Apex Journal of Business and Management
Volume 04, Issue 02, 2025. pp. 131–141
Research Article
DOI: https://doi.org/10.61274/apxc.2025.v04i02.011

Understanding the Factors Influencing Nepalese Youth's Intention to Buy Electric Vehicles

Gaurab Raj Pandey[1], Bishal Kumar Khadka[2], Krishna Khanal[3]
[1]Master Student and Swedish Institute Scholar, Mälardalen University
[2]Lecturer, King's College
[3]Assistant Professor, King's College

Article Info.

Corresponding Author
Krishna Khanal

Email
krishna@kingscollege.edu.np

Article History
Received: 2025, June 02
Revised: 2025, July 12
Accepted: 2025, August 27

Cite
Pandey, G. R., Khadka, B. K., & Khanal, K. (2025). Understanding the factors influencing Nepalese youth's intention to buy electric vehicles. *Apex Journal of Business and Management* (*AJBM*), *4*(2), 131–141. https://doi.org/10.61274/apxc.2025.v04i02.011

Abstract

Electric vehicles (EVs) are emerging as a sustainable alternative to traditional fossil fuel-powered transportation, offering significant environmental and economic benefits. Despite global advances, EV adoption in developing countries such as Nepal remains limited due to socio-economic and infrastructural challenges. This study investigates the behavioral intentions of Nepalese youth to purchase EVs, focusing on five key factors drawn from the Unified Theory of Acceptance and Use of Technology (UTAUT): performance expectancy, environmental concerns, effort expectancy, social influence, and facilitating conditions. Data was collected through an online survey completed by 289 respondents predominantly from urban areas. Partial Least Squares Structural Equation Modeling (PLS-SEM) was utilized to analyze relationships between these constructs. The results indicate that performance expectancy, environmental concerns, and social influence significantly influence the intention to adopt EVs, while effort expectancy and facilitating conditions did not emerge as significant predictors. These findings highlight the importance of emphasizing practical benefits and environmental impacts of EVs, leveraging social endorsement, and shaping youth-targeted awareness campaigns to accelerate adoption. This research contributes to understanding sustainable transportation adoption in emerging economies, offering valuable insights for policymakers, manufacturers, and marketers aiming to promote EV adoption within Nepal's youth demographic and support the country's transition towards a greener, low-carbon transport future

Keywords: electric vehicles, behavioral intentions, UTAUT model, youth adoption, sustainable mobility

Introduction

The transport industry is at a pivotal intersection between environmental sustainability and economic development, contributing nearly 30% of global greenhouse gas emissions, with road transportation and internal combustion engine (ICE) vehicles alone accounting for approximately 11.9% (Tunçel, 2022). Continued dependence on fossil fuels exacerbates climate change and urban air pollution, resulting in severe public health and economic repercussions. In Nepal, this challenge is acute in urban centers like Kathmandu, ranked among the world's most polluted cities (Himalayan News Service, 2023). Emissions from petrol and diesel vehicles are major contributors to this pollution, linked directly to respiratory and cardiovascular diseases (Fukusaki et al., 2021).

Electric vehicles (EVs) are vital for Nepal's sustainable development by reducing dependence on fossil fuels, improving urban air quality, and supporting climate commitments. With Kathmandu among the world's most polluted cities, EVs offer a zero-emission and energy-efficient alternative that aligns with Nepal's abundant hydropower resources (Tunçel, 2022; Himalayan News Service, 2023; Pavić et al., 2020). Government incentives and policies aim to electrify substantial portions of the transport sector by 2030, promoting energy security and economic growth through job creation in manufacturing and infrastructure (Bist, 2023; Celestin & Mishra, 2024; Ananda et al., 2023). The shift to EVs promises healthier urban environments, reduced greenhouse gas emissions, and progress toward Nepal's carbon neutrality goals, marking a critical step for the country's green and inclusive development (Tamang & Mishra, 2022; Celestin & Mishra, 2025).

Electric vehicles (EVs), powered by advanced rechargeable batteries such as lithium iron phosphate (LFP) and lithium nickel manganese cobalt oxide (NMC), offer a promising solution by producing zero tailpipe emissions and providing a quieter, cleaner, and more energy-efficient alternative (Pavić et al., 2020). Globally, the adoption of EVs supports sustainability and aligns with renewable energy goals (Energy Transitions Commission, 2020; International Energy Agency, 2024). In Nepal, government incentives and evolving policies have strategically promoted electric mobility to address urban pollution and reduce greenhouse gas emissions (Post Report, 2025; Bist, 2023). Youth populations, comprising nearly 40% of Nepal's demographic (Shrestha & Subedi, 2022), are pivotal in influencing EV adoption trends, driven by increasing environmental consciousness and technology engagement (Axsen et al., 2012).

