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Beyond Purchase Intention: Examining the Gap Between Consumers' Willingness to Adopt Electric Vehicles and Their Actual Purchasing Behaviour

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Abstract
Purchase intention is often used as a proxy for EV adoption in the research literature, and positive intentions and current ownership refer to different behavioral stages. This study explores their empirical difference by conducting secondary analysis on a 2019 survey of 982 licensed drivers which included 238 existing EV owners, 327 conventional-car owners, and 417 respondents without cars all in Hong Kong. Nonparametric and categorical tests were used to assess group differences in seven-point intention ratings. High next-car and five-year purchase intentions were analysed using binary logistic regression among conventional-car owners (N = 324, complete cases) and existing EV ownership was analysed among car owners (N = 551). Owners of conventional cars had a next-car intention of 49.8% while EV owners had a next-car intention of 82.8%. Environmental concern/obligation, knowledge-related confidence in EV purchase and the importance of charging availability positively related to both intention outcomes. The reduced 5-year model had a Nagelkerke R^2 of 0.434 and apparent area under the ROC curve (AUC) of 0.847. The AUC of the adjusted model for existing ownership was 0.750 and was related to environmental concern/obligation, purchasing confidence and respondent sex. These results show that there are overlapping, but nonidentical, correlates of stated willingness and current ownership. This is a cross-sectional survey: there is no individual intention-to-purchase conversion. The study provides a clear, ownership-based re-reading of the literature on EV history and highlights measurement and policy issues for intention in urban settings.

Keywords: electric vehicle adoption; purchase intention; existing ownership; intention–behaviour gap; charging infrastructure; Hong Kong

Introduction

1.1 Electric Vehicle Adoption and Sustainable Mobility

The shift of internal combustion engine vehicles to electric vehicles is a well-known element of transport decarbonisation plans. EVs can have a positive environmental impact, including the elimination of tailpipe emissions, but this depends on electricity generation, manufacturing and vehicle-use conditions. According to International Energy Agency [IEA] (2026), global automotive transition has three interdependent dimensions: electric mobility, charging infrastructure and vehicle affordability and policy design. These changes have led to an even greater interest in knowing what people like about EVs, but also when a positive consumer attitude translates to EV ownership.

This question can be answered in a unique Hong Kong context. The practicality of EV use is also very relevant, given high density residential development, shared parking facilities, and the competition for access to publicly controlled charging infrastructure and the complexity of negotiating privately controlled charging spaces. Previous studies in Hong Kong examined perceived charging accessibility (He, Sun, & Luo, 2022), environmental norms and consumer purchase intentions (Sun et al., 2022), and spatial planning of charging infrastructure (He, Kuo, & Sun, 2022). In February 2026, the Hong Kong Government released its latest EV roadmap, which continues the long-term goal of phasing out the registration of new fuel-propelled private cars by 2035 or earlier and introduces a stronger focus on the development of a wider charging network (Environment and Ecology Bureau, 2026). These modern developments call for renewed interest in adoption decision-making, however, they are not necessarily in congruence with consumer attitudes measured under previous market conditions.

1.2 Purchase Intention and Actual Adoption

A stated purchase intention is widely used in research on emerging mobility technologies, as future vehicle purchases are not easily measured within the context of one survey. Although intention is an important behavioural antecedent it is not synonymous with action. The Theory of Planned Behaviour posits that intentions are determined by attitudes, perceived social expectations, and perceived behavioral control and that behavior is determined by intentions, opportunity, and control (Ajzen, 1991). More general behavioural research shows that there can be significant fluctuations in behaviour even for large changes in intention (Webb & Sheeran, 2006).

This distinction is particularly relevant to EV acquisitions. An advocate might put on an even strong front when it comes to environmental concerns, but postpone replacing a car if there isn't an easy place to park it overnight, or because of financial and household pressures. On the other hand, current owners can claim positive attitudes once they come to know and have an EV. But one time point's ownership cannot be considered as the subsequent realization of

what has been intended at another time point. The discrepancy between intention and behaviour has been the subject of recent research using simulated purchase choices that has demonstrated the importance of distinguishing between behavioural outcomes and self-reported preferences (Wang & Mohamed, 2025). A more limited but defensible comparison for the present study is to compare stated purchase intention with current ownership status and how their statistical correlates compare.

1.3 Research Gap and Problem Statement

A good amount of literature has identified that environmental concern, attitudes, prices and incentives and charging opportunities are influencing factors of EV preferences (Coffman et al., 2017; Liao et al., 2017). Research in the Hong Kong context has also tested psychological predictors of purchase intentions, the comparative importance of norms, and the availability of charging opportunities. Ng et al. (2018) analyzed purchase-intention mechanisms and Sun et al. (2022) compared the Hong Kong and Nordic context. Other studies on the 2019 survey have considered objective and perceived charger accessibility in relation to intention to adopt, or they have included estimates of demand in their charging-location planning (He, Kuo, & Sun, 2022; He, Sun, & Luo, 2022).

These contributions make it especially important to explain what added value a further analysis of the identical public survey can provide. This study is not about a new sampling exercise, a new consumer survey in 2026 or directly observing behavioural conversion. Its specific analytical contribution, however, is to structure the published survey into three groups of current owners (as a proxy for who will be buying the next car), describe the intentions to purchase a next car and a five-year car separately, estimate high-intention associations within the conventional-car-owner group, and compare them to a model of existing ownership. It also offers an explicit high-intention threshold, a sensitivity analysis and model-fit diagnostics at a lower threshold. Together this combination offers a clear comparison of results that are frequently talked about together but cannot be operationally substituted.

1.4 Research Objectives and Contributions

The study is aimed at achieving three objectives. First, it looks to see if EV purchase intentions vary between EV owners, conventional-car owners, and licensed drivers who do not own a car. Secondly, it identifies demographic and attitudinal factors that are correlated with high next-car and 5-year intentions among conventional car owners. Third, those results are compared to factors correlated to current EV ownership among the auto-owning population. These goals are stated in terms of exploratory research questions, rather than as confirmatory hypotheses.

