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Factors Demand Electric Vehicles: A Meta-Analysis

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Abstract
Electric vehicle (EV) adoption is influenced by economic, infrastructural, psychological, and policy-related factors, but the magnitude and consistency of these impacts vary across empirical studies.A meta-analytic framework was employed in this research to summarize the EV adoption literature quantitatively. By identifying 9 independent study-country units (total N=32,479), the authors extracted effect sizes (standardized coefficients (β), elasticities, marginal effects, willingness-to-pay (WTP) values) to be pooled and described the variability between studies even though formal heterogeneity statistics (Q, I^2) were not available due to a lack of reported standard errors. The pooled (β) findings indicated that technology perceptions had the most substantial positive impact on adoption intention (mean β≈0.29, k=3), social influence (β=0.19, k=3), and environmental concern (β=0.17, k=2) ranked next.The analysis of charging-related variables revealed that the effects were quite mixed (β=0.01, k=4), positive being seen as facilitating conditions and negative as barriers; technological constraints (limited range, slow charging) had a consistent negative effect (β= 0.36, k=1). Price factors were heterogeneous: financial barriers (β= −0.75) and positive perceived value (β=0.23) yielded an overall negative mean (β=−0.26, k=2). EV demand was highly sensitive to purchase price (elasticity=-2.0) and operating cost (elasticity=−1.2, k=2 each), with charging infrastructure positively associated with sales (elasticity=1.22, k=1). WTP estimates showed consumers paid a premium for lower costs, extended range, and faster charging. Moderator patterns indicated stronger charging and cost effects in developing markets, with psychological and social factors consistent across contexts.
The present study gathers the factors leading to the adoption of electric vehicles (EVs), elucidates the relative importance of the main factors, and identifies gaps, mainly the lack of studies on driving range and policy incentives.

Key words: Electric Vehicle Adoption, Purchase Intention And Behavior, Charging Infrastructure, Economic And Psychological Determinants, Meta-Analysis

Introduction
Transportation is a significant source of greenhouse gases on a global scale. It is responsible for a huge chunk of the total carbon emissions from human activities. In fact, this sector is considered to be the main obstacle for the world in achieving climate

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goals. Among different transportation modes, road vehicles (passenger cars, light commercial vehicles, and heavy-duty trucks) have been the main source of transportation sector's emissions. A great portion of these emissions are generated by vehicles with internal combustion engines locally, in most cases (Wang et al., 2025). Actually, converting the passenger vehicle fleet to electric is globally regarded as the primary solution to climate change, at both the national and international stages, as electric cars (EVs) have an extremely high potential to drastically cut down carbon emissions in the long term and to decrease therefore also the levels of the air pollutants and subsequently the hazards to our environment and public health (Hofmann et al., 2016).

Thanks to enhanced battery energy density and cycle life, falling battery production costs, and ongoing government initiatives such as consumer incentives, tax breaks, and the introduction of zero-emission vehicle mandates, which have been put not only in the world's powerhouse economies but also in the developing markets, EV sales have skyrocketed over the last few years (Muratori et al. 2021).

However, EVs adoption is uneven, with some countries and specific consumer segments more easily welcoming the new technology than the others. Developed countries with strong infrastructure and well-functioning policies have done best in this regard, whereas many developing countries have fallen behind due to various limitations (Morton et al., 2017). Moreover, even at a single market level, there exist differences between higher income and middle- to low-income consumers as well as between urban and rural dwellers in terms of vehicle uptake. This is an indication that the mere technological advancement will not be able to bring electric vehicles into the lives of all consumers and that wider social and economic factors are at the core of the issue.

There is an increasing number of studies that are focusing on understanding the main factors and obstacles affecting the varying degrees of consumer willingness to adopt electric vehicles. This is done in order to comprehend why some consumers decide on EVs while others postpone or simply reject them (Adnan et al., 2017a). Prior research has repeatedly pinpointed several drivers that are mutually dependent and which among the main four dimensions are the economic factors (Sierzchula et al., 2014) that deal with the purchase price (Liao et al., 2019), the initial cost premiums (Mandys, 2021), and the long-term operating costs (Haddadian et al., 2015); the next are the infrastructure and technology factors that include the availability of charging, the charging speed, and the driving range (He et al., 2022); the third are policy instruments which are made up of financial subsidies, non-financial incentives, and regulations (Hardman, 2019); and the last of the four major categories are the psychological and social influences which consist of environmental awareness, social norms, perceived technology reliability, and brand perceptions (Liu et al., 2020). Nevertheless, the size and even the direction of these effects differ quite a lot between the studies that have been done so far (Coffman et al., 2017). These contradictions can be explained by differences in the level of market maturity (Yang et al., 2023), the nature and degree of policy implementation, cultural and societal contexts, research methodologies, and

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measurement tools (Zhao et al., 2024). Also, the focus of a study on either behavioral intentions or actual adoption outcomes (Adnan et al., 2017b) plays a role.

With the expansion of the literature on EV adoption covering various regions and research paradigms, it has become increasingly difficult to estimate the size and to derive the relative importance of the key adoption drivers just by looking at individual studies or narrative reviews. A meta-analytic approach bridges this gap by systematically combining quantitative evidence for the purpose of estimating the average effect sizes and finding the moderating variables that explain cross-study discrepancies. This is especially useful when one wants to compare the roles of affordability, infrastructure readiness, psychological and social determinants, and policy incentives in different contexts and for various types of outcomes.