The Unified Theory of Acceptance and Use of Technology (UTAUT) framework provides a useful lens to understand youth adoption of EVs, highlighting key factors including Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions that shape purchase intentions (Venkatesh et al., 2003; Acar & Sahin, 2025; Mashahadi et al., 2023).

Problem Statement

Despite the rapid increase in EV adoption globally and in Nepal, empirical research on the behavioral intentions and influencing factors among Nepalese youth remains scarce. While studies from countries like China and Pakistan have explored drivers of EV adoption, Nepal's unique socio-economic and infrastructural context demands localized investigation. Nepal faces challenges of affordability, infrastructure readiness, and limited awareness alongside social and environmental considerations impacting youth purchase intentions. Moreover, the interplay of multiple constructs identified in the UTAUT model has yet to be comprehensively studied within Nepal's dynamic youth demographic. Without such insights, policy and marketing interventions risk ineffectiveness, potentially slowing the nation's transition to sustainable transportation.

Research Objectives

This study aims to fill the research gap by examining the behavioral intentions of Nepalese youth (aged 16-40) toward purchasing electric vehicles using the UTAUT framework.

Literature Review

The transportation sector significantly contributes to global greenhouse gas emissions, accounting for an estimated 11.9% of total emissions from fossil fuel combustion, with road transport and internal combustion engine (ICE) vehicles as major culprits (Tunçel, 2022). Urban areas bear the brunt of vehicular emissions, deteriorating air quality and negatively impacting public health. Cities such as Kathmandu rank among the most polluted worldwide, primarily due to emissions from petrol and diesel vehicles, which have been linked to respiratory and cardiovascular ailments (Himalayan News Service, 2023; Fukusaki et al., 2021). Within this context, electric vehicles (EVs) have emerged as environmentally sustainable alternatives. Unlike ICE vehicles, EVs utilize rechargeable batteries (e.g., lithium iron phosphate and lithium nickel manganese cobalt oxide), producing zero tailpipe emissions and offering quieter, more energy-efficient mobility solutions aligned with global sustainability goals (Pavić et al., 2020; Energy Transitions Commission, 2020; International Energy Agency, 2024).

The adoption of EVs is influenced by a range of behavioral and contextual factors. Environmental concern (EC), defined as awareness and willingness to support eco-friendly alternatives, is positively correlated with consumer attitudes toward EVs (Rezvani et al., 2015). This is particularly pertinent in Nepal, where rising pollution and government awareness campaigns have heightened environmental consciousness (Shrestha & Subedi, 2022). Performance expectancy (PE), rooted in the Unified Theory of Acceptance and Use of Technology (UTAUT), refers to perceived benefits such as efficiency and cost-effectiveness, which strongly motivate adoption (Venkatesh et al., 2003). Given Nepal's elevated fuel costs and consumer concern for vehicle performance, PE is a critical determinant of purchase intentions.

Effort expectancy (EE), or perceived ease of use, also affects behavioral intentions, with prior research indicating that technological complexity reduces adoption rates (Ayaz, Yanartaş, 2020; Kapser & Abdelrahman, 2020). Social influence (SI) plays a formative role, especially in collectivist cultures like Nepal's, where peer norms and family opinions strongly impact major purchase decisions (Venkatesh et al., 2003; Zhao et al., 2022). Facilitating conditions (FC), encompassing infrastructural support such as charging stations, government incentives, and after-sales services, constitute essential enablers or barriers (Selvi & Önem, 2025; Karamany & Hariry, 2025). Insufficient infrastructure remains a significant impediment in developing countries, including Nepal (Rahman, 2024), contributing to 'range anxiety' and reluctance in adoption despite financial incentives.

Behavioral intention (BI) synthesizes these influences into a measurable predictor of actual EV adoption (Venkatesh et al., 2003). Marketing strategies and policy interventions that effectively elevate environmental concern, highlight performance benefits, simplify user experiences, leverage social endorsements, and improve infrastructure can enhance BI and thus accelerate EV market penetration (Rezvani et al., 2015). However, Nepalese empirical studies examining these interconnected factors remain limited.