The article does two things that contribute to the interpretation of EV adoption research. Substantively, it separates the responsibilities of environmental obligation, confidence in EV knowledge and charging availability between stated and ownership outcomes. From a methodological standpoint, it demonstrates that a one-time preference statement does not necessarily represent an observed purchase, and can therefore be avoided using the ownership-stratified secondary analysis. Implications are drawn with explicit understanding of the historical context of the survey, its nonprobability sampling and cross sectional design.

2. Literature Review

2.1 Purchase Intention and Consumer Adoption Behaviour

The Theory of Planned Behaviour is still important when it comes to preferences concerning technologies where consumers have to make a conscious decision. Attitude is defined as a positive or negative assessment, subjective norm is an evaluation of the expectations of others, and perceived behavioural control is an evaluation of perceived control to execute the behaviour (Ajzen, 1991). The framework is often expanded in EV studies to incorporate environmental values, moral norms, technology-confidence, financial barriers and infrastructure conditions. For instance, Buhmann et al. (2024) adopt the framework to gain insights into the intentions to adopt BEVs, and Prakhar et al. (2024) summarize the co-occurrence of psychological, economic and infrastructural influences throughout the literature.

One of the major drawbacks is that an intention measure is not directly related to acquisition; it is in a different temporal and conceptual domain. Sheeran (2002) demonstrates the relationship between intentions and behaviour, but not their equivalence. Even if attitudes are positive, vehicle replacement choices can involve costs, if the vehicles are not available and if the charging infrastructure is not feasible. The concept of purchase intention can thus be seen as a statement of motivational readiness which is contingent on some other unobserved practical circumstances. Moreover, Haustein and Jensen (2018) show that current EV and conventional-vehicle users may differ in terms of their demographic attributes as well as their attitudes and functional limitations. This warrants a separate consideration of ownership groups, rather than a uniform driver population of all licensed drivers.

The title of the study is the well known concept 'intention–behaviour gap', but the empirical concept needs to be precisely defined. A prospective conversion gap would involve asking respondents about their intentions to convert, and then measuring if they did purchase an EV. A cross-sectional comparison of ownership, by contrast, can determine differences in profiles and correlates but cannot determine the proportion of those who want to own but do not who go ahead and buy. Wang and Mohamed (2025) emphasize the difference, as they incorporate simulated purchase behaviour as an outcome. The present analysis adds the former, but not a longitudinal conversion estimate.

2.2 Environmental Concern and Psychological Readiness

Environmental concern and personal moral norms can provide a rationale for the motivational component of EV purchase intention. First studies focused on environmental identity, symbolism, attitude and innovativeness of potential adopters (Rezvani et al., 2015). Perceived environmental performance may be more important for attitudes toward purchasing than chosen financial or range factors, as indicated by Degirmenci and Breitner (2017). Environmental propensity and attitude are also found to be significant factors in the intention to adopt EVs (Kumar et al., 2025).

The ‘operational distinction' between environmental concern and moral obligation is relevant in this data set. There are two different statements in the questionnaire that ask whether owning an environmentally unfriendly vehicle brings a person a bad conscience and whether the person feels a duty to buy or own an environmentally friendly vehicle.

These are much nearer internalised environmental obligation than a wide-ranging multidimensional expression of environmental concern. The composite is therefore called as 'Environmental concern/obligation', where the underlying items are clearly mentioned. A positive coefficient should not be interpreted as suggesting that climate concern in general is a push towards purchasing for this specific moral norm score, rather it should be read as an association of this moral norm score with the given outcome.

Confidence that is related to knowledge may also be very significant. If the customer feels he/she is well enough informed to purchase an EV, uncertainty regarding operation, maintenance or use may not be perceived as as dangerous. The survey statement available includes a question about whether the knowledge that the respondent has makes them feel safe to purchase an EV. It thus reflects subjective buying confidence and not objective, verifiable technical safety or vehicle crashworthiness. Among the barriers for consumer acceptance cited are technological unfamiliarity and perceived risk (Egbue & Long, 2012). A confident answer to this item could thus signal less perceived uncertainty, but at the same time openness to the possibility that experience of EV ownership can boost confidence.

2.3 Economic, Infrastructural and Demographic Factors

For EV adoption, we need to bring about an alignment of motivation and conditions. Purchase price, expected operating costs, range, charging infrastructure and policy incentives are consistently cited as salient decision attributes (SDA) in the literature ((Coffman et al., 2017; Liao et al., 2017). Bjerkan et al. (2016) report on the significance of Norwegian purchase-related fiscal incentives to existing EV owners and Sierzchula et al. (2014) relate national EV adoption trends with charging infrastructure and financial incentives. Both lines of evidence do not necessarily suggest that the same policy impact will occur in the context of Hong Kong or in a specific survey sample.

There are several conceptually different dimensions to the charging domain. Availability can mean the number of chargers installed and geographical access, or expected availability in the specific areas and/or consumer expressed need for facilities. They are not intended to be used as equivalent measures. In high-density Hong Kong, He, Sun, and Luo (2022) linked the objective, perceived and prospective accessibility to charging to the adoption intention and He, Kuo, and Sun (2022) used a location-allocation approach in a contextualised way to investigate charging deployment. Budnitz et al. (2026) provide evidence for the outside of Hong Kong on how household parking can affect charging perceptions and EV adoption intentions. This survey specifically assesses the importance attributed to charging availability and the perceived inconvenience of charging and perceived charger shortage. This distinction will inform the interpretation of these models and policy discussion.

Demographic correlates may also vary from one market stage to another and from one ownership group to another. Current EV users have often been described by specific income and education levels, sex, age and driving behaviours, but the direction and strength of these relationships are different from context to context (Haustein & Jensen, 2018; Sierzchula et al., 2014). Financial capacity may enable actual acquisition, but does not necessarily have the greatest impact on attitudinal willingness. So, demographic adjustment should be performed when comparing purchase intention and ownership; however, differences should not be taken for granted as barriers or facilitators.

2.4 Analytical Framework and Empirical Expectations

The outcome areas are split into three areas – next-car EV purchase intention, 5-year EV purchase intention and current EV ownership. They have some common explanatory variables such as environmental concern/obligation, knowledge-related purchasing confidence, charging perceptions, importance of price and subsidy and demographic characteristics. The intention models are estimated among conventional-car owners, who would experience a potential change in vehicle technology if they were to buy an EV. The ownership model is an estimation of current car owners and reflects the current phase that has been achieved at the time of the survey.

