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Applying the Unified Theory of Acceptance and Use of Technology to Analyze the Adoption of Battery Electric Vehicles in Nepal

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Abstract

Aim/Purpose: This study examined factors influencing battery electric vehicle (BEV) adoption in Kathmandu, Nepal, where transitioning from combustion engines to BEVs could advance sustainable transportation and renewable energy growth. Using the extended Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, and Government Incentives were analyzed. It also explored how Environmental Concerns mediate Purchase Intention and Usage Behavior, linking intent to actual BEV utilization. The findings aim to inform policies accelerating Nepal's green mobility transition.

Background: With its abundant hydropower resources, Nepal has a unique opportunity to shift toward green mobility and reduce dependence on imported fossil fuels. Despite the increased use of BEVs, there has been limited research on purchase intention factors that significantly impact consumer adoption. This study provides actionable insights for policymakers, manufacturers, and marketers to encourage BEV adoption. This research examined the impact of performance expectancy, effort expectancy, social influence, and facilitating conditions alongside additional constructs such as hedonic motivation, environmental concerns, price value, and government incentives on the purchase intention and subsequent use behavior of BEVs in Nepal.

Methodology: A quantitative research approach was employed in this study to analyze the constructs of the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). This study focused on vehicle owners aged 18 and above who were interested in purchasing BEVs in Kathmandu, Nepal. The data were collected through a structured questionnaire using a purposive stratified random sampling method. A sample size of 400 respondents was targeted; however, 572 surveys were distributed to enhance reliability, yielding 536 valid responses. Data collection took place between May and June 2024 through online surveys and self-administered questionnaires distributed across various digital platforms. The survey questionnaire included three sections: demographic data (e.g., gender, age, income, education), consumer behavior, and BEV adoption constructs (Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Condition, Hedonic Motivation, Government Incentives, Environmental Concerns, and Price Value), which were measured on a five-point Likert scale. Descriptive statistics (mean, median, mode) and frequency distributions were used to summarize key variables and demographic trends. This study used a partial least squares structural equation modeling (PLS-SEM) analysis tool to determine factors direct and indirect effects on BEV adoption intention in Kathmandu, Nepal.

Findings: The study revealed that purchase intention significantly and directly affected the use behavior of BEVs in Nepal. The UTAUTS constructs, such as Effort Expectancy, Hedonic Motivation, Price Value, Government Incentives, and Facilitating Conditions, significantly impacted the purchase intention of BEV in Kathmandu, Nepal, leading to use behavior. This indicated that purchase intention was a strong predictor of usage behavior. However, Performance Expectancy, Social Influence, and Environmental Concerns did not have a significant impact, suggesting that consumers prioritized affordability and practical considerations over perceived vehicle performance. These findings indicate that in the Nepalese context, consumers' decisions are more driven by practical benefits and individual preferences rather than performance expectations or social pressures. This divergence from typical UTAUT2 outcomes indicates that Nepalese consumers prioritize immediate and tangible benefits over perceived performance and societal influences. Environmental Concerns, while relevant, did not emerge as a primary factor influencing purchase intentions, which may reflect the current state of environmental awareness and prioritization among Nepalese consumers.

Contribution/Impact on Society: This study provides theoretical insights into BEV adoption by demonstrating that facilitating conditions have a positive influence on adoption intention. By empirically validating this relationship, the findings of the study demonstrated the UTAUT2 framework’s applicability to BEV adoption. These findings underscore the essential role of supportive infrastructures, such as charging networks and governmental incentives, in reducing adoption barriers and enhancing consumer willingness to adopt BEVs. This study equips decision-makers with the necessary tools to foster a more sustainable and electrically driven transportation ecosystem in Kathmandu, paving the way toward a cleaner and more livable urban environment.

Recommendations: The adoption of BEVs in Nepal offers wide-ranging benefits. For policymakers, the study provides insights to guide evidence-based decisions, including incentives, infrastructure, and regulatory frameworks. Industry stakeholders can better understand consumer preferences and adoption barriers, informing strategies for product development and market positioning. Environmental organizations can use these findings to advocate for policies that promote emissions reduction and sustainable transport. Consumers gain awareness of BEVs' economic and environmental benefits, empowering informed choices. Academically, the research enriches the literature on technology adoption in developing countries, serving as a foundation for future studies in Nepal and similar contexts.

Research Limitations: This study has a few limitations. First, the sample primarily included owners of combustion engine vehicles, which may limit direct insights into the purchasing behavior of actual BEV users. Second, the geographical scope was confined to Kathmandu and specific regions of Nepal, restricting the generalizability of findings to other areas; future research could benefit from broader geographic coverage. Lastly, the study focused on selected UTAUT2 constructs. At the same time, other potentially influential factors, such as prior use experience, fuel efficiency, and brand loyalty, were not explored, leaving room for future studies to investigate these aspects.

Future Research: Future studies could be expanded to include a larger, more diverse sample of existing BEV users across various regions of Nepal, capturing regional variations and developing targeted strategies. They could also explore additional factors like user experience, perceived fuel efficiency, and brand loyalty to enrich understanding consumer decision-making and adoption dynamics. This study also could be extended into longitudinal research by collecting data from various regions of the country. This would diversify the research findings, providing valuable insight into consumer behavior in this evolving BEV market. Furthermore, consumer perceptions and behavior vary due to changing market demands and government policies.