Globally, studies reinforce that affordability, technological performance, infrastructural availability, social norms, and consumer awareness coalesce to drive EV adoption, yet barriers like high upfront costs, insufficient charging networks, and limited public knowledge persist (Karamany & Hariry, 2025). This underscores the necessity for multifaceted approaches combining technological innovation, policy support, and behavioral insights to sustain the transition toward low-emission transport systems.

understanding the roles of environmental concern, performance expectancy, effort expectancy, social influence, and facilitating conditions is critical for advancing EV adoption, especially in contexts like Nepal's where rapid urbanization, pollution, and demographic factors intersect. Future research applying comprehensive frameworks such as UTAUT combined with Structural Equation Modeling (SEM) can empirically unravel these dynamics, guiding targeted interventions for sustainable transport transitions.

Methodology

Questionnaire Design

The questionnaire used in this study was developed based on the validated instrument from Lee et al. (2021) and further refined through consultations with experts possessing over a decade of experience in Nepal's electric vehicle

(EV) and transportation sectors. Informed consent was communicated explicitly at the beginning, ensuring respondents understood that all data collected would be used exclusively for academic research purposes, with strict assurances on data privacy and anonymity—no personally identifiable information, such as names or contact details, was collected.

The questionnaire comprised two principal sections. The first captured respondents' sociodemographic variables: gender, age, marital status, education level, occupation, and vehicle ownership—categorized as petrol/diesel cars, electric scooters, and electric private cars. These demographic variables enabled subgroup analyses within the study's conceptual model. The second section assessed latent constructs derived from the Unified Theory of Acceptance and Use of Technology (UTAUT): Environmental Concerns (EC), Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), and Behavioral Intentions (BI). Responses were recorded via a five-point Likert scale ranging from "Strongly Disagree" to "Strongly Agree."

Data Collection

Data gathering was conducted through an online survey distributed randomly across multiple digital platforms including social media (LinkedIn, Facebook) and messaging applications (WhatsApp, Messenger). Although the questionnaire did not explicitly inquire about respondents' exact locations to preserve privacy, most respondents were residents of Kathmandu, Nepal's capital, with smaller contingents from metropolitan cities such as Pokhara, Birgunj, and Butwal. Initially, 289 responses were collected. After excluding incomplete and unengaged responses, the final analyzable dataset comprised 286 responses.

Sample Size Justification

Adopting the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach, which accommodates relatively small sample sizes and complex models (Goodhue et al., 2012; Marcoulides & Saunders, 2006), the sample size adequacy was evaluated. Following Barclay et al. (1995) heuristic, a minimum sample of ten times the maximum number of independent variables was required. Considering a non-response buffer of 10%, the 289 responses were deemed sufficient to provide acceptable statistical power for the model estimation.

Data Analysis

The study tested hypothesized relationships between latent variables using PLS-SEM, implemented via the R open-source package "seminr" version 2.3.4 (Ray et al., 2024). PLS-SEM was chosen over covariance-based SEM (CB-SEM) due to its robustness with non-normally distributed data, suitability for small samples, and capacity to handle both reflective and formative measurement models without identification issues (Cassel et al., 2010; Hair et al., 2019).

The analytic procedure commenced with validating the measurement model by assessing reliability and validity. Reliability was evaluated at both the indicator level (indicator reliability) and construct level (internal consistency reliability), while validity assessments included convergent validity using Average Variance Extracted (AVE) and discriminant validity following established criteria (Hair et al., 2022).

Subsequently, the structural model was assessed to test the hypothesized paths. Hypothesis testing involved bootstrapping with 1,000 resamples to estimate standard errors and construct confidence intervals, thereby determining the significance of the path coefficients.

Hypotheses

H1: Environmental concern positively affects individuals' behavioral intentions to purchase EVs.

H2: Performance expectancy positively affects individuals' behavioral intentions to purchase EVs.

H3: Effort expectancy positively affects individuals' behavioral intentions to purchase EVs.

H4: Social influence positively affects individuals' behavioral intentions to purchase EVs.

H5: Facilitating conditions positively affect individuals' behavioral intentions to purchase EVs.

This methodology offers a clear roadmap for rigorously examining the determinants of EV adoption intentions among Nepali consumers, leveraging advanced statistical techniques and validated theoretical constructs.