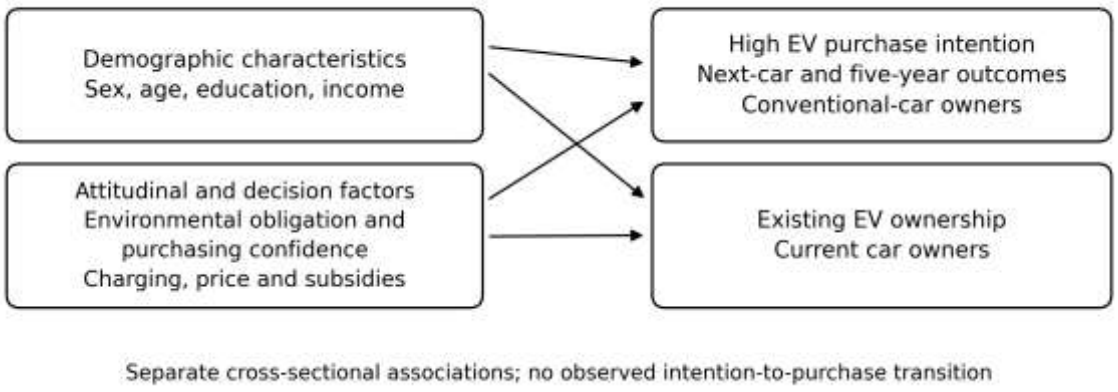

Figure 1. Analytical framework comparing stated EV purchase intention and existing ownership. Arrows denote separate hypothesised associations, not causal transitions.

The framework is deliberately associational. Variables are measured at the same time and there is no estimation of the structural causal sequence from attitude to intention to purchase and ultimately, to purchase. The descriptive comparison across all three current ownership groups gives an indication if there is a difference in willingness across the market positions investigated. Multivariable regression then finds relationships given the factors included in the model. Such separation between group comparison and adjusted association can determine which findings might be

used to suggest possible implications for consumers' engagement and which ones the data does not support.

3. Research Methodology

3.1 Research Design and Data Source

The design of this study is quantitative, cross sectional secondary data. This dataset is from Hong Kong Public Policy Research Funding Scheme project 2017.One of them, A4.037.17C, 'Promoting e-mobility in Hong Kong: Institutional and Spatial Contexts, Public Acceptance, and the Location Choice of Public EV Charging Facilities', was conducted by Sylvia Ying He at the Chinese University of Hong Kong (He, 2020). The initial online survey was conducted in March 2019 to explore purchase intentions, EV experience, charging behaviour and demographic characteristics. A survey panel, EV user alliances and social media communities were all recruited. The research team saw that its convenience sampling technique was not representative of the general population (He, 2020).

On 19 July 2024, the de-identified empirical data and dictionary were then published by Hong Kong's Chief Executive's Policy Unit on the public open data portal (Chief Executive's Policy Unit, 2024). This article is an independent reanalysis of the public csv. No additional respondents were recruited and no direct administration of the survey was conducted for this analysis, and the original project and its research team are credited as data collection and funding sources. The level of analysis is the individual licensed driver.

3.2 Study Population, Sampling and Variable Measurement

982 valid respondents were analysed in this study. Three mutually exclusive groups were created based on current vehicle ownership: 238 EV owners, 327 conventional-car owners and 417 licensed drivers who do not own any cars. These categories were developed from the car-ownership and EV-ownership indicators of the questionnaire. All responses were used for group comparisons. For the multivariable intention analyses, the selection was completed for conventional-car owners followed by complete cases, resulting in 324 respondents. The ownership model included 551 out of 565 current car owners (227 EV owners and 324 conventional-car owners) with complete information on the specified covariates.

The reported probability of buying an EV in the future (next purchase and next 5 years) was measured using two single item questions. Both were measured on a seven-point ordered scale, where higher responses are indicative of stronger intention. The scores for regression were coded as high intention (5-7) and lower intention (1-4). Sensitivity tests were performed using a tighter definition (6–7 vs. 1–5). These cutoffs do not represent thresholds that have been tested against subsequent purchase data. Ownership of an EV was coded as 1 and of a non-EV car as 0; those who did not own a car were not included in this model.

Table 1. Analytical variables and operational definitions

Variable	CSV field(s)	Operational definition
Next-car purchase intention	int_next	Seven-point intention rating; high = 5–7; strict = 6–7
Five-year purchase intention	int_5y	Seven-point intention rating; high = 5–7; strict = 6–7
Existing EV ownership	car_own; ev_own	Binary status within current car owners: EV = 1, conventional = 0
Environmental concern/obligation	v16; v17	Mean of bad-conscience and obligation items (1–7); α = 0.822
Purchasing confidence	v4	Single item: feeling safe buying an EV given existing knowledge (1–7)
Charging inconvenience	c1; c2	Mean of home/public charging inconvenience (1–7); α = 0.758
Charging scarcity	c5; c6	Mean of too-few/hard-to-find charging statements (1–7); α = 0.837
Charging availability importance	factor_charge	Single-item rated decision importance (1–7); not objective access
Price and subsidy importance	factor_price; factor_sub	Two distinct single-item importance ratings (1–7)
Demographic characteristics	sex; age; edu; income	Sex coded categorically; other covariates entered as ordered category trends

Note. All substantive attitude or importance items are rated from 1 to 7. α = Cronbach's alpha. The ownership outcome is not a later purchase following the measured intention.

The environmental concern/obligation score is the average of two seven-point items: bad conscience of car ownership that is bad for the environment and felt obligation to own an environmentally friendly car. Perceived charging inconvenience is the average of home-charging inconvenience and public-charging inconvenience items, while perceived scarcity is the average of too few charging stations and hard to find charging items. An extra single question assesses the respondent's sense of safety when buying an EV based on his or her personal knowledge level. Three 7-point importance ratings focus on vehicle purchase price, availability of charging stations and government subsidies. Demographic covariates are sex, age group, educational attainment and monthly income category. In the fitted models, the category trends for age, education and income were coded as ordered numeric category trends, an explicit modelling assumption rather than as an assumption of equal underlying socioeconomic distances.