In light of this, the present research performs a meta-analytic synthesis of the determinants of EV adoption, tackling four main objectives in particular. It measures the combined effects of the purchase/upfront cost, operating cost, charging accessibility, and driving range on the EV adoption intention and behavior, together with those of government incentives and the environmental-psychological factors, which include environmental awareness, social influence, and technology perceptions. Besides, the study explores the differences in the combined effects between developed and developing markets and between intention-based and actual adoption outcomes, while at the same time pointing out the most influential factors and explaining the relative importance of the economic, infrastructure, psychological, and policy drivers. Through the measurement of these effects and the structuring of evidence among effect-size families, market types, and outcome categories, this research aims to promote the development of theories through a rigorous approach and provide practitioners with a roadmap for EV policy-making, infrastructure planning, and market strategy, thus, solving the inconsistencies in the existing research and furnishing a solid empirical ground for a wider stakeholder base to contribute to EV adoption as a vital decarbonization measure.

Methodology

Review Design, Search, and Eligibility Criteria

The study employs a quantitative meta-analysis method to combine data from different studies in the literature about the factors influencing the intention and behavior of adopting electric vehicles (EVs). We set up an a priori review protocol to pre-define our research questions, a search strategy, the criteria for article selection, data extraction methods, the way we calculate effect sizes, and a statistical analysis plan. This protocol is in line with the criteria for systematic reviews and meta-analyses in social and environmental sciences that guarantee openness and reproducibility (Field & Gillett, 2010).

Systematic literature searches were carried out in Scopus, Web of Science, ScienceDirect, IEEE Xplore, and Google Scholar to identify empirical studies exploring relationships between EV adoption outcomes and key drivers. The search period spanned 2011 to 2025, with the final update conducted in December 2025. The core search string combined keywords across three domains: electric vehicles, adoption behavior, and potential determinants. It was formulated as: ("electric vehicle" or EV or BEV or PEV) AND (Adoption or purchase intention or choice or diffusion) AND (price or cost or charging or infrastructure or range or subsidy or incentive or attitude or norm or environmental concern or social influence or performance expectancy). Where feasible, this string was applied to titles, abstracts, and keywords. Reference lists of relevant reviews and included articles were additionally screened through backward snowballing to identify further eligible studies. Studies were included only if they met all criteria: adoption of empirical quantitative designs, namely survey-based structural equation modelling, regression, and discrete choice experiments; focus on EV adoption intention willingness to adopt or actual adoption/choice (sales and registrations) as the dependent variable; investigation of at least one determinant within four factor groups (economic: purchase price, operating cost, financial barriers; infrastructure/technology: charging availability, driving range, charging time; psychological/social: environmental concern, social influence, technology perceptions; policy: subsidies, tax credits, incentives); and provision of sufficient statistical information to compute effect sizes, namely standardized coefficients β, marginal effects, elasticities, odds ratios, and willingness-to-pay (WTP).

Exclusion criteria encompassed purely qualitative studies, such as interviews conducted without quantitative modelling; macro-level automobile market studies that failed to isolate EV adoption; conceptual papers, reviews, or commentaries lacking original empirical estimates; and studies without extractable quantitative relationships between the specified determinants and EV adoption outcomes. Technical multi-criteria decision-making studies and narrative reviews were excluded from the meta-analytic dataset but may be cited in the background and discussion sections for contextual purposes. Study selection proceeded in line with the PRISMA guidelines. Following duplicate removal, titles and abstracts were screened to eliminate irrelevant records, and the remaining articles underwent full-text assessment against the aforementioned eligibility criteria (Takkouche & Norman, 2011). Full-text exclusion applied to studies lacking extractable effect sizes, those using multi-criteria decision-making methods for fleet selection, studies modeling aggregate automobile sales without isolating EV outcomes or EV-specific determinants, and non-empirical reviews or editorials (Polanin et al., 2016). The final meta-analytic dataset comprised k = 9 study–country units for quantitative synthesis.

Data Extraction and Effect Size Processing

A structured coding template was designed to extract comparable information from eligible studies. For each study, we included relevant subsamples like country-specific models and extracted the following information: bibliographic details including authors and year; study country or region and its classification as a developed or developing market; sample size and respondent type including private consumers and households; outcome type, distinguishing between adoption intention and actual adoption; determinants mapped to the four factor groups; statistics required for effect-size calculation; and variables relevant to moderating analyses, including data collection year and whether respondents were consumers or fleet buyers. Each distinct quantitative relationship between a determinant and EV adoption outcome was treated as one effect-size entry, provided it met the eligibility criteria. When a single study reported multiple coefficients for the same determinant-outcome pair across different models or subgroups, each coefficient was included as a separate entry.

Because the studies in the review used such different methods and reported such different metrics, four effect size categories were harmonized for the analysis: standardized coefficients (β) from regression or structural equation models, which show the standardized change in the outcome for a one-standard-deviation change in the factor; marginal effects, which show the changes in the predicted probability of EV adoption for a unit change in the factor; elasticities, which show the percentage changes in EV adoption resulting from a one-percent change in price or operating cost; and WTP measures, which represent the monetary values of changes in attributes such as driving range and charging time.