Table 1

Presents the Criteria and Thresholds for Evaluating Reflective Measurement Models (Hair et al., 2022)

Criterion	Metric	Threshold
Reflective Indicator Reliability	Indicator Loadings	≥ 0.708 o In social science research, Loadings between 0.40 and 0.708 should not be automatically discarded but evaluated based on their impact on reliability and validity measures. o Indicators with loadings below 0.40 should be removed.
Internal Consistency Reliability	Cronbach's Alpha, Composite Reliability (rhoC), rhoA	o Minimum: 0.70 (or 0.60 for exploratory research) o Maximum: 0.95 (to avoid redundancy) o Recommended: 0.80 to 0.90
Convergent Validity	Average Variance Extracted (AVE)	≥ 0.50
Discriminant Validity	Heterotrait-Monotrait Ratio (HTMT)	o For conceptually similar constructs: HTMT < 0.90 o For conceptually different constructs: HTMT < .85 o Test if HTMT is significantly lower than the threshold (using bootstrap confidence intervals)

Structural Model

Hair et. al. (2022) have suggested four main steps of model evaluation. In the first step, the model is examined for collinearity issues. Since the estimation of path coefficients is based on Ordinary Least Squares (OLS) regression, the presence of high collinearity among the constructs may cause bias in path estimates. Once ensuring collinearity is not an issue, the significance and relevance of path coefficients are checked in the second step. Finally, the 3rd and 4th step involves examining the model's predictive and explanatory power.

Table 2

Presents the Criteria and Thresholds for Evaluating Reflective Measurement Models (Hair et al., 2022)

Criterion	Metrics and Thresholds
Collinearity	o Critical collinearity issues likely occur if VIF ≥ 5 o Collinearity issues are usually uncritical if VIF = 3–5 o Collinearity is not a problematic issue if VIF < 3
Significance and relevance of the path coefficients	o Apply bootstrapping to assess the significance of the path coefficients on the grounds of t-values or confidence intervals o Assess the magnitude of path coefficients
R2 value	R2 values of 0.75, 0.50, and 0.25 are considered substantial, moderate, and weak. However, R2 values have to be interpreted in the context of the model and its complexity. Excessive R2 values indicate that the model overfits the data.

Results and Discussion

Upon evaluating the measurement model, all indicator loadings, except the PE3 item (loading = 0.472), were greater than or close to the recommended threshold of 0.708, indicating acceptable indicator reliability. The removal of the PE3 item did not significantly improve the reliability or validity of the model. Consistent with Hulland (1999), the item was retained for further analysis due to its minimal impact on the overall model performance.

Table 3

Evaluating the Reliability and Validity of the Measurement Model

	Alpha	RhoC	AVE	RhoA
EC	0.867944	0.905197	0.657499	0.871648
PE	0.811683	0.869373	0.579687	0.857807
EE	0.840758	0.92623	0.862596	0.841514
SI	0.940446	0.961762	0.893444	0.944091
FC	0.838974	0.892156	0.674498	0.847266
BI	0.918831	0.942641	0.804267	0.918885

Note. alpha = Cronbach's alpha, rhoC = Composite Reliability,
AVE = Average Variance Extracted, rhoA = reliability coefficient

Table 3 shows that our measurement model has fulfilled the above-mentioned criteria. The values of Cronbach's alpha and rhoC in the range of 0.84 to 0.94 imply all the constructs are highly reliable. Similarly, rhoA values show a high value of internal consistency. All the values of AVE are greater than a threshold of 0.5, implying all constructs have a high level of convergent validity. Similarly, Table 4 shows the HTMT values for all pairs of constructs with a 90% two-sided confidence interval, which is equivalent to running a one-tailed test at 5%. The values of HTMT are below the threshold and significantly different from 1, implying good discriminant validity. These findings all reveal that our measurement model is good for structural modelling.