Keywords: *Electric vehicles, Nepal, purchase intention, usage behavior*

Introduction

The increased demand for addressing climate change and reducing carbon emissions has highlighted the necessity of sustainable transportation solutions. Global conflicts have exacerbated these concerns by exposing the world's dependency on fossil fuels and causing significant disruptions in the global energy landscape (IEA, 2023). These factors emphasize the need to transition to cleaner energy sources, such as renewables and nuclear power, to mitigate economic and environmental impacts. A McKinsey & Company (2022) report forecasted that renewables will account for 80% to

90% of global power generation by 2050, increasing the demand for Electric Vehicles (EVs). They play a crucial role in reducing oil consumption and greenhouse gas emissions. Global EV sales have seen an average annual growth rate of 62% over the past four years, with a 96% surge in 2021, reaching 6.6 million units (McKinsey & Company, 2022). To prevent global temperatures from rising beyond 1.5°C., Asia Pacific economies need to have policy and market-led transition shifts to renewable energy means of transport, such as EVs (Low & Chee, 2023). In 2022, electric car sales surpassed 10 million units, reflecting a 55% increase from 2021, despite supply chain disruptions and economic uncertainties (Irle, 2023).

In Nepal, a developing country heavily reliant on fossil fuel imports, the adoption of EVs is accelerating. EV imports rose from 200 units in 2020/21 to 4,050 units in 2022/23, a 124.12% increase (The HRM Nepal, 2023). Nepal's hydroelectric power generation has bolstered its capacity to support EV adoption (Ingram, 2023). Despite progress, Nepal faces challenges in promoting clean transportation, including infrastructure limitations, economic constraints, cultural attitudes, and policy issues. The research gap addressed in this study lies in understanding these factors within Nepal's socioeconomic and geographical context. The Unified Theory of Acceptance and Use of Technology has been widely used to study technology adoption behavior, but has not been extensively applied to BEV adoption in Nepal. Addressing this gap provides valuable insights for alternative mobility in Nepal and other developing nations.

The purpose of this study was to find answers to the following research questions:

1. How do UTAUT2 Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, and Government Incentives affect the Purchase Intention of BEVs?
2. How does Environmental Concern affect Purchase Intention and subsequent Use Behavior of BEVs?
3. How does Purchase Intention lead to Use Behavior of BEVs?

Literature Review

Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh et al. (2003), combined major elements from eight existing innovation acceptance theories into a unified model that revealed a comprehensive understanding of the factors influencing behavioral intention to adopt new technology. The UTAUT model identifies four primary factors influencing behavioral intention: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC). These primary factors are critical in understanding technology adoption across various contexts.

UTAUT theory was later extended with the addition of three new variables—Hedonic Motivation (HM), Price Value (PV), and Habit (a crucial predictor from sociology) to formulate UTAUT-2 (Venkatesh et al., 2012). This research study focused on the core UTAUT2 constructs while intentionally omitting habit. As noted by Venkatesh et al. (2012), habit is most relevant in post-adoption or mature markets where repetitive usage is established. In Nepal, where BEV ownership remains below .5% of total vehicles (MOPIT, 2023), habitual behavior is not yet a measurable factor.

Performance Expectancy (PE)

Performance expectancy is when individuals believe that technology use will significantly impact productivity and effectiveness (Venkatesh et al., 2003). Studies have consistently demonstrated that higher perceived performance expectancy positively influences EV adoption. Research in Austria and Pakistan has highlighted that perceived benefits, such as cost savings and environmental advantages, significantly impact consumers' intention to adopt EVs (Wolf & Seebauer, 2014; Lee et al., 2021). Empirical studies have suggested that when delivery drivers perceive higher performance expectancy in electric trucks compared to combustion trucks, particularly in terms of cost savings, parking convenience, and environmental concerns, they were more inclined to use electric trucks in China (Zhou et al., 2021)

H_1: Performance expectancy affects BEV purchase intention.

Effort Expectancy (EE)

Effort expectancy refers to a technology's perceived ease of use and user-friendliness. Prior studies have indicated that lower perceived effort in operating BEVs enhances adoption rates. The intention to buy BEVs is influenced by various factors, with a significant consideration being the perceived ease of use. A previous study showed that effort expectancy was positively linked to expected EV purchase intentions (Samarasinghe et al., 2024). In a case study in Shenzhen and Guangzhou, China, taxi drivers' intentions to drive electric taxis highlighted factors such as easy driving, charging, driving experience, and maintenance, which indicated that effort expectancy positively affected EV purchase intention (Zhou et al., 2021).

H_2: Effort expectancy affects BEV purchase intention.

Social Influence (SI)

Social influence refers to the degree to which an individual believes that significant others consider it necessary for them to utilize a new system (Venkatesh et al., 2003). An empirical study in Malaysia showed a positive and statistically significant relationship between social influences and usage intentions of EVs (Sang & Bekhet, 2015). Research conducted in China showed that consumers' social attribute variables had a significant impact on BEV purchase intentions (Wang et al., 2021).

H_3: Social influence affects BEV purchase intention.

Facilitating Conditions (FC)

Facilitating conditions refers to the degree to which an individual perceives the existence of organizational and technical infrastructure that supports the utilization of a technology (Venkatesh et al., 2003). Research findings in Pakistan revealed a positive relationship between facilitating conditions and individuals' intentions to adopt public cloud technology, underscoring the importance of infrastructural support and regulatory frameworks (Ali et al., 2019). This showed that a new technology's perceived ease of use and usefulness may affect consumers' purchase intention. Similarly, research has shown that facilitating conditions positively impact consumers' behavioral intention to purchase electric vehicles (Tu & Yang, 2019). A study conducted by Jain et al. (2022) showed that facilitating conditions positively affected the adoption intention of EVs.