3.3 Data Preparation and Measurement Checks

The CSV file (54 columns) was imported into IBM SPSS Statistics 26 with explicitly defined variable types. Response codes and skip-pattern fields were reviewed against the public data dictionary and missing data were coded as missing, not as substantive zero. Respondent codes and counts of ownership groups/complete case sample sizes were reviewed prior to modelling. Scale meaning was only computed when both the source items were observed. This eliminated the need for composite scores of conceptually different single item importance ratings.

Cronbach's alpha was checked for internal consistency for every composite of two items. The alpha values for charging inconvenience, charging scarcity, and environmental concern/obligation were 0.758, 0.837, and 0.822, respectively. A one factor principal axis exploratory factor analysis of the four charging-perception items yielded KMO = 0.769 and a significant Bartlett test, chi-square(6) = 1,742.519, $p < 0.001$. The charging items were not combined into a composite charging scale for the regressions, however, because there are different substantive meanings for perceived inconvenience and perceived scarcity. The a priori checks outlined here are for internal consistency and exploratory structure but do not provide full construct validity.

3.4 Statistical Analysis

Current ownership group descriptive distributions and high-intention percentages were calculated. Differences between the three groups in the seven levels of intention outcomes were tested using Kruskal-Wallis tests and Mann–Whitney tests between EV owners and conventional-car owners. Binary high-intention proportions were compared using chi-square tests, Cramér's V summarised high-intention association strength. These analyses kept the original ordinal outcomes, if applicable.

The adjusted association for high next-car intention and high five-year intention among conventional-car owners was estimated using binary logistic regression. Eleven demographic and attitudinal predictors were included in the next-car model. The main specification was a four-predictor model with four years of data, and without education, because it was felt to be more parsimonious. It was chosen because an eleven-predictor model, having a significant Hosmer–Lemeshow statistic, was compared with a simpler theory-guided specification. The original full 5-year model was kept as model comparison result. Car owners were asked about their current EV ownership and correlates of current EV ownership were assessed using an eleven-predictor logistic regression. Sex was modelled categorically, and other ordered demographic covariates were modelled as numerical category trends, with men as the reference.

Analyses include adjusted odds ratios (ORs), 95% confidence intervals (CIs), likelihood-ratio chi-square tests, Nagelkerke pseudo-R2, Hosmer–Lemeshow statistics and the area under the receiver operating characteristic curve (AUC). All of the classification rates are based on the default probability cutoff value of 0.50. Sensitivity analyses were conducted by redefining high intention as scores 6-7 and by parameterising less in the smaller event groups using parsimonious models with 6 predictors. The original seven-category proportional-odds models did not meet the assumption and sparse-cell diagnostic criteria and so were not used for main inference. Apparent AUC and classification is in-sample performance and not evidence of externally validated prediction (Steyerberg et al., 2010). A conventional level of significance was set at two-sided $p < 0.05$, and effect sizes and uncertainty intervals were used to interpret the results.

4. Results

4.1 Sample Characteristics and Existing EV Ownership

There were 982 licensed drivers who responded: 238 EV owners (24.2%), 327 conventional-car owners (33.3%) and 417 respondents without cars (42.5%). 42.1% of the 565 car-owning respondents were EV owners. This is not a penetration estimate for EV among Hong Kong population or registered vehicles but a carefully chosen study sample. There was a male predominance in sex distribution with 638 (65.0%) males out of the 982 response. The majority (679, 69.1%) had a bachelor's or postgraduate degree. The features are similar to what was reported in the original report for a nonprobability recruitment design.

Table 2. Selected respondent characteristics by current ownership group

Characteristic	EV owners (n = 238)	Conventional (n = 327)	Without cars (n = 417)
Men	183 (76.9)	189 (57.8)	266 (63.8)
Age ≤34	82 (35.0)	138 (42.2)	138 (33.2)
Age 35–54	129 (55.1)	156 (47.7)	241 (57.9)

Characteristic	EV owners (n = 238)	Conventional (n = 327)	Without cars (n = 417)
Age ≥55	23 (9.8)	33 (10.1)	37 (8.9)
Bachelor's/postgraduate degree	183 (76.9)	232 (70.9)	264 (63.3)
Income ≥HK$40,000/month	117 (50.0)	107 (32.9)	81 (19.5)

Note. Entries are n (% among respondents with nonmissing data on that characteristic). Age and income have limited missing responses. Group proportions reflect convenience sampling.

Significant differences in group composition are seen in Table 2. The EV-owner group included more men (76.9%) than women (57.8%) in the conventional-car group. A higher percentage of EV owners than conventional-car owners and respondents without cars earned HK$40,000 or more monthly. These descriptive patterns suggest that there may be demographic confounding in comparing attitudes or intentions across groups and justify the adjustment ownership regression. As population-weighted estimates, overall source-sample statistics should not be interpreted.

4.2 Reliability and Measurement Assessment

The three two-item scales showed acceptable to good alpha values of 0.758 for charging inconvenience, 0.837 for charging scarcity and 0.822 for environmental concern/obligation. The KMO statistic for the charging-item was 0.769, showing an adequate correlation pattern for exploratory factor analysis, and Bartlett's test showed a correlation matrix that was not an identity matrix, chi-square(6) = 1,742.519, $p < 0.001$. The exploratory extraction of principal axes indicated that one common charging factor was used, but the factor score was not used in the analysis in place of the two separately defined charging composites.

The results suggest that the observed composite scores can be used for exploratory association analysis. They should not be interpreted as meaning that confidence in buying an EV, charging-availability importance or government-subsidy importance were separately measured multi-item latent variables. Those variables are still single question indicators and conclusions are on the wording of the questionnaires.

4.3 Purchase Intention Across Current Ownership Groups

High next-car EV intention was reported by 197 of 238 EV owners (82.8%), 163 of 327 conventional-car owners (49.8%) and 247 of 417 respondents without cars (59.2%). The corresponding five-year figures were 161 (67.6%), 168 (51.4%) and 199 (47.7%), respectively. For EV owners, strong next-car intention is likely to be understood as a likelihood of purchasing an EV again rather than as initial EV adoption. The most relevant segment to study for a potential transition to conventional-car ownership is conventional-car owners.