Table 4

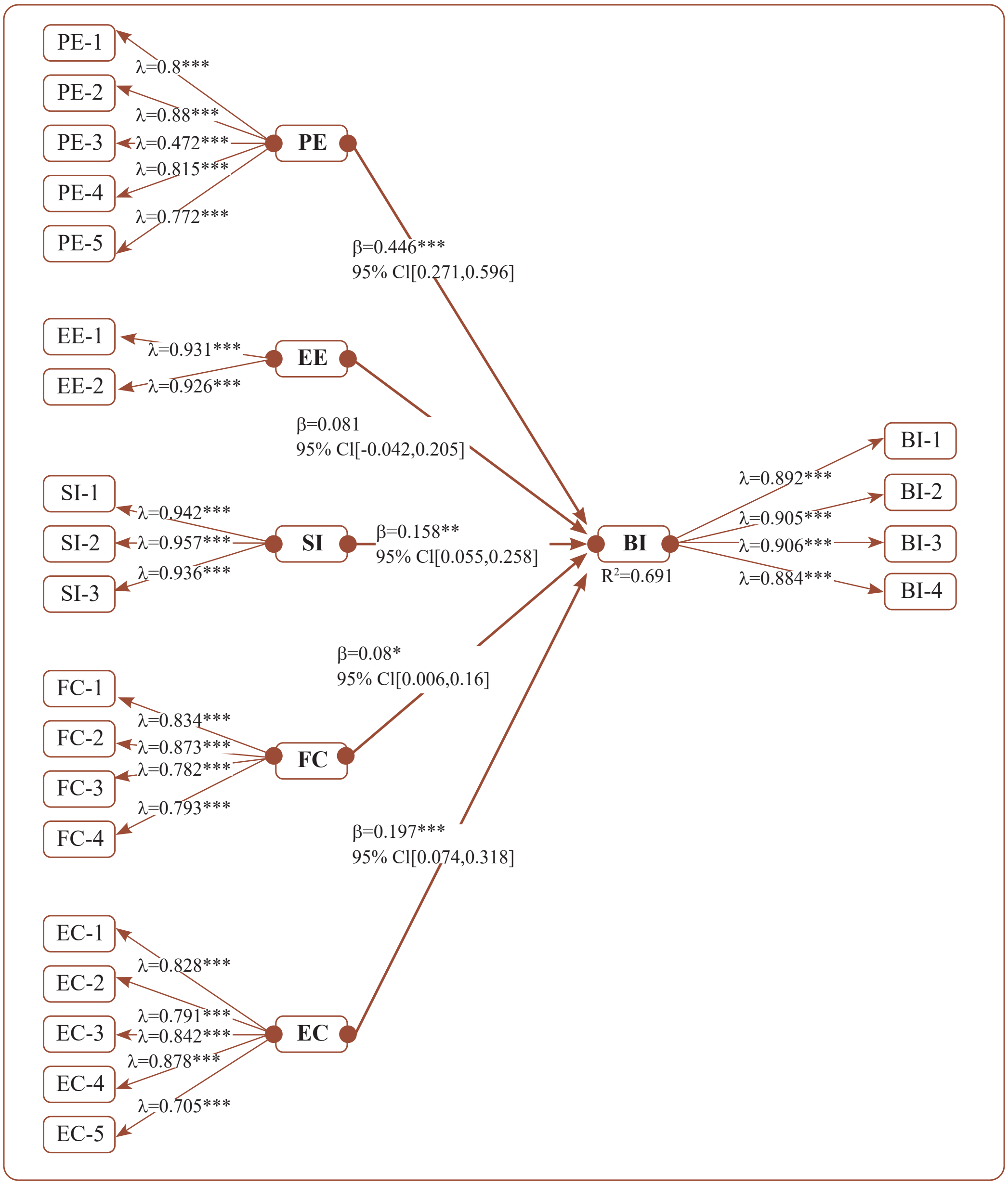
HTMT Values With 90% Two-sided Bootstrap Confidence Interval

	Original Est.	Bootstrap Mean	Bootstrap SD	T Stat.	5% CI	95% CI
EC → PE	0.84317955	0.844252316	0.035975678	23.43749	0.781688	0.900052
EC → EE	0.688004748	0.687544766	0.05880197	11.70037	0.583827	0.77742
EC → SI	0.612994709	0.613867696	0.04418213	13.87427	0.54022	0.686359
EC → FC	0.553143761	0.554193305	0.046936206	11.78501	0.477377	0.633411
EC → BI	0.775635816	0.775774751	0.04087395	18.97629	0.704157	0.839367
PE → EE	0.871231541	0.87156952	0.036582116	23.81578	0.806396	0.927246
PE → SI	0.757029546	0.758357835	0.036622067	20.6714	0.697157	0.812125
PE → FC	0.683191639	0.684619183	0.049737886	13.73584	0.599362	0.762207
PE → BI	0.895458409	0.896365651	0.028589353	31.32139	0.847411	0.9385
EE → SI	0.646082841	0.644994217	0.050076736	12.90186	0.561637	0.726254
EE → FC	0.590324018	0.591058607	0.055831243	10.57336	0.488186	0.678075
EE → BI	0.748719436	0.747459209	0.046444119	16.12087	0.665506	0.818122
SI → FC	0.510752476	0.5115006	0.05804638	8.799041	0.410978	0.601331
SI → BI	0.691685317	0.690825663	0.040878468	16.92053	0.621029	0.754871
FC → BI	0.607351456	0.608019188	0.045732323	13.28057	0.531823	0.679312

Table 4 shows the VIF values for all constructs. All the values are well below the threshold of 5, implying no serious multicollinearity problem exists.

Figure 1

SEM Model With 95% CI for Path Coefficients



The significance and relevance of the path coefficient are tested by performing a 1000 bootstrapped sample test. Figure 1 shows the path coefficients with a 95% bootstrapped confidence interval.