H_4: Facilitating conditions affect BEV purchase intention.

H_{4a}: Facilitating conditions affect BEV use behavior.

Hedonic Motivation (HM)

Hedonic motivation posits that use of technology is encouraged by a user's enjoyment experience. It was a significant factor in shaping technology acceptance and usage in research conducted by Brown and Venkatesh (2005). Another study showed that hedonic motivation positively affected attitudes toward using electric vehicles in Indonesia (Gunawan et al., 2022). Research has also shown that hedonic attitudes influence consumers' intentions to adopt hybrid electric cars (Zamil et al., 2023).

H_5: Hedonic motivation affects BEV purchase intention.

Price Value (PV)

Price value is an individual's cognitive trade-off between the perceived benefits and costs of using various technologies (Venkatesh et al., 2012). Price value identifies consumers' assessment of the financial trade-offs between the perceived benefits and costs of adopting a technology. Studies have highlighted that favorable financial incentives and cost-effectiveness significantly enhance EV adoption intentions (Larson et al., 2014; Bjerkan et al., 2016).

H_6: Price value affects BEV purchase intention.

Environmental Concerns (EC)

Environmental concerns reflect individuals' awareness and commitment to sustainability, influencing their preference for eco-friendly technologies. Empirical research has confirmed that heightened environmental consciousness is significantly correlated with increased consumer interest in EV adoption (Okada et al., 2019; Manutworakit & Choocharukul, 2022).

H_7: Environmental concerns affect BEV purchase intention.

Government Incentives (GI)

Government incentives include tax reductions, subsidies, and financial and policy mechanisms to promote EV adoption. Studies have indicated that government incentives play a critical role in shaping consumer purchase decisions (Wang et al., 2017; Kim et al., 2019). This shows that government incentives lead consumers to purchase BEVs.

H_8: Government incentives affect BEV purchase intention.

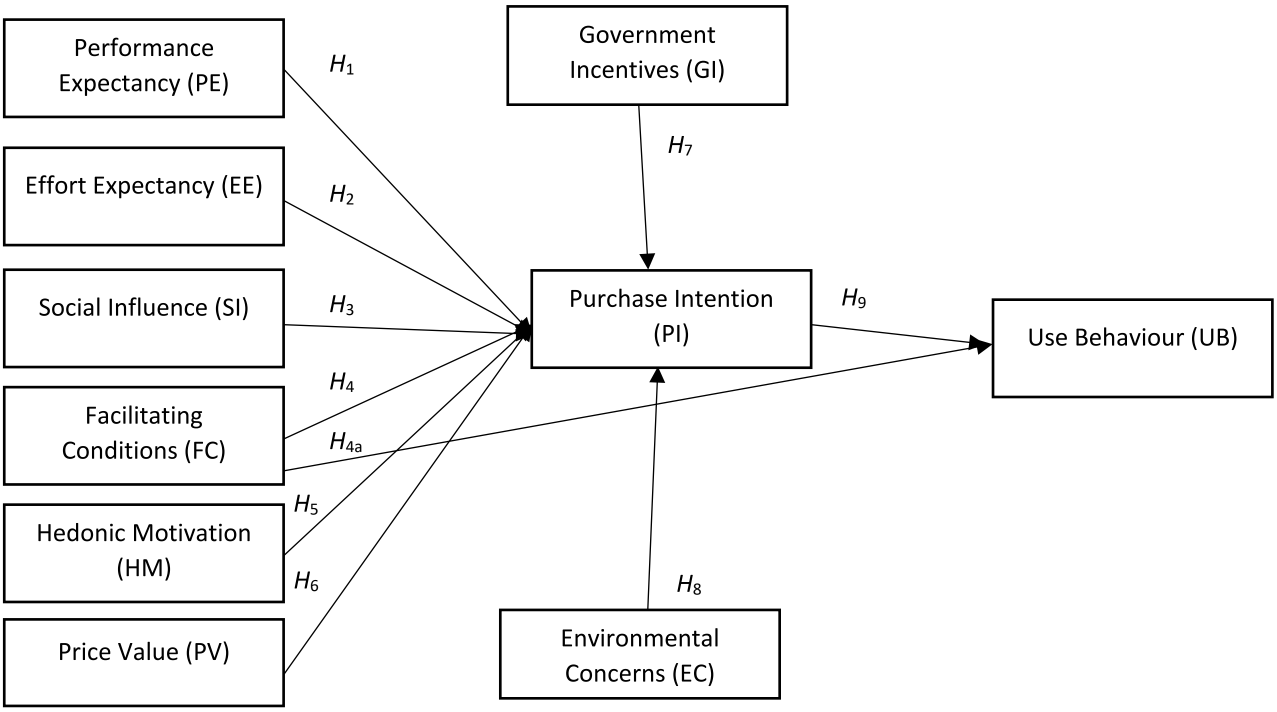
Purchase Intention (PI) and Use Behavior (UB)

Purchase intention represents an individual's likelihood of purchasing an EV, which strongly predicts actual usage behavior. Previous research has established a direct link between purchase intention and subsequent adoption behavior, supporting its relevance in understanding EV market growth (Fishbein & Ajzen, 1975; Ajzen, 1991). A consumer's intention to purchase contributes to the creation of subsequent usage behavior. A study conducted in Beijing showed that consumer intentions to buy EVs were positively affected by attributes such as attitude, perceived behavioral control, cognitive status, product perception, and monetary incentive policies (Huang & Ge, 2019). A study conducted on food delivery applications in Malaysia showed that technology acceptance significantly influenced consumer loyalty (Tiep et al., 2023). Additionally, purchase intention is positively affected by attitude, subjective norms, perceived behavioral control, price value, and environmental self-image (Vafaei-Zadeh et al., 2022).