Table 3. High EV purchase intention by current ownership group

Ownership group	n	Next-car, scores 5–7	Five-year, scores 5–7
EV owners	238	197/238 (82.8%)	161/238 (67.6%)
Conventional-car owners	327	163/327 (49.8%)	168/327 (51.4%)
Without cars	417	247/417 (59.2%)	199/417 (47.7%)

Note. Percentages are within each ownership group. Next-car: $\chi^2(2) = 65.308$, $p < .001$; five-year: $\chi^2(2) = 25.328$, $p < .001$.

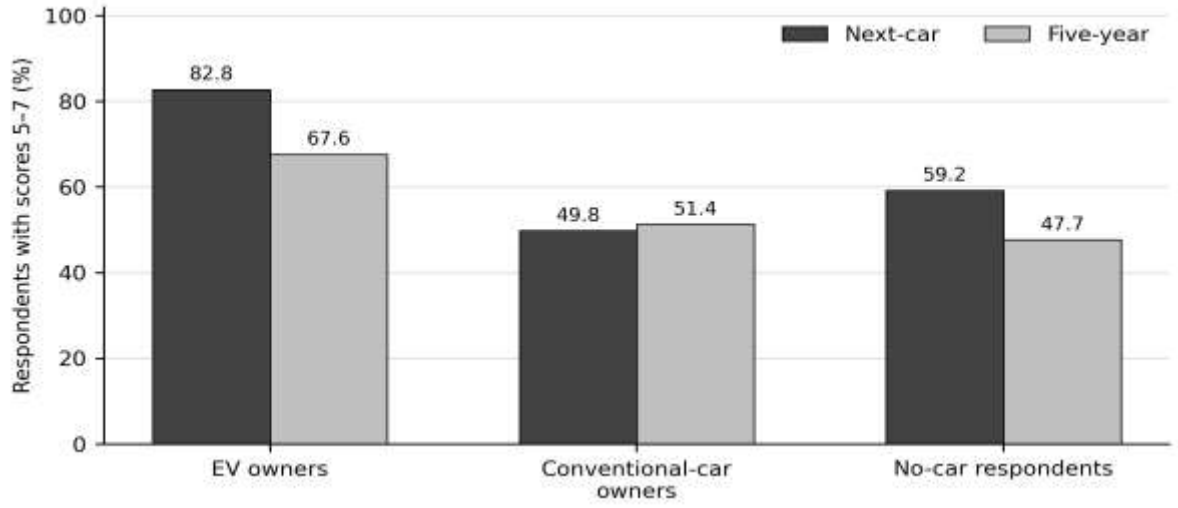

Figure 2. Proportion of respondents scoring 5–7 on next-car and five-year EV purchase intention, by current ownership group. Source: secondary analysis of the 2019 Hong Kong survey.

Differences in distribution of original seven-point ratings were found among the three groups on next-car intention (Kruskal–Wallis H = 104.764, p < 0.001) and five-year intention (H = 37.075, p < 0.001). Mann–Whitney comparisons of both outcomes were also significant when comparing the two groups (EV owners and conventional-car owners; both p < 0.001). When the intention variables were dichotomised at 5–7, ownership group was associated with next-car intention, chi-square(2) = 65.308, p < 0.001, Cramér's V = 0.258, and five-year intention, chi-square(2) = 25.328, p < 0.001, V = 0.161. The higher (next-car) association indicates that the next-vehicle intention is more distinct from current ownership status than the overall five-year expectation. These are inter-group, not intra-individual changes.

4.4 Next-Car Purchase Intention Regression

The next-car logistic model included 324 complete cases, consisting of current conventional-car owners, including 162 high-intention respondents. Likelihood-ratio chi-square(11) = 115.923, p < 0.001, and Nagelkerke R^2 = 0.401 indicated that the eleven-predictor model outperformed the intercept-only specification. Based on the Hosmer–Lemeshow test, the test was nonsignificant (p = 0.603) and the apparent AUC was 0.827 with an overall in-sample classification accuracy of 75.3%.

Table 4. Adjusted associations with high EV purchase intention (scores 5–7)

Predictor	Next-car OR (95% CI)	p	Five-year OR (95% CI)	p
Female vs male	0.700 (0.400–1.225)	0.212	Not included	—
Age group	0.967 (0.733–1.276)	0.813	Not included	—
Education category	1.069 (0.773–1.477)	0.688	1.303 (0.963–1.765)	0.087
Income category	0.928 (0.776–1.109)	0.412	Not included	—
Environmental concern/obligation	1.726 (1.322–2.252)	<0.001	1.724 (1.322–2.249)	<0.001
Charging inconvenience	0.875 (0.637–1.202)	0.409	Not included	—
Charging scarcity	1.101 (0.781–1.553)	0.583	Not included	—
Purchasing confidence	1.681 (1.318–2.144)	<0.001	1.933 (1.507–2.479)	<0.001
Purchase-price importance	1.151 (0.822–1.612)	0.412	Not included	—
Charging-availability importance	1.355 (1.027–1.789)	0.032	1.723 (1.351–2.198)	<0.001
Government-subsidy importance	1.266 (0.935–1.714)	0.127	Not included	—

Note. Conventional-car owners; n = 324. Next-car model includes 11 predictors; final five-year model includes 4. OR = adjusted odds ratio; CI = confidence interval. Sex reference = male; other ordered demographic coefficients represent per-category increments. p-values < .001 shown as <0.001.

There was a positive association between next-car intention and environmental concern/obligation (OR = 1.726, 95% CI 1.322–2.252, p < 0.001). The level of confidence with knowledge also had a positive correlation with EV purchase (OR = 1.681, 95% CI 1.318–2.144, p < 0.001). An increase of 1 point in the importance of charging availability increased the likelihood of high intention by 36% (OR = 1.355, 95% CI 1.027 – 1.789, p = 0.032). The other covariates charging-inconvenience, charging-scarcity, purchase-price-importance and subsidy-importance were not statistically significant in the adjusted specification. The positive charging coefficient represents the value that is placed on the availability of charging when purchasing, not objectively measured infrastructure provision.