Each effect size was coded so that positive values indicate higher adoption intention or behavior of EV, while negative values refer to barriers. To keep this consistency, the signs were changed where it was necessary. To keep the results understandable, different meta-analytic syntheses were done for each effect-size family, thus the factor groups were still comparable but there was no need to combine scaling into one metric.

Meta-Analytic Model

Random-effects models were used for all syntheses, as true effects are expected to vary across countries, policy environments, and study design. This framework conceptualizes each observed effect size as an estimate of a study-specific true effect, which is derived from a distribution of true effects (Borenstein et al., 2010). For each determinant within an effect-size family, pooled descriptive statistics, including mean and range, were employed instead of formal random-effects meta-analysis with confidence intervals. Insufficient standard error data restricted the use of inverse-variance weighting, so results are interpreted as an exploratory quantitative synthesis rather than fully parameterized pooled estimates. Between-study heterogeneity was evaluated using Cochran's Q statistic, I^2 index, and between-study variance τ^2. I^2 values of 25%, 50%, and 75% correspond to low, moderate, and high heterogeneity, respectively. Moderator and subgroup analyses were performed where data allowed to address Research Question 3 and explore sources of heterogeneity. Pooled effects were compared across developed and developing markets, as well as between intention-based and actual adoption outcomes. Exploratory moderators, including data collection year and modeling approach, were considered when supported by data, with tests conducted via subgroup meta-analysis or meta-regression. Differences were interpreted based on existing theory and prior reviews.

Publication bias and small-study effects were assessed for determinants with at least three effect-size estimates, combining visual inspection of funnel plots and formal tests where appropriate. If asymmetry was detected, adjusted pooled estimates were reported alongside original values, with relevant discussions included in the limitations section. Sensitivity analyses were performed to verify the robustness of conclusions. Leave-one-out checks recalculated the pooled means by sequentially removing each study for

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determinants with three or more effect sizes. Results were compared across effect-size families to confirm directional consistency, and sign conventions for determinants framed as facilitators or barriers were verified through rechecks after excluding barrier-based constructs. Conclusions remained substantively consistent across all checks, confirming robustness. Formal standardized risk-of-bias assessment tools were not applied due to the diverse study designs, for which no universal quality instrument exists. Instead, study quality was evaluated using a structured checklist covering outcome clarity, model transparency, reporting of sample size and data sources, and construct validity. All included studies met minimum quality criteria and provided original empirical estimates. Potential biases arising from differences in design, measurement, and reporting, notably the limited availability of standard errors, are noted in the limitations section, emphasizing the need for cautious interpretation of pooled results. Extracted effect-size data and study characteristics were compiled into a structured database, which is provided as Supplementary Material. The database contains study identifiers, country and market classification, sample size, outcome type, determinant group, effect-size format and value, and interpretation notes. Each row corresponds to a distinct determinant-outcome relationship, thereby ensuring transparency and reproducibility while facilitating future updates as additional studies become available.

Results

Descriptive overview of included studies

The final meta-analytic dataset includes nine independent study-country units, encompassing the United States, China, India, Spain, Vietnam, and a regional case study of California. Across these studies, 27 distinct effect-size entries were extracted, each capturing a quantitative relationship between at least one determinant and an EV adoption outcome, either intention or actual adoption. Sixteen effects derive from developed markets and eleven from developing or emerging markets, laying the groundwork for contextual comparison.

Table1. The key characteristics of the included studies, including country/region, market type, outcome type, sample size, and the main predictors represented in each case.

	Author – Year	Country/Region	Market type	Outcome type	Sample size (N)	Main predictors included
1	Anh et al. 2024 (Made-in-Vietnam EV demand)	Vietnam	Developing	Intention (Demand/WTP)	212	Price, Operating Cost

2	Cai & Yan 2022 (California sales)	USA EV(California)	Developed	Actual adoption/sales	431	Charging, Incentives
3	Chen et al. 2021 (US DCE + CGE)	USA	Developed	Intention/choice (stated preference)	1,657	Price, Operating Cost
4	Hidrue et al. 2011	USA	Developed	Intention/choice (stated preference DCE)	3,029	Charging, Operating Cost, Range/Technology
5	Higueras-Castillo et al. 2023	India	Developing	Intention	378	Charging, Environmental Concern, Social Influence, Technology Perception
6	Higueras-Castillo et al. 2023	Spain	Developed	Intention	265	Charging, Environmental Concern, Social Influence, Technology Perception
7	Lohawala & Rahman 2025	USA	Developed	Intention	25,426	Environmental Concern, Charging
8	Pamidimukkala et al. 2023 (US barriers SEM)	USA	Developed	Intention	733	Charging, Range/ Technology, Price/Operating Cost (Financial barriers)
9	Wang et al. 2023 (China UTAUT)	China	Developing	Intention	348	Price (Price value), Charging (Facilitating conditions), Social Influence, Technology Perception, Incentives

Standardized effects on EV adoption intention

Several included studies used structural equation or regression models to estimate standardized coefficients β for the determinants of EV adoption intention. These β coefficients allow for direct comparison of the relative strength of psychological, social,

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economic, infrastructural, and policy-related drivers both within and across studies. Table 2 presents the number of standardized effect sizes available for each core predictor, alongside the mean, standard deviation SD, and observed range.