H_9: BEV purchase intention has a significant positive effect on use behavior.

The study's conceptual framework is shown below in Figure 1.

Figure *1* *Conceptual Framework*



Adapted from Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012)

Methodology

In this study, a hybrid sampling strategy was employed, integrating stratified random sampling to ensure demographic diversity across age, income, education, and vehicle ownership categories. The population was estimated to be more than 3 million smart license holders in Kathmandu (Paudel, 2023). To enhance contextual relevance, purposive selection criteria prioritized respondents who expressed interest in battery electric vehicles (BEVs) and resided in the Kathmandu Valley, where BEV infrastructure is concentrated. This approach balanced statistical representativeness with targeted insights into Nepal's nascent EV adoption landscape.

A quantitative approach was employed within a positivist framework to investigate factors influencing electric vehicle (EV) adoption in Nepal. Guided by a literature review, a conceptual model was developed and tested through hypotheses. Using Yamane's formula (1973) with a 95% confidence level and a ±5% margin of error, the target sample size was set at 400 respondents. The survey data was collected through online media. The study utilized a questionnaire adapted from established BEV adoption scales and was validated through pilot testing (n = 30) with participants from Kathmandu to enhance item clarity and internal consistency (Cronbach's $\alpha > .85$).

A rigorous translation protocol—comprising bilingual forward/backward translation and academic review—ensured Nepali contextualization. Partial Least Squares-Structural Equation Modeling (PLS-SEM) analysis was done to confirm robust model fit. The study's final sample of 536 respondents exceeded both Yamane's (1973) calculated minimum (n = 400) and PLS-SEM's requirements, which prioritize model complexity and statistical power over population-based formulas. With six exogenous constructs (3–4 indicators each), the 10-times rule suggested a minimum of 60–80 respondents, making the expanded sample statistically robust, enhancing reliability, predictive accuracy ($Q^2 > .15$), and generalizability without violating methodological guidelines (Hair et al., 2017).

Data Analysis

The survey was conducted in Kathmandu, Nepal, with 536 respondents, a slight majority of whom were females (51.5%) and young (aged 23 to 29 years = 37.1%). Occupations varied, with 40.1% being students and 27% working in private organizations. Half of the respondents held a bachelor's degree, and 38.1% earned above Rupees 40,000 monthly. Consumer behavior survey responses showed that more than 50% of individuals used a vehicle daily. Furthermore, it highlighted the factors influencing respondents' decisions to purchase a BEV. Cost savings, including lower fuel and maintenance costs, were the most significant factors, with 282 respondents identifying this as an influence. Environmental impact followed closely, with 272 respondents considering it an important factor. Government incentives, such as tax credits and rebates, were also influential, as noted by 164 respondents.

Before conducting the PLS-SEM analysis, reliability and validity were assessed through Factor Loading, Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE). Cronbach's Alpha measures internal consistency reliability (Cronbach, 1951), where values equal to or greater than .70 are considered acceptable for further analysis. In this study, Cronbach's alpha values ranged from .79 to .90, indicating reliability. Composite Reliability assesses internal consistency reliability in structural equation modeling, with values above .70 deemed acceptable. The CR values in this study ranged from .81 to .91. Convergent validity, evaluated through factor loadings and AVE, showed all values exceeding .50, confirming the validity of the measurement model. The factor loadings for each indicator were examined to assess the strength of the relationship between the indicators and their respective constructs. Most indicators exhibited strong loadings above .70, indicating good convergent validity, with values ranging from .61 to .91. Items with lower loadings, such as SI5 (.61) and PE4 (.62), were still deemed acceptable (Hair et al., 2017). Overall, the factor loadings supported the validity of the measurement model.

Table 1 *Convergent Validity (Factor Loadings, Composite Reliability, and Average Variance Extracted)*

Constructs	Items	Factor Loading	Cronbach's Alpha	Composite Reliability (ρ_A)	(ρ_c)	AVE
Performance Expectancy	PE1	.715	.817	.818	.816	.671
	PE2	.710				
	PE3	.688				
	PE4	.621				
	PE5	.696				
Effort Expectancy						
	EE1	.804	.869	.871	.867	.568
	EE2	.722				
	EE3	.712				
	EE4	.692				
	EE5	.830				
Social Influence						
	SI1	.849	.861	.866	.858	.551
	SI2	.778				
	SI3	.755				
	SI4	.695				
	SI5	.612				
Facilitating Conditions	FC1	.748	.830	.833	.831	.596
	FC2	.653				
	FC3	.757				
	FC4	.677				
	FC5	.6810				
Hedonic Motivation	HM1	.912	.897	.906	.899	.749
	HM2	.766				
	HM3	.910				
Price Value	PV1	.722	.795	.811	.802	.576
	PV2	.689				

	PV3	.855				
Environmental Concerns	EC1	.669	.883	.894	.8777	.595
	EC2	.662				
	EC3	.684				
	EC4	.882				
	EC5	.917				
Government Incentives	GI1	.864	.857	.862	.858	.603
	GI2	.817				
	GI3	.884				
Purchase Intention	PI1	.828	.891	.892	.891	.732
	PI2	.739				
	PI3	.819				
	PI4	.715				
Use Behaviour	UB1	.792	.894	.896	.894	.629
	UB2	.737				
	UB3	.823				
	UB4	.844				
	UB5	.764				

Source. Developed by Authors

The Fornell-Larcker criterion was used to analyze the constructs' discriminant validity. The diagonal values in Table 2 represent the method for comparing the square root of the AVE with the correlation for each construct, which should be greater than .50 to ensure the validity of the data (Fornell & Larcker, 1981). All constructs exhibited satisfactory convergent validity, with AVE values ranging from .55 to .75. The off-diagonal values represent the correlations between constructs and demonstrated good discriminant validity according to the Fornell-Larcker criterion.