Table 5

Path Coefficient Estimates, Significance, and Confidence Intervals

Paths	PLS Est.	Bootstrap Mean	Bootstrap SD	T Stat.	5% CI	95% CI	VIF	Effect size(f^2)	Remarks	R^2
EC → BI	0.1965	0.2006	0.0629	3.1222 (***)	0.0963	0.3012	2.198	0.0562	Supported	0.691
PE → BI	0.4460	0.4453	0.0834	5.3471 (***)	0.3019	0.5736	3.577	0.1791	Supported	
EE → BI	0.0805	0.0787	0.0657	1.2251	-0.0242	0.1870	2.339	0.0091	Not Supported	
SI → BI	0.1578	0.1551	0.0513	3.0725(**)	0.0728	0.2389	1.879	0.0421	Supported	
FC → BI	0.080	0.0819	0.0399	2.0107(*)	0.0209	0.1495	1.533	0.0133	Doubtful	

The result of bootstrapping shows that PE has a significantly strong positive impact on BI (0.446). A similar relationship pattern is found between EC, SI, and BI (0.1965,0.1578), but with a lower effect size. On the contrary, the relationship between FC and BI is doubtful as T- T-values are on the borderline. Finally, no significant relationship is found between EE and BI, as zero is found in the bootstrapped confidence interval.

Discussion

This study explored the behavioral intentions of Nepalese youth toward the adoption of electric vehicles (EVs), employing constructs from the Unified Theory of Acceptance and Use of Technology (UTAUT), including Performance Expectancy (PE), Environmental Concerns (EC), Social Influence (SI), Effort Expectancy (EE), and Facilitating Conditions (FC).

Performance Expectancy emerged as the most influential predictor of EV adoption intentions among these factors. This suggests that young consumers in Nepal strongly emphasize the utilitarian benefits of EVs, such as cost savings on fuel, low maintenance requirements, and efficient performance. This finding aligns with previous studies within the UTAUT framework, affirming that perceived usefulness significantly drives technology acceptance (Venkatesh et al., 2003).

Environmental Concerns also significantly influenced behavioral intentions. This reflects a growing awareness among Nepalese youth about the deteriorating air quality in urban areas like Kathmandu and the broader implications of carbon emissions. The high salience of this factor underscores a generational shift toward environmentally responsible consumption behavior, similar to patterns observed in other emerging economies (Hoang et al., 2022).

Social Influence was another substantial predictor, highlighting the role of peer groups, family opinions, and social trends in shaping the adoption of green technologies. The youth demographic appears exceptionally responsive to social validation and recommendations, suggesting that EV adoption is not only a matter of individual utility but also of social alignment and identity.

Interestingly, Effort Expectancy was not found to be statistically significant. This may be attributed to the relatively high technological proficiency among younger consumers who often perceive the adoption and use of new technologies, including EVs, as intuitive and manageable. As a result, ease of use may not be a differentiating factor in their purchase decisions.

Facilitating Conditions, while relevant, showed only a weak correlation with behavioral intention. This suggests that although infrastructure and supportive policies matter, they are not yet critical barriers. This may be because EV ownership is still viewed as aspirational among youth. Nonetheless, inadequate charging stations, inconsistent policy support, and lack of after-sales service remain concerns that could affect actual long-term adoption if left unaddressed.

The study also acknowledged that demographic moderators such as age, gender, and income could subtly influence the strength of these relationships. Younger respondents might be more enthusiastic but financially constrained, while older youth with stable incomes may have a greater capacity to translate intent into action. Gendered perceptions may also play a role, with performance-related features possibly resonating more with male consumers and environmental or safety aspects appealing more to females.

These findings have notable policy and marketing implications. Government bodies must prioritize sustainable infrastructure development and offer consistent incentives such as tax reductions and subsidies to promote EV uptake. At the same time, marketers should tailor messages emphasizing cost-efficiency, environmental impact, and social prestige to appeal to Nepalese youth. Educational campaigns through institutions and digital platforms can further boost environmental literacy and reduce misperceptions about EV usability.

Conclusion

This study contributes to the growing literature on electric vehicle adoption by identifying the key psychological and contextual factors influencing the purchase intentions of Nepalese youth. Performance Expectancy, Environmental Concerns, and Social Influence were the most significant predictors, suggesting that both personal utility and socio-environmental motivations drive EV interest among the younger demographics.

Although effort expectancy and facilitating conditions were less influential, they remain relevant in ensuring that behavioral intentions are successfully converted into actual adoption. A holistic approach involving technological innovation, supportive infrastructure, environmental education, and culturally resonant marketing strategies is essential for achieving long-term growth in Nepal's EV market.