4.5 Five-Year Purchase Intention Regression

The final 5-year model was estimated with the same 324 conventional-car owners, 166 of whom were in the 5-7 high-intention group. The reduced four-predictor model was statistically significant (likelihood-ratio chi-square(4) = 127.574, p < 0.001), with Nagelkerke R^2 = 0.434, apparent AUC = 0.847. Its Hosmer–Lemeshow statistic was chi-square(8) = 14.499, p = 0.0696. If it is a nonsignificant result at the 5% level, that's one thing, but not proof of perfect calibration. The accuracy of overall classification was 78.1%.

Five-year high intention was positively related to the environmental concern/obligation index (OR = 1.724, 95% CI 1.322–2.249, p < 0.001). Confidence in purchasing an EV given the respondent's knowledge yielded OR = 1.933 (95% CI 1.507–2.479, p < 0.001), while charging-availability importance yielded OR = 1.723 (95% CI 1.351–2.198, p < 0.001). The reduced model showed a positive but not statistically significant association for education (OR = 1.303, 95% CI 0.963–1.765, p = 0.087). All three main attitudinal associations consequently emerged in both intention horizons, albeit with different levels of magnitude.

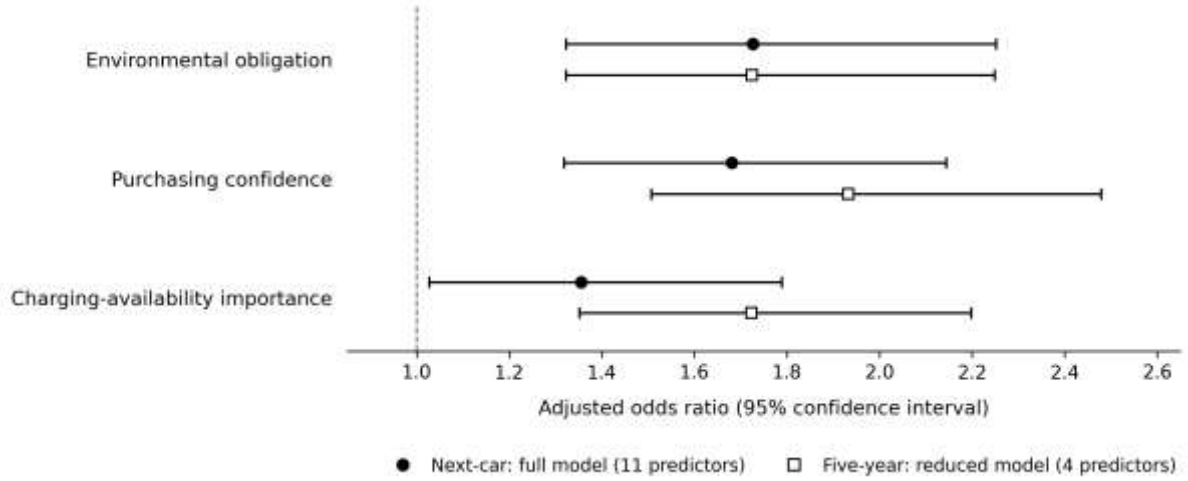

Figure 3. Adjusted odds ratios for the three common attitudinal correlates of high intention. Next-car estimates are from the full model; five-year estimates are from the reduced model. Horizontal whiskers show 95% confidence intervals.

The AUC for the original eleven-predictor five-year model was slightly higher (0.853), but the Hosmer-Lemeshow test was significant ($p = 0.0044$). No statistically significant difference was found between the reduced and the full model as evidenced by the lower Akaike information criterion (AIC 331.39 versus 339.55) and chi-square(7) = 5.839, $p = 0.559$. It had a slightly higher brier score (0.1589 vs. 0.1553), and the reduced specification might be wished as more parsimonious and diagnostically less challenging, but not as uniformly superior with regard to every measure of prediction.

4.6 Factors Associated With Existing EV Ownership

Of the 551 complete-case car owners, 227 owned an EV and 324 owned a conventional car. The eleven-predictor model with the adjustments made to it significantly improved upon the null specification, likelihood-ratio chi-square(11) = 103.362, $p < 0.001$, with Nagelkerke $R^2 = 0.230$. Apparent AUC was 0.750 (95% CI 0.709–0.792), overall classification accuracy 69.3%, and the Hosmer–Lemeshow p-value 0.325. Overall, the accuracy was affected by identification of conventional-car owners, with the model correctly identifying about 51.5% of EV owners, using the 0.50 probability cutoff.

Table 5. Adjusted factors associated with existing EV ownership

Predictor	Adjusted OR (95% CI)	p
Female vs male	0.571 (0.377–0.865)	0.008
Age group	1.149 (0.948–1.391)	0.156
Education category	1.191 (0.943–1.505)	0.142
Income category	1.098 (0.971–1.242)	0.134
Environmental concern/obligation	1.188 (1.016–1.388)	0.031
Charging inconvenience	0.909 (0.755–1.094)	0.313
Charging scarcity	1.004 (0.819–1.231)	0.972
Purchasing confidence	1.567 (1.325–1.853)	<0.001
Purchase-price importance	0.869 (0.706–1.070)	0.186
Charging-availability importance	1.053 (0.868–1.279)	0.599
Government-subsidy importance	0.868 (0.734–1.027)	0.100

Note. n = 551 current car owners (227 EV owners, 324 conventional-car owners). Reference group for sex = male. Covariates are measured contemporaneously with ownership; coefficients are associational.

Relative to men, women had lower adjusted odds of existing EV ownership (OR = 0.571, 95% CI 0.377–0.865, $p = 0.008$). Environmental concern/obligation (OR = 1.188, 95% CI 1.016–1.388, $p = 0.031$) and knowledge-related purchasing confidence (OR = 1.567, 95% CI 1.325–1.853, $p < 0.001$) were positively associated with ownership. After adjustment, income, charging-availability importance and perceived charging inconvenience and perceived charging scarcity were not statistically significant. Notably, the charging-importance item in this multivariable specification is not related to ownership. This gap is descriptive and provides evidence of associations in the pattern of charging preferences with outcomes; it does not mean that charging preferences are no longer relevant once a purchase is made.