Table 2 *Fornell-Larcker Criterion: Matrix of Correlation Constructs and the Square Root of AVE*

	PE	**EE**	**SI**	**FC**	**HM**	**PV**	**EC**	**PI**	**GI**	**UB**
PE	.571									
EE	.406	.568								
SI	.490	.449	.551							
FC	.440	.401	.473	.496						

HM	.400	.459	.418	.425	.749					
PV	.462	.417	.386	.427	.434	.576				
EC	.416	.485	.219	.433	.342	.418	.595			
PI	.452	.501	.433	.426	.540	.500	.505	.603		
GI	.4081	.3654	.428	.364	.322	.538	.288	.482	.732	
UB	.478	.463	.507	.495	.462	.422	.374	.571	.386	.629

Note. Square roots of average variance extracted (AVEs) shown on diagonals

Table 3 displays the Coefficient of determination (R^2) and Adjusted R^2 values for Purchase Intention (PI) and Use Behaviour (UB). The results indicate that the model explained approximately 74.32% of the variance in PI, with an adjusted R^2^22 of .739, suggesting a robust fit. For UB, the model accounted for about 78.05% of the UB variance, supported by an Adjusted R^2 of .780. These findings underscore the model's effectiveness in elucidating factors influencing electric vehicle adoption behaviours among the surveyed population, providing valuable insights into both purchase intentions and subsequent usage behaviour.

Table 3 *Coefficients of Determination for R-Squared*

Construct	**Coefficient of Determination (R^2)**	**Adjusted R^2**
PI	.743	.739
UB	.781	.780

Note. PI = Purchase Intention; UB = Use Behaviour

The model fit was assessed using several indices, including the Standardized Root Mean Square Residual (SRMR), Unweighted Least Squares (dULS), the Geodesic Discrepancy (dG), and the Normed Fit Index (NFI) as shown in Table 4. The SRMR values for the saturated and estimated models were .085 and .087, respectively, below the recommended threshold of .10, indicating an acceptable model fit. The NFI values were .922 (saturated) and .919 (estimated), exceeding the .90 benchmark and further supporting a good model fit. The model fit was further evaluated using two distance-based discrepancy measures: the Unweighted Least Squares Discrepancy (dULS) and the Geodesic Discrepancy (dG). These indices assess how well the estimated model reproduces the observed variance-covariance matrix, with lower values indicating better fit (Dijkstra & Henseler, 2015; Henseler et al., 2014). For the saturated model, dULS was 11.114 and dG was 19.374, while for the estimated model, these values were slightly higher at 11.869 and 19.632, respectively. Although no strict cutoffs exist for these indices, the relatively small increases from the saturated to the estimated model suggested that the proposed model maintained a reasonable fit, while being more parsimonious (Henseler et al., 2014).

Table 4 *Model Fit Assessment*

	Saturated Model	Estimated Model
SRMR	.085	.087
d_{ULS}	11.114	11.869
d_G	19.374	19.632
NFI	.922	.919

Note. Standardized Root Mean Square Residual (SRMR), Unweighted Least Squares (dULS), the Geodesic Discrepancy (dG), and the Normed Fit Index (NFI).

The latent variable prediction summary from the PLS-SEM analysis assessed the model's predictive power using metrics such as Q^2–predict, RMSE (Root Mean Squared Error), and MAE (Mean Absolute Error); the results are shown in Table 5. For Purchase Intention (PI), the Q^2–predicted value was .474, with RMSE and MAE values of .730 and .541, respectively. For Use Behavior (UB), the Q^2–predicted value was .450, with RMSE and MAE values of .749 and .566. Since both constructs showed positive Q^2–predicted values, this indicated that the model had acceptable predictive relevance (Shmueli et al., 2016). Moreover, the RMSE and MAE values were within a reasonable range, supporting the model's ability to generate accurate predictions.

Table 5 *Latent Variable Prediction Summary (PLS-SEM)*

	Q^2–Predict	RMSE	MAE
PI	.474	.730	.541
UB	.450	.749	.566

Partial Least Squares-Structural Equation Modeling Analysis

The inner structural model of Partial Least Squares (PLS) was conducted to evaluate the importance of the regression paths and the model's predictive performance. Table 3 below presents beta values (β), *t*-statistics, *p*-values, and the results of hypotheses, as per the work of Chin et al. (2003); these results are also shown in Figures 2 and 3. Upon analyzing the research model, seven hypotheses were found to exhibit statistical significance. Specifically, Effort Expectancy (EE) significantly influenced Purchase Intention (PI) (β = .049, *t* = 3.498, *p* = .001**), indicating a significant role in the decision to purchase a BEV. Hedonic Motivation (HM) also significantly affected Purchase Intention (β = .273, *t* = 2.026, *p* = .043*), suggesting that the enjoyment of using electric vehicles is an important factor. Price Value (PV) significantly positively affected Purchase Intention (*β* = .028, *t* = 6.055, *p* = .000**), highlighting the importance of cost considerations. Furthermore, Government Incentives (GI) significantly influenced Purchase Intention (β = .216, *t* = 5.408, *p* = .000**), underscoring the role of supportive regulatory frameworks, along with Facilitating Conditions (FC), which also exhibited a significant impact on Purchase Intention (β = .094, *t* = 4.921, *p* = .000***). In addition to this, Facilitating Conditions significantly impacted Use Behavior (UB) (β = .140, *t* = 6.364, *p* = .000**), indicating that external support and resources are essential for the actual use of electric vehicles. The most decisive influence was observed between Purchase Intention and Use Behavior (β = .777, *t* = 19.090, *p* = .000**), suggesting that intentions are highly likely to translate into behavior.