Referring to Table 2, the technology perceptions which are later referred to as performance expectancy have the strongest average positive impact on adoption intention, with a mean β of 0.290 coming from three effect sizes. This work indicates that when individuals perceive EVs as useful and technologically advanced, the probability of their expressing adoption intention is significantly increased.

Social influence has another substantial positive effect with a mean β of 0.188 over three effect sizes, which is explained by the fact that peer norms and perceived social pressure play a major role in a person's decision to support the adoption of EV.

Environmental concern is shown to be a factor with a smaller but steady positive effect with a mean β of 0.167 from two effect sizes, which is the case that individuals who are more aware of the environmental issues are more likely to express their intention to adopt EVs.

Incentives reveal a slight positive effect with a mean β of 0.099 from one effect size, though due to the small sample size this result cannot be generalized.

Table 2. Summary of standardized effects (β).

Predictor (core)	k (effects)	Mean β	SD β	Min β	Max β
TechnologyPerception	3	0.290	0.130	0.163	0.422
SocialInfluence	3	0.188	0.185	0.017	0.384
EnvironmentalConcern	2	0.167	0.039	0.139	0.194
Incentives	1	0.099	–	0.099	0.099
Charging	4	0.007	0.285	−0.401	0.221
Price	2	−0.259	0.693	−0.749	0.231
Range/Technology	1	−0.360	–	−0.360	−0.360

In contrast, price- and cost-related constructs show more heterogeneous effects that are often negative, with a mean β of −0.259 across two effect sizes. A composite financial-barriers index in one study yields a strongly negative coefficient of −0.749, while a perceived "price value" measure in another study generates a positive coefficient of 0.231. Beyond this heterogeneity, the pooled mean β for price-related constructs reflects the net barrier role of costs particularly when framed as financial obstacles rather than value-based perceptions. Charging-related constructs exhibit mixed standardized effects: positive coefficients correspond to facilitating conditions such as charging accessibility, while negative coefficients relate to infrastructure barriers, resulting in a near-zero mean β of 0.007 from four effect sizes. Technological constraints, including limited driving range, prolonged charging time, and battery-related concerns, show a consistently negative effect with a β of −0.360 from one effect size, underscoring their role as a key barrier to EV adoption intention.

The figure 1 illustrates the relative size of the average standardized effects of core predictors on EV adoption intention. It can be clearly seen in the figure that among the

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factors considered, Technology Perception is the one that has the strongest positive effect on adoption intention, as evidenced by its tallest positive bar. Social Influence and Environmental Concern come next, showing smaller but still positive impacts on intention, while Incentives account for a somewhat limited positive effect. Charging-related factors indicate very little overall impact, which is in line with the mixed directional effects at the study level. On the other hand, Price and Range/Technology behave as deterrent factors: both of them have negative effects on adoption intention, with Range/Technology being the most significant deterrent among all predictors.
This figure summarizes the relative magnitude and sign of the influence of each factor, thus it is an easy-to-understand comparative overview of the facilitators and inhibitors of EV adoption intention that have been extracted in the form of effect sizes.

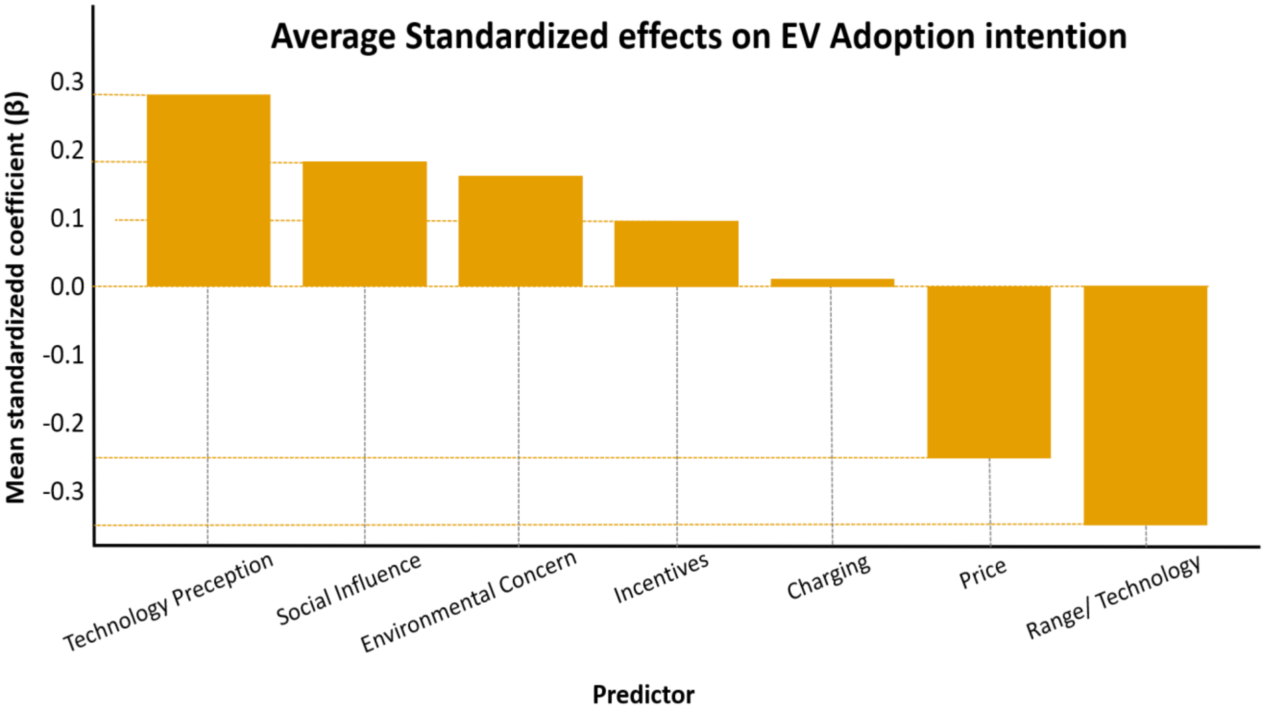

Figure 1. Average standardized coefficients (β) of key determinants on EV adoption intention.