4.7 Robustness Checks and Model Diagnostics

A high-intention threshold change was tested by changing scores from 5 to 7 to scores from 6 to 7 in a sample of 324

conventional-car owners, which resulted in a lessening of the number of positive cases to 57 for next-car intention and 82 for five-year intention. The sensitivity models with the six predictors were parsimonious and statistically significant with apparent AUCs of 0.861 and 0.863, respectively. Their Hosmer–Lemeshow tests were not significant. The pattern of positive associations held for confidence in buying an EV and charging-availability importance with the stricter cutoff, and for environmental concern/obligation with the strict next-car intention ($p = 0.061$).

Table 6. Regression diagnostics and strict-threshold sensitivity

Model	n	LR χ^2 (df)	Nag. R^2	AUC	Accuracy (%)	HL p
Next-car intention, 5–7	324	115.92 (11)	0.401	0.827	75.3	.603
Five-year intention, 5–7	324	127.57 (4)	0.434	0.847	78.1	.0696
Current EV ownership	551	103.36 (11)	0.230	0.750	69.3	.325
Next-car intention, 6–7	324	91.15 (6)	0.405	0.861	84.0	.703
Five-year intention, 6–7	324	119.18 (6)	0.454	0.863	81.2	.171

Note. All reported AUC and classification metrics are apparent (in-sample). HL = Hosmer–Lemeshow test; LR = likelihood-ratio. The primary five-year model is the reduced four-predictor specification. HL p-values reflect SPSS output, not deciles independently reconstructed outside SPSS.

There was no indication of severe collinearity issues as the largest variance inflation factor (VIF) recorded during the auxiliary multicollinearity was 2.024. Strict sensitivity to next car, however, was only 33.3% with an overall accuracy of 84.0% and 51.2% for the five-year strict model. The numbers warn against using a high overall accuracy as an indicator of accurate predictions for individuals. An independent test sample, temporal validation or external sample was not available and the ROC measures should be considered apparent in-sample discrimination.

5. Discussion

5.1 Interpretation of Principal Findings

The study makes a distinction between three empirical observations. For one, reported purchase intention for EVs varies significantly based on current vehicle ownership. Second, conventional-car owners who have high next-car and five-year intentions have positive relationships with environmental concern/obligation and confidence based on their own EV knowledge, as well as the importance of charging availability. Third, the distribution of EV ownership is linked to environmental concern/obligation and purchasing confidence, and is also statistically different regarding sex distribution. It is noteworthy that the intention and ownership models overlap, but for this set of data, the difference in the charging-importance coefficients indicates that intention and ownership should not be considered interchangeable dependent variables.

The ownership-group comparison can be helpful but is not to be interpreted without caution. Owners of EVs were more likely to say they had a high next-car intention than owners of conventional cars, possibly the result of satisfaction with their car, familiarity with EV use, or a preference to retain an electric drivetrain. They do not necessarily represent those who changed their minds from what is reported in this survey at the present time. Similarly, 49.8% of car owners who indicated a high likelihood of buying their next car as conventional cars is not an indication that half of these respondents eventually bought EVs. Observed percentages denote a reserve of stated willingness at the 2019 survey date and are dependent on the wording of the survey question and the nonrepresentative sample.

It is important to note the pattern of adjusted associations. Environmental obligation was found to have a significant positive role for both main intention horizons and existing ownership, which is in line with the argument that moral evaluations can lead to preferences related to EVs. There was a relatively high correlation between intentions and ownership and knowledge-related purchasing confidence. Charging availability importance, on the other hand, was found to be significant for stated intention and not existing ownership. This is not reduced to an infrastructure effect because the scale measures rated importance, not access. It could also be the result of varying experiences with respondents, and unmeasured household parking options, or reverse causality where respondents had already purchased an EV.

5.2 Comparison With Previous Research

The general function of environmental motivation aligns with EV adoption reviews that have shown personal norms, environmental concern and positive attitudes to be recurrent correlates of EV consumer acceptance (Prakhar et al., 2024; Rezvani et al., 2015). It also resembles the results of Degirmenci and Breitner (2017), who identified the importance of perceived environmental performance for EV purchase intentions. In the current study, however, this composite refers to felt responsibility and conscience, and is more limited in scope than a broader construct of environmental attitude. In this survey, the continuousness of its coefficient is a proof of association, not a general causal law.

Due to the importance of subjective purchasing confidence, this is in line with previous reports on EV acceptance which have shown a lack of familiarity and perceived technological risk (Egbue & Long, 2012). A more modern behavioural interpretation to this is that knowledge can enable confidence to consider an unfamiliar vehicle technology. The explanation is provisional as subjective confidence might be a result of EV post purchase. Thus, the effect of selection into EV ownership on the cross-sectional ownership regression cannot be separated from changes in attitudes after EVs have been adopted.

Existing Hong Kong work needs to be interpreted as well in the light of charging considerations. Sun et al. (2022) examined environmental norms and EV purchase intentions in Hong Kong, whereas He, Sun, and Luo (2022) investigated objective, perceived, and prospective charger accessibility. In contrast, He, Kuo, and Sun (2022) examined the spatial planning of public charging infrastructure using a contextualised location-allocation model. The current analyses are drawn from the same or similar research programme and hence the findings should be viewed as a secondary analysis of the same data and not as a new confirmation with a new sample. An extra advantage of it is that it allows for transparency in comparing ownership-stratified high-intention regressions with a separate current-ownership model and explicit threshold sensitivity.

Comparisons with research in other markets provide perspective and do not lend to simplistic generalisation. The results of Haustein and Jensen (2018) indicated that there were different psychological and functional profiles for the ownership groups, which is why they were separated in the present study. Adoption-intention studies should be focused on the residential parking and charging constraints, as Budnitz et al. (2026) shows. Results from Norway suggest that fiscal policy can play a large role in a particular policy context (Bjerkan et al., 2016). Since the Hong Kong data provides information on the importance of subsidies as perceived by the respondents and not the subsidy exposure exogenously varied, the inability to find a significant adjusted subsidy-importance coefficient does not prove that tax concessions are ineffective.