In contrast, some hypotheses were not supported. Performance Expectancy (PE) did not significantly influence Purchase Intention (β = .202, *t* = .168, *p* = .867), indicating that perceived performance may not be critical in this context. Social Influence (SI) was also not a significant determinant of Purchase Intention (β = .019, *t* = .296, *p* = .767), suggesting that peer and social pressure may not strongly affect purchasing electric vehicles. Lastly, Environmental Concerns (EC) did not significantly affect Purchase Intention (β = .250, *t* = 1.572, *p* = .116), indicating that ecological factors may not have been a primary motivator for purchasing electric vehicles in this study.

Figure 2 *Summary of the PLS-SEM Results*

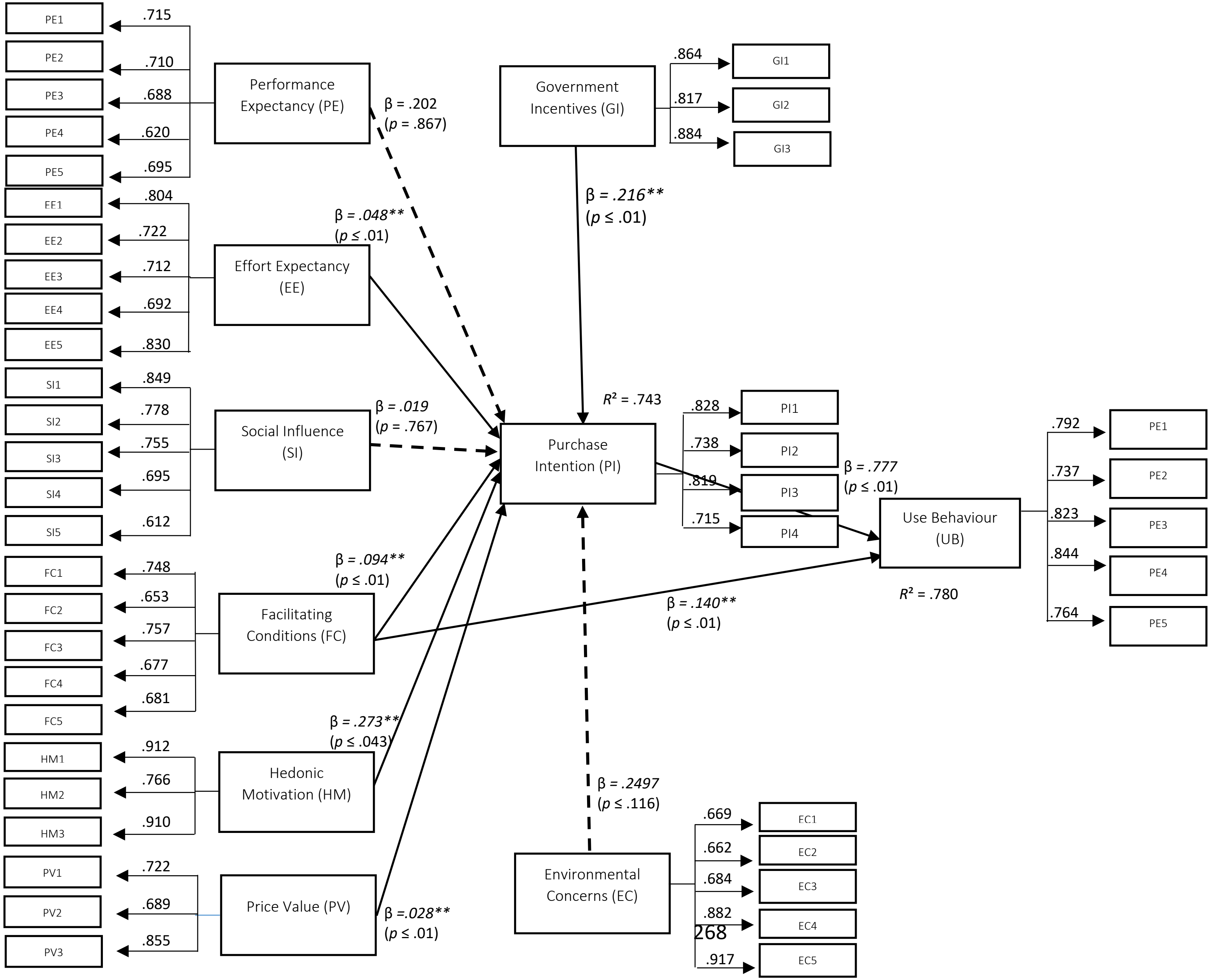
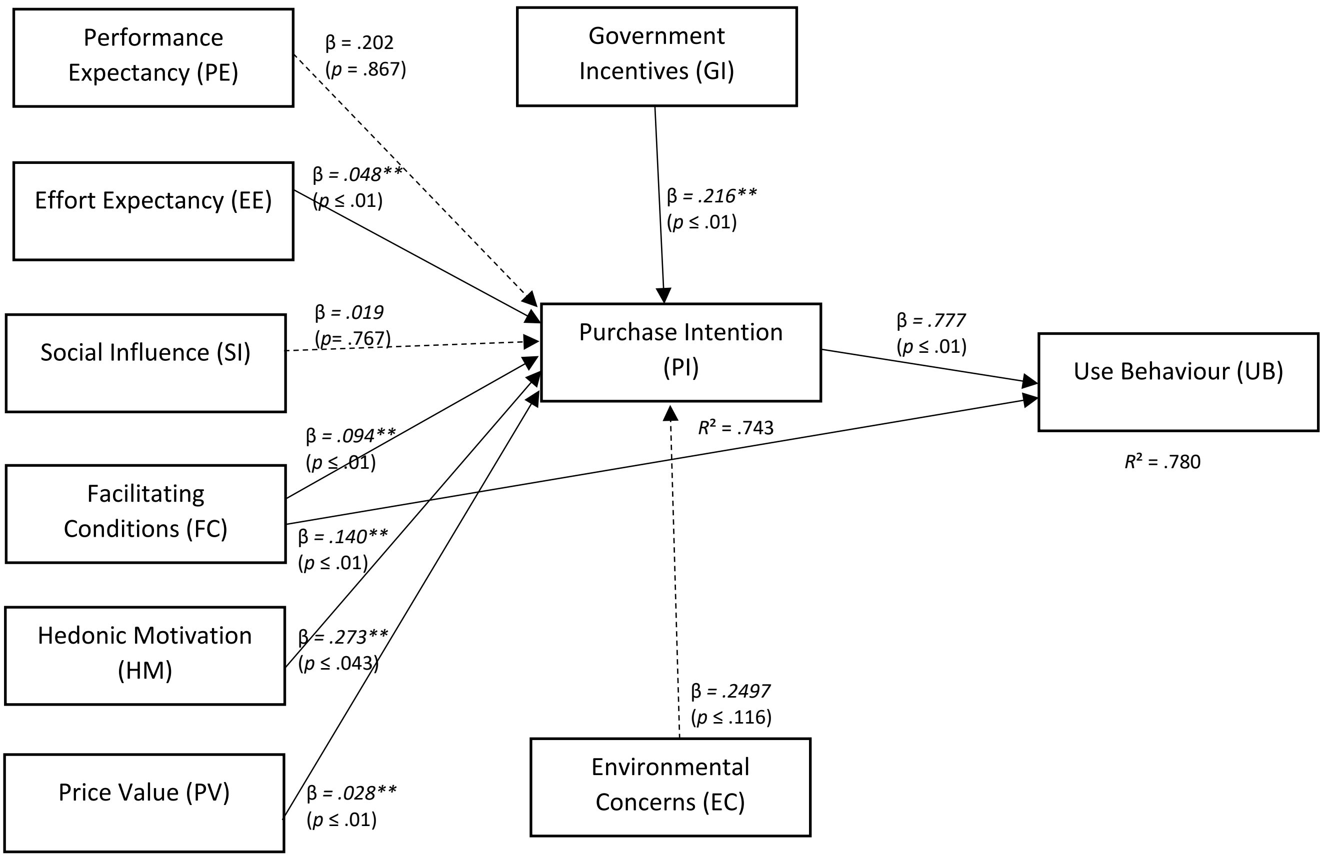


