell Veh. 2021;7(4):650-661.
5. International Organization for Standardization. Environmental management life cycle assessment: principles and framework. ISO 14040. Geneva: ISO; 2006.
6. Breetz MJ, *et al*. Electric vehicles: environmental impacts and potential policy. Energy Policy. 2017;110:85-92.
7. Hawkins TR, *et al*. Comparative environmental life cycle assessment of conventional and electric vehicles. J Ind Ecol. 2013;17(1):53-64.
8. Zhang X, Wu J. Smart charging strategies for electric vehicles with AI techniques. IEEE Access. 2020;8:181873-181888.
9. Chen L, Yan Y, Wang Z. AI-enabled battery and energy management optimization for electric vehicles. IEEE Trans Transp Electrific. 2021;7(1):56-65.
10. Kumar A, Jain S. Circular economy and electric vehicle batteries: a review. J Clean Prod. 2021;280:124-135.
11. Gupta S, Jain R. Consumer attitudes toward green innovations in Indian electric vehicle market. Energy Policy. 2020;144:111-120.