The approach of the intention–behaviour gap adopted in the paper is congruous with other papers in the behavioural literature. Webb and Sheeran (2006) demonstrate that intention strengthening does not necessarily lead to the same level of behaviour change. Wang and Mohamed (2025) add another simulated purchase outcome to the EV research literature, and demonstrate the type of design required to study discrepancies more directly. The findings from the present cross-sectional data show that there are partly different correlates to different groups and to different types of outcome, but not an estimate of the individual probability of the expression of intention materializing as an EV purchase.

5.3 Theoretical and Policy Implications

The basic theoretical proposition is to maintain the separation between motivation to adopt and actual adoption. The results of the regressions of stated intentions to buy on environmental obligation and purchasing confidence are comparable across the regressions of ownership. However, care must be taken in comparing the coefficients, since the intention sample consists of conventional-car owners, the ownership sample consists of both EV and conventional-car owners, and the attitudes were measured concurrently with ownership. This strengthens the argument for EV adoption plans including concrete timelines for measuring outcomes, definitions of outcomes and the role of concrete purchase opportunities.

The second implication is related to the level of granularity of infrastructural measurement. Charging access is meaningful and a decision criterion, but is not the same as public charger density or right to install charger at home or confirmed charger usability. Future datasets should link individual vehicle intentions and purchases with parking at home, availability of charging stations, and charging rates in each area. The chargers accessibility studies show that these dimensions are particularly important in compact cities (He, Sun, & Luo, 2022). Increased linkage would make a larger distinction between the unmet need for practical facilities and a general preference for convenient facilities.

The historical boundary of the data should also be taken into account in interpreting the policy. Changes in EV models, charging and fiscal arrangements lagged significantly behind the 2019 survey. In February 2026, Hong Kong's revised roadmap reiterated the long-term path of electrifying its road transport, with a focus on expanding the charging network (Environment and Ecology Bureau, 2026). In parallel, tax exemptions for first-registered electric private cars, such as the One-for-One Replacement Scheme, expired on 31 March 2026, and with a specific transitional period (Hong Kong Special Administrative Region Government, 2026). While these developments provide context to the 2019 regression values, the coefficients do not measure the impact of the developments.

In that scope, the results point towards the necessity of considering clear information about EVs, confidence-building opportunities, and reliable charging infrastructure. If the public has to be informed, it is important to distinguish between vehicle technology and the requirements for use, and charging policy should pay attention to practical availability and distribution of charging facilities rather than simply the number of installed charging stations. Existing ownership gaps also indicate the importance of taking into account the potential actor of purchase preferences in terms of demographics. They are not tested interventions, but wise guesses at associative evidence.

5.4 Limitations and Directions for Future Research

Firstly, there is no prospective behavioural follow-up. Current ownership and current purchase intention were measured concurrently; thus, it is not possible to determine what percentage of those who intended to buy EVs went ahead and did, or how much time passed between the two, or what percentage of those who intended to buy EVs did.

The second constraint is sampling. The original convenience sample targeted EV owners and economically privileged licensed drivers, and the intention prevalence and group shares were not necessarily representative of the general adult population of Hong Kong and vehicle fleet (He, 2020).

Third, the measures are self-report and contain single item indicators that could be vulnerable to response style and common method variation. Seven-point intention outcomes can be dichotomized to allow for logistic comparisons, but at the cost of providing information on order and being based on an arbitrary cutoff point. This dependence is somewhat alleviated through the more stringent 6–7 sensitivity analysis, but not eliminated. The assumption of ordered coding for age, education and income is a linear trend in log-odds, which was not independently confirmed with fully categorical contrasts. This 5-year model was a reduced version, based on fit diagnostics in the same sample, and the performance is exploratory, rather than prospectively validated. Before use for prediction at an individual level, out-of-sample verification of calibration, apparent AUC and classification rates is required.

Fourth, the data set doesn't directly measure total cost of ownership, objective access to household charging, confirmed

availability of infrastructure or EV purchasing timing. There can be reverse causation, as the current EV ownership could affect perceived confidence or environmental identity. Lastly, market conditions shifted between the 2019 fieldwork and current policy conditions. A better future study would involve a random selection of people or a well-designed sample, and capture initial plans and barriers to buying a vehicle and charging access, before following up on vehicle purchases and charging access over time. Longitudinal data on events would allow a direct evaluation of intention realisation and help to determine whether the factors that were found to be related to willingness also predict actual purchase behavior.

6. Conclusion

This study reanalysed a public EV survey to explore how stated purchase intentions differ among EV ownership groups and differences between the associations of stated purchase intentions and current EV ownership. There are significant differences in stated "next car" intentions by current market position, with about half of conventional-car owners and more than four-fifths of current EV owners indicating that they would purchase an EV. For conventional-car owners, environmental concern/obligation, knowledge-related confidence for EV purchase and charging availability were found to have a positive relationship with next-car and 5-year high intention. In addition, there were positive relationships between existing EV ownership and environmental concern/obligation and purchasing confidence and an adjusted demographic difference by sex. Good but non-definitive fit diagnostics were obtained from the final reduced five-year model, which provided a parsimonious account of the corresponding intention outcome.

Results of the findings show that there is a relationship between stated willingness to adopt and current EV ownership, which are conceptually different measures of EV adoption. Importantly, the study failed to measure the conversion of intentions to purchase as the intentions and purchase behavior were not observed longitudinally. Its contribution is in the transparent comparison across ownership strata, careful operationalisation of the attitudinal and charging-related measures, and explicit recognition of the limits of historical cross sectional evidence. Future, longitudinal studies should link purchase intentions with actual vehicle acquisition and with independently-measured charging opportunities. This evidence is required to identify the policy and consumer constraints that hinder the shift from EV intention to EV purchase.

Data Availability and Acknowledgement

The de-identified CSV and data dictionary is publicly accessible at the Chief Executive's Policy Unit, Government of the Hong Kong Special Administrative Region, under Public Policy Research Funding Scheme (2017) project.A4.037.17C (https://data.gov.hk/en-data/dataset/hk-cepu-prfs-funding-scheme-project-no-2017-a4-037-17c). The research team at the Chinese University of Hong Kong led by Sylvia Ying He originally did the project, funded by the Public Policy Research Funding Scheme of the Hong Kong Special Administrative Region Government. The current article is a stand-alone secondary analysis, and the data collectors and funder are credited appropriately.

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