Table 3 *Results of Inner Model Testing*

Hypothesis	β	*t*-Values	*p*-Values	Hypothesis Results
PE -> PI	.202	.168	.867	Rejected
EE -> PI	.049	3.498**	.001	Supported
SI -> PI	.019	.296	.767	Rejected
HM -> PI	.273	2.026*	.043	Supported
PV -> PI	.028	6.055**	.000	Supported
EC -> PI	.250	1.572	.116	Rejected
GI -> PI	.216	5.408**	.000	Supported
FC -> PI	.094	4.921**	.000	Supported
FC -> UB	.140	6.364**	.000	Supported
PI -> UB	.777	19.090**	.000	Supported

Note. ** = *p*-value ≤ .01 and * = *p*-value ≤ .05.

Figure 3 *Partial Least Square – Structural Equation Modeling Results*



Discussion

The results of the PLS-SEM analysis show that seven out of the 10 proposed hypotheses were supported. These findings underscore the complex nature of consumer behavior toward BEVs in Nepal and highlight the varying impact of different UTAUT2 constructs.

Effort Expectancy (H_2) significantly affected the purchase intention of BEVs. Multiple studies have revealed that the perceived ease of use of electric vehicles positively impacts purchase intentions. For instance, a recent study reported that effort expectancy had a significant positive impact on the purchasing intention of EVs (Samarasinghe et al., 2024). Similarly, another study found that EE positively influenced travelers' behavioral intentions to use electric car-sharing systems in developing countries, where the perceived ease of use and maintenance of EVs were integrated into daily life

(Tran et al., 2019). These studies indicate that when consumers perceive BEVs as easy to use and maintain, they are more likely to consider purchasing one.

Facilitating Conditions (*H_4* and *$H_{4a)}$* have shown a significant impact on both purchase intention and use behavior. Research findings in Pakistan revealed a positive relationship between facilitating conditions and individuals' intentions to adopt public cloud technology, underscoring the importance of infrastructural support and regulatory frameworks (Ali et al., 2019). This highlights the role of facilitating conditions in overcoming barriers and enhancing the perceived ease of use and usefulness of new technology. Similarly, facilitating conditions have been shown to positively impact consumers' behavioral intention to purchase electric vehicles (Tu & Yang, 2019).