Elasticities of adoption with respect to price, operating cost, and charging
A second set of included studies reports elasticities of EV adoption or demand relative to purchase price, operating cost, or infrastructure metrics; these elasticities quantify the percentage change in EV adoption corresponding to a 1% change in the focal determinant, with results summarized by predictor in Table 3.
Consistent evidence identifies higher purchase price as a barrier to EV adoption: a U.S. A discrete choice study shows that a 1% increase in the purchase price of an EV leads to a 2.66% decrease in the share of battery electric vehicle adoption, whereas a demand analysis for Vietnam gives a price elasticity of 1.39. These different measures taken

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together mean that EV demand is very sensitive to prices; being more sensitive in developing countries where consumers are more budget-constrained. Likewise, operating cost-related demand elasticities importantly determine the adoption results: one of the studies suggests that a 1% rise in the battery rental price decreases the demand for EV by 3.12%, whilst a scenario-based study points out that an increment in the prices of conventional fuels for internal combustion vehicles is raising the market share of the battery electric vehicle with a positive elasticity of 0.73. The latter thus reflects that lower running costs of EVs (Electric Vehicles) are a source of greater attraction for them, whereas an increase in recurring EV-related costs is a very strong factor of deterrence. For charging infrastructure, a California regional case study estimates that a 1% increase in public charging station count correlates with a 1.22% rise in EV sales; this finding indicates that physical infrastructure provision is not only symbolically relevant but also measurably tied to greater realized adoption.

Table 3. Elasticities by predictor.

Predictor (core)	Effect-type example	k	Mean elasticity	Min	Max
Price	Arc elasticity of BEV share w.r.t. purchase price (US DCE); demand-price elasticity (Vietnam)	2	−2.02 (approx.)	−2.66	−1.39
Operating Cost	Elasticity of EV demand w.r.t. battery rental price (Vietnam); BEV share w.r.t. fuel price (US)	2	−1.20 (approx.)	−3.12	0.73
Charging	Elasticity of EV sales w.r.t. number of charging stations (California)	1	1.22	1.22	1.22

Figure 2 depicts the most common elasticities of electric vehicle (EV) adoption with respect to the three main predictors. It shows not only the direction but also the relative size of each factor's impact on the model. Among the predictors, Charging is identified with a positive elasticity, thus a positive, enabling relation with EV adoption. On the other hand, both Operating Cost and Price are identified with negative elasticities, thus they are inhibitory or have the opposite effect to EV adoption. In fact, the Price variable has been identified as the one that shows the most drastic negative elasticity, while the negative effect of Operating Cost is comparatively minor. Altogether, such a plot provides a clear conceptual picture of how Price is the strongest limiting factor for EV adoption among the three predictors, it also shows that Operating Cost has a limiting effect, and Charging is a facilitating factor for EV-adoption

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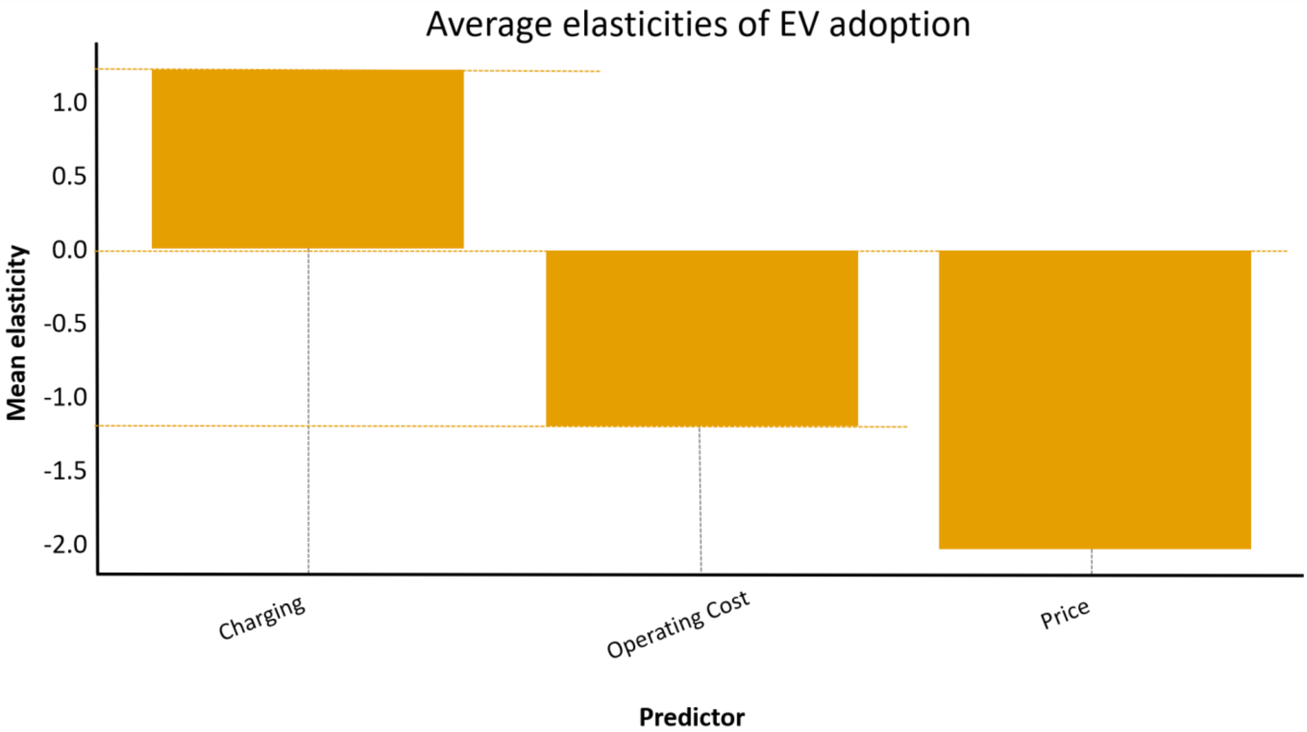