The study offers valuable implications for both policymakers and EV manufacturers. It recommends that the government enhance awareness through targeted campaigns, provide consistent financial incentives, and invest in developing reliable charging infrastructure. At the same time, manufacturers should focus on communicating EVs' performance benefits and environmental value through youth-oriented marketing strategies, including social media and community-based promotions.

Notably, the findings highlight the need for educational institutions, civil society, and local governments to collaboratively raise awareness and demystify the usage of EVs through events, demonstrations, and digital literacy initiatives. A key challenge remains the limited information about EVs, which hinders informed decision-making among potential buyers.

While this study focused on literate youth with internet access, future research should aim to include a more diverse demographic profile. Broader studies could explore additional factors such as pricing, policy incentives, individual perceptions, and cultural attitudes to gain a more holistic understanding of EV adoption behavior across different segments of Nepalese society.

In sum, the road to increased EV adoption in Nepal will depend on a combined effort from policymakers, businesses, and civil society. If supported by strategic policies and informed public outreach, Nepal's youth can play a pivotal role in accelerating the country's transition toward sustainable and cleaner transportation systems.

References

Acar, E., & Sahin, B. (2025). Impact of variables in the UTAUT 2 model on the intention to use a fully electric car. *Sustainability, 17*(7), Article 3214. https://doi.org/10.3390/su17073214

Ananda, N., Kobayashi, S., Mishra, A. K., & Aithal, P. S., (2023). Mandala in operation of web 3.0. *International Journal of Case Studies in Business, IT, and Education* (*IJCSBE*),*7*(1), 220–229. https://doi.org/10.5281/zenodo.7727160

Axsen, J., TyreeHageman, J., & Lentz, A. (2012). Lifestyle practices and pro-environmental technology. *Ecological Economics*, *82*, 64–74. https://doi.org/10.1016/j.ecolecon.2012.07.013

Ayaz, A., & Yanartaş, M. (2020). An analysis on the Unified Theory of Acceptance and Use of technology theory (UTAUT): Acceptance of electronic document management system (EDMS). *Computers in Human Behavior Reports, 2*, 100032. https://doi.org/10.1016/j.chbr.2020.100032

Barclay, D. W., Higgins, C. A., & Thompson, R. (1995). The partial least squares (PLS) approach to causal modeling: Personal computer adoption and use as an illustration. *Technology Studies, 2*(2), 285–309

Bist, P. (2023). Policy discourse on electric mobility in Nepal. *Southwestern Research Journal*, *1*(1), 58–69. https://doi.org/10.3126/srj.v1i1.62266

Cassel, C. M., Hackl, P., & Westlund, A. H. (2010). Robustness of partial least squares method for estimating latent variable quality structures. *Journal of Applied Statistics*, *26*(4), 435–446. https://doi.org/10.1080/02664769922322

Celestin, M., & Mishra, A. K. (2024). The evolution of green bonds and sustainable finance in public sector budgeting and development projects. *Journal of Advanced Research in Humanities and Social Sciences, 12*(1), 7–16. http://dx.doi.org/10.2139/ssrn.5215437

Celestin, M., & Mishra, A. K. (2025). The digital transformation of financial disclosure: How emerging technologies are revolutionizing corporate transparency and investor trust. *Journal of Advanced Research in Operational and Marketing Management*, *8*(1), 11–25. https://doi.org/10.24321/2582.5399.202502

Energy Transitions Commission. (2020, September). *Making mission possible*: *Delivering a net-zero economy* [Report]. Energy Transitions Commission

Fukusaki, Y., Umehara, M., Kousa, Y., Inomata, Y., & Nakai, S. (2021). Investigation of air pollutants related to the vehicular exhaust emissions in the Kathmandu Valley, Nepal. *Atmosphere*, *12*(10), 1322. https://doi.org/10.3390/atmos12101322

Goodhue, D. L., Lewis, W., & Thompson, R. (2012). Does PLS have advantages for small sample size or non-normal data? *MIS Quarterly, 36*(3), 981–1001. https://doi.org/10.2307/41703490

Hair, J. F., Hollingsworth, C. L., Randolph, A. B., & Chong, A. Y. L. (2017). An updated and expanded assessment of PLS-SEM in information systems research. *Industrial Management & Data Systems*, *117*(3), 442–458. https://doi.org/10.1108/IMDS-04-2016-0130

Hair, J. F., Jr., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *Partial least squares structural equation modeling (PLS-SEM) using R: A workbook* (Classroom Companion: Business). Springer. https://doi.org/10.1007/978-3-030-80519-7

Hair, J. F., Sarstedt, M., & Ringle, C. M. (2019). Rethinking some of the rethinking of partial least squares. *European Journal of Marketing*, *53*(4), 566–584. https://doi.org/10.1108/EJM-10-2018-0665

Himalayan News Service. (2023, March 17). Kathmandu one of world's most polluted city. *The Himalayan Times*.