Hedonic Motivation H_5 significantly impacted the purchase intention of BEVs. A study showed that hedonic motivation positively affected attitudes toward using electric vehicles in Indonesia (Gunawan et al., 2022). Research has also shown that hedonic attitudes positively influence consumers' intentions to adopt hybrid electric cars (Zamil et al., 2023).

Price value H_6 had a significant impact on the purchase intention of BEVs. Research studies have indicated that consumers are willing to pay a premium for EVs within a specific price range (Larson et al., 2014). Financial incentives and reductions in upfront prices are significant factors driving EV adoption (Bjerkan et al., 2016)

Government Incentives H_8 also displayed a significant impact on the purchase intention of BEVs. Studies have shown that financial benefits and policy privileges positively influence BEV purchases (Wang et al., 2017). Similarly, research has found that previous experience with driving BEVs and perception of government incentives significantly influence purchase intentions (Kim et al., 2019).

Purchase intention H_9 significantly impacted the use behavior of BEVs. The intention to purchase reflected consumers' willingness to adopt BEVs, and plays a crucial role in shaping subsequent usage behavior (Huang & Ge, 2019). This study found that attitude, perceived behavioral control, and monetary incentive policies positively influenced consumers' intentions to buy EVs. Similarly, research has shown that purchase intention significantly impacts use behavior (Vafaei-Zadeh et al., 2022).

Contrary to much of the existing literature, this study found that Performance Expectancy (PE) did not significantly influence BEV purchase intention among respondents in Kathmandu, Nepal. Similar to findings by Verkijika (2018) and Abbasi et al. (2021), this outcome may have reflected the profile of the sample—predominantly young adults (37.1% aged 23–29), with a large proportion being students (40.1%) and early-career professionals. For this group, affordability and practicality likely outweighed expectations of performance, especially given their limited exposure to electric vehicles.

Social Influence (SI) was also non-significant, which may be attributed to the low visibility of BEVs in respondents' social environments. Even though more than half drove vehicles daily, BEVs were not yet prevalent in peer groups, limiting normative pressure. This aligned with findings in other developing contexts (e.g., Tran et al., 2019), where social influence was weak due to low market penetration.

While Environmental Concern (EC) was reported as important by 272 respondents, it did not translate into a significant predictor of purchase intention. This suggested a gap between environmental awareness and actual consumer behavior, likely driven by economic priorities. Cost savings, cited by 282 respondents, emerged as the most influential factor, underscoring the financial motivations behind the adoption of BEVs. Given that only 38.1% of respondents earned above Rupees 40,000 per month, price sensitivity may have overridden environmental considerations, consistent with previous research findings (Liu et al., 2015; Thananusak et al., 2017).

In sum, the insignificance of PE, SI, and EC can be better understood within the socio-economic realities of Nepal. BEV adoption is currently driven more by tangible financial benefits and practical considerations than by performance perceptions, peer influence, or environmental values. Policy and marketing efforts should therefore prioritize affordability, government incentives, and infrastructure development, while gradually building public awareness and environmental engagement.

Limitations and Implications

First, this study was limited by reliance on a sample of combustion engine vehicle owners due to the early stage of BEV adoption in Nepal, which restricted the ability to study actual BEV users' purchasing behavior. Future research should include more extensive consumer data with a more representative sample of BEV users. Second, the geographical scope was confined to Kathmandu, limiting the generalizability of the findings. This study could be expanded to other regions in Nepal, which would provide a broader understanding of BEV adoption in Nepal. Lastly, while the study focused on UTAUT2 constructs, it did not explore other potentially influential factors such as brand loyalty, fuel efficiency, etc. Future research should incorporate these factors to provide a more comprehensive view of BEV adoption in Nepal.

Conclusion and Recommendations

This study employed PLS-SEM to investigate the factors influencing the adoption of BEVs in Nepal, guided by the UTAUT2 framework and extended constructs. Effort Expectancy, Facilitating Conditions, Hedonic Motivation, Price Value, and Government Incentives significantly influenced consumers' Purchase Intention. These findings underscore the importance of ease of use, infrastructure availability, driving enjoyment, affordability, and supportive government policies in shaping consumer attitudes toward BEVs.

However, Performance Expectancy and Social Influence were not significant, suggesting that potential buyers in Nepal prioritize practical and experiential aspects over perceived performance or peer influence. Furthermore, Environmental Concerns did not significantly impact Purchase Intention or Usage Behavior, indicating that while sustainability is a global priority, Nepali consumers currently emphasize more immediate and tangible benefits. This suggests a need for awareness campaigns that translate environmental impact into more personally relevant terms for consumers.

This study confirmed a strong positive relationship between Purchase Intention and Usage Behavior, indicating that fostering strong intentions through favorable conditions and incentives is likely to lead to actual adoption. No significant mediators or moderators were identified in the current model, but further research could explore demographic or regional factors as potential influencers.

Based on these findings, policymakers should continue to improve BEV infrastructure and extend financial incentives to lower the adoption barrier. Marketers and manufacturers should design user-friendly and enjoyable BEV experiences to attract potential buyers, and environmental organizations and educators should create targeted campaigns that connect environmental benefits with consumers' personal values and daily lives. These recommendations align directly with the study's objectives and offer actionable insights for stakeholders aiming to accelerate BEV adoption in Nepal.

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