Figure 2. Average elasticities of EV adoption or demand with respect to price, operating cost, and charging infrastructure.

WTP for EV attributes

In the dataset, a portion of discrete choice experiments revealed the willingness-to-pay for upgrades of main electric vehicle attributes. Table 4 summarizes the consumer willingness-to-pay (WTP) for operating-cost savings, driving range, and charging convenience along with the attribute measurement specifications, sample size k, and shared monetary value range for each renovation. By taking each WTP figure from one separate research, the mean, minimum and maximum values for each attribute are in fact the same. A study conducted in the US concerning the reduction of fuel-cost-equivalent by one gallon per USD along the vehicle note an WTP of USD 2,706 for such an operating-cost saving brought about by a method of the fuel's life cycle. This number indicates that customers have a very high preference for lower long- term operating costs since the savings made from recurring expenses will be helpful enough economically to make one decide to adopt EV. As for the driving range, this study identifies a WTP of USD 75 per extra mile within 75-150 miles segment, showing that limited range still remains the main issue consumers have with EVs that the incremental improvements in terms of money can be seen there. To quantify the charging convenience the estimate provides a WTP of USD 930 for a one-hour decrease in charging time, for instance, from 5 hours to 1 hour charging. In view of these results, it is confirmed that consumers set a high monetary value on faster charging thus making charging convenience a key feature in consumer EV purchase decision.

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Taken together, the evidence revealed through these WTP tests confirms that the operational, range, and charging-related attributes of one's electric vehicle not only carry economic weight with the consumers but are the factors that most influence their preferences. In fact, consumers are so willing to spend money to get something better in each of these areas that it correlates well with previous elasticity and coefficient studies which demonstrate that these are the key determinants for consumer EV adoption.

Table 4. WTP-based effects by predictor

Predictor (core)	WTP measure (from DCE)	k	Mean WTP (USD)	Min	Max
OperatingCost	WTP per 1 USD/gal equivalent reduction in fuel cost	1	2,706	2,706	2,706
Range/Technology	WTP per additional mile of driving range (75–150 mile segment)	1	75	75	75
Charging	WTP per 1-hour reduction in charging time (1h to 5h)	1	930	930	930

Market-type and outcome-type patterns

Research Question 3 explored whether the strength of effects varies between developed and developing markets, and between intention-based and actual adoption outcomes. Limited reporting of standard errors means these patterns are interpreted descriptively rather than through formal statistical tests. Comparing standardized coefficients across market types suggests that the importance of charging-related constructs is context dependent. Table 4 presents the market and the outcome type differences in EV adoption.

Table 5. Market and Outcome Type Differences in EV Adoption

Construct/Factor	Effect in Developed Markets	Effect in Developing Markets	Outcome Type
Charging-related constructs	Negative effect (β= -0.40) when measured as barriers	Positive effect (β= 0.18–0.22) on intention	Intention-based outcomes (intention to adopt)
Economic constructs (financial barriers)	Strong negative effect (β= -0.75) from financial barriers	Positive effect (β = 0.23) from perceived price value	Actual adoption outcomes (sales, registrations)
Psychological and social determinants (e.g., social	Estimated on intention outcomes, moderate effect (β = 0.17–0.19)	Estimated on intention outcomes, moderate effect (β = 0.17–0.19)	Intention-based outcomes

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influence, environmental concern)		(intention to adopt)

In developing or emerging markets like India and China, facilitating conditions and building confidence have been found to positively impact intention, with beta values around 0.18 to 0.22. It means that having a charging infrastructure available is still regarded as a key factor that determines the adoption of EVs in those areas. On the other hand, in developed markets, charging-related coefficients generally come out as negative when assessed as barriers, with a beta value of about -0.40. Indeed, this indicates that the inadequacy of infrastructure alone works can still demotivate the intentions even in zones with better network coverage.

Economic constructs also exhibit cross-market variation. In one developed-market study, financial barriers that combine high purchase prices, home upgrade costs, and fears of battery replacement have a strong negative standardized effect, with a beta value of around -0.75. In contrast, a developing-market study found perceived price value has a positive effect, with a beta value of approximately 0.23. This contrast underscores the need to distinguish between objective financial burdens and subjective value perceptions, as well as to account for income differences across markets. Regarding outcome type, most psychological and social determinants, including technology perceptions, social influence, and environmental concern, are estimated based on intention outcomes and show moderate standardized effects. Economic and infrastructural determinants, by contrast, feature more prominently in models of actual adoption, including sales, registrations, and demand elasticities. This aligns with theoretical expectations: psychological and social factors are particularly influential in shaping stated intentions, while realized sales are especially sensitive to prices, operating costs, incentives, and physical infrastructure.

Conclusion and Discussion

Conclusion

This study makes a meta-analytic synthesis of the published works where it systematically explored economic, infrastructural, psychological, and policy factors that influence electric vehicle adoption using evidence from Tables 1 4 and averaged effects in Figures 1 and 2 to find consistent patterns as well as significant contradictions. Most of the changes in these factors have been attributed to market context, method of measurement, and research design. When comparing the results of standardized coefficient studies, the perception of technology or performance expectancy is the characteristic factor which most consistently and strongly positively influences the intention to adopt an electric vehicle, continuing to have a quite stable impact even across markets of different levels of development such as Spain, a developed market, and China and India, developing markets. Besides the social influence and environmental concern also show moderate, reliable positive impacts across the studies, with hardly any differences in market type and these findings are in line with prior behavioral research. However, if we look at actual electric vehicle adoption that is obtained from sales or registration data, we can see that this is mainly influenced by

economic and infrastructure factors. Price elasticities in the range of 1.39 to 2.66 provide evidence of very high price sensitivity. On the other hand, operating cost and charging infrastructure elasticities also indicate strong customer responsiveness and a direct positive effect respectively. There is also a case study from California that illustrates this point, where the number of charging stations went up by 1% and the sales of electric vehicles increased by 1.22%. This difference in focus is explained by the fact that intention models put more emphasis on psychological constructs, whereas real world market data tend to highlight structural and economic enablers.
Key contradictions in the literature stem from measurement framing, metric type, and outcome distinction. Charging-related factors present the most striking inconsistency: positive effects when measured as facilitating conditions in India and China, strongly negative effects when framed as infrastructure barriers in the USA, a robust positive elasticity when quantified by objective charger counts, and substantial willingness-to-pay values for charging time reductions. This mix of positive and negative effects explains the near-zero average coefficient for charging, as opposing values offset each other. Also, price effects are in contradiction with each other based on the framing: they are negative if financial barriers are the frame, positive if price value is the frame, and very negative in elasticity measures. This is a mirror of the difference between price value as a benefit that is perceived and financial barriers as a real cost burden. Range-related evidence is similarly mixed, appearing as a psychological constraint via negative standardized coefficients and as a valued attribute via positive willingness-to-pay for additional miles. Each metric highlights the importance of the range from different angles. To some extent, the discrepancies between the two are clarified when considering outcome type: intention models focus on psychological variables whereas behavioral models emphasize economic and infrastructure factors. Differences between markets also play a role with positive charging effects largely found in the developing markets, negative charging barrier effects mainly located in the developed markets such as the USA, and price sensitivity being greater in developing regions. This is a manifestation of the fact that structural barriers are intensified by the lack of infrastructure and low incomes in the developing markets, while there is a move towards psychological and experiential factors in the developed contexts.

Relevant Recommendations

The study findings offer practical implications for accelerating EV adoption from two perspectives, i.e., policymakers and manufacturers.
For policymakers, reducing upfront cost burdens and safeguarding affordability stands as a priority measure: elasticity estimates confirm EV adoption is highly sensitive to purchase price, while standardized intention evidence indicates perceived financial barriers can significantly suppress adoption intentions, underscoring the enduring policy relevance of instruments that lower upfront costs including purchase subsidies, tax credits, and reduced registration fees especially in developing and emerging markets where price sensitivity tends to be higher, and clear messaging on affordability is also crucial to help consumers perceive EVs as valuable rather than financially risky. Policymakers should also focus on lowering operating costs and mitigating uncertainty

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around recurring expenses, as operating cost effects are substantial in both elasticity-based evidence and willingness-to-pay results; targeted strategies include transparent electricity pricing for charging, standardized charging cost information, warranty protections, and programs to alleviate battery-related risk perceptions, with regulation and consumer protections essential in markets with recurring charges like battery rental models to avoid deterrent effects. Investing in charging infrastructure with an emphasis on convenience is another high-impact measure, given charging's multifaceted relevance objective infrastructure availability correlates positively with sales outcomes, and consumers attach significant value to time-saving and convenience, so policies must go beyond increasing charger quantities to enhance reliability, accessibility, charging speed, equitable geographic coverage, and reduce queuing uncertainty, with visible infrastructure expansion playing a key role in building consumer confidence in developing markets. Additionally, policy incentives are effective but context and design-dependent: evidence on incentives is positive yet limited, with well-designed subsidies boosting real-market adoption and incentives operating partly through indirect channels like improving perceived value, so policy design should prioritize clarity, simplicity, and consumer salience such as point-of-sale rebates over delayed tax refunds, and align incentive programs with infrastructure improvements and trust-building measures to maximize effectiveness.

One of the ways through which the study results benefit the producers is that they get to have a checklist of features that new products and marketing strategies should have in order to satisfy the identified typical consumers. Since the consumers' perceptions of technology can lead to their usage intentions, manufacturers are strongly encouraged to concentrate on the core performance characteristics of electric vehicles (EVs) first and then communicate to consumers the technical advantages in such a way that it increases their positive perceptions of EVs in terms of utility and reliability. Eliminating users' fears about the EV range is a must. Range anxiety, which is mostly a mental barrier, does not prevent consumers from valuing extra range quite highly; thus, manufacturers should give more support to battery technology capable of longer-range driving, and use this as a selling point, together with keeping customers well-informed about real-world driving range to lessen doubt. As far as cost is concerned, manufacturers might tailor their pricing approaches to make an allowance for the combination of consumers' preference for low initial prices and the perceived value, since consumers are sensitive to both purchase price and operating costs. The ability to cut production costs can enable one to set lower prices, whereas the simultaneous promotion of lower long-term running costs is possible through the offering of battery-related services such as a flexible rental model which may be very inviting. Additionally, understanding that consumers are very eager to pay more for the convenience of charging, manufacturers ought to work together with the infrastructure providers in order to make charging compatible and faster, as well as incorporate the easy-to-use charging features in the vehicle design, and at the same time give consumers clear information about charging costs and the whole experience in order to lower their uncertainty.

Discussion

This work helps to better understand the main motivators for and barriers to the adoption of electric vehicles through a systematic meta-analytic synthesis. It resolves the turmoil of the present literature by integrating various economic, infrastructural, psychological, and policy aspects in different markets and with different measures. One of the essential results points out that technology perceptions are the most consistent factor influencing the adoption intention of a new technology. This is in line with the Theory of Planned Behavior that considers attitude and perceived behavioral control as the most important factors leading to intention. Such a pattern being confirmed in both developed and developing markets proves that consumers globally are mainly concerned with the utility and performance of electric vehicles, which supports the findings of the previous study that technological trust is the main barrier to electric vehicle adoption. The difference between the intention and actual behavioral drivers makes the explanation of this in-between gap even clearer: the models of intention are mostly influenced by psychological factors while economic and infrastructure variables determine the real adoption. Hence, it is implied that attitudes-only research might understate the influence of the presence of structural factors, which is also in harmony with the studies on sustainable consumption.

In the literature, the inconsistencies seen mainly on charging, price, and range point out the very important role of how the research is framed and which metric is chosen in determining the final research results. As for charging, the presence of both positive and negative effects indicates that the infrastructure has a double nature of being a facilitating condition on one hand and a potential barrier on the other. Contextual factors such as market development stage explain this inconsistency. Developing markets have been described as having a scarcity of infrastructure, whereas developed markets have been characterized as perceiving infrastructure as a barrier (Priessner et al., 2018). This already complicates previous literature that predominantly concentrates on single market contexts. Price effects vary by framing because price value captures subjective benefit perceptions, while financial barriers reflect objective cost burdens (Kim et al., 2017). The consumers' reaction to price is not only economically motivated but also influenced by their mental framing, a finding that deepens the existing literature on price sensitivity in electric vehicle uptake. At the same time, the paradoxical evidence concerning range highlights the difference between psychological barriers, e.g. range anxiety, and the economic valuation of the range extension (Scott & Qin, 2025). Therefore, it can be seen that the consumers are emotionally as well as rationally evaluating the concept of 'range', a dual aspect hardly ever explicitly tackled in the previous meta-analyses.

Cross-market differences have greatly helped in understanding the contextual influences (Liu et al., 2024). Developing markets tend to react more heavily to physical and economic obstructions such as prices and facilities, whereas established markets focus their attention on emotional and experiential issues. This is in line with the theory on the diffusion of innovations which says that the reasons for the adoption of a technology change over time. Hence the markets in developing countries which are at the early stages of adoption mainly emphasize accessibility, whereas mature markets in developed countries which are at the later stages focus more on the user experience.

These are but a few of the evidences that question a one-size-fits-all policy approach and even more strongly advocate for locally tailor-made strategies that consider the market development level.

There are some limitations of this research. Firstly, a meta-analytic synthesis depends on the scope and quality of the existing literature. There is very little empirical evidence supporting variables such as policy incentives which can make it difficult to generalize the findings related to them. Secondly, different measurement instruments and research methodologies used in the studies included resulted in heterogeneity. However, attempts were made to systematically categorize the factors. Thirdly, the synthesis mainly focuses on the aggregate effects and ignores the individual-level differences such as demographic variations in willingness-to-pay or price sensitivity. These issues need to be looked at more closely. Future research can address these problems by extending the literature scope to include less represented regions and new electric vehicle markets. Using standardized measurement frameworks will be beneficial in lowering heterogeneity. Besides, longitudinal studies will be able to capture the changing nature of adoption drivers.Also, the combination of individual-level data with aggregate market data will reveal how the interaction of personal characteristics with structural factors happens. Also, looking at how manufacturer strategies and policy tools interaction can be a very useful way of gaining eyes- wide-closed insights into accelerating the adoption of electric vehicles. On the whole, the study is basically a framework explaining the practices leading to the growth of electric vehicles. It gives the industry's needs and sets a productive way for the research to walk on.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Conflict of Interest

There is no conflict of interest with the publication of the present manuscript.

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