Hoang, T. T., Pham, H. T., & Vu, H. M. T. (2022). From intention to actual behavior to adopt battery electric vehicles: A systematic literature review. *The Open Transportation Journal*, *16*(1). https://doi.org/10.2174/18744478-v16-e2208100

Hulland, J. (1999). *Use of partial least squares (PLS) in strategic management research: A review of four recent studies*. Strategic Management Journal, 20(2), 195–204. https://doi.org/10.1002/(SICI)1097-0266(199902)20:2<195::AID-SMJ13>3.0.CO;2-7

International Energy Agency. (2024). *Electric vehicles*. IEA

Kapser, S., & Abdelrahman, M. (2020). Acceptance of autonomous delivery vehicles for last-mile delivery in Germany: Extending UTAUT2 with risk perceptions. *Transportation*

Research Part C: Emerging Technologies, 111, 210–225. https://doi.org/10.1016/j.trc.2019.12.016

Karamany, H., & Hariry, A. Z. E. (2025). The future of electric vehicles in developing countries. *International Journal of Scientific Research and Management (IJSRM)*, 13(05), 2168–2173. https://doi.org/10.18535/ijsrm/v13i05.ec03

Lee, J., Baig, F., Talpur, M. a. H., & Shaikh, S. (2021). Public intentions to purchase electric vehicles in Pakistan. *Sustainability*, *13*(10), 5523. https://doi.org/10.3390/su13105523

Marcoulides, G. A., & Saunders, C. (2006). PLS: A silver bullet? *MIS Quarterly, 30*(2), iii–ix. https://doi.org/10.2307/25148727

Mashahadi, F., Mahmod, R., & Saidon, J. (2023). Development in electric iehicle intention and adoption: Integrating the extended unified theory of acceptance and use of technology (UTAUT) and religiosity. *Information Management and Business Review*, 15(3(I)), 173–182. https://doi.org/10.22610/imbr.v15i3(i).3527

Mishra, A. K. (2018). Sustainability and risk assessment of Salyankot water supply project in post-earthquake scenario. *International Journal of Operations Management and Information Technology, 8*(1), 1–30.

Pavić, I., Pandžić, H., & Capuder, T. (2020). Electric vehicle-based smart e-mobility system: Definition and comparison to the existing concept. *Applied Energy*, *272*, 115153. https://doi.org/10.1016/j.apenergy.2020.115153

Post Report. (2025, May 29). Government keeps taxes on electric vehicles unchanged for FY 2025–26. *The Kathmandu Post*.

Rahman, A. (2024). Study on Eeectric vehicles (EVs) in Nepal: Opportunities and challenges. *Pacific Business Review*, 14(7), 11–18.

Ray, S., Danks, N. P., & Valdez, A. C. (2024). *Seminar: Building and estimating structural equation models* [Dataset]. https://doi.org/10.32614/cran.package.seminr

Rezvani, Z., Jansson, J., & Bodin, J. (2015). Advances in consumer electric vehicle adoption research: A review and research agenda. *Transportation Research Part D Transport and Environment*, *34*, 122–136. https://doi.org/10.1016/j.trd.2014.10.010

Selvi, M. S., & Önem, Ş. (2025). Impact of variables in the UTAUT 2 model on the intention to use a fully electric car. *Sustainability*, *17*(7), 3214. https://doi.org/10.3390/su17073214

Shrestha, R., & Subedi, D. (2022). Youth, politics, and youth-led political violence in Nepal. *Asian Politics & Policy*, *14*(3), 332–350. https://doi.org/10.1111/aspp.12658

Tamang, S., & Mishra, A. (2022). Green-HRM trends and their effects on educational institutions workplace. *Journal of Advanced Research in HR and Organizational Management*, *9*(3&4), 1–5. https://doi.org/10.24321/2454.3268.202201

Tunçel, N. (2022). Intention to purchase electric vehicles: Evidence from an emerging market. *Research in Transportation Business & Management*, *43*, 100764. https://doi.org/10.1016/j.rtbm.2021.100764

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425–478. https://doi.org/10.2307/30036540

Zhao, X., Ma, Y., Shao, S., & Ma, T. (2022). What determines consumers' acceptance of electric vehicles: A survey in Shanghai, China. *Energy Economics, 108*, 105805. https://doi.org/10.1016/j.eneco.2